Agents for educational games and simulations

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Workshop on the uses of Agents for Education, Games and Simulations

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Preface

Training for complex situations in human societies such as in education, business transactions, military operations, medical care and crisis management can be provided effectively using serious games and simulations. In these types of games and simulations the role of agents to model and simulate naturally behaving characters becomes more and more important. Especially in situations where the games are not just meant to provide fun, but are used to support the learning process it is important that the games achieve their goal and do not just distract (or entertain) the trainee. This workshop bringe sogether several strands that have been developing in a number of different workshops at AAMAS over recent years, and provides an opportunity to discuss common issues and to develop common understanding.

A major aim of this workshop is to discuss how to model rational (or non-rational, but natural) behaving agents who are embedded in a social context with other characters and humans. This is especially important when both characters and humans can be pro-active but also have to react to the behaviour of others in their environment. Thus these characters should have some social conscience of themselves and others and base their decisions for actions on this knowledge. Of course social knowledge may consist of detailed knowledge such as that some person has been your long time friend and thus can be trusted to help you, but also general knowledge such as that society looks bad at people that cheat but adores people that grasp opportunities. Thus we aim to model also different levels of action and interactions. Both the operational ones such as gestures and general way of animating characters, the tactical decisions such as negotiation tactics when trying to get some help and long term strategies such as behaving cooperative towards your boss in order to secure a promotion. One of the interesting questions is how these should be modelled and how they interact? And how do current agent architectures support these models?

In general the technologies used in game engines and multi-agent platforms are not readily compatible due to some inherent differences of concerns. Where game engines focus on real-time aspects and thus propagate efficiency and central control, multi-agent platforms assume autonomy of the agents. And while the multi agent platforms offer communication facilities these can or should not be used when the agents are coupled to a game. So, although increased autonomy and intelligence may offer benefits for a more compelling game play and may even be necessary for serious games, it is not clear whether current multi agent platforms offer the facilities that are needed to accomplish this.

The workshop therefore four main themes:

1. Technical
   What techniques are suitable for agents that are incorporated in educational contexts, games and simulations. How to balance intelligence and efficiency? How to couple the agents to the game or simulation and manage this couplings information flow? How to deal with the inherent real time nature of the game engine environment? How to couple long and short time interactions?
2. Conceptual
   What information is available for the agents' use, either through the educational context, or from the system, through for example, the game or simulation engine? How can reaction to events be balanced with goal directed behaviour? How are ontological differences between information used by agents and information from the domain handled? How do we choose the actions of an agent? Too high level gives little control; too low level makes the agent inefficient.
3. Design
   How do we design interactive systems containing intelligent agents? How do we determine what agents should do and should not do, such that local autonomy and story line are well balanced. How do we design the agents themselves that are embedded in other (possibly diverse) systems (including the behaviour authoring tools and methodologies)?
4. Education
   It is also important that we introduce both the design and construction of these collaborative autonomous systems into the computer science curriculum and develop ways of encouraging their

effective utilisation across the curriculum. Contributions to the workshop will be welcomed that provide a mixture of relevant theoretical and practical understanding of both the teaching and use of multi-agent systems in educational and entertainment research, together with practical examples of the use of such systems in real application scenarios. These will be written for students, teachers, producers, directors and other professionals who want to improve their understanding of the opportunities offered by the use of multi-agent systems in teaching and entertainment scenarios of all types.

These are all issues that will become increasingly important as agents are used increasingly to assist interactions with social and other media. One interesting trend in the papers presented is the interaction of agents with cooperative immersive environments, such as Second Life, which raises a number of technical and social issues that will need to be explored further in later workshops.

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Contents

Dialogues and Learning

Interfacing a Cognitive Agent Platform with Second Life

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Abstract. Second Life is a popular multi-purpose online virtual world that provides a rich platform for remote human interaction. It is increasingly being used as a simulation platform to model complex human interactions in diverse areas, as well as to simulate multi-agent systems. It would therefore be beneficial to provide techniques allowing high-level agent development tools, especially cognitive agent platforms such as belief-desire-intention (BDI) programming frameworks, to be interfaced to Second Life. This is not a trivial task as it involves mapping potentially unreliable sensor readings from complex Second Life simulations to a domain-specific abstract logical model of observed properties and/or events. This paper investigates this problem in the context of agent interactions in a multi-agent system simulated in Second Life. We present a framework which facilitates the connection of any multi-agent platform with Second Life, and demonstrate it in conjunction with an extension of the Jason BDI interpreter.

1 Introduction

Second Life [1] is a popular multi-purpose online virtual world that is increasingly being used as a simulation platform to model complex human interactions in diverse areas such as eduction, business, medical and entertainment. This is mainly because of the rich platform it provides for remote human interactions, including the possibility of enabling software-controlled agents to interact with human-controlled agents. Second Life is more sophisticated than conventional 2D simulation tools, and is more convenient than cumbersome robots, thus it has started to gain attention as a simulation platform for testing multi-agent systems and other AI concepts. It would therefore be beneficial to provide techniques allowing high-level agent development tools, especially cognitive agent platforms such as belief-desire-intention (BDI) programming frameworks, to be interfaced with Second Life.

When interfacing agent platforms with Second Life, there are two important aspects to be addressed: how the sensor readings from Second Life environments are mapped to a domain-specific abstract logical model of observed properties and/or events, and how the agent actions are performed in the Second Life virtual environment. The first aspect can be quite complex when considering the high volumes of potentially unreliable sensor readings an agent receives. As for the latter, it is important to identify ways of correctly interfacing the agents with their representation module inside Second Life (the Second Life avatar), because Second Life may have synchronization issues with respect to carrying out the actions specified by the agent model.

With the use of the *LIBOMV* client library [2], we have developed a framework that facilitates the connection of any multi-agent framework with Second Life and addresses the above challenges. The main focus of this paper is to highlight the importance and difficulty of creating an abstract logical model of the sensory inputs of an agent deployed in Second Life, and to present the solution we developed in our connection framework to address this problem.

Creating a high-level abstract logical model of agent sensory data involves two main steps: extracting sensory readings from Second Life accurately, and formulating a high-level domain-specific abstract logical model to be passed to an agent's cognitive module. The latter has not gained much attention in the related research with respect to deploying intelligent agents inside Second Life.

In our framework, an agent deployed in Second Life can sense the Second Life environment around it with the use of its LIBOMV client, and the framework records these sensor readings. There are some difficulties in obtaining accurate sensor readings from Second Life simulations. Therefore we have introduced a novel technique in our framework, which extracts sensor readings from Second Life more accurately than the commonly used data extraction methods.

The extracted sensory data result in a high volume of low-level information (avatar and object position information and avatar animation information), making it difficult to directly use these data in an agent's reasoning process. In order to convert this low-level information into a form that can be used by the multi-agent system, we employ a complex event processing mechanism and identify the high-level domain-specific complex events embedded in the retrieved low-level data. The output of the framework is a snapshot of the Second Life environment that contains all the low-level and high-level events and other contextual information that took place in a given instant of time, encoded as propositions. This provides an agent a complete view of the environment around it, thus eliminating the possibility of having to base its reasoning on a partial set of data.

We also note that our framework facilitates the co-existence of agents belonging to multiple agent platforms in the same Second Life simulation. In this paper, we demonstrate this framework in conjunction with an extension of the Jason BDI interpreter that allows agents to specify their expectations of future outcomes in the system and to respond to fulfilments and violations of these expectations [3]. An agent's expectations we consider here are constraints on the future that are based on published norms, agreed contracts, commitments created through interaction with other agents, or personally inferred regularities of agent behaviour. An agent may base its practical reasoning on the assumption that one or more of its expectations will hold, while ensuring that it will receive notification events when these rules are fulfilled and/or violated.

With the extended functionality of the Jason platform, we demonstrate how a Jason agent deployed in Second Life using our framework can take part in complex simulations and respond to the received percepts from Second Life, as well as to the identified fulfilments and violations of its expectations. The fulfilments and violations of an agent's expectations are detected by an expectation monitor [4] that is integrated with the framework through an interface, and the agent's expectations are defined as temporal logic formulae to be monitored by the expectation monitor. The framework forwards the processed sensory readings from Second Life to both the Jason environment and the expectation monitor. Therefore, in parallel to a Jason agent being able to respond to the observed changes in the environment, the expectation monitor matches these changes with the monitored formulae and identifies the fulfilment or violation of the defined expectations. The notifications of the identified fulfilments or violations are also passed to the Jason agent, and the agent can have plans that respond to these identified fulfilments and violations.

The rest of the paper is organized as follows. Section 2 describes the potential of Second Life as a simulation environment and the related implementation problems. Section 3 describes the developed framework and in Section 4, we demonstrate this developed system by means of an example. Section 5 discusses some related work. Section 6 concludes the paper.

2 Second Life as a Simulation Environment

Second Life provides a sophisticated and well developed virtual environment for creating simulations for different domains and to test AI theories, including agent-based modelling. With the average monthly repeated user logins at around 800000[1], and with the virtual presence of many organizations, Second Life contains many interaction possibilities, which inherently lead to the provision of new scenarios to be used in simulations. Second Life is not restricted to a specific gaming or training scenario. Developers can create a multitude of scenarios as they wish, using the basic building blocks that are provided. For example, in Second Life, these scenarios could be in the areas of education, business, entertainment, health or games. The significance of using Second Life scenarios lies in the fact that they can be carried out between software-controlled agents, and also between software-controlled agents and human-controlled agents.

Second Life has been identified as a good simulation platform for testing AI theories [5] and specifically multi-agent systems [6]. A detailed analysis on the benefits of using Second Life over traditional 2D simulations and physical robots has also been done [5], with the main advantage reported being the ability to create sophisticated test beds in comparison to 2D simulations, and more cost effective test beds when compared to physical robots.

Despite this, still we do not see Second Life being used for complex simulations of AI theories or multi-agent systems modelling. The lack of use of Second

[1] http://blogs.secondlife.com/community/features/blog/2011/01/26/the-second-life-economy-in-q4-2010

Life as a simulation environment for AI research can be, to a certain extent, attributed to the previous lack of a convenient programming interface. Traditional programming in Second Life is done using in-world scripts created using the proprietary *Linden Scripting Language (LSL)*. These scripts are associated with objects, and in order to use them to control an agent inside Second Life, the objects should be attached to the agent. This approach has many limitations when used for AI simulations, for reasons such as the limited control over the agent wearing the scripted object. We discuss this in more detail in Section 2.1.

With the development of the third party library LibOpenMetaverse (LIBOMV), Second Life can now be accessed through a more sophisticated programming interface. LIBOMV is a ".Net based client/server library used for accessing and creating 3D virtual worlds" [2], and is compatible with the Second Life communication protocol. Using the LIBOMV client-side API, "bots" can be defined to control avatars in Second Life. With appropriate programming techniques, the LIBOMV library can be used to create avatars that have behavioural abilities similar to those controlled by humans. This includes moving abilities such as walking, running or flying, performing animations such as crying, or laughing, communication abilities using instant messaging or public chat channels, and the ability to sense the environment around it.

2.1 Challenges in Monitoring Agent Interactions in Second Life

For Second Life simulations that contain a lot of agents and objects moving at speed, there is a challenge in retrieving accurate position information at a high frequency to make sure that important events are not missed out.

Although an in-world sensor created using an LSL script can retrieve accurate position information of avatars and objects, it has limitations when extracting position and animation information of fast moving objects and avatars. A sensor can detect only 16 avatars and/or objects in one sensor function call, and the maximum sensor range is 96 metres. One approach to overcoming this problem is to employ multiple sensors; however multiple scripts operating for long durations at high frequency introduce "lag" to the Second Life servers, i.e. they slow the rate of simulation. For the same reason and because of the imposed memory limitations on scripts, an LSL script cannot undertake complex data processing, and since there is no provision to store the recorded data in-world at runtime, recorded data must be communicated outside the Second Life servers using HTTP requests which are throttled to a maximum of only 25 requests per 20 seconds. Moreover, there is a possibility that avatar animations with a shorter duration (e.g. crying or blowing a kiss) may go undetected, because a sensor can record only animations that are played during the sensor operation.

With a LIBOMV client deployed in Second Life, all the aforementioned limitations can be avoided. Avatar and object movements and avatar animations inside a Second Life environment generate corresponding update events in the Second Life server, and the server passes this information to the LIBOMV client using the Second Life communication protocol. The processing of this information is done outside the Second Life servers, thus causing no server lag.

However, this approach does have its own limitations which affect the accuracy of recorded information. As with other viewer clients, the Second Life server sends information to the LIBOMV client only if there is any change in the environment perceived by the LIBOMV client. This means that the client has to "assume" its perceived environment. For objects and avatars that are moving, the client has to keep on extrapolating their position values based on the previously received velocity and position values until it receives an update from the server. Extrapolated position values may not be completely in tally with the server-sent values and this situation is evident when extrapolating position values for objects and avatars that move fast. Moreover, it was noted that there is an irregularity in the recorded position data for small objects that may easily go out of the viewing range of the LIBOMV client, which directly affects the recording of accurate position information for small objects.

In order to overcome these challenges, we introduce a combined approach (described in Section 3) based on attaching an object containing an LSL script to a LIBOMV client deployed in Second Life. These communicate with each other and produce near-accurate position information about avatars and objects that move at speed.

This data extraction mechanism can only generate low-level position and animation information, making it difficult for a multi-agent system to directly utilize the retrieved data. Therefore the retrieved data should be further processed to identify the high-level domain-specific information embedded in the low-level data. In doing this, it is important that the data collected using the LIBOMV client and the LSL script are formed into one coherent snapshot which resembles the state of the Second Life environment. When deducing the high-level domain-specific information, it is important that these coherent snapshots are used, in order to make use of all the events and other related information that took place in a given instant of time. Otherwise an agent's decision may be based on partial information.

3 System Design

Figure 1 shows how different components of the system are interfaced with each other. The LIBOMV client creates and controls an avatar inside the Second Life server. It continuously senses the environment around it, and carries out movement, animation and communication acts as instructed and passes back the result notifications to the connected agent module whenever necessary (e.g. the result notification of the login attempt). We have used the Jason agent development platform [7], which is based on the BDI agent model, to demonstrate the integration of multi-agent platforms with Second Life using our framework. Here, a Jason agent acts as the coordinator component of this system. It instantiates the LIBOMV client to create the corresponding Second Life avatar, and commands the LIBOMV client to carry out actions inside Second Life on behalf of it.

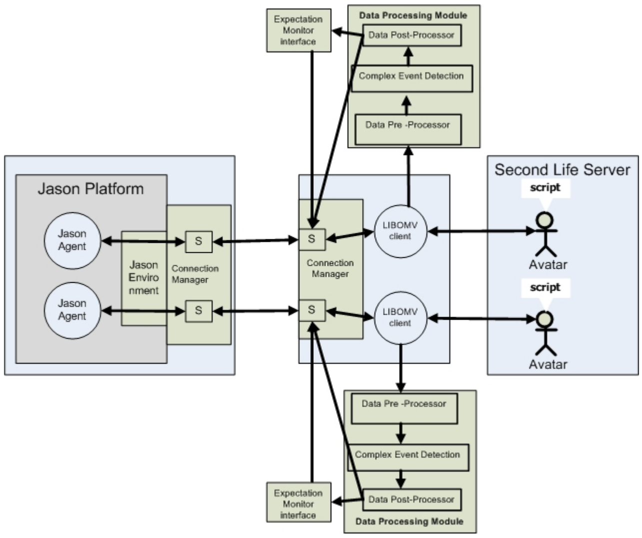

Fig. 1. Overall System Design

3.1 The Extended Jason Platform

The Jason platform we have integrated with the framework is an extended version [3] of Jason. The Jason agent platform contains an environment interface that facilitates the easy integration of Jason agents with other simulations. With this interface, it is possible to execute agent actions in an external simulated environment and it is also possible to retrieve the sensory readings of the simulated environment to be presented as percepts for agents.

The extended version of the Jason architecture used in this work implements a tight integration of expectation monitoring with the Jason BDI agent model. With this Jason extension, domain-specific individual agents can directly react to the identified fulfilments and violations of their expectations, by specifying plans that are executed in response to those fulfilments and violations. The Jason interpreter is extended with built-in actions to initiate and terminate monitoring of expectations, and with these built in actions, any expectation monitoring tool can be "plugged in" to the Jason environment.

3.2 Interface Between the LIBOMV Client and the Jason Agent

The interface between the LIBOMV client and the Jason agent is facilitated using a simple protocol we have developed (which we intend to develop further), and they communicate through sockets (denoted by 'S' in Figure 1). This decoupling makes it possible to connect any agent platform with the LIBOMV clients easily, and it could well be the case that different LIBOMV clients are connected with agents in different agent platforms. The protocol currently defines how an agent should pass commands to the LIBOMV client such as requesting the LIBOMV client to log into the Second Life server, uttering something in the public chat channels, sending instant messages to other avatars, moving to a given location and executing an animation. It also defines how an agent platform can interpret a message sent by the LIBOMV client. These messages are formulated based on the environment information recorded and processed by the data processing modules of the framework. The Jason environment class makes use of this protocol and converts the agent actions into the corresponding protocol constructs and passes them to the LIBOMV client. Similarly, it interprets the messages sent by LIBOMV clients to generate percepts for the Jason agents.

The module that contains LIBOMV clients is capable of handling multiple concurrent LIBOMV clients and socket connections. Therefore if the corresponding multi-agent system is capable of creating concurrently operating agents, this can easily create a multi-agent simulation inside Second Life. Consequently, the module that contains the Jason platform is designed in such a way that it is capable of handling multiple concurrent instances of socket connections connected to the Jason agents. As shown in Figure 1, a Jason agent connects to its interface socket through the Jason Environment class, and the Jason Connection manager interface. The Jason connection manager and the LIBOMV connection manager together ensure that all these individual Jason agents are connected to the correct LIBOMV client, through the interface sockets.

3.3 Interface Between the LIBOMV Client and the Second Life Server

As an attempt to overcome the limitations of data extraction using LSL and LIBOMV, we have implemented a combined approach to extract data from Second Life. In this new approach, a scripted object is attached to the bot deployed in Second Life, as shown in Figure 1. Detection of the avatars and objects to be monitored is done by the LIBOMV client, using their initial animation and movement updates that are received. Identification information for these identified avatars and objects is then sent to the script. As the script already knows what is to be tracked, a more efficient, light-weight function can be used to record movement information instead of the normal LSL sensor function. Position and velocity data recorded by the script are sent back to the LIBOMV client, while avatar animation updates are directly captured by the LIBOMV client to make sure animations with short durations are not missed. Any messages received as instant messages or in the public chat channels are also directly captured by the LIBOMV client. With this combined approach, the LSL script guarantees the retrieval of accurate movement information, while the LIBOMV client takes the burden of complex data processing off the Second Life servers, thus providing an accurate and efficient data retrieval mechanism.

3.4 Data Processing Module

The data processing module consists of three main components; the data preprocessor, the complex event detection module and the data post-processor.

The responsibility of the data processing module is to map the received sensor readings from complex Second Life environments to a domain-specific abstract logical model. In essence, it creates snapshots of the system which include low-level movement and animation information of avatars and movement information of objects in the given Second Life environment in a given instant of time, along with the identified high-level domain-specific information and other contextual information, which are encoded as propositions.

Data Pre-Processor: First, the low-level data received from Second Life are used to deduce basic high-level information about the avatars and objects, e.g. whether an avatar is moving, and if so, in which direction and the movement type (e.g. walking, running or flying), and whether an avatar is in close proximity to another avatar or an object of interest. Other contextual information such as the location of the avatar or the role it is playing can also be attached to this retrieved information as needed.

As mentioned above, the LIBOMV client receives movement information of objects and avatars from the script, and updates corresponding to avatar animations and communication messages are directly captured by the LIBOMV client. This means that a received movement information update does not contain the information about the current animation of the avatars, and the received animation and message updates do not contain the information about the current position or velocity of the avatar. Moreover, these animation and communication updates do not contain the movement information of other avatars and objects in the environment, or animation information of avatars. However, whenever an update is received by the LIBOMV client (whether it be the movement updates from the script, or an animation or a communication update), it is important that we create a snapshot that contains movement and animation information of all the avatars and objects of interest, in order to make it a complete snapshot representing the Second Life environment.

Therefore the data pre-processor caches the latest received animation and movement information for all the avatars and objects of interest. When a new set of movement information is received from the script, for all the avatars that have a movement record in that received information set, their cached animation values are associated with the received movement information. The LIBOMV client receives an update corresponding to every avatar animation change (e.g. if an avatar is currently standing, and suddenly starts running, the LIBOMV client receives an animation update 'run'). Therefore it is safe to assume that an avatar keeps on performing the animation already recorded in the cache. When an animation update is received for an avatar, it is associated with the extrapolated movement information of that avatar, based on the cached movement information. Since the LIBOMV client receives movement information from the script every 500 milliseconds, the extrapolation error can be assumed to be very low. We also generate the movement and animation information of other avatars and objects in that Second Life environment, for the time instant represented by that received animation update. This is because a received animation update does not contain any information related to other avatars and objects in that simulation as mentioned earlier. Whenever, a communication message is received by the LIBOMV client, the movement and animation information of avatars and objects are generated for the time instant corresponding to that communication update, using the cached information. Thus, for every set of movement information sent by the script and every animation and communication message update sent by the Second Life server, the data pre-processor generates a complete snapshot of the environment that contains the avatar and object movement information and avatar animation information. These snapshots can be easily distinguished from each other with the use of the associated timestamp.

These processed data are then sent to another sub-component of the data pre-processor which prepares data to be sent to the complex event detection module. We specifically extracted this sub-component from the main data pre-processing logic in order to make it possible to easily customize the data preparation logic according to the selected complex event detection module. For example, for the complex event detection module we have employed currently, this sub-component decomposes the generated snapshot into the constituent data structures corresponding to individual avatars and objects, and sends the information related to objects to the complex event detection module before those corresponding to avatars.

Complex Event Detection Module: An event stream processing engine called Esper [8] is used to identify the complex high-level domain-specific events embedded in the data streams generated by the data pre-processor. The Esper engine allows applications to store queries and send the low-level data streams through them in order to identify the high-level aggregated information. Esper keeps the data received in these data streams for time periods specified in these queries, thus acting as an in-memory database. Esper also has the ability to process multiple parallel data streams.

Esper provides two principal methods to process events: event patterns and event stream queries. We make use of both these methods when identifying the high-level domain-specific events. The received data streams are sent through the event stream queries first, to filter out the needed data. Then these filtered data are sent through a set of defined patterns which correspond to the high-level events that should be identified. Event identification using patterns is done in several layers to facilitate the detection of events with a duration. The output of each layer is subsequently passed on to the layer that follows, thus building up hierarchical patterns.

The output of the complex event detection module is sent to the data post-processor.

Data Post-Processor: The data post-processor is required to convert the recognized low-level and high-level information into an abstract model to be passed to the connected multi-agent system.

The detected low-level data, as well as high-level events and other context information are converted to propositions and are grouped into states to be sent to the multi-agent system. Essentially, a state should represent a snapshot of the Second Life environment at a given instant of time. Therefore the times at which the basic events (e.g. receipt of avatar animation, or receipt of movement information from the script) were received by the system were selected as the instants modelled in the output state sequence. This creates separate states consisting all the low-level events that took place at the same basic event, high-level events as well as the related contextual information.

Expectation Monitor Interface: The expectation monitor interface shown in Figure 1 is an optional sub-component that processes the output of the data post-processor a step further by adding a reference to the dependent state for those events that depend on previous other high-level events. It sends these data to an expectation monitor attached to it, and in this work we use an expectation monitor that was developed in previous research [4]. The responsibility of the expectation monitor is to identify the fulfilments and violation of agent expectations that are defined using the extended version of the Jason platform explained in Section 3.1.

When an expectation monitor is initially started, it receives a rule (a condition and an expectation) and its type (fulfilment or violation) through the expectation monitor interface to start monitoring. The rule's condition and resulting expectation are provided as separate arguments using a specific form of temporal logic, with the expectation expressing a constraint on the future sequence of states [4]. When the monitor starts receiving the output of the data post-processor as a sequence of states, it matches these against the rule's condition to determine if the expectation has become active. It also evaluates any active expectations (created by a condition evaluating to true), progressively simplifies the monitored expectation and finally deduces fulfilment or violation of the expectation[2].

The fulfilments and violations of agent expectations add a new level of abstraction above the state descriptions generated by the data post-processor, where the expectations are introduced by the agent dynamically and the fulfilments and violations of those expectations are detected based on the already identified information in the snapshots. Therefore, in addition to the continuous stream of domain-specific high-level events and state information that our framework supplies to the agent from Second Life, an agent developed using this extended version of the Jason platform can dynamically subscribe to fulfilment and violation events for specific rules of expectation that are appropriate to its personal or social context.

[2] The system employs multiple expectation monitor instances in parallel in order to monitor multiple concurrently active expectations an agent may have. This is due to a limitation in the expectation monitor we have employed that it cannot monitor for concurrently active individual expectations.

4 Example - A Jason Agent Engaged in the Football Team Play Scenario "Give and Go"

In this section we demonstrate how a Jason agent can engage in a SecondFootball [9] virtual football training scenario with a human controlled player[3], and how it can reason based on received percepts and the detected fulfilments and violations of its expectations.

SecondFootball is an interesting simulation in Second Life which enables playing virtual football. It is a multi-avatar, fast-moving scenario which promises to be a hard test case to test our framework when compared with most of the publicly accessible environments in Second Life. This system provides scripted stadium and ball objects that can be deployed inside Second Life, as well as a "head-up display" object that an avatar can wear to allow the user to initiate kick and tackle actions.

In this example, we implement a simplified version of the football team play scenario "give and go". Here, the Jason agent Ras_Ruby is engaged in the team play scenario with the player Su_Monday, who is controlled by a human. When Ras_Ruby receives the ball, she adopts the expectation that Su_Monday will run until she reaches the PenaltyB area, so that she can pass the ball back to Su_Monday, to attempt to score a goal.

In order to implement this team-play scenario, the high-level complex events of the SecondFootball domain we wanted to detect were whether the ball was in the possession of a particular player, whether the ball is being advanced towards a goal, and successful passing of the ball among players by means of up-kicks and down-kicks. Though not used in the example, the framework is also capable of detecting goal scoring by up-kicks and down-kicks, dribbling the ball over the goal line, and successful or unsuccessful tackles. The developed framework had to be customised to achieve these requirements, and in the future we intend to introduce options(e.g. configuration files and run-time scripts) that can be utilized to customize the framework for a given Second Life simulation more easily.

When the system starts, the Jason agent corresponding to Ras_Ruby is initialized. When the Jason agent starts executing, it first tries to log itself in Second Life. The following Jason plan initiates the login process.

```
// The '+!' prefix resembles a new goal addition
+!start
   <-
   connect_to_SL("xxxx", "Manchester United, 88, 118, 2500");
   !check_connected.
```

The parameters specify the login password and the login location, respectively.

After sending this login request to the LIBOMV client, the agent has to wait till it gets the confirmation of the successful login from the LIBOMV client, as shown in the following plan:

[3] One of our agents is currently controlled by a human as our Jason agents are still not capable of handling complex reasoning involved with playing football.

```
+!check_connected: not connected
   <-
   .wait(2000);
   // '!!' means tail-recursion optimised posting of a goal
   !!check_connected.
```

When it finally receives the successful login notification, the agent instructs the LIBOMV client to run the avatar to the area MidfieldB2 using the plan shown below.

```
+!check_connected: connected
    <-
    action("run","MidfieldB2").
```

Once in the area MidfieldB2, the agent Ras_Ruby waits for Su_Monday to kick and pass the ball to it. Once it successfully receives the ball the agent gets the "successful_kick(su_monday, ras_ruby)" percept (which is generated by the framework and states that Su_Monday successfully passed the ball to Ras_Ruby through a kick), and this generates a new belief addition event ('+successful_kick') which triggers the corresponding plan given below.

In this plan, we have used the internal action start_monitoring defined in the extended version of the Jason platform [3], and initiate monitoring for the fulfilment and violation of the expectation. Here, in the first parameter we define the type of expectation; whether it is a fulfilment or a violation. The second parameter assigns a name for the expectation. The third parameter is the name of the expectation monitor used. The fourth parameter is the triggering condition for the expectation, and in this example, it is a keyword with a special meaning (`#once`). For this scenario the initiating agent wants the rule to fire precisely once, as soon as possible, and this can be achieved in our current expectation monitor by using a 'nominal' (a proposition that is true in exactly one state) for the current state as the rule's condition. However, the BDI execution cycle only executes a single step of a plan at each iteration, and any knowledge of the current state of the world retrieved by the plan may be out of date by the time the monitor is invoked. The `#once` keyword instructs the monitor to insert a nominal for the current state of the world just before the rule begins to be monitored. Here, the actual expectation formula is given by the fifth parameter, and the sixth parameter is a list of optional context information, which we do not utilize in this example.

The fulfilment of this expectation occurs when Su_Monday advances towards GoalB (`'advanceToGoalB(su_monday)'`), until (`'U'`) she reaches PenaltyB, denoted by `'penaltyB(su_monday)'`. Similarly, the violation of this expectation occurs if Su_Monday stopped somewhere before reaching penaltyB, or she moves in the opposite direction before reaching PenaltyB area[4].

[4] The conditions and expectations are defined in temporal logic and we do not wish to elaborate on them in the scope of this paper. These are written as nested Python tuples, as this is the input format for the expectation monitor written in Python.

```
//The '+' prefix resembles an event relating to belief addition
+successful_kick(su_monday,ras_ruby)
   <-
   //internal actions
   .start_monitoring("fulf",
      "move_to_target",
      "expectation_monitor",
      "#once",
      "('U',
         'advanceToGoalB(su_monday)',
         'penaltyB(su_monday)')",
      []);

   .start_monitoring("viol",
       "move_to_target",
       "expectation_monitor",
       "#once",
       "('U',
         'advanceToGoalB(su_monday)',
         'penaltyB(su_monday)')",
      []).
```

If Su_Monday fulfilled Ras_Ruby's expectation, the expectation monitor detects this and reports back to the Jason agent. The following plan handles this detected fulfilment and instructs the avatar to carry out the kick action[5].

```
+fulf("move_to_target", X)
   <-
   //Calculate kick direction and force, turn, then ...
   action("animation", "kick").
```

On the other hand, if Su_Monday violated the expectation, the expectation monitor reports the violation to the Jason agent, and the agent uses the first plan below to decide the agent's reaction to the detected violation, which creates a goal to choose a new tactic for execution. The second plan (responding to this new choose_and_enact_new_tactic) is then triggered, and the agent adopts the tactic of attempting to score a goal on its own by running towards the PenaltyB area with the ball[6] .

```
+viol("move_to_target",X)
   <-
   !choose_and_enact_new_tactic.
```

[5] Due to technical problems the Second Life avatar cannot currently perform the actual 'kick' animation

[6] When an avatar is in possession of the ball and the avatar starts moving, the ball moves in front of the avatar

```
+!choose_and_enact_new_tactic : .my_name(Me)
   <-
   action("run", "penaltyB").
```

5 Related Work

Research involved with programming with Second Life has focused either on extracting sensory readings from Second Life, or controlling avatar movement and conversational behaviours to create Intelligent Virtual Agents (IVA). Not much research has attempted to model reactive agents that generate behavioural responses to their observations on the Second Life environment, or addressed the issue of mapping low-level sensory data to high-level domain-specific information.

Most of the research that worked on extracting sensory readings from Second Life has utilized this retrieved information for statistical purposes. It can be seen that both LSL scripts and LIBOMV clients have been used for sensory data extraction from Second Life servers, but the latter had been more effective in collecting large amounts of data. LIBOMV clients have been successfully used to create crawler applications that collected large amounts of data about avatars and user-created content, to statistically analyze the number of avatars and objects present in various different Second Life regions over periods of time [10, 11]. There has also been an attempt to exploit the power of both these approaches in designing a multi-level data gathering tool which collected more than 200 million records over a period of time [12]. There have also been several attempts to collect data from Second Life to examine social norms related to gender, interpersonal distance, dyantic interaction proximities and spatio-temporal dynamics of user mobility in a virtual environment [13–15].

Cranefield and Li presented an LSL script-based framework that sensed the Second Life environment and tried to identify the fulfilments and violations of rules defined in structured virtual communities [16]. However, this research had been conducted in a narrow scope which dealt only with animations of human-controlled avatars.

Burden provided a theoretical proposal for creating IVAs inside Second Life with the sophisticated abilities of concurrent perception, rational reasoning and deliberation, emotion and action, and also pointed out the complexities of a practical implementation [17]. A theoretical framework has also been proposed which integrates different modules that handle these different capabilities [6], but the practical implementation of both of these is still limited to simple sensory, movement and conversational abilities.

There have been several research attempts on creating IVAs inside Second Life using LIBOMV clients, but their main focus had been on improving the conversational and animation abilities of virtual agents [18, 19].

Research has been carried out by Bogdanovych and colleagues who developed a number of useful libraries for connecting agents to Second Life (including their own BDI interpreter for controlling agents inside Second Life), in specially designed environments that were instrumented to connect to "electronic institution" middleware [20]. In contrast, our research focused on developing a framework that supports connecting multi-agent systems with existing Second Life environments. Moreover, they have not much focused on how to create coherent snapshots that provide a complete view of a given Second Life environment at a given instant of time to be presented to the multi-agent system, or how the extracted low-level data can be used to identify much complex high-level information, which was the main focus of our work.

6 Conclusion

In this paper we presented a framework that can be used to deploy multiple concurrent agents in complex Second Life simulations, and mainly focused on how the potentially unreliable data received by an agent deployed in a Second Life simulation should be processed to create a domain-specific high-level abstract model to be used by the agent's cognitive modules. This problem has not gained much attention from the past research on Second Life. We hope the implementation details we provided would be a valuable road map for future researchers hoping to use Second life for multi-agent simulations in various different paradigms, apart from the developed framework being a potential starting point for further research in integrating multi-agent systems with Second Life.

We note that any multi-agent platform can be connected with Second Life using our framework, and demonstrated this with an extended version of the Jason BDI interpreter. With the use of an example, we demonstrated how a Jason agent can execute actions inside Second Life and how it can respond to the observed changes in the environment. We also integrated an expectation monitor with our framework and demonstrated how Jason agents can use the sensory data to identify higher level events associated with fulfiled and violated personal expectations, based on the complex interactions that they take part in.

Although the current framework is customized for the SecondFootball simulation, in the future we plan to enhance this framework to be more generalized, and experiment with it in various simulations such as medical training scenarios. Moreover, we intend to enhance the capabilities of Jason agents, so that they will be able to actively participate in more complex scenarios.

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CIGA: A Middleware for Intelligent Agents in Virtual Environments

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Abstract. Building intelligent behavior in (educational) games and simulations can greatly benefit from the use of agent technology. Intelligent agents within a multi-agent system can be developed for controlling virtual characters in a simulation environment within a game engine. Coupling a multi-agent system to a game engine is not a trivial task and introduces several conceptual design issues concerning embodied agent design. In this paper we present CIGA, a middleware to facilitate this coupling tackling the design issues in a structured approach, not only for embodied agent design but also for the system as a whole.

Key words: Middleware, Multi-Agent Systems, Virtual Environments, Intelligent Agents, Simulation

1 Introduction

As the technology to create more realistic, complex and dynamic virtual environments advances, there is an increasing interest to create intelligent virtual agents (IVAs) to populate these environments for the purpose of games, simulations or training. Designing an IVA, game engine technology can be employed to simulate its physical embodiment, equipped with sensors and actuators interacting with the virtual environment. The use of agent technology in the form of multi-agent systems (MASs) is a good fit to realize the cognitive and decision-making aspects of an IVA.

Combining these technologies is not a trivial task and introduces conceptual and technical design issues. First of all, both technologies often work at different abstraction levels. Games engines work with low-level data representations for virtual environments and the characters populating it. MASs work with more high-level semantic concepts designed to form a suitable abstraction from the physical environment representing an agent's perceptive view on the environment and the actions for influencing it. Second, agent actions in a typical MAS environment are non-durative. When embodied in a real-time environment, actions become durative and low-level reasoning over their execution is required. MASs are generally not designed to handle this aspect. Third, the designs of an agent's embodiment in a game engine and its cognitive counterpart in the MAS are highly depend on each other. An agent's view on the environment is dependent on his sensory capabilities provided by its embodiment whereas its ability to influence the environment through its embodiment is bounded by the possible control over an avatar in the game engine. This, in turn, has implications on an agent's deliberation on possible goals, plans and actions. Last, the required connection between the two specialized software systems introduces some technical issues concerning software engineering.

Current attempts in combining these technologies often use a pragmatic approach when tackling these design issues. A direct connection between a game engine and a MAS is created either with or without the help of standard technologies or interfaces that may provide access to a specific game engine [1] or range of MASs [3]. Although such an approach can be a productive solution, design decisions are often influenced and bounded by the individual capabilities of the employed technologies. There is often no structured approach in bridging the conceptual gap between the two systems. There are systems that focus more on the conceptual issues attempting to employ agent technology by translating the physical world model to a social world model suitable for cognitive reasoning [5, 16]. Though, these systems don't pretend to give a structured approach for tackling the technical issues when using their system with alternative MASs or game engines.

In this paper we present CIGA[1], a middleware to facilitate the coupling between agent technology and game engine technology, tackling the inherent design issues in a structured way. An architecture for using this middleware is presented to solve technical issues when connecting agents in a MAS to their embodiments in a game engine. Additionally we show the need for using ontologies to provide a design contract between not only an agent's mind and body connection but also for the system as a whole. This can lead to a new methodology for game design using agent technology. An initial fully functional version of CIGA has been implemented and currently undergoes evaluation.

The paper is organized as follows. In the following section we outline the motivation for introducing CIGA. Section 3 describes the architectural design of the proposed middleware. In section 4 we compare the middleware with related technologies. Finally, section 5 we conclude and discuss results.

2 Bridging the Conceptual Gap

Designing an embodied agent with current game engine and agent technology, one must overcome several inherent conceptual design issues. In this section, we provide a description of each issue and present the functional role CIGA plays to overcome these issues.

[1] Creating Intelligent Games with Agents

2.1 Social World Model

In a MAS, an agent's interpretation of the environment is based on semantic concepts forming an abstraction of the virtual physical world. The data representations of these concepts in a game engine often are at a different abstraction level than what is suitable for agents in a MAS to work with. For example, an agent's concept of "a person sitting on a chair" may be represented in the game engine by a character's location in the vicinity of a chair in combination with the positions of each skeletal bone, forming a sitting posture. Instead of the physical world state representations in a game engine, agents work with (high-level) semantics concepts. The use of rich semantic concepts is particularly important for the more socially-oriented simulations with communicating agents like in serious games. Though, the demand for rich semantics in the more action-oriented games is getting increasingly important [17].

CIGA overcomes the difference of data representation by translating the *physical simulation* to a *social simulation* for agents. To accomplish this, semantic data is generated during agent sensing which is translated from raw data of game objects or events. This semantic information forms the basis for an agent's view and interpretation of the environment. Inferences can be made to provide agents with semantic concepts relevant for the social simulation. For example, the meaning of a certain gesture performed by an embodied agent can be inferred from an animation in the game engine. Making higher-level information directly available for agents is efficient as agents don't have to infer these themselves. CIGA employs *domain ontologies* to specify a formal representation of the semantic concepts. The ontologies are accessible in both the game engine to perform the required translations and in the MAS representing the agent's *social world model*.

The risk of translating raw data to semantic data is the problem of *over-inference*. As implemented inferences are the same for all agents we might make an inference we don't want a certain agent to be able to make. Further, we might loose the ability for an agent to interpret perceived information in his own way. For example, how an agent interprets the meaning of a perceived gesture can be dependent on an agent's cultural identity. This makes it important to design the semantic concepts in the domain ontology at the right abstraction level such that agents don't have to perform too much low-level inferences on their own, but can still make different interpretations based on their individual context. CIGA doesn't enforce the use of any abstract level as this is dependent on the application domain.

2.2 Perception

Agents in a MAS get information from their environment through percepts. If an agent becomes embodied in a virtual environment, these percepts are based on sensory information retrieved from one or more sensors attached to the embodiment in a game engine. When creating percepts directly from sensory information, we do not only face the problem of information representation as described above, but there's also the risk for an agent to become flooded with percepts that are irrelevant with respect to his current state of mind. An agent should have the ability to direct his attention to selected information from the environment such that irrelevant information can be filtered, though still allowing an agent to be susceptible to unexpected events. Filtering sensory information should not be performed in the game engine as this process is dependent on the agent's mind in a MAS. On the other hand, delegating this process to the MAS is not ideal as the cost of communicating the unfiltered information can have a negative performance impact on the system as a whole. Additionally, MASs generally don't provide standard facilities implementing perception filtering.

CIGA tackles this problem by introducing a *filtering mechanism* located closely to an agent's sensors in the game engine. Agents in a MAS can show their *interest* in the environment in the form of subscriptions that define how sensory information has to be filtered. Using the environment semantics defined in the domain ontology introduced before, powerful subscriptions can be made to give an agent full control over the range of percepts to receive. A description of this mechanism can be found in [20] and falls out of the scope of this paper.

2.3 Action

In a MAS, an agent's capability to influence the environment is defined by a set of actions designed to change the state of an environment. The success or failure of an action denotes that the desired state of the environment was reached or could not be reached respectively. In a typical MAS environment, actions are instantaneous and the result is known immediately. When an agent becomes embodied in a virtual environment, its capability to influence the environment becomes bounded by the available actuators of the embodiment. Since these actuators work in real-time, actions become durative and the environment may change during the execution, possibly preventing the action from finishing successfully. For example, an action like *open door* can fail during execution if the door is opened from the other side by another agent. Further, this raises questions about the meaning of the success or failure of an action performed by an embodied agent. Is an action said to be successfully executed if the body performed the action or if the desired state of the environment was reached?

To deal with this different view on *actions*, CIGA provides a generic *action monitoring* facility to deliver action requests from an agent to its embodiment and communicate feedback about the realization of the action, allowing an agent to follow the progress and intervene if necessary. The meaning of the success or failure of an action is left to the designer where he can use the feedback mechanism to specify the state of the action and how it was reached (E.g. the agent didn't fully perform the action in the environment, but we still consider the action to be succeeded as the desired environment state defined by the semantics for the action was reached). A more elaborate overview is given in section 3.2.

A well known design issue is the need for finding a suitable abstraction level for behavior control. Choosing an abstraction level has implications on both agent design and system performance. The use of more low-level, physically-oriented actions gives an agent more control over its body but increases the communication cost of delivering the instructions to the game engine. Using more high-level, cognitive-oriented actions delegates more control to the game engine, but the ability is lost to take an agent's individuality into account. For example, it becomes harder to reflect an agent's own personality or mental state on his behavior if this information is defined in the MAS (E.g. drunk and sober agents will walk in the same way). Although the communication cost for sending instructions is decreased, agents are more dependent on perception to see if the intents of their actions have been achieved. The aim is to find the right *balance of intelligence* distributed between the mind and body of an agent in the MAS and game engine respectively. CIGA doesn't enforce the use of any abstraction level for actions as this is dependent on the specific application domain.

2.4 Communication

MASs often provide an inter-agent communication mechanism for agents to communicate. The messages being communicated usually adhere to standards like FIPA ACL where content can be represented using formal semantics understood by both agents. Simulating human-like communication requires agents to perform (non)verbal communicative behavior and perception through their body's actuators and sensors in the environment. Like actions, communication becomes durative. Further, the desired effect of the communication cannot easily be determined as this is dependent on mental processes within the receiving agent. Successful reception of a communicative act is not trivial as this depends on the available medium from sender to receiver, bounded by the simulated laws of physics in the environment. For example, two agents may not be able to hear each other in a noisy bar when they are at different sides of the room.

CIGA facilitates in the communication process between embodied agents by introducing its own communication mechanism taking into account both the durative nature of communication and environmental factors. For example, the delivery of a communication message is only performed when the corresponding action realizing the communicative act in the environment is successfully achieved and the receiving agent is physically able to perceive this act. This mechanism is briefly mentioned later in this section but an elaborate functional overview falls outside the scope of this paper.

3 CIGA Framework

In this section we present an architectural framework for integrating the CIGA middleware with both game engine and agent technology. An illustration of the main framework is given in figure 1.

Since the proposed middleware must connect to two specialized software systems, the common design approach was taken to internally divide the middleware into two functional components. The *Physical Interface* layer connects to a game

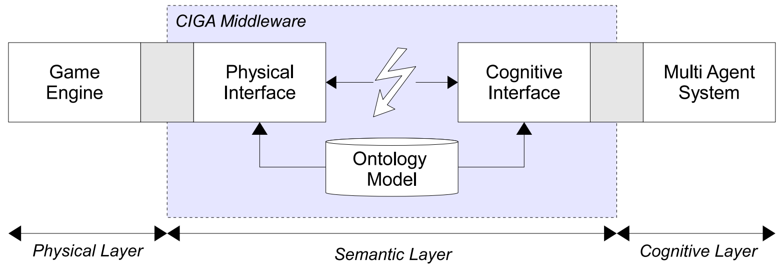

Fig. 1. Middleware Framework.

engine whereas the *Cognitive Interface* layer connects to a MAS. Both components are internally connected using a communication mechanism. The *Ontology Model* provides access to domain ontologies specified for a specific application domain containing formal representations of the communicated content between an agent's mind and body.

This internal distributed design several advantages. First, it helps to bridge the conceptual gap between a game engine and a MAS by dedicating separate components for the integration with the technologies. Second, from a technical point of view, it allows both components to be implemented in different programming languages. It is often the case that the used game engine and MAS are written in different languages. For the middleware as a whole to be able to interface with both technologies while matching the language of that technology results in an easy integration process and an efficient, tight connection. Last, the design introduces connection transparency since the game engine and MAS can run in different processes or distributed over different computers or platforms, depending on the used internal connection mechanism.

Next we'll first describe the role of ontologies within the middleware after which we'll look at the individual components connecting to game engine and MAS respectively.

3.1 The Role of Ontologies

The *Ontology Model* represents a storage facility for semantic concepts. It consists of domain ontologies designed for a specific application domain to capture an agent's perceptual and interactional capabilities within an environment. The use of ontologies forces an agreement between a game engine and a MAS on the required domain concepts. This is known as a *design by contract* [14], increasing robustness and reusability within the system.

Building a domain ontology for the simulation environment encompasses defining object and event classes with their attributes. Attributes for objects represent their physical or functional properties whereas attributes for events represent parameters specifying event details. Classes can be organized in a hierarchical fashion where attributes are inherited from parent classes. To form an agreement on the actions agents can perform in an environment, (parameterized) action classes should be specified in the domain ontology.

Domain ontologies can be created using an ontology editor like Protégé. An interesting feature is the ability to change and extend meta-classes for objects, events or actions. This allows the ontology to support custom data fields for specific types of concepts. For example, a *perceptibility type* can be assigned to an object property to specify its perceivability (e.g. visual, auditory or tactile) which use will be described later. Additionally, *affordances* can be specified for object classes which can facilitate agents in understanding their world in terms of interactions they can have with it. The use of Affordance Theory has been previously explored in [6, 4]. Related to affordances, information associated with *smart objects* can be stored [11, 15]. A small example showing the possibilities of a simple domain ontology is illustrated in figure 2.

Objects	**Properties**
PhysicalObject	location,size
– Human	gender,age
– Fire	type,heat
– FireExtinguisher	type
– Bucket	content,amount
Actions	**Parameters**
AttackFire	fire,equipment
Pickup	target
Communicate	target,message

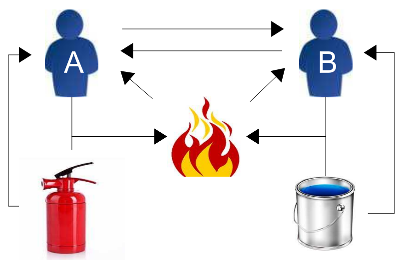

Fig. 2. Domain Ontology Example.

The left side of the illustration shows a domain ontology consisting of several object classes and actions for human actors. The right side of the example shows a simple scene with two human agents (A and B), a fire and two objects which can be used to attack a fire. Now assume *agent A* notices a small fire starting near *agent B* who is unaware of this. *Agent A* would like to resolve the situation and has several options. He can pick up the fire extinguisher and use it to put out the fire or he can use the bucket of water positioned near *agent B*. This choice may depend on the size and type of the fire and the type fire extinguisher. For example, an electrical fire should not be extinguished using water which makes the first option preferable if it concerns a chemical fire extinguisher. Further, *agent A* can communicate with *agent B* to advise him to deal with the fire, although this choice may not be suitable if *agent B* is a small child.

Agent A is able to perform this line of reasoning based on the given domain ontology. Here, object properties provide information about the objects (E.g. object positions, the type of fire extinguisher or the age of *Agent B*). Object classes can be annotated with *conditional affordances* helping an agent to understand how he can interact with objects being perceived. For example, physical objects of a certain size can be picked up or a bucket filled with water can be used to attack a fire. The concepts in the domain ontology are also interesting for use as content in communication languages between agents [21].

These domain ontologies cover concepts relevant to both an agent's embodiment and his mind. In CIGA they are fully accessible at runtime to both the game engine and MAS as will become clear in the next parts of this section.

3.2 Connecting the Game Engine

As shown in Figure 1, the *Physical Interface* layer of CIGA connects to a game engine. Its main task is the administration of agent embodiments participating in the middleware and individually control their sensors and actuators. Abstraction from the game engine is achieved using an intermediate layer, hereafter called the *GE Interface* layer, connecting a specific game engine. Figure 3 illustrates the design focusing on the functional interfaces and data flows.

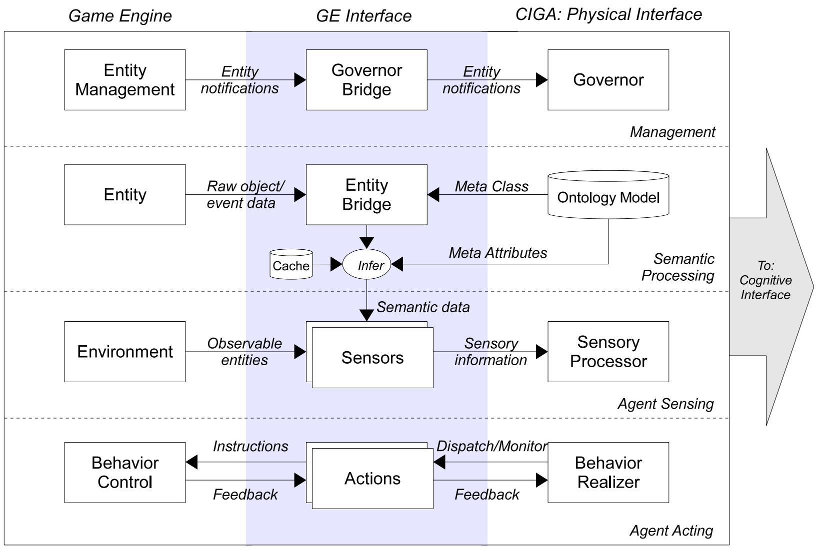

Fig. 3. Integration Middleware in Game Engine.

A prerequisite for using CIGA is the ability to modify the game engine allowing implementation of the *GE Interface* layer. This layer is responsible for integrating CIGA's *Physical Interface* component as an external game engine component to be included in the engine's update loop which allows it to run processes on its own. For example, agent sensing can be controlled to run at a configurable frequency or the MAS can be provided with regular time updates. This approach makes CIGA less dependent on specific features that may or may not be available in a specific game engine. Next we describe each horizontal layer from figure 3 in more detail.

Management The role of the *Governor* in the *Physical Interface* is to provide a connection mechanism for synchronizing the simulation between the game engine and the MAS. It monitors the creation and destruction of entities in the environment that are candidates for agent embodiment and notifies the MAS about their existence. Additionally, simulation time is synchronized by sending regular time updates to the MAS, who often don't have an internal clock explicitly defined.

Semantic Processing The goal of semantic processing is to translate raw object and event data available in the game engine to semantic data. Semantic data is used as sensory information which allows an agent to build a social model of the environment based on meaningful concepts. The *Ontology Model* can be accessed to retrieve the formal representation of those concepts.

Creating semantic data from raw data at runtime is a process performed in the *GE Interface* layer. Here, at design time, entity bridges are created associating object classes from a domain ontology to entities defined in the game engine (E.g. associating the *fire* concept to a fire class in the game engine). During runtime, the object's attributes are generated from raw entity data (E.g. an object's *size* property is calculated). This translation process is performed when agents sense environment entities. Furthermore, semantic event classes can be generated based on raw game events or as a result of custom inferences. Inference based on previously sensed information is achieved using a cache belonging to an agent's sensory processor.

Note that translation and inference rules for generating semantic data are the same for all agents. At this stage, although agents have their individual view of the environment determined by their sensors, their interpretation of it is the same as specified by the domain ontology. This fact must be taken into account when designing the ontology.

Agent Sensing Agent sensing is performed using a *Sensory Processor* provided for each participating agent within CIGA. Its goal is to collect sensory information from all sensors assigned to an agent's embodiment and prepare them as *percepts* for the MAS agent to receive.

Sensors obtain sensory information from the environment. The processing logic for a sensor is implemented in the *Physical Interface* using a sensor base class. Specific sensors must be created in the *GE Interface* layer and are required to assign a *perceptibility type* (e.g. visual, auditory, tactile) to the sensor and provide an implementation of the abstract method **GetObservableEntities()**. This method is responsible for building a list of entities from the environment the sensor is currently able to observe. Access to game engine queries can support this process (E.g. to determine if an agent can observe another agent standing behind a wall or if a sound can still be heard at a certain distance from its origin). We assume the game engine offers us the functionality to achieve the required queries. With this approach, one can easily build a sensor library in the *GE Interface* layer to store different sensors with more or less advanced algorithms.

Since sensors can be dynamically replaced, one can support different level of details (LODs) for sensors.

Based on the list of *observable entities*, sensing in the base class continues by extracting sensory information from these entities using the *Semantic Processing* described before. The sensor's *perceptability type* is used to filter the object properties and events that can be sensed. E.g., In the example from figure 2, the *heat* property of the *fire* entity can only be sensed by a *tactile* sensor.

After all sensors have been processed, the *Sensory Processor* filters the collected data as further described in [20].

Agent Acting Agent behavior is performed using a *Behavior Realizer* provided for each agent participating within CIGA. Its goal is to realize semantic actions instructed by a MAS by managing an action's life cycle and communicating feedback about its state back to the MAS agent. Actions are executed in parallel in an interleaved fashion driven by the game engine loop.

Actions themselves are implemented in the *GE Interface* layer. They are responsible for realizing the intended action semantics by accessing game engine instructions. The *Physical Interface* layer provides an abstract base class for actions. Creating specific actions involves implementing the following methods:

- **CheckPreconditions()**: This method is called before the action is executed. Here any preconditions can be checked which must pass before the realization of the action can be started. If the preconditions are not met the action will not continue further and the agent is notified.
- **Body():** This is the main execution loop. Here game engine functionality can be addressed to realize the intent of the action. This includes controlling the actuators of the agent's embodiment and monitoring its progress. For virtual characters, this often involves interacting with an *Animation System* in the game engine. The action can end prematurely when problems arise during realization after which the agent is notified about the cause.
- **CheckEffects():** This method is called after the action was successfully realized. Here the intended effects of the action on the game state can be validated. If the effects are not met the action will end with a corresponding notification.
- **OnAborted():** A MAS agent has the ability to abort any scheduled action. This method is called when it decides to do so. Here logic can be implemented to properly interrupt and clean up the action's realization in the game engine.

Note that it is up to the MAS agent to infer success or type of failure of an action based on the received action feedback notifications. Further, CIGA doesn't impose any rules for the implementation technique or data formats used for actions. It merely provides a generic facility to deliver instructions from a MAS agent to its embodiment and to communicate feedback about the realization of these instructions. For example, a common technique for behavior control is the use of *parameterized actions* representing an API for agents to control their embodiment [1, 22, 2]. In CIGA, *parameterized actions* can be defined in the domain ontology to form an agreement on the used API.

This does not restrict the use of more specialized techniques. For example, upcoming language standards such as *BML* can still be used [12], which is an XML-based language for communicative behavior realization. Here, a single action can be defined for communicative behavior sending BML data and feedback information between the MAS and the game engine.

3.3 Connecting the MAS

The *Cognitive Interface* layer of CIGA connects to a MAS, providing a generic interface for agents in a MAS with their embodiment in a real-time environment. This interface should allow for the communication of percept data and action instructions whose data is associated with semantic concepts from the domain ontology. Similar to the interface with the game engine, abstraction from the MAS is achieved using an intermediate layer, hereafter called the *MAS Interface* layer. Figure 4 illustrates the connection framework.

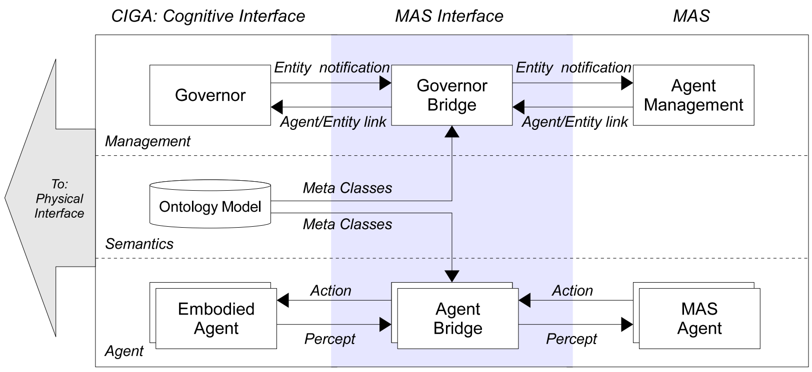

Fig. 4. Integration Middleware in MAS.

Unlike the *Physical Interface*, the *Cognitive Interface* is a pure event-based component passing information to and from the MAS. An *MAS Interface* layer must be implemented for a specific MAS to comply with the provided interfaces by the *Cognitive Interface* layer. This layer is less complex than the *GE Interface* layer since it's a simple message-passing connection for data that is already rooted in semantics (no conceptual translation is required).

Management Interface As described previously, the *Governor* notifies the MAS about the creation and destruction of candidate embodiments in the simulation. Based on this information, the MAS can create and destroy agents. To link an agent with an embodiment, the MAS must notify the *Governor* about the entity it wants to embody. The *Governor Bridge* in the *MAS Interface* can achieve this functionality for a specific MAS to be used. The *Ontology Model* can be accessed to retrieve semantic data about the embodiments. This information can support the MAS in deciding what type of agent to associate with an entity.

Agent Interface The agent interface between CIGA and a MAS consists of the common act and sense interfaces required for MAS agents. The *Agent Bridge* in the *MAS Interface* is responsible for converting the different message formats used between the CIGA middleware and a specific MAS. Here, the *Ontology Model* can play several roles. The model can be accessed to retrieve semantic meta-data associated with incoming percepts. For example, agents can retrieve the *affordances* associated with perceived objects. Also type hierarchies of objects in the ontology can be inspected, allowing agents to make generalizations about objects they perceive. In addition, the model can be used to validate the semantics of action instructions performed by a MAS agent. Being able to validate actions can greatly support the development of agents whose code for action-selection cannot be type-checked at design time (E.g. in 2APL).

Three types of percepts have been defined in CIGA's *Cognitive Interface* layer:

- *Object percepts* contain semantic data about objects perceived from the environment. A unique object identifier is provided giving agents the ability to relate subsequent percepts with the same object.
- *Event percepts* contain semantic data about events from the environment. An object's identifier provides the source where the event originated from.
- *Action percepts* contain feedback information about ongoing actions. The MAS agent can associate this feedback with a dispatched action using the included unique action identifier. Feedback information includes the progress status of the action and possible failure conditions.

Two types of actions have been defined in CIGA's *Cognitive Interface* layer:

- *Action instructions* are used for the physical (durative) actions agents perform. They correspond to the actions implemented in the *GE Interface* layer described previously and are executed by the *Behavior Realizer*.
- *Communication instructions* are used for physical communication between agents. These are *special* actions consisting of two parts. The first part contains the physical action the agent performs to realize the communication, corresponding to the previous type of instruction. The second part includes the communicative intent which may be represented in an agent communication language. This part cannot be send directly to the receiving agent if the physical communication action has not started yet. The *Cognitive Interface* layer is responsible for orchestrating this process.

For the implementation of the *MAS Interface* layer, interface standards like EIS [3] can be employed which has been explored to interface with multi-agent platforms like 2APL, GOAL, Jadex and Jason. Though, such platforms focus on high-level decision-making and deliberation aspects of agents and lack other aspects of behavior that may be required to form a fully cognitive architecture (E.g. the modeling of physiology, emotion or reflexive behaviors). These aspects can play an important role in simulating virtual humans for example. This issue has been addressed before as seen in CoJACK [8] which extends the JACK platform by combining its symbolic decision-making module with what is called a moderator layer for emotional and physiological factors. The *MAS Interface* layer can easily be used to connect such an additional MAS layer with its environment.

4 Related Technologies

In this section, we compare CIGA with related research and technologies with similar functionalities. First we'll look at technologies providing an interface to an environment in a game engine for external access. Gamebots [1] is a modification of the UT game engine and provides fixed sense-act interfaces for in-game avatars accessible using socket communication. It is often used in research on embodied agents mainly because of the lack of good alternatives for accessing virtual environments [7, 9]. Gamebots can be compared to CIGA's *GE Interface* layer (see Figure 3). Though, in Gamebots, there is no methodology for using domain ontologies as the interface messages are fixed and geared specifically towards the UT engine. Further, *action monitoring* is not supported since Gamebots doesn't offer explicit execution and monitoring of actions.

The High Level Architecture (HLA) is an architecture for distributed simulations. Its goal is to synchronize environments running in separate simulations. There have been attempts to connect external agents to simulation environments using HLA [13]. We consider HLA not suitable for connecting MASs since it was not designed for this purpose and therefore lacks facilities for agent-centric sensing and acting. Similarities between CIGA and HLA are the use of *ontologies* as a design contract and the use of a subscription mechanism to control the flow of information send between components. For CIGA, this is described in [20].

Next we'll compare the system of *Pogamut* which has a goal similar to CIGA. *Pogamut* is designed as a mediation-layer between a game engine (GE) and a decision-making system (DMS) to bridge the "representational gap" [10]. It is based on a general abstract framework for connecting a DMS to a GE [9]. The architecture of a Pogamut agent consists of a *WorldView* component for GE facts, augmented with optional components like a *Working Memory*, an *Inference Engine*, a *Reactive Layer* and a *DMS*. The main conceptual difference between Pogamut and CIGA is that where Pogamut presents an agent architecture connected to a game engine, the CIGA middleware offers facilities to connect an agent in a MAS directly to an avatar in the game engine. It doesn't enforce any agent architecture as we consider this to be contained in the MAS. Providing a tight connection with an avatar in the game engine requires CIGA to enforce modifying the game engine. Although this is a strong requirement, we think it is a necessity to better aid in the connection design of an agent's mind and body, allowing us to perform *perception filtering* and *action monitoring* in the game engine's native programming language. Although Pogamut is more flexible in connecting to different game engines (using Gamebots or HLA), it is highly dependent on the specific game engine. Here, the game engine not only dictates the mechanisms for sensing and acting, but also the use of fixed data representations for actions and sensory information. Although ontologies can be implicitly defined as Java classes, there is no explicit formal agreement between the GE and a Pogamut agent.

Facilitating the connection between MAS agents and MAS environments, the *Environment Interface Standard* (EIS) has been proposed. It provides a general purpose interface for associating environment entities with MAS agents and their sense-act interface [3]. The proposed interface is not primarily geared towards connecting agents directly to a real-time virtual environment. Although EIS can be used for real-time environments, little is said on how to deal with the design issues presented in section 2. EIS has been used in connecting agents to an environment using Pogamut [18].

Last, there are systems which have addressed a subset of the design issues presented in the paper. For example, in [22, 16], Mimesis is presented as an architecture to integrate special-purpose intelligent components with a game engine. The architecture addresses both the gap of information representation and action execution, though its design is less geared towards an agent-body connection such that issues in perception and communication are not addressed. In [5], a cognitive middleware layer is introduced which has a similar goal to the semantic processing in CIGA, providing agents with a *social world model*. Unlike CIGA, this system doesn't discuss the technological issues in creating embodied agents. In [19], the *ION Framework* is said to separate the simulation environment from a realization engine. Although it recognizes similar issues, it is unclear about the methods for implementing these guidelines.

5 Conclusion & Future Work

In this paper we presented CIGA, a middleware for facilitating the coupling of MASs to game engines providing a connection between a MAS agent and its embodiment in a virtual environment. It is designed as a general-purpose middleware employable in a wide range of applications with different requirements for agents. For example, in one simulation, believable embodied conversational agents (ECAs) are required where detailed (non)verbal communicative behavior and perception is important. In another simulation an agent's interaction and understanding of the environment may be more important requiring a more extended model of the environment and the actions for influencing it. A combination of such qualitative and quantitative aspects may also be desired. Here, CIGA facilitates the development of such simulations by supporting developers to bridge the conceptual gap between a MAS and a game engine without enforcing agent design decisions.

CIGA employs domain ontologies to form an agreement between the game engine and the MAS on the semantics of an agent's perceptual and behavioral interfaces. This allows designers to formally specify the concepts used within a specific application domain and reference them directly from within the game engine or the MAS. A sensory processing mechanism allows an agent to perceive its environment and build a *social world model* based on formal semantics. Designers are able to choose the required realism for sensors and control the way sensory information is filtered [20]. An action monitoring mechanism enables agents to be synchronized with the realization of their actions performed by their embodiments. Designers are left to provide an implementation of the actions specified for the application domain.

CIGA has been implemented connecting several MASs to an in-house developed game engine[1]. The *Physical Interface* of CIGA has been developed in C++ and the *Cognitive Interface* in Java. The internal connection mechanism employs TCP/IP sockets. MASs that have been tested include *2APL*, *Jadex* and a custom developed MAS testing industry-standard techniques. On top of the middleware platform a graphical user interface has been developed to provide logging and debugging facilities during the development process.

Future work involves validating the principled approach taken by CIGA by exploring different application settings where agents have different requirements. This also involves creating an interface with an alternate game engine. On the conceptual side, further research will be performed concerning the topic of agent communication within CIGA, dealing with formal agent communication in MASs on one side and believable human-like interactions in real-time environments on the other side.

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How to compare usability of techniques for the specification of virtual agents' behavior? An experimental pilot study with human subjects

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Abstract. Reactive or dynamic planning is currently the dominant paradigm for controlling virtual agents in 3D videogames. Various reactive planning techniques are employed in the videogame industry while many reactive planning systems and languages are being developed in the academia. Claims about benefits of different approaches are supported by the experience of videogame programmers and the arguments of researchers, but rigorous empirical data corroborating alleged advantages of different methods are lacking. Here, we present results of a pilot study in which we compare the usability of an academic technique designed for programming intelligent agents' behavior with the usability of an unaltered classical programming language. Our study seeks to replicate the situation of professional game programmers considering using an unfamiliar academic system for programming in-game agents. We engaged 30 computer science students attending a university course on virtual agents in two programming assignments. For each, the students had to code high-level behavior of a 3D virtual agent solving a game-like task in the Unreal Tournament 2004 environment. Each student had to use Java for one task and the POSH reactive planner with a graphical editor for the other. We collected quantitative and qualitative usability data. The results indicate that POSH outperforms Java in terms of usability for one of the assigned tasks but not the other. This implies that the suitability of an AI systems-engineering approach is task sensitive. We also discuss lessons learnt about the evaluation process itself, proposing possible improvements in the experimental design. We conclude that comparative studies are a useful method for analyzing benefits of different approaches to controlling virtual agents.

1 Introduction

Reactive planning is currently the dominant paradigm for controlling virtual agents in 3D videogames and simulations. Prominent reactive planning techniques used in the industry are derivations of finite state machines (FSMs) [1], and more recently, behavior trees [2]. Technically, these are implemented in a scripting language, be it a general-purpose language such as Lua [3] or a special-purpose language tailored at a particular game, such as UnrealScript [4], or hard-coded in a game's native language, typically C++ [5]. Advantages and drawbacks of different approaches used by the industry have been commented on widely [6,7,8].

At the same time, academic action-selection systems for AI planning are becoming increasingly mature, and the question arises whether they have advantages over the solutions employed presently by the industry. These systems include decision making modules of several cognitive architectures, e.g., Soar and ACT-R [9, 10], stand-alone BDI-based programming languages, e.g. GOAL [11], and stand-alone reactive planners such as POSH [12]. It has been already demonstrated that some of these systems, for instance Soar [9], POSH [13], GOAL [11] and Jazzyk [14], can be used for controlling virtual agents acting in game-like environments. From the perspective of efficacy of code execution, these systems are sluggish and can be considered as prototypes only at the present stage of maturity; however, they could potentially outperform some industry solutions in terms of usability (from the programmers' perspective), re-usability (of parts of code) and agent's cognitive performance, as assumed, for instance, by part of the academic community studying BDI-based languages [15].

Sound empirical data demonstrating the alleged advantages of different reactive planning technique, both industrial and academic, are generally lacking. Tyrell analyzed various robotics and ethology-based action selection mechanisms in terms of agent performance given approximately equal amounts of time devoted by a programmer [16]. This work was extended by Bryson in an effort to provide an evaluation for her own POSH action selection. [17]. Tyrrell's system was to test a single action-selection mechanism over a large number of "lifespans" by agents inhabiting an extremely rich and varied environment. The complexity of the environment lead to enormous variation in the results, so statistical significance was determined by running enough trials to compare the standard error rather than the standard deviation.

Bryson also provided a more theoretically formal but less rigorous comparison of POSH action selection to FSMs, showing that POSH plans were able to express action an intelligence was likely to choose to do in a more efficient way than an FSM [18]. However, none of these studies engaged programmers other than the authors themselves in the mechanisms' evaluation. In contrast, Hindriks et al [19] conducted an extensive qualitative analysis of the code of 60 first year computer science students developing (in teams of five students) three Capture The Flag agents for the videogame Unreal Tournament 2004 (UT 2004) using GOAL agent programming language. Hindriks's team aimed at "providing insight into more practical aspects of agent development" and "better understanding problems that programmers face when using (an agent programming) language" and identified a number of structural code patterns, information useful for improvements to the language. However, that study was not comparative and did not report the programmers' feedback.

Here, we are interested in a complementary approach, namely feasibility of quantitative comparative quasi-experimental studies (as used in psychology and social sciences) for investigating usability of action selection systems from the users' (programmers') perspective. We specifically address the usability issue as opposed to the efficiency or performance issue. This perspective encompasses various objective and subjective measures, such as steepness of the learning curve, time spent by development, programming vs. testing time ratio, number of bugs made by the programmer, subjective attitude towards the technique etc. We designed and conducted a pilot study with the following objectives:

a) to investigate the subjectively-perceived usability of an academic action selection system designed to be useful for programming agents' behavior, when compared to perceived usability of an unenhanced classical programming language; this mimics the situation of game programmers considering using an academic system they are not familiar with for programming in-game artificial intelligence;

b) to compare the quality of solutions implemented in the academic action selection system and in the classical programming language; this measure plays an important role in the adoption of new systems in general;

c) to consider whether the experimental method *per se* is useful and whether (and under which conditions) it can produce helpful results.

We have been running a course on virtual agents development for computer science students at Prague University since 2005. Students are taught various techniques for controlling virtual agents [20] and trained to program their behavior in the virtual environment UT 2004 (similarly to Hindriks et al.). For that task, our integrated development environment Pogamut [21] is used by the students. In the academic year 2009/10, we turned the final exam for the course into a scientific experiment engaging 30 computer science students in two programming assignments lasting 3 hours each. Each student had to code the high-level behavior of a 3D virtual agent solving a game-like task in the UT 2004. The conventional language and the language underlying the academic system were both Java. We use Java because its learning curve is less steep than that of C++ (a more usual game development language) and because our students are expected to be at least to some extent familiar with Java. For the academic system, we used the POSH reactive planner with a graphical editor. This is because POSH has been already demonstrated for controlling UT agents [13] and because POSH has previously been investigated by our postgraduates and integrated into Pogamut.

For both the tasks and in both programming environments, the students' task was to organize low-level action and sensory primitives to produce complex behavior, but not to program the primitives as such. The drag-and-drop graphical editor we developed for POSH disguised its Lisp-like underlying plan syntax students might have struggled with. The study was only possible because the Pogamut platform provided the same development environment for both tasks and allowed us to predesign the same sets of behavior primitives, isolating the features of the language as the subject of the study.

We collected various quantitative and qualitative usability data in four questionnaires. Our main hypothesis was that subjects' attitude towards POSH would be at least as high as towards Java. As this is a pilot study, we kept the research question as simple as possible. Of course, for practical, commercial application of POSH, it would be an advantage to specifically identify its benefits compared to Java (and other systems), but this was not our aim for this study and is left for future work.

The rest of the paper proceeds as follows. We introduce POSH in Section 2 and detail the methods of our study in Section 3. The results are presented in Section 4 and discussed in Section 5, and Section 6 concludes.

2 POSH

POSH action selection was originally developed in the late 1990s in response to criticism of what was at the time an extremely popular agent design approach (at least in academic discussion): the Subsumption Architecture (SA) [27]. SA was used to produce considerable advances in real-time intelligent agents, particularly robotics. It consists primarily of two components: a highly modular architecture where every action is coded with the perception it needs to operate; and a complex, highly distributed form of action selection to arbitrate between the actions that would be produced by the various modules. Although extremely well-known and heavily cited, the SA was seldom really used outside of its developers. Bryson hypothesized that the emphasis on modular intelligence was actually the core contribution of SA, but that the complexity of action selection, while successfully enforcing a reactive approach, confused most programmers who were not used to thinking about concurrent systems.

POSH was developed then to simplify the construction of action selection for modular AI. Briefly, a programmer used to thinking about conventional sequential programs is asked to first consider a worst-case scenario for their agent, then to break each step of the plan to resolve that scenario into a part of a reactive plan. Succeeding at a goal is the agent's highest priority, so should be the thing the agent does if it can. The programmer then describes for the agent how to perceive that its goal has been met. Then for each step leading up to the goal the same process is followed: a perceptual condition is defined allowing the agent to recognize if it can take the action leading most directly to its goal [12, 18]. The actions are each small chunks of code that control the agent, so-called behavior primitives (see Tab. S2 – all supplementary figures and tables can be found in the appendix), and the perceptions are sensory primitives (Tab. S4).

After a period of experimenting with the system, Bryson embedded POSH in a more formal development methodology called Behavior Oriented Design (BOD). BOD emphasizes the above development process, and also the use of behavior modules written in ordinary object-oriented languages to encode the majority of the agent's intelligence, and to provide the behaviour and sensory primitives. BOD includes a set of heuristics for recognizing when intelligence should be refactored either from a plan towards a behavior module or from a module into a plan. BOD and POSH have now been adopted or recommended by a number of leading thinkers and toolkits in AI, including Pogamut [21], RePast [28] and AIGameDev [6].

Recently, a graphical editor for POSH plans has been developed as part of the Pogamut effort. Its new version is used in the present study (Fig. S1).

3 Method

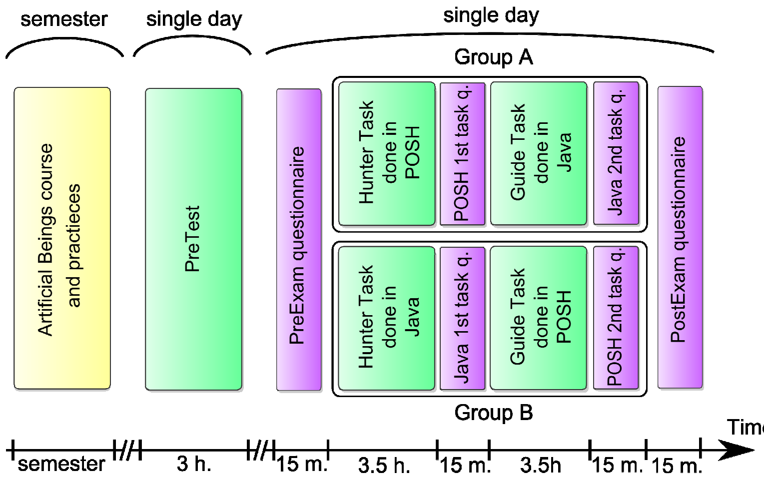
3.1 Experimental design

As explained earlier, the study compares the usability of an academic reactive planner, POSH, and an unenhanced classical programming language, Java. Low-level behavior primitives were prepared for both groups in advance by the authors of the study. The set of primitives were fully sufficient for solving the presented tasks.

The study was set in an AI course for computer science students in Charles University in Prague. The syllabus of course is described in [20, 22]. Subjects were given a pretest (3 hours) after the course to ensure that they have acquired elementary skills for solving sub-problems from the final exam. Only subjects that have passed the pretest were admitted to the final exam.

The final exam was structured to obtain comparative data on Java and POSH usability. In the final exam, each subject had to solve two tasks, the Hunter Task (3 hours) and the Guide Task (3 hours), see Sec. 3.3. Subjects were split into two groups, Group A and Group B. Group A was instructed to solve Hunter Task in POSH first and Guide Task in Java second while Group B was instructed to solve Hunter Task in Java first and Guide Task in POSH second. For both tasks, syntax highlighting was available for Java and a graphical editor for POSH plans (Fig. S1).

Figure 1. The course of the experiment.



Subjects were given 4 questionnaires in total during the exam (15 minutes each). There was a 30 minutes long break for a light lunch between the tasks. The course of the experiment is summarized in Fig. 1. Subjects were informed that the study will take about 8 hours in total in advance, but the structure and the exact content were revealed only during the study. The assignments were administered immediately prior to each task and the subjects given 30 minutes to read them.

3.2 Participants

We recruited 30 students for the study out of 52 attendants of the AI course. The study was the course's final exam and if students succeeded in its both parts, they were given a final grade based on their agent's performance. Students had the option of withdrawing from the study if they preferred a different kind of final exam.

We excluded 3 students from the analysis due to data incompleteness. In total, we analyzed data from 27 students of which 2 were female. Students were sampled into two groups. Due to the low number of subjects, the groups were not assigned to conditions entirely at random. Rather the students were ranked by their ability as determined by their pretest performance, and then the two groups were matched with as close to equal sums of rank status as possible. The number of students according to their years of study and assigned groups is presented in Tab. S1.

3.3 Materials

The Course. The students attended an introductory course on the control of virtual characters. The course is intended for students without previous AI or 3D graphics knowledge but with previous programming experience. Only students from the second or a higher year of study can attend. The course comprises of 12 theoretical lectures (90 minutes each) and 6 practical lessons at computers (90 minutes each). The theoretical classes are detailed in [20, 22]. During practical lessons, the students are taught how to work with Pogamut 3 platform library (2 lessons) and develop behavior of virtual agents using both Java (2 lessons) and POSH (2 lessons) [23].

The Pretest. The general aim of the Pretest was to rule out subjects that were not sufficiently prepared for the final exam. Unprepared subjects would bias the data as they would likely fail during the final exam which would influence their answers in questionnaires.

The Pretest task was to create an agent capable of exploring the environment of UT2004 game and collect items of a specific type only. The agent had no adversaries in this task. Subjects were not given behavior primitives in advance; they had to create them in Java for themselves. Regarding programming of a high-level behavior, subjects had the opportunity of choosing between Java and POSH. This approach was chosen to test the level of subjects' comprehension of the Pogamut library so that they would be able understand behavior primitives provided to them during the final exam.

Three programmers skilled in VR technology solved the pretest task in advance to calibrate the difficulty of the test. The time allotment (3 hours) was at least three times longer than average time needed by these programmers to finish the task. Subjects had 3 attempts to pass the Pretest. Most passed on their first attempt.

Task Hunter. The Hunter Task was designed as a game-like scenario. Subjects were to create an agent (called Hunter) that explores the environment collecting blood samples of another computer-driven agent called Alien either by finding them around in the environment or by shooting Alien. Alien was an adversary agent that was capable of killing Hunter when nearby. If Hunter or Alien got killed, they were restarted in the environment far from each other. In addition, Hunter started with no weapons. Thus, the AI behavior must correctly prioritize the following intentions: 1) finding a weapon, 2) collecting blood samples, 3) responding to Alien. For instance, the Hunter agent should stop pursuing a blood sample item and responded to Alien if Alien has approached, otherwise Hunter could be killed resulting in the loss of weapons and blood samples collected so far.

In contrast to the Pretest, subjects were given a full set of behavior primitives (`canSeeEnemy`, `runToItem`, `shootEnemy` etc., see list in Tab. S2) that were sufficient to solve the task. All behavior primitives were carefully commented inside the code to make their usage clear. Action primitives did not contain any decision making logic, e.g., `shootEnemy` action did not contain any checks whether the agent has a loaded weapon to shoot from or whether the enemy is close enough for the weapon to be effective. Such logic was to be created by each subject using proper sensors, e.g., `hasWeapon` and `getEnemyDistance` (example can be seen in the Fig. S1). The task was again solved by two skilled programmers in advance using these primitives and their feedback was used to adjust them.

After filling in a pre-exam questionnaire, each subject was given the assignment written on the paper and was provided a sufficient time (30 minutes) to read it and ask questions to clarify any ambiguities. Group A was then instructed to solve the task in Java while Group B in POSH. Time allotment was 3 hours, which is roughly three times more than was required by the skilled programmers. Both groups had the same set of primitives. The POSH version of the primitives differed only in implementation details so that they could be easily used inside POSH reactive plans.

Group A and Group B were working in parallel in two different rooms. Subjects were not allowed to cooperate on the solution but they were allowed to utilize any documentation about the Pogamut library available on the Internet [24].

Task Guide. The Guide Task was designed to be more cognitive than the Hunter Task. Subjects were to create an agent called Guide that can find a Civilian agent inside the environment and guide it back to its home. The Civilian agent was created to wander aimlessly around the environment far from its home unless the Guide agent instructed it otherwise. The Guide agent must communicate with the Civilian agent if it wants the Civilian agent to follow its lead. The communication has a fixed and rather simplistic protocol described in the assignment (see Tab. S3).

Communication was reliable and the two agents could hear each other up to a specific distance. Apart from finding Civilian, there were three obstacles that Guide had to overcome in order to successfully lead Civilian home. First, Civilian was willing to start to follow Guide only if it can see it. Second, if Civilian lost Guide from view, it stopped following. Third, Civilian was created to be absent-minded and ceased to follow the Guide agent from time to time for no reason. Thus, the challenge was not only to find Civilian and persuade it to follow the Guide agent to its home, but also to constantly observe whether Civilian is doing so.

As in the previous task, subjects were given a full set of behavior primitives (Tab. S4) and the task was tested by two skilled programmers both in Java and POSH. The only exception was the handling of the communication was always in Java, but it was sufficient to write three lines of Java code to solve the task in the POSH variant.

Group A was instructed to solve the task in POSH while Group B in Java. Everything else (the assignment description, the space for questions, the prohibition of cooperation, the allowance of Internet usage, slight differences in the POSH primitives) remained the same as in the previous task.

3.4 Questionnaires

Every subject was given four questionnaires in total. Questionnaires were: 1) PreExam questionnaire, 2) Hunter Task questionnaire (in Java and POSH variants), 3) Guide Task questionnaire (in Java and POSH variants) and 4) PostExam questionnaire. The timing of administration of each questionnaire is pictured in Fig. 1.

The PreExam questionnaire contained questions about the subject's biographical background and their AI/Agent/Programming literacy. Only relevant results are presented in this paper. The main questions for the present interest are: "How many person-months of programming/AI/Java experiences do you have?" and "How many hours have you spent experimenting with Pogamut at home?"

The two task questionnaires were designed to elicit data about comprehensibility of sensory and behavior primitives and subjects' preferences for the programming formalism used in the task. The main questions for present interest are: "Did you find POSH/Java sensor/action primitives comprehensible?" (1: I had a lot of troubles understanding them, 3: I did not understand a few primitives, 5: I had no troubles at all, everything was perfectly clear.), "Did you find the number of POSH/Java sensor/action primitives sufficient?" (1: totally insufficient, 3: I had to create a few for myself, 5: totally sufficient), "Which formalism do you prefer, Java or POSH?" (1: strong Java preference, 2: weak Java preference, 3: can not tell which is better, 4: weak POSH preference, 5: strong POSH preference.

The PostExam questionnaire contained many questions about the comfort of the Pogamut library API, Java, POSH GUI and other features of the Pogamut platform. It also contained the final question about the overall preference between POSH and Java: "Which formalism do you generally prefer for high-level behavior specification, POSH or Java?" (1: strong POSH preference, 2: weak POSH preference, 3: can't tell which is better, 4: weak Java preference, 5: strong Java preference). Subjects were also given a space for a free-text explanation of their answer.

The POSH/Java preference question was given three times in total and they have appeared in both (POSH/Java) variants of task's questionnaires. Our aim was to observe subject preferences with regard to the different tasks (Hunter Task vs. Guide Task) they had to solve as well as their overall. The questionnaires were not anonymous so we were able to pair them with concrete agents later on (see 4.2).

3.5 Data analysis

Answers of subjects from questionnaires of both groups were analyzed. We used χ^2-tests of independence to confirm that both groups had same or different language preferences. As the number of subjects in each group is rather small, we have grouped subjects with Java/POSH preferences into 3 classes (instead of 5) for the purpose of the χ^2-tests. Answer 1-2 is considered as *Java preference*, answer 4-5 as *POSH preference* and answer 3 as indifference.

Additionally, all agents were tested for quality. We executed a corresponding task scenario for every agent 15 times and checked whether the agent fulfilled the task's objective within the time frame of 10 minutes. We marked every run with either 0 (agent failure) or 1 (agent success). Average number of successes was counted as the *agent success rate (ASR)*. Even though every run was identical (the same environment setup was used, the same starting positions of bots were used, the same random seeds, etc.), we had to perform multiple runs due to small non-determinism caused by UT2004 and by asynchronous execution of agents' behaviors which resulted in different outcomes from the behavior deliberations.

ASR was taken as the degree of agent quality. An ASR of 1 indicates the agent always succeeded, while an ASR of 0 indicates the agent always failed – real values could fall between these. Logistic regression was used to identify relationships between the agent quality and the chosen technique, subject experiences and their understanding of the provided primitives. The regression was made for every task/group combination (4 regressions) as well as for all agent runs for Task 1 and for Task 2 (combining data from Group 1 and Group 2) and is presented in 4.2.

There were 4 questions testing subject understanding of the behavior primitives. For the subsequent analysis, we averaged responses of these questions and used this average as the *Primitives apprehension* variable.

4 Results

4.1 Comparison of the two groups with regards to subjective Java/POSH preference

The attitude of the students towards the languages in the two tasks is shown in Fig. 2, 3, S2-S7 together with their means and standard deviations.

Regarding the first task, Group A exhibits a strong preference to POSH (Hunter in POSH) while Group B (Hunter in Java) was more indifferent.

Figure 2. Left: Group A, Hunter Task (in POSH), Java/POSH preference. Right: Group B, Hunter Task (in Java), Java/POSH preference.

Ans.	#	%
1	0	0
2	2	15.4
3	1	7.6
4	3	23.1
5	7	53.9
Mean	4.15±1.14	

Ans.	#	%
1	0	0
2	5	35.7
3	4	28.6
4	1	7.1
5	4	28.6
Mean	3.29±1.27	

The contingency table of Java/POSH preference after the first task is shown in Tab. 1. The preferences in Group A and B are not significantly different (p-value = 0.12).

Table 1. Contingency table of the Java/POSH preferences after the first task.

	Java pref. (1-2)	*Can't decide (3)*	*POSH pref. (4-5)*	*Total*
Group A	2	1	10	13
Group B	5	4	5	14
Total	7	5	15	27

Concerning the second task, Group A (using Java) was indifferent and Group B (using POSH) exhibited preference to Java (Tab. 2). The preferences in Group A and B are not significantly different (p-value = 0.36). In general, the students shifted their preference to Java after the second task, which is summarized by Tab. S5.

General preference between Java and POSH, as assessed by PostExam questionnaires, is not a clear one. The preferences in Group A and B were significantly different with Group A preferring POSH while Group B preferring Java (p-value = 0.01) (summarized in the Tab. 3).

Figure 3. From left to right: i) Group A, Guide Task (in Java), Java/POSH preference, ii) Group B, Guide Task (in POSH), Java/POSH preference, iii) Group A, PostExam, Java/POSH preference, iv) Group B, PostExam, Java/POSH preference.

Ans.	#	%
1	2	15.4
2	4	30.8
3	1	7.6
4	4	30.8
5	2	15.4
Mean	3.00±1.41	

Ans.	#	%
1	3	21.5
2	7	50.0
3	2	14.3
4	1	7.1
5	1	7.1
Mean	2.29±1.14	

Ans.	#	%
1	0	0
2	3	23.1
3	2	15.4
4	3	23.1
5	5	38.4
Mean	3.77±1.19	

Ans.	#	%
1	3	21.5
2	6	42.8
3	4	28.6
4	1	7.1
5	0	0
Mean	2.21±0.86	

Table 2. Contingency table of the Java/POSH preferences after the second task.

	Java pref. (1-2)	*Can't decide (3)*	*POSH pref. (4-5)*	*Total*
Group 1	6	1	6	13
Group 2	10	2	2	14
Total	16	3	8	27

Table 3. Contingency table of the general Java/POSH preferences as answered in the PostExam questionnaire.

	Java pref. (1-2)	*Can't decide (3)*	*POSH pref. (4-5)*	*Total*
Group A	3	2	8	13
Group B	9	4	1	14
Total	12	6	9	27

4.2 Comparison of the two groups with regards to objective task solution quality

Logistic regression was used to identify relationships between an agent's quality (dependent variable) and chosen technique (Java or POSH), subject experiences and apprehensions of provided primitives. The parameter for the group was statistically insignificant and was left out from the model for the sake of simplicity. We have created 3 models (using data from both Group A and B, from Group A only and from Group B only) for both tasks (6 models in total).

Models description. The models' parameters are summarized in Tab. 4. Some dependencies between model variables and agent's quality are presented in Figs. S8 –

S10. Every figure contains graphs for Task 1 (left) and Task 2 (right) models separately. Models using data from both groups contain the additional discrete variable *Technique* (Java / POSH), therefore they are visualized with two graphs separately in each picture (for the Java and POSH cases separately). As all models amount to a function from the n-dimensional space (yielded from the Cartesian product of model variables' ranges) into <0;1> (agent success rate, model dependent variable), every presented graph can be seen as a planar cut through chosen variable of the whole model's n+1-dimensional graph where all other variables are fixed at data's means.

Tasks comparison. Task 1 was solved considerably better by subjects from higher years of study (Fig. S8, left). The data for Task 1 also suggests that subjects' comprehension of provided primitives affects the quality of their agents (Fig. S9, left); this is more pronounced in Group A's subjects. Additionally, solutions from Group B (implementing the Hunter agent in Java) indicate correlation with previous Java experiences (Fig. S10, left). The chosen technique (Java or POSH) did not influence the agents' success (see first row *POSH-influence* column in Tab. 4) in Task 1.

The interpretation of results of Task 2 is not as clear. Task 2 was also sensitive to Java experience as well as primitive comprehension (Fig. S10, S9 right), but results were more widely distributed this time. Also, agents of Group B driven by POSH did considerably worse than agents of Group A that were controlled by Java (see the fourth row *POSH influence* column in Tab. 4).

Table 4. Logistic models of agent success with respect to programming technique, subject's year of study, his/her experiences and primitives comprehension. Every row contains the parameters of one model. Column *POSH-influence* (discrete variable) explains how the probability of an agent's success changes when the agent was programmed using POSH (present only when data from both groups are used). All other columns (continuous variables) show how respective variables contribute to ASR. *Odds ratio* describes how the variable influences the probability of an agent's success. Values greater than one indicate that the probability grows proportionally with the variable and vice versa. Values in bold are discussed in Section 5.

Data used	Model fit comp. against empty model	POSH influence		Year of study		Java experience		Pogamut used at home		Primitives comprehensi on	
	P-Value	Odds ratio	Sig.	Odds ratio	Sig.	Odds ratio	Sig.	Odds ratio	Sig.	Odds ratio	Sig.
GA+B, T1	10^{-12}	**1.10**		**2.08**	***	1.08		0.96		**2.58**	***
GA, T1 (POSH)	10^{-10}	X		**2.10**	**	1.19		1.04		**1.24**	***
GB, T1 (Java)	10^{-6}	X		**1.81**	***	**1.30**	**	0.96		**0.74**	
GA+B, T2	10^{-5}	**0.44**	**	0.88		**1.11**	**	1.05	.	1.58	*
GA, T2 (Java)	0.057	X		0.99		**0.91**		0.91	*	2.37	**
GB, T2 (POSH)	10^{-7}	X		0.81		**1.09**		1.23	**	1.46	

Significance (P-Value): 0 < *** < 0.001 < ** < 0.01 < * 0.05 < . < 0.1

5 Discussion

This pilot study compared the usability of an academic reactive planning system to the usability of a common programming language when applied to programming the behavior of virtual agents in 3D game-like tasks. The POSH reactive planner empowered by a graphical editor of plans was chosen for the former and the Java programming language for the latter. This quantitative experimental study is, to our knowledge, the first in the field of virtual agent programming techniques (but see also [29]). The purpose of the study was twofold. First, we aimed at investigating objectively the usability of the two techniques, making a small step towards the grand goal: isolating features that contribute to usability of different approaches to control virtual agents in 3D videogames and simulations. Secondly, we aimed at answering the question whether the chosen experimental method *per se* is promising for future studies. We now discuss these two points.

5.1 Results

Summary of the data. The answer for the question of usability of Java and POSH has two sides which are intertwined. First, there is a subjective answer of comfort in using a chosen system as presented in Sec. 4.1. Second, there is an objective answer that comes of assessing the quality of agents as presented in Sec. 4.2.

Regarding the subjective answer, there are two main outcomes. a) Subjects, in general, reported that they preferred POSH for the first task (Fig. 2, S2, S3; Tab. 1) while they preferred Java for the latter (see Fig. 3, S4, S5; Tab. 2). b) Group A subjects tend to prefer POSH while Group B subjects tend to prefer Java (Tab. 3).

The objective answer as showed by logistic regression indicates several outcomes. c) students in a higher year of study tend to perform better in the first task while there was no such influence in the second task (see Fig. S8) d) previous Java experience was important in Task 1 in Group B (using Java in that task) but not in Task 2 in Group A (using Java in that task) (Fig. S10, left; Tab. 4), e) comprehension of the provided primitives was high in general (Fig. S9 left; means in both tasks were higher than 4.1) and seems to influence ASR a bit (Fig. S9 left; Tab. 4), f) the first task was done equally well in both POSH and Java (see *Odds ratio* of *POSH influence* in the first row of Tab. 4) while in the second task, subjects using POSH performed significantly worse (see *Odds ratio* of *POSH influence* in the third row of Tab. 4).

General comments. Arguably, the main underlying theme is that the data indicates different outcomes for the two groups. Why? Let us start with comments on distribution of subjects into Group A and B with respect to major variables (Comment 1), proceed with comments on several uncontrolled variables that may have influenced the outcome (Comments 2, 3, 4), and finally return to the individual outcomes A-F above.

1. Is the average programming experience of the subjects the same for the two groups? Tab. S6 indicates that Group B may have consisted of slightly more Java experienced subjects, but the difference between the groups is rather small. Data for the total previous programming experience look similarly (note that mean is not a

useful aggregative variable here since the learning curve is not linear). Students from Group B also have higher years of study on average (A: mean=3.3; SD=1. B: mean=4.4; SD=1.5). This is the outcome of the rank-based sampling procedure, which will be commented in Sec. 5.2. For present purpose, it is important that Group B may have comprised slightly more experienced programmers on average than Group A.

2. Subjects were undergoing a coding marathon as the final exam lasted 8 hours so the results from the second task could have been biased by subjects' tiredness. However, it seems reasonable to assume that both groups were equally tired.

3. It may be that the second task is harder in general, independently of the tiredness. We did not consider the complexity of tasks beforehand; therefore we have asked *post hoc* four independent VR experienced programmers to judge tasks' complexity out of the assignments (they did not perform them, we have just presented them written assignments) and task suitability for the chosen technique. The second task was perceived as easier only by one of them; the others thought that the second task is harder. Their comments regarding the suitability of techniques diverged.

4. It also may be that POSH fits better for solving the first task while Java for the second. This idea is actually supported by free-report parts of questionnaires. Some subjects indicated that Java was more suitable for the second task while none the other way round. Some subject's comments to the 2^{nd} task:

"There were more if-then rules in the first task than here, therefore POSH would have suited the first task more, using it here was mere overkill."

"Using POSH for this task would be a nuisance."

"In contrast with the first task, this was too complex to niggle with POSH plan graphical editor. It was better to address it in Java."

Main interpretation. In our opinion, the most plausible explanation of the results is that they are produced by combination of two effects: the fact that the second task can be more easily solved using Java (unlike the first task), and the fact that the graphical drag&drop editor and POSH (it is not clear which of these or whether both of them together) is more appealing to a less skilled audience and such an audience can use it more effectively than Java. This statement agrees with Results (A) and (B) and partly with (C), and is further supported by Comments 1 and 4. Of course, our data only indicates that this can be the case; a useful hypothesis for further testing rather than a conclusive result.

It is also possible that the essential difference was that Task 2 was best completed by altering or adding to the provided the primitives. Because of the way POSH was introduced with the emphasis on the graphical tool, most subjects appeared to feel obliged not to alter any Java code while they were in the POSH condition. One student did provide an exceptionally good agent in Task 2 by combining POSH and altered Java primitives. This strategy is more in keeping with the way POSH is presented in the academic literature as a part of a development methodology (Behaviour Oriented Design) rather than a stand-alone approach. However, only one exceptional programmer tried this strategy.

Another way of looking at the data is that POSH scored surprisingly well (Tab. 1, 8) given many subject's initial Java experience but no initial POSH experience. Investigation of steepness of the learning curve might be fruitful in the future. Useful information could also come out of studies of programmers already skilled in using an agent-based technique. Sadly, finding such a subject pool is presently a difficult task.

It is not surprising that understanding the primitives (Result (E)) has a positive effect on ASR. In fact, the influence is rather small, which is most likely caused by a ceiling effect: the average understanding of primitives was high in general, suggesting that our primitives were well chosen, prepared and documented.

Several questions remain open. We do not know why there was no influence of the students' years of study on the agents' performance in the 2nd task (Result (C), 2nd part); perhaps the assignment was not sensitive enough, or perhaps the difference on the 1st task indicated more advanced students become more adept at a new problem more quickly, whether through learning more quickly or due to being less stressed by exam conditions.

Concerning Result (D), it is not surprising that previous Java experience was important in Task 1 in Group B but not A, because the former group used Java. We do not know why previous Java experience had no influence on Group A in Task 2; again perhaps the 2nd assignment was not sufficiently sensitive to this variable. Also the sensitivity to previous Java experience in Task 1 suggests that classical programming languages are not as suitable for less-experienced programmers such as game designers as higher-level graphical tools and planning languages are.

Generalization. The results of this study indicate that academic techniques may in certain cases provide advantages over classical programming languages, but it is too soon to generalize based on the results of one study performed on two particular approaches and tasks. More studies are needed to obtain more conclusive data for further supporting or refuting such a claim. Nevertheless, it is a good sign for developers of various agent-based languages such as Jason [26] or GOAL [11]. Closer examination is needed to identify different complexities underlying virtual agents' development. Such examination may help recognize possibilities and limits of various techniques and uncover their strong and weak points. For instance, it may be that when augmented by drag&drop graphical editors (as POSH was in our study), some of these languages may be better suited than scripting languages for people with mediocre programming skills, such as some game designers. We believe that without such analysis the gaming industry would unlikely embrace academic techniques for virtual agent's development.

5.2 Lessons learned

As the comparative study of different techniques usable for virtual behavior development is new, we report lessons learned and suggest improvements for future studies. The main lessons are:

1) Performing the study in two consecutive parts promotes biased data on the second part due to subjects' tiredness. This can be addressed by altering the experiment design either by a) dividing subjects into 4 groups giving every group only *one* combination from the task-technique pairs, which would however require at least twice as many subjects, or b) by dividing each group into two subgroups, which

would solve both tasks each but in the reverse order; that would allow the statistical computation of the effect of tiredness, or c) to perform the second task in another day.

2) It would be beneficial to administer one more questionnaire during the pretest to obtain the initial preferences of subjects regarding the techniques compared in the study. In general, several other variables could be controlled better, e.g. the task difficulty (see also Comments 2, 3, 4 in Sec. 6.1).

3) The analysis should be complemented with qualitative studies to gain more insight. This may have several forms. a) Interesting data can be obtained by analyzing the agent code as has been previously done by Hindriks and colleagues [19]. We may still do this with the code from the present study. b) Focus groups or structured interviews can be conducted after the main study to obtain more precise explanations for subjects' preferences and their solutions' quality. c) Questionnaires should encourage subjects to describe reasons for their preference (the importance of this has been highlighted in Comment 4 in Sec. 5.1).

4) Attention should be paid to the evaluation's tasks. Each task should be judged not only for its general difficulty by programmers skilled with VR technologies, but also for its difficulty regarding the technique being tested. In general it is presumably a good thing to make assigned tasks varied so that an over-general conclusion is not reached without adequate justification. After the evaluation, subjects should be asked for their own assessment of the tasks to check if it correlates with the experts'. Note that both subject and expert assessment should be checked against actual quantifiable results.

5) The sampling procedure should be carefully considered. Evidently, even a rank-based sampling may produce unequal groups (with respect to some variables). When there are a lot of variables and a relatively small sample size, such an outcome may be inevitable. The sampling procedure will also be different for different questions asked, e.g., if one would like to assess group of experienced Java programmers against inexperienced ones, the criterion for sampling would be previous Java experience.

6) Pretests are important in order to ensure that students have certain minimal skills for the main study, e.g. from the present study the ability to understand behavior primitives. Pretests are also important for obtaining data for the sampling procedure.

5.3 Future work

Our results clearly indicate a need to continue with comparative studies and to begin to identify the different aspects of the complex task of virtual behavior development. We are considering performing another study this year, taking into account the lessons learnt, possibly utilizing GOAL [10] as an academic reactive planning technique that is based on the BDI paradigm. We may also run the same test again but with POSH clearly set forward not as an alternative to Java but rather as a way to supplement it. AI action selection systems are intended to simplify the development of agent intelligence, not to replace it.

6 Conclusions

This pilot study compared an academic reactive planning technique (namely POSH) against a common programming language (namely Java) with respect to their usability for programming behaviors of virtual agents in 3D game-like tasks. The study has investigated the performance of subjects' agents with respect to the technique used as well as subjects' preferences towards the techniques.

The conclusion, stated with caution, is threefold. First, from a general perspective, POSH scored comparable to Java. Second, in a more fine-grained manner, usability of Java and POSH seem to be task-sensitive and subjectively perceived usability of the techniques as well as objective quality of the subjects' agents with respect to the techniques may change with subjects' programming experience. Third, the experimental method is useful, but should be complemented by other approaches.

Taken together, these are promising news for agent-based control mechanism developers. Future studies are needed and they should focus on isolating mechanisms' features that contribute most to the mechanisms' usability for different target groups of users, e.g., game designers vs. programmers.

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Appendix

This section contains additional tables, figures and some additional text concerning presented study.

Reusable package. The package containing the assignment texts, Pogamut 3 platform, template agent projects and the scenario map can be downloaded from [25].

Table S1. Number of students in groups according to their types of study and years of study. Master students have number of years spent for their bachelor studies included into their years of study. Note that bachelor studies last 3-4 years typically and master studies takes usually extra 2-3 years.

Group A

Study / Year of study	*2nd*	*3rd*	*4th*	*5th*	*Total*
Bachelor	4	2	0	0	6
Masters	0	0	6	1	7
Total	4	2	6	1	13

Group B

Study / Year of study	*2nd*	*3rd*	*4th*	*5th*	*6th*	*8th*	*Total*
Bachelor	2	1	3	0	0	0	6
Masters	0	0	3	2	2	1	7
Total	2	1	6	2	2	1	14

Table S2. List of all behavior primitives that were provided in the Task 1.

Sensors		
class of primitives	*X parameter*	*Y parameter*
canSee X	AlienBlood, Ammo, Enemy, Weapon, WeaponOrAmmo	
get/know X	NavPointToExplore	
know X Y	SpawningPoint	AlienBlood, Ammo, Weapon, WeaponOrAmmo
	Spawned	AlienBlood, Ammo, Weapon, WeaponOrAmmo
get X Y	Random	NavPoint
	Nearest	NavPoint
	NearestVisible	AlienBlood, Ammo, AmmoOrWeapon, Enemy, NavPoint, Weapon
	NearestSpawned	AlienBlood Ammo Weapon WeaponOrAmmo
	AlienBlood, Ammo, Item, Weapon, DistanceToTarget	
has X	Ammo, Weapon	
is X	Moving, Shooting, RunningToItem, RunningToPlayer, RunningToNavPoint	
wantToSwitchToItem		

Actions	
run X	ToItem ToNavPoint ToPlayer
shootEnemy	
stop X	Movement, Shooting

Figure S1. Example of the code that the subjects were creating. Top: part of a POSH plan of the Hunter task as visualized by the graphical editor. Below: Hunter code in Java. The code and the plan were taken from an exemplary solution created by one of VR experienced programmers.

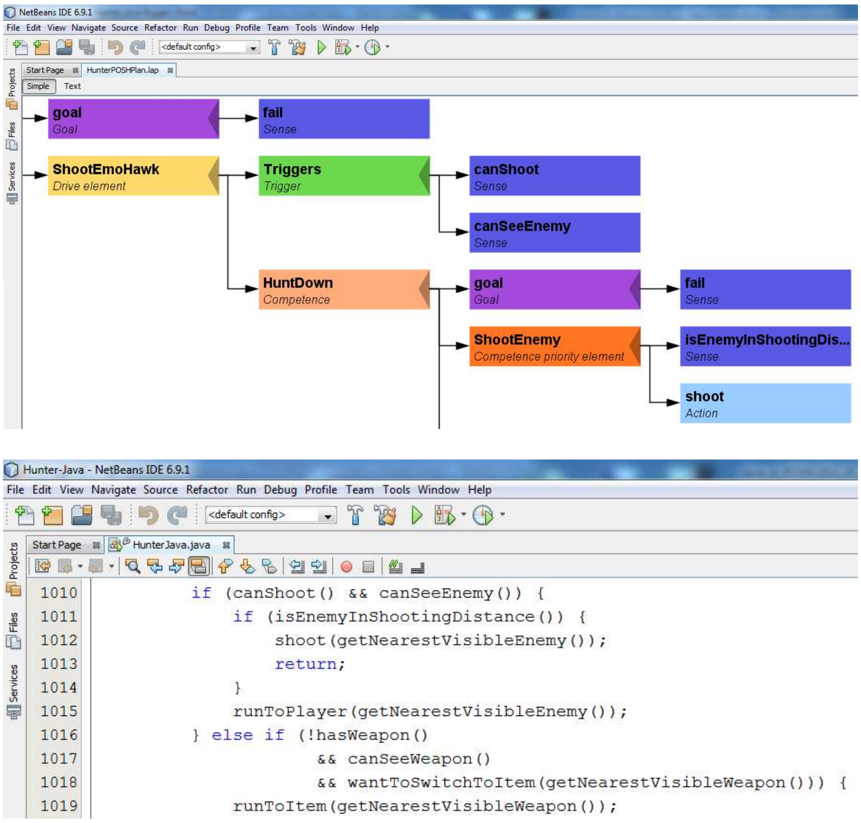


Table S3. List of possible commands that can be issued by the Guide and corresponding possible answers.

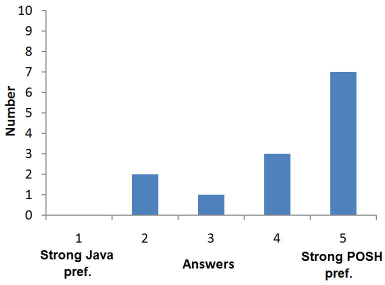
Guide commands	*Possible Civilian answers*
commandCivilianCanSee	answerAngry answerDontUnderstand answerCanSee answerCantSee
commandCivilianFollowMe	answerAngry answerDontUnderstand answerCantFollowingCantsee answerFollowingOk
commandCivilianStop	answerAngry answerDontUnderstand answerStopped
commandCivilianTurn	answerAngry answerDontUnderstand answerTurning

Table S4. List of all behavior primitives that were provided in the Task 2.

Sensors		
class of primitives	*X parameter*	*Y parameter*
can X Y	See	Civilian, Player
	FollowCivilian	
get/know X	NavPointToExplore	
get X Y	NearestVisible	NavPoint, Player
	DistanceTo	Civilian, NearestPlayer, Target
is X	CivilianFollowing, CivilianMoving, CivilianNear PlayerInTalkingDistance, Moving, RunningToPlayer,	

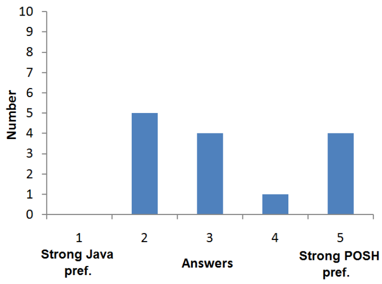
Actions		
command X Y	Civilian	CanSee, FollowMe, Turn, Stop
faceCivilian		
followCivilian		
run X	ToNavPoint, ToPlayer	
set X	CivilianSpeed, GuideSpeed	
stopMovement		

Figure S2. Group A, Hunter Task (in POSH), Java/POSH preference.



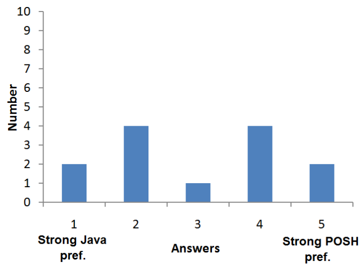
Ans.	#	%
1	0	0
2	2	15.4
3	1	7.6
4	3	23.1
5	7	53.9
Mean	4.15±1.14	

Figure S3. Group B, Hunter Task (in Java), Java/POSH preference.



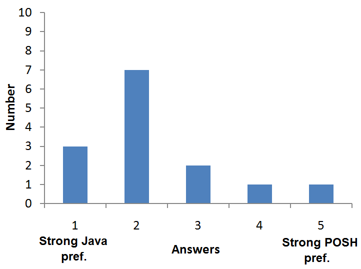
Ans.	#	%
1	0	0
2	5	35.7
3	4	28.6
4	1	7.1
5	4	28.6
Mean	3.29±1.27	

Figure S4. Group A, Guide Task (in Java), Java/POSH preference.



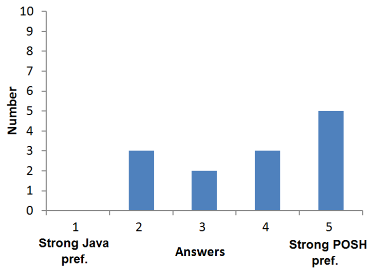
Ans.	#	%
1	2	15.4
2	4	30.8
3	1	7.6
4	4	30.8
5	2	15.4
Mean	3.00±1.41	

Figure S5. Group B, Guide Task (in POSH), Java/POSH preference.



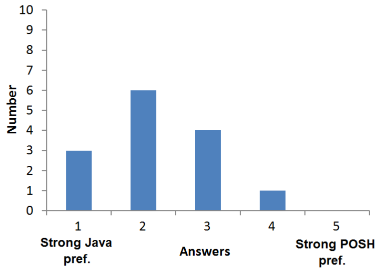
Ans.	#	%
1	3	21.5
2	7	50.0
3	2	14.3
4	1	7.1
5	1	7.1
Mean	2.29±1.14	

Figure S6. Group A, PostExam, Java/POSH preference.



Ans.	#	%
1	0	0
2	3	23.1
3	2	15.4
4	3	23.1
5	5	38.4
Mean	3.77±1.19	

Figure S7. Group B, PostExam, Java/POSH preference.



Ans.	#	%
1	3	21.5
2	6	42.8
3	4	28.6
4	1	7.1
5	0	0
Mean	2.21±0.86	

Table S5. Contingency table of the Java/POSH preferences shift.

Change in preferences of Group A

	T2 - Java	*T2 - Can't decide*	*T2 - POSH*	*Total (Task 1)*
T1 - Java	2	0	0	2
T1 - Can't decide	1	0	0	1
T1 - POSH	3	1	6	10
Total (Task 2)	6	1	6	13

Change in preferences of Group B

	T2 - Java	*T2 - Can't decide*	*T2 - POSH*	*Total (Task 1)*
T1 - Java	5	0	0	5
T1 - Can't decide	3	1	0	4
T1 - POSH	2	1	2	5
Total (Task 2)	10	2	2	14

Table S6. Table summarizing previous Java experiences in both groups (in man-months).

	0-1 months	*2-5 months*	*6-9 months*	*> 9 months*	*Total*
Group A	9	2	0	2	13
Group B	6	4	1	3	14
Total	15	6	1	5	27

Figure S8. Dependency of ASR on subject's year of study (Left – Task 1; Right – Task 2).

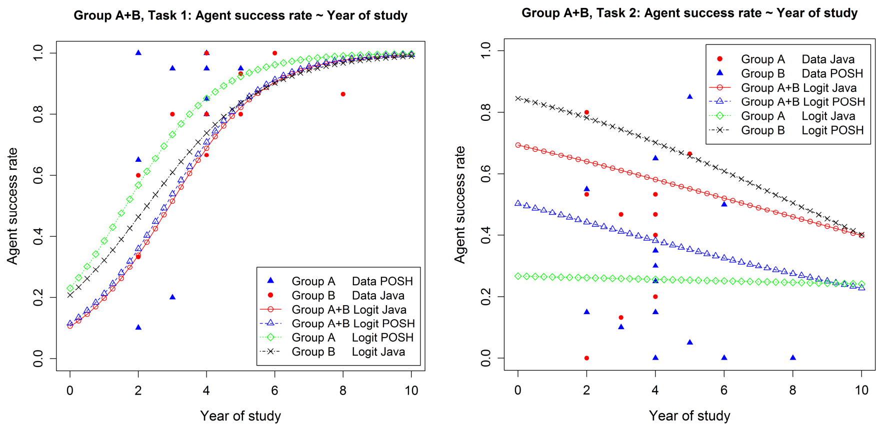


Figure S9. Dependency of ASR on primitives' comprehension (Left – Task 1; Right – Task 2).

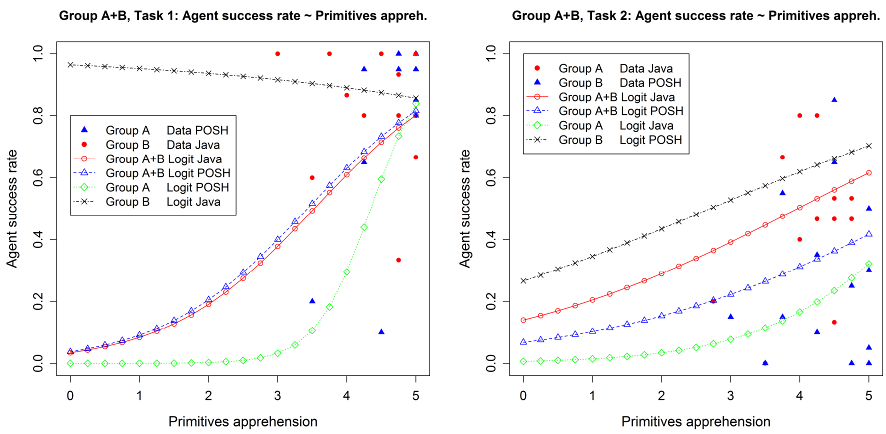
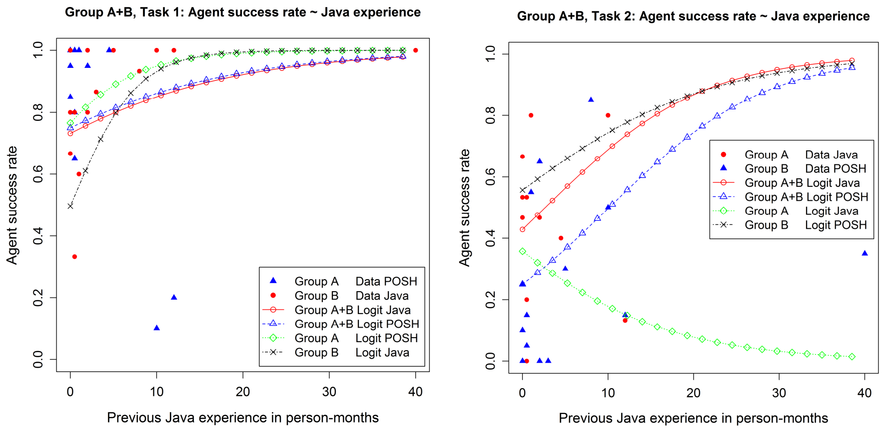


Figure S10. Dependency of ASR on previous Java experience (Left – Task 1; Right – Task 2)..



ADAPT:
Abstraction Hierarchies to Better Simulate Teamwork *

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Abstract. In this paper we present a lightweight teamwork implementation by using abstraction hierarchies. The basis of this implementation is ADAPT, which supports **A**utonomous **D**ynamic **A**gent **P**lanning for **T**eamwork. ADAPT's novelty stems from how it succinctly decomposes teamwork problems into two separate planners: a **task** network for the set of activities to be performed by a specific agent and a separate **group** network for addressing team organization factors. Because abstract search techniques are the basis for creating these two components, ADAPT agents are able to effectively address teamwork in dynamic environments without explicitly enumerating the entire set of possible team states. During run-time, ADAPT agents then expand the teamwork states that are necessary for task completion through an association algorithm to dynamically link its task and group planners. As a result, ADAPT uses far fewer team states than existing teamwork models. We describe how ADAPT was implemented within a commercial training and simulation application, and present evidence detailing its success in concisely and effectively modeling teamwork.

1 Introduction

Effectively quantifying teamwork problems is critical in many environments [4, 10]. However, one of the key challenges in creating teamwork models is how inter-agent rules can be encoded such that the team can still effectively behave in complex and dynamic environments [1, 10]. In particular, when multiple agents operate in these types of environments, their different mental states must be resolved so that a unified behavior can be formed for the team. One key research challenge for distributed artificial intelligence researchers is how these models can be created and implemented [10].

One leading solution is to decompose the group's actions into a set of rules which must be solved [10]. Following this approach, the group's actions can be represented as a hierarchical structure of joint intentions and individual intentions and beliefs about others' intentions. However, this approach has two major drawbacks. First, the size of the model might be too large to realistically solve. Previous research found that many classes of teamwork problems exist for which finding the optimal sequence of actions is of intractable computational complexity [9]. Second, the structure of the tree must be flexible to dynamically changing conditions, such as changes in the environment, goal changes, and local or general constraints. Thus, even if a solution could be found

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for a given time period, that solution might quickly become irrelevant. Hence, solutions must be found that reduce the size and structure of the team model such that it may be tractably and quickly solved, even in dynamic environments.

In this paper we present ADAPT, a novel approach for **A**utonomous **D**ynamic **A**gent **P**lanning for **T**eamwork. The key difference between ADAPT and other teamwork hierarchical approaches [1, 4, 5, 10, 11] stems from how teamwork is modeled. Previous approaches attempted to exhaustively depict all possible teamwork states. However, as has been previously demonstrated [9], the number of possible interactions between team members grows exponentially for many real-world domains, making these approaches difficult to implement, even in small to medium-sized groups.

Instead, ADAPT uses hierarchical abstraction as its basis in order to reduce the number of states which need to be considered. Specifically, a given teamwork problem is converted into two hierarchical networks: a **task** network to model the set of activities a given agent can perform and a separate **group** network for addressing organization factors. Within both hierarchical networks, behaviors are decomposed such that the general task and group problems are progressively redivided into partial plans involving smaller sets of subtasks and subgroups. ADAPT contains two novel elements designed to further reduce the size of these hierarchies. First, as hierarchical abstraction is used, agents incrementally add only relevant task and group information during task execution. Second, ADAPT uses an association algorithm to effectively perform task allocation. Agents only check those constraints which it may possibly perform, further adding to ADAPT's concise nature. The net result is that ADAPT can effectively simulate teamwork problems, even in dynamic environments, yet uses far fewer states than existing approaches.

While the ADAPT framework is general and is likely applicable to a variety of teamwork problems, in this paper we focus on how ADAPT was critical in implementing a multi-agent simulation. In Section 2 we present related teamwork models and compare those approaches to ADAPT, while Section 3 formally defines ADAPT and its algorithms. Sections 4 and 5 detail how ADAPT was implemented. Specifically, Section 4 focuses on describing the existing commercial multi-agent simulation into which ADAPT added. In Section 5 we discuss how ADAPT was successfully implemented into this framework, detail results which demonstrate the effectiveness of this framework in dynamic environments and show that the number of teamwork states that must be considered within ADAPT is significantly less than in other state-of-the-art approaches. This allowed the existing simulation to more effectively handle complex multi-agent tasks. Section 6 provides our conclusions.

2 Background and Motivation

Because of the importance of coordination problems, a variety of teamwork frameworks and formalizations have been proposed by the multi-agent research community [4, 1, 10]. The SharedPlans approach [1] consists of creating teamwork recipes based on modeling agents' beliefs and intentions. Tambe's STEAM teamwork engine [10] provides a set of generalized teamwork rules. The TAEMS framework [4] consists of hierarchical rule based approach where coordination relationships are quantified into groups, tasks, and methods.

ADAPT decomposes teamwork in a novel fashion by creating two hierarchical networks: a **task** network which addresses how the agent must plan its actions, and a **group** network that addresses how inter-agent assignments must be set. Previous work of multi-agent planning (e.g., [2]) and teamwork structures [4, 1, 10] suggested addressing the team's **task** planning as one multi-agent network which needs to be decomposed. Other works from social sciences [12] address how people within a team should be organized in order to facilitate the best planning of the activity. This approach parallels our creating a **group** network based on the agents in the team. However, ADAPT's novelty stems from applying abstract search techniques [7] to address multi-agent planning in its task and group network.

Previous approaches also separate team behavior into different components. Most similar to our approach, BITE is a behavior based teamwork architecture that separates task behaviors from behaviors between a single agent and its organization [5]. Similarly, ADAPT compartmentalizes teamwork between the task and the group. More generally, the TEAMCORE architecture uses a decision-theoretic structure to select different hierarchical team behaviors [11]. TAEMS separates team activities into tasks that are performed by the team with methods that can be performed by the agent [4]. However, in previous approaches, teamwork models were completely defined before task execution. They are required to explicitly define how every agent interacts with every other agent, and even how dynamics may affect these relationships, a process that can potentially lead to an exponential number of inter-agent states. When implementing these models, this state explosion can be prohibitively difficult as the number of team members grows.

In ADAPT, the task and group abstractions are incrementally built and dynamically changed during task execution. This difference allows us to significantly reduce the number of inter-agent states even when addressing dynamics. Additionally, ADAPT enables replanning for specific subproblems, allowing for more effective teamwork. Consequently, ADAPT allows for a more concise model which, in turn, facilitates easier simulation of complex, real-world tasks. We detail this approach in the next section.

3 Technique Description

ADAPT's model is based on taking a teamwork problem and then decomposing it into both task and group elaboration processes. As such, each of the task and group problems are decomposed in a top-down manner from a higher level, into progressively lower levels. The planning strategies of the elaboration processes in ADAPT are based on abstract search techniques [7]. Accordingly, the planning procedures of each elaboration process involves three major steps: (1) A *branching* step identifies possible candidates for expanding a partial plan; (2) A *refinement* step for adding constraint information to the partial plan; (3) a *pruning* step for removing unpromising candidates based on these constraints in order to avoid failure. While abstract-search is a well known technique for automated task planning [7], ADAPT's contribution stems from applying these techniques to teamwork modeling.

3.1 A Dynamic Planning Teamwork Example

To clarify how we intend to use these concepts, consider the following general example. Assume that a group must work as a team on a joint mission, say to capture a flag. A group of blue agents must plan how they will infiltrate the territory of the opposing team of red agents who are defending the flag. This type of scenario is typified in many real-world scenarios, such as military missions involving destroying an enemy target. In dynamic environments it is almost impossible to predict all possible event permutations that may occur while the blue agents complete their task.

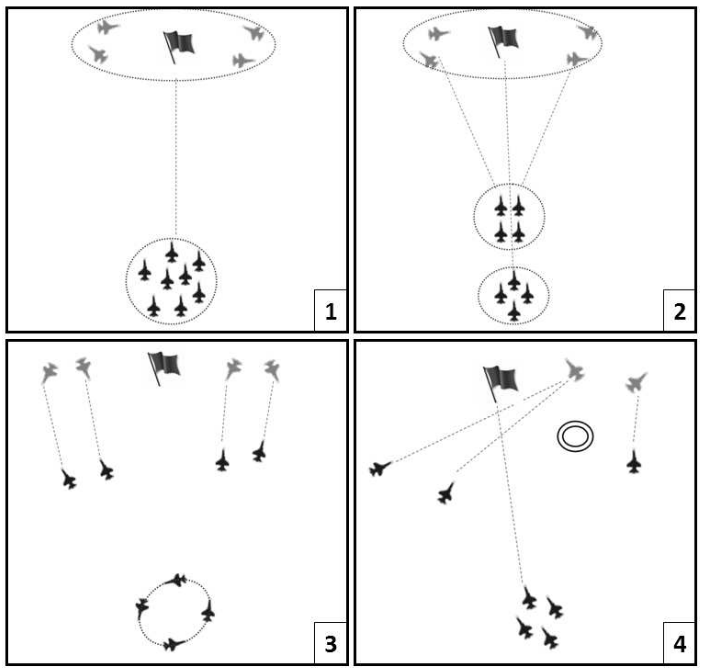

Fig. 1. Four Stages in a Mission Storyboard

Figure 1 depicts one series of group states during the execution of the “Capture the Flag mission”. At the start, a group of 4 red agents are divided into 2 subgroups of pairs located on either side of the flag to defend it (see the top left corner). At the same time, a group of 8 blue agents approach the flag area. In the second stage (see top right corner), the blue group splits into two subgroups of 4 agents according to their capabilities. One subgroup splits again into two subgroups of 2 agents and each subgroup approaches and engages the 2 red subgroups. In the next stage (bottom left) the blue agents engage the red ones to attempt to capture the flag. However, during this stage an unplanned event occurs, and one of the blue agents is incapacitated by a member of the opposing red team. The result of this change is that the group must replan their mission with only 7 of the 8 agents. In the final stage (bottom right), we see the group of 7 remaining blue agents still completing the task and capturing the flag.

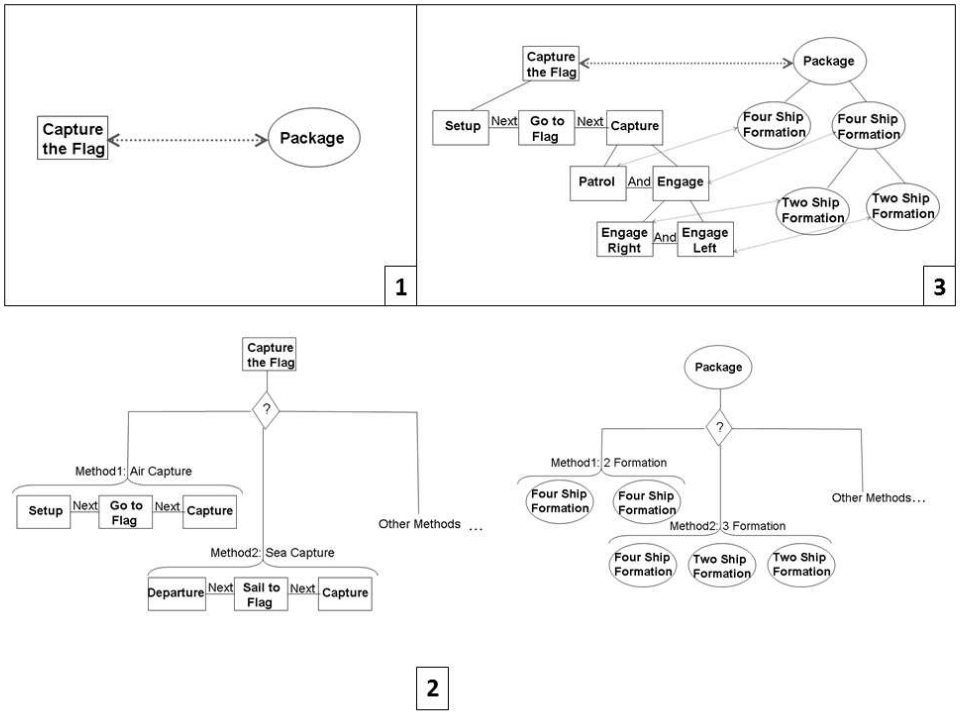

Fig. 2. Three Stages in Building the Teamwork Model in a Mission Storyboard (see Figure 1)

3.2 High Level Overview of ADAPT

While the ADAPT agents plan their task, they use the branching, refinement and pruning stages of abstract search techniques to limit the size of the teamwork model. We depict the stages of the teamwork model formation for the blue team in Figure 2. As previously described, ADAPT decomposes teamwork into both task and group networks. In the first stage (Stage 1 in Figure 2) each of these components are described only generally in the form of one abstract node. To graphically differentiate between the two task and group abstractions, we present the task hierarchy in rectangles, and the group hierarchy in ovals. At the beginning of execution, one rectangular task node describes the high level "Capture the Flag" task, and the group hierarchy "Package" describes the blue agents' attributes and capabilities which can be used to perform this task. In order for the blue agents to perform the team task, "Capture the Flag", their group and task planners must decide exactly how they will properly connect these two hierarchies. To make this decision, the agents' planners must apply their *branching* step to expand their abstract components of all applicable group and task options, which we refer to as *methods*. This is graphically represented in Stage 2 of Figure 2. However, unique to ADAPT and beyond similar previous teamwork approaches such as BITE and TEAMCORE [5, 10, 11], we then apply a *refinement* step where each agent generates the best applicable option based on its locally available information and the set of constraints associated with each option. We model each distributed agent as having a planner which uses a Distributed Constraint Optimization Problem (DCOP) solver to help create teamwork plans. In our implementation, the DCOP solver is based on the existing OptAPO algorithm [6]. As per the OptAPO algorithm, a mediator agent is elected which collects each of the distributed agents' constraints. In the next *punning* step, the mediator agent selects the best option given the choices each distributed agent presents. The mediator agent then informs each distributed agent about the option chosen, which is then selected by the local agent and executed.

Referring again to the example in Figure 2, the distributed planner decides that the best sequence for the blue agents to execute the team task, "Capture the Flag", is to first select the "Setup" subtask, then "Go to Flag", and lastly the "Capture" subtask. Within each subtask a further decomposition may occur into additional subtasks and subgroups. For example, the "Capture" subtask is decomposed into two subtasks which are assigned to 2 subgroups. One subgroup of four agents performs the "Patrol" subtask, while the second subgroup of four agents perform the "Engage" activity, where they engage the red agents defending the flag. The allocation step, where each agent is assigned to a given subtask, is also performed by the *refinement* step (Stage 3 of Figure 2). The best assignment is decided by the OptAPO mediator agent. As only a subset of all agents can perform certain activities, we can then apply the *pruning* step by which we reduce the teamwork model to only those states which are theoretically feasible. The mediator is also responsible for checking, or associating, between the task and group networks in order to ensure that the solution is feasible. Combining the *refinement* and *pruning* steps allows for a significantly smaller teamwork model than previous approaches [5, 10, 11] as their approaches stop model construction at the *branching* step. Thus, our work searches for a teamwork solution in a much smaller state space than in previous approaches.

In the following sections we formally describe and further detail the exact process by which these group and task networks are built. We also describe how these networks are associated such that teamwork problems can be solved in real-time and yet address dynamic changes from within the problem.

3.3 Modeling ADAPT's Constraint Networks

We model each task and group network as having a hierarchical structure which must be solved as a type of distributed constraint optimization problem (DCOP). Following previous DCOP work we define a DCOP problem as a set of variables where each variable is assigned to an agent who has control of its value. Cooperative agents must then coordinate their choice of values so that a global utility function is optimized. Formally, this process has previously been described as [6]:

- A set of N agents A = A_1, A_2 ... , A_N
- A set of n variables V = X_1, X_2 ... , X_n
- A set of domains D = D_1, D_2 ... , D_n where the value of X_i is taken from D_i. Each D_i is assumed finite and discrete.
- A set of cost functions f = f_1, f_2 ... , f_m where each f_i is a function f_i: $D_{i,1} \times \ldots \times D_{i,j} \rightarrow$ N $\cup\, \infty$. Cost functions are also called *constraints*.
- A distribution mapping Q : V $\rightarrow$ A assigning each variable to an agent. Q(X_i) = A_i denotes that A_i is responsible for choosing a value for X_i. A_i is given knowledge of X_i, D_i and all f_i involving X_i.

– An objective function F defined as an aggregation over the set of cost functions. Summation is typically used.

In the following sections we describe how we have implemented DCOP to create teamwork behavior in ADAPT's task and group network.

Modeling ADAPT's Task Network As our goal is to succinctly implement the simulation of group behavior, ADAPT contains many similarities to previous Hierarchical Task Network (HTN) planning approaches [4, 8, 7, 3] but includes extensions for dynamic multi-agent environments. Formally, we define an *atomic task* (or primitive task) as an action $act(\vec{v})$ that can be directly executed by the agents (e.g., $FlyTo(origin, dest)$). A (higher-level) *complex task* $c(\vec{v})$ is one that cannot be executed directly and is decomposed into subtasks (e.g., $Defend(v_1, v_2, v_3, v_4)$. Each task may be associated with two kinds of boolean formulas – a *precondition rule* and *postcondition rule* – to indicate the required situations for starting and ending the task execution (e.g., $(IsFuel > 200.lib) \wedge (IsTime =$ 5:00PM). We define tasks as being either a *single-agent task* or a *multi-agent task*. A single-agent task can be executed by one agent by itself and multi-agent tasks require 2 or more cooperative agents to complete the task.

To execute a high-level complex task $c(\vec{v})$, agents must identify a *method* that encodes all constraints for how this task may be performed, including key information about which agent can perform this task and constraints as to how it can be performed. Specifically, we define a method, m, as a 5-tuple containing: $\langle \text{name}(m), \text{task}(m), \text{constr}(m), \text{subtasks}(m), \text{relation}(m) \rangle$, where name$(m)$ is the name of the method and task(m) is the name of the complex task. We define $subtasks(m)$ as the sequence of tasks and $constr(m)$ as the set of constraints $\{\rho_1 \dots \rho_p\}$ that may apply when using the method m. Each constraint ρ_k involves a subset of variables and specifies all combinations of values for these variables. We define these variables as the set of $\{X_1 \dots X_n\}$ where each value X_i is taken from a set of D_i possible values for a given problem. Constraints may include specific required capabilities that a certain number of agents perform specific $subtasks(m)$. For example, there may be a constraint stating that the number of agents required to perform a subtask must be between 2 and 5 (formally, $2 \geq X_{agentNun} \leq 5$). Alternatively, these constraints may specify the type of agent that can perform a certain subtask, for example that the type of agent must be a fighter plane. In our implementation, we assumed these constraints were boolean. The relationship, $relation(m)$, contains constraints on the execution of the $subtasks(m)$ and may be one of the following: (i) AND denotes that the task(m) is accomplished iff all the $subtasks(m)$ are accomplished; (ii) OR denotes that the task(m) is accomplished iff at least one of the $subtasks(m)$ is accomplished; and (iii) NEXT orders constraints between $subtasks(m)$ such that one subtask must be performed before another. These constraints contain similarities to the QAF and NLE constraints within the TAEMS teamwork framework [4].

We define a *task network* $d_{task} = [G_{task}, \rho]$ as a collection of tasks that have to be accomplished under constraints ρ. The task network is represented by an acyclic digraph $G_{task} = (V_{task}, E_{task})$ in which V_{task} is node set, E_{task} is the edge set, and each node $v \in V_{task}$ contains a task. The *task planning domain* $\mathcal{D}_{task} = (\mathcal{M}_{task}, \mathcal{A})$

consists of a library task methods $\mathcal{M}_{task}$ of methods and library $\mathcal{A}$ of atomic tasks. A *task planning problem* is defined as a triple $P_{task} = \langle d_{task}, \mathcal{B}, \mathcal{D}_{task} \rangle$ where d_{task} is the task network to be executed, $\mathcal{B}$ is the initial state and $\mathcal{D}_{task}$ is the planning domain. A *task plan* is a sequence $act_1 \ldots act_n$ of atomic actions.

Given a task planning problem instance, the planning process involves the *branching*, *refinement* and *pruning* steps. The *branching* step is defined by retrieving the entire set of methods in $\mathcal{M}_{task}$ which may be applied to the required task. *Refinement* then has each local agent check its $constr(m)$ and send what it considers to be its best option to the mediator agent within the DCOP solver. More formally, given a set of possible applicable methods $\{m_1, \ldots, m_t\}$ each method contains constraints $constr(m_j)$ that contain sets of variables $\{X_1^{m_j} \ldots X_n^{m_j}\}$ where each value $X_i^{m_j}$ is taken from a set of $D_i^{m_j}$. Consistent to the general DCOP formalization, the ADAPT agent must minimize the cost functions $f = \{f_1, \ldots, f_m\}$ where each $f_i(d_{i,1}^{m_j}, \ldots, d_{i,k}^{m_j})$ is a function of $f_i : D_{i,1}^{m_j} \times \ldots \times D_{i,k}^{m_j} \rightarrow N \cup \infty$. The teamwork problem is considered solved if an assignment $A^* = \{d_1^{m_j}, \ldots, d_n^{m_j} | d_i^{m_j} \in D_i^{m_j}\}$ is found such that the global cost, F^{m_j}, is minimized. As DCOP problems have been proven to be NP-complete [6], keeping the search space as small as possible is critical for implementing a working application, especially one capable of running in real-time even as it handles dynamics.

In ADAPT's *pruning* stage, the mediator uses the OptAPO algorithm to search for this teamwork solution. If a solution for $\mathcal{M}_{task}$ cannot be constructed, the mediator agent asks each agent to iteratively select its next possible method until a solution is found. This process can either result with a plan being found, or a NULL plan in failure. Assuming dynamics change the environment, the entire planning process is repeated from the *branching* step.

For example, referring back to Figure 2, a complex task by the name of "Capture the Flag" is to be performed (Stage 1). The complex task may be decomposed according to a set of methods from $\mathcal{M}_{CapturetheFlag}$ which can be used to indicate different ways to plan this task (Stage 2). In this example, the selected method includes the subtask Setup which is an atomic task, while the subtask Capture is a complex subtask which must then continue to be decomposed by additional methods. Stage 3 in Figure 2 depicts the last stage in task network for $G_{CapturetheFlag}$.

Modeling ADAPT's Group Network In parallel to the task hierarchy, ADAPT also deconstructs teamwork into a group component to model constraints about which agents can perform given tasks. We refer to the hierarchy about the entities combined capabilities as the **group**. Parallel to our task definitions, we decompose the hierarchy as per the **group decomposition** into higher levels of **complex entities** and **atomic entities** which cannot be divided into further levels.

More formally, an *atomic entity* indicates a single agent and its basic capabilities $agent(\overrightarrow{v})$ (e.g., $Airplane(Engine, Fuel, \ldots)$). A (high-level) *complex entity* $c(\overrightarrow{v})$ indicates a multi-agent group that can be decomposed into subgroups. The decomposition of the *complex entity* into subgroups is done according to group decomposition *method*. Specifically, method m is defined as a 4-tuple:
$\langle \text{name}(m), \text{entity}(m), \text{constr}(m), \text{subgroups}(m) \rangle$, where $\text{name}(m)$ is the name of the *method* and $\text{entity}(m)$ is the name of the *complex entity*. The $subgroups(m)$ indicates

either atomic or complex entities. Similar to task method the $constr(m)$ indicates set of constraints $\{\phi_1 \dots \phi_r\}$ that may apply when using the method m. These constraints indicate the required capabilities from agents to be assigned to the $subgroups(m)$ and the different constraints on the group (e.g, maximum group members). A *group network* $d_{group} = [G_{group}, \phi]$ is a collection of groups that have been organized in a hierarchical manner under constraints ϕ. The group network is represented by $G_{group} = (V_{group}, E_{group})$ in which V_{group} is a node set, E_{group} is the edge set, and each node $v \in V_{group}$ contains group information.

The *group planning domain* $\mathcal{D}_{group} = (\mathcal{M}_{group}, \mathcal{E})$ consists of a library $\mathcal{M}_{group}$ of methods and a library $\mathcal{E}$ of atomic entities. A *group planning problem* is defined as a triple containing P_{group}, which is defined as $\langle d_{group}, \mathcal{B}, \mathcal{D}_{group}\rangle$ where d_{group} is the group network to be executed, $\mathcal{B}$ is a set of agents with their concrete capabilities and $\mathcal{D}_{group}$ is the planning domain. A *group plan* assigns agents to the appropriate nodes in the group network based on their capabilities in such a way that all the constraints are satisfied.

Similar to the task planning process, given a group planning problem instance, the planning process again involves the *branching*, *refinement* and *pruning* steps as well. The *branching* step is defined by retrieving the entire set of methods in $\mathcal{M}_{group}$ which may be applied to the *complex entity*. The *refinement* stage then has each local agent check its $constr(m)$ and send what it considers to be its best option to the mediator node within the DCOP solver. In the *pruning* stage the mediator node then checks all received constraints and checks if a solution for $\mathcal{M}_{group}$ can be constructed. If several solutions are possible, it selects the solution with the highest expected utility (or the lowest cost). If no plan can be formed based on these constraints, each agent iteratively selects its next possible method until a solution is found. This process can either result with a plan being found, or a NULL plan in failure. Assuming dynamics change the environment, the entire planning process is repeated from the *branching* step.

For example, referring back to Figure 2, a *complex entity*, “Package” contains all possible group configurations. The *complex entity* may be decomposed according to a set of methods from $\mathcal{M}_{Package}$ which can be used to indicate different group compositions to plan this group organization. In this example, the selected method “FourShip Formation” includes that a group decomposition of two groups of four agents to be formed from the *complex entity* “Package”.

3.4 Association to Create Teamwork

It is important to stress that after the *pruning* stages described above in both the task and group networks, the mediator agent must check the consistency, or what we refer to as the *association*, between these two sets of constraints to see what teamwork action should be selected. The association process serves as an intermediary between the DCOP mediators for both the task and group planners within the two abstract networks. The association process may connect one or more vertices of the task and group networks. Thus, the association enables loose coupling between the planners by allowing each of them to modify the corresponding plan independently.

The major steps of solving a teamwork problem are given in Algorithm 1. The teamwork problem is divided into a two separate networks, d_{task} and d_{group}. An initial network is represented as a single vertex of the highest level task or group. The group planner is responsible to assign the initial agent(s) to the vertex of the initial network and the association process creates a link between these initial networks (line 1). Then the task planner creates a partial plan by expanding its task network as much as possible based on the constraint's world state W currently available to the agents' mediator (line 2). These constraints will typically include data such as the current states of the environment (e.g. weather) or the informational status of the agent (e.g. fuel level or position). During the task planning process, the mediator is responsible to assign an agent (or agents) to subtasks in the task network. The mediator then sends a request with the proposed assignment to the association process so possible group constraints can be checked. The association process connects to the group mediator (line 3) which checks all possible ways a given task can be allocated by expanding its group network under the constraints of the task planner (line 4). This is our implementation of the branching step. The association process is then responsible for linking the new vertices that were added to the group network to the corresponding vertices in the task network (lines 6-7). ADAPT then applies the partial solution on the environment through interleaving planning with execution (line 8). In this way, plans are built incrementally during real-time. Note that steps 6–8 correspond to the *refinement* and *pruning* stages of abstract search techniques. Next, if it is impossible to generate a partial plan because of information obtained from the *refinement* step, the association sends a replanning request to either the task planner or group planner (lines 9-10), and each local agent sends additional constraints and the plan is expanded as described in the former section. Finally, the association algorithm checks if the changes to the available data cause conflicts with the existing assignments (lines 11-13). If any conflict with the existing plan is detected due to the dynamic changes to the environment, the entire process is repeated.

Algorithm 1 *The major steps for dynamic association*
Input: *Initial vertices* $v_t \in V_{task}$ *and* $v_g \in V_{group}$
Output: *Teamwork plan for current world state W*
01 *Create initial links between* v_t *and* v_g;
02 ***while*** *the task plan is not completed:*
03   ***if*** *request from task planner is received* ***then:***
04   *Send request for elaboration to group planner*
05   *Receive the set of the vertices* V'_{task} *and* V'_{group}
06   ***if*** *Can-Associate* (V'_{task}, V'_{group}) ***then:***
07   *Generate-links* (V'_{task}, V'_{group})
08   *Apply partial teamwork plan if possible;*
09   ***else***
10   *Send request for replanning (task or group)*
11   *Receive perceptions from the world:*
12   ***if*** *the new data causes to conflicts between links*
13   *Send request for replanning (task or group)*

4 Implementation Issues

We have implemented ADAPT within a commercial training and simulation system at Elbit Systems LTD. Elbit specializes in large-scale defense solutions in the areas of aviation, land and naval military systems with ten of thousands of workers worldwide. One division within Elbit has been developing sophisticated simulation systems such that personnel can be trained without the cost and potential risk of using actual equipment. Towards this goal, Elbit has already developed realistic simulators for airplane cockpits, naval stations and ground forces. We propose a new application that builds upon Elbit's existing simulators to simulate more complex team training missions through using ADAPT to help reduce the teamwork model size so it may be effectively implemented.

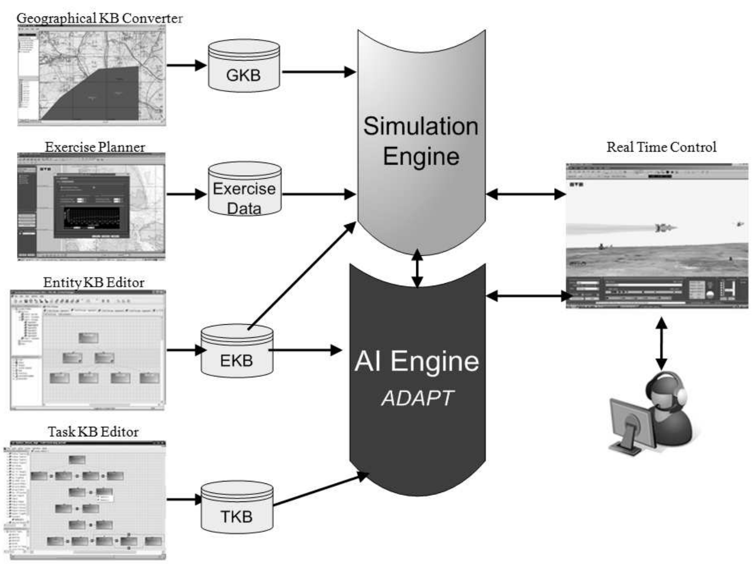

Fig. 3. A high level overview of the simulation system

Towards this goal, we created a working system at Elbit by integrating ADAPT within existing single-workstation simulation systems. Figure 3 depicts a high level description of the system's four major components. Elbit's previously developed simulation engine is still responsible for creating the base simulation environment. As part of this component, a Geographical Knowledge Base (GKB) contains geographical data about the training scenario and an exercise planner (EP) database is created with initial data of the training exercise (e.g., agents types, agents' forces, their initial location, their initial mission). Special to the ADAPT project, a Entity Knowledge Base (EKB) is created containing properties on each agent (e.g. aircraft type, max, min velocity). In addition, it includes various types of entities, including complex entities (e.g., platoon, battalion), and their decomposition methods that describes possible ways of decomposing the groups into subgroups. Thus, this database contains all relevant information about ADAPT's group network. Also, a Task Knowledge Base (TKB) is created containing a set of tasks that the agent can perform and their appropriate methods. Within military applications, this database represents a **doctrine**, or the key task that must be performed, or ADAPT's task network. Agents' decisions are based on the dynamic and static knowledge that the agents gather from the simulation engine as well as the constraint information in the EKB and the TKB. The Real Time (RT) control component enables the human trainer to interact with the simulated arena. Additionally, it provides the human interface to the simulation system.

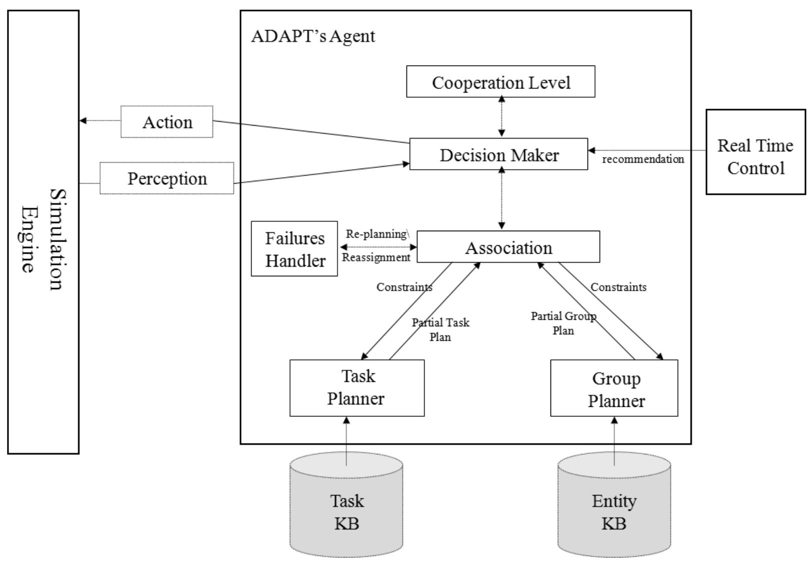

Fig. 4. General description of an ADAPT agent

Figure 4 provides a detailed description of how ADAPT and the algorithms presented in section 3, are integrated as the basis for creating this behavior. Moving from top to bottom within the Figure, each simulated entity is comprised of: a decision making process; a cooperation level; a failure handling process; and two types of planners (connected through the association process). Note that the Task Planner in Figure 2 is used to solve ADAPT's task network, and the Group Planner is used to solve ADAPT's group network. The decision maker is responsible for receiving the agent's perceptions and deciding on the agent's next steps accordingly.

5 ADAPT's Usefulness in a Simulation System

In studying ADAPT's usefulness in Elbit's simulation system, we focused on three key issues: 1. Can content experts easily work with the application to effectively impart their knowledge? 2. Does ADAPT indeed succinctly model teamwork, and how does it compare with other state of the art models? 3. Does the system perform effectively, and can it deal with system dynamics?

Specifically, we applied the general technique in Section 3 regarding the Capture the Flag problem, and applied this technique to scenarios involving fighter jets attempting to destroy an enemy target. Each scenario involved a target that needed to be destroyed, as well as groups of attacking and defending planes. The attacking planes form the blue group and are constructed from bomber and fighter planes (e.g. F16 fighters and Stealth bombers), and the defending group consist exclusively of red fighter planes (F16). The goal of the blue fighters is to disable the enemy's red fighters after which the blue bombers are able to destroy the target. The scenarios focused on different group sizes for the blue and red teams. Dynamics focus on unknown issues including the number of planes on each team that were disabled. In order to create the task and group networks, we consulted with a group of professional fighter pilots whose expert knowledge was then directly encoded. We relied on these experts to provide details about how they would perform theoretical missions. We then successfully encapsulated this information as the Doctrine and Technical databases to form ADAPT's task and group methods. A pictorial description of one scenario involving seven blue and six red planes is given in Figure 5.

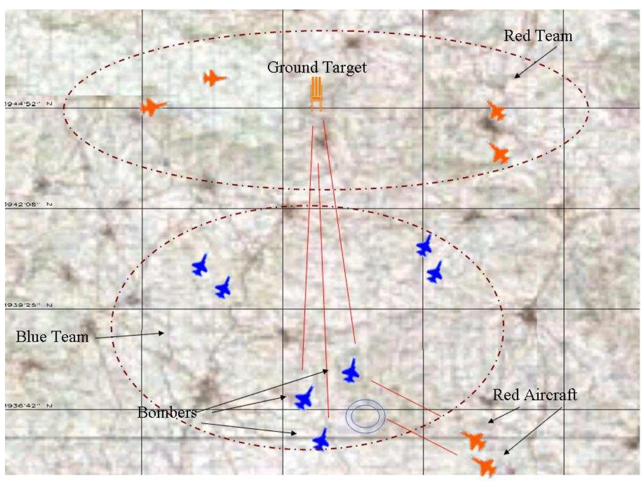

Fig. 5. Attack a ground target - simulation view snapshot

To study the savings in the number of states within ADAPT versus other previous static approaches [5, 10, 11], we focused on missions with groups of 5, 8 and 12 blue planes which needed to destroy one target on the red team guarded by a fixed number of 5 jets. We recorded the number of task and group nodes required to encode teamwork within ADAPT throughout the task's execution. We then compared how many states would be needed in these same problems by BITE [5]. We decided to compare the number of states needed by BITE as it too divides teamwork into Task and Group hierarchies and thus is the closest comparable model to ADAPT. However, as ADAPT uses abstract search as well, we would expect BITE to use a fixed number of possible task and group permutations, while ADAPT would only store those states actually needed to deal with problem execution. Furthermore, one would expect that the number of states in ADAPT can and will change during task execution, especially as problem dynamics are addressed. To study this point, we assumed 2 blue agents were disabled during task execution.

	BITE		**ADAPT** max		**ADAPT** average	
Number of Agents	Task States	Group States	Task States	Group States	Task States	Group States
5	561	18	44	5	37.1	3.67
8	624	146	53	8	39.65	6.29
12	829	400	68	8	56.86	6.17

Table 1. Comparing the number of task and group teamwork states in ADAPT versus BITE teamwork models

As Table 1 demonstrates, we found that ADAPT's use of abstraction yielded an enormous savings in the number of teamwork states needing to be stored. In columns 2 and 3, we present the size of BITE's task and group network within the problems we implemented. Compare these values to the **maximal** size of ADAPT's task and group networks in columns 4 and 5. The average state size is even smaller, and is presented in columns 6 and 7. These very significant savings are because ADAPT only stores task and group network nodes that are found to be relevant based on the current conditions as dictated by *branching*, *refinement*, and *pruning* stages. In contrast, static approaches such as BITE must preplan for all possible contingencies. This difference becomes more pronounced as ADAPT uses real-time planning based on the agent's current state. ADAPT interleaves planning and execution and thus applies partial group and task networks. This is why ADAPT has no need to create complete plans for all contingencies in advance. The net result is that ADAPT's group and task networks are initially defined abstractly and incompletely and built incrementally only as needed, based on the specific environment settings that the agents encounter during task execution based on ADAPT's associative algorithm. Thus, the maximum number of task and group nodes within ADAPT is far larger than its average. This difference can be observed by comparing the differences in the maximal model size and the average size for task states (columns 4 and 6) and group states (columns 5 and 7).

In addition to studying the size of ADAPT's teamwork model, we also evaluated the ease by which ADAPT could be implemented to verify that in fact it did facilitate tractably computing the team's optimal behavior even when faced with dynamics. Recall that the task and group planners are based on a state-of-the-art DCOP algorithm [6] to solve these constraints. However, as these problems are NP-complete, no DCOP algorithm can yield definite performance guarantees for all theoretical problems. As our production simulation must be able to run without noticeable lags, even when simulating complicated scenarios with high levels of dynamics, we believe that having a

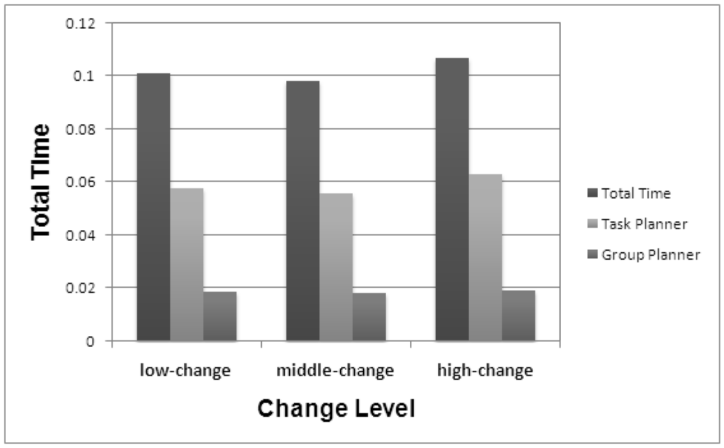

Fig. 6. The influence of dynamics on ADAPT's teamwork planners.

smaller teamwork model is critical towards achieving this goal. To evaluate this point, we implemented 3 variations of scenarios involving a team of 8 blue agents attempting to achieve their joint mission, i.e. *attack ground target*, versus a group of 5 red agents. To study the impact of dynamics on ADAPT, three levels of dynamic changes were tested: low-change, middle-change and high-change. In the low-change scenario the red force tried to defend the ground target but could not eliminate any of the blue force members and the group planner did not need to replan due to dynamics. This case represents the baseline of the study, as it allowed the blue force to complete its task with no changes in its force and with little need to change its mission plans. In the middle-change scenario, the red force succeeded in eliminating one or two of the blue fighters from the arena (based on non-deterministic effects), triggering some changes in the group hierarchy of fighters and requiring a moderate degree of mission and group replanning. In the high-change scenario the red force succeeded in eliminating three or more planes from both the fighter and bomber planes, causing more changes in the group hierarchy. This necessitated significant replanning efforts in both the task and group networks.

We measured the total planning time needed by the blue team agents using ADAPT to plan successful joint missions. We defined mission success as the elimination of the ground target and the blue team returning home. To examine ADAPT's performance, we compared the time needed by its problem solvers in 30 trials for each of the 3 different levels of dynamic changes (90 total trials) from sets of 5 minute simulations. We ran the ADAPT simulation on a 2.8 GHz Pentium D computer with 2 GHz of memory.

Figure 6 shows the total time utilized by the task planner, group planner and the decision maker to completely plan the joint mission. The total time represents the overall time used by the ADAPT engine to solve the teamwork problem. This time includes the component needed by the task planner, the group planner and the association process. In all cases, the task and group planners operated within fractions of seconds. Similarly, the total time used by ADAPT was under 0.12 seconds in even the most dynamic scenarios. Thus, we found that ADAPT facilitated real-time teamwork simulation, even in highly dynamic environments.

6 Conclusions

In this paper, we present ADAPT, a framework to decompose teamwork into abstract task and group networks. As ADAPT is the first teamwork model to use abstract search methods, it represents a radical departure over previous models which need to exhaustively describe all possible interactions prior to task completion [5, 10, 11]. As these models can be of exponential size, the problem of finding the optimal teamwork behavior can be of intractable complexity [9]. In contrast, ADAPT builds teamwork models incrementally during task execution, thus allowing agents to apply *refinement* and *pruning* steps to limit the size of the teamwork model needing to be stored. This fundamental difference not only yields teamwork models that are smaller by several orders of magnitude, but allows agents to quickly find their optimal behavior within this smaller model as described in this paper.

This paper also described how ADAPT was implemented within a challenging military simulation domain. We present results pertaining to how ADAPT formed the basis of a commercial system. We detail the specific task and group networks ADAPT created, how ADAPT can handle domain dynamics, and the time required by ADAPT to identify the optimal team behavior. While we have only implemented ADAPT to date in one series of planning problems, we are confident that this approach can be equally successful in other planning and scheduling problems due to ADAPT's generality.

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An Architecture for Affective Behaviours Based on Conservation of Resources

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Abstract. *This paper presents a model for autonomous virtual agents that enables them to display affective behaviours. Our goal is to obtain believable behaviours, i.e. behaviours that are similar to those of human beings, for various simulation contexts in an urban environment. The proposed architecture is based on a principle of conservation and acquisition of resources.*

Keywords: affect, emotion, virtual agent, simulation, behaviour

1 Introduction

Modelling believable behaviours is required to design human-like agents that can be used for credible simulations in domains such as security, urban planning, or video games. In this paper we present an architecture for autonomous virtual agents that enables them to display affective behaviours. The context is a realistic virtual city, with waiting lines as locations where conflicts can emerge between agents, and where danger like fire or riots can arise in the environment. Our objective is to define a model able to produce lifelike affective behaviours compatible with these situations.

Emotions have been considered as necessary components for lifelike virtual agents [1]. Inspired by psychological theories [2], some computational models rely on cognitive appraisal processes, in which a category of emotion is triggered by a specific context, and favours a set of cognitive strategies or behaviours [4, 6]. However, neither psychology nor computational science have come to an agreement on a basic set of emotions necessary and sufficient to cover the range of human behaviours : some claim for only two affective variables [7], others for six basic emotions [8], or even for twenty-two emotional variables [4], and their choice is justified by different criteria that all seem valid. This emotional parsing does not solve the issue of behaviour in computational models, since the same emotion is associated with multiple behaviours, and a behaviour can be associated with several emotions.

Considering these observations, and relying on the work of psychologist L.F. Barrett [11], we propose to view emotions as concepts independent from the core architecture that generate behaviours. Our hypothesis is that emotions are categorizations that are useful for reasoning and communication purpose, but are not components at the origin of affective behaviour. Hence we aim at an affective architecture that should be able to generate behaviours descriptible with emotional lexicon by a human observer, without using emotional categories as components of the model. In this paper we propose a generic model for affective behaviours based on the theory of conservation of resources formulated by psychologist S.E. Hobfoll [13]. The central tenant of this theory is that humans try to protect their acquired resources, and seek to gain new ones.

After having considered related work, we present in this paper the core architecture of our model. The description of resources and how they fulfill an agent's needs is explained, along with the selection process for resource-oriented behaviours. Finally we discuss the proposed model.

2 Related Work

Common sense lets one think that everyone knows what an emotion is, and that they are identifiable components of our brain system. "Fear", "anger", "joy", "sadness" are words often used in our everyday vocabulary. However a close look at the litterature shows that emotions are all but *natural kinds* [11], and that there is currently no consensus on the number of existing emotions, neither on their role or consequences on cognition and behaviour [5, 14].

J. A. Russell [7] identifies only two types of *core affect* dimensions which are valence, i.e. how good or bad a feeling is, and arousal. He points out that any additional differenciation is based on contextual differences made upon various non-emotional processes. In a study on culture and categorization of emotions, Russell lists emotional words for which there is no equivalence from a language to another, revealing that emotion categories are culture specific, and that even the categories of *fear* and *anger* are not universal [9]. P. Ekman distinguishes among six basic emotions, grounded on the hypothesis of universal facial expressions, and on distinctive patterns of physiological changes during emotional episodes. These distinctions are still under debate, because even if autonomic specificity has solid support, it is difficult to match these patterns with definite emotional categories [3]. Besides, it is worthy of note that, according to R. W. Levenson, these studies do not prove the existence of emotions, but the existence of a correlation between an autonomic response and an emotional interpretation of this response by the subject.

Psychological theories of emotion are numerous and propose different emotion sets based on different valid criterias. S. S. Tomkins enumerates nine affects and three valences [16], adopting a functional approach of emotions, and Ortony, Clore and Collins (OCC model) account for twenty-six emotions using Lazarus' evaluation theory [4]. The OCC model has been widely used in computational science. It aims at predicting which emotional category could be associated to a situation. However it is not suitable for simulating behaviours. In this model categories are considered as interpretations leading to cognitive strategies, or what we may call reasoning. It is not possible to match a unique behaviour with each emotion. For example fear and anger can both lead to agressive behaviours. This results from the fact that Lazarus' original model of cognitive appraisal is centered around the question of how individuals interpret a situation to cope with it, not at how universal emotion categories could trigger behaviours.

Besides the fact that emotions are culture specific [9], they are also individual specific [10]. According to psychologist L.F. Barret, if no set of clearly defined emotional patterns has been found, it is because emotions are concepts instead of being distinct entities in our affective system [11]. Human beings experience emotions the same manner as they experience colors, they use their kwnowledge to label their perceptions with categories. Hence if emotions are concepts, it is possible to parse our affective space with a infinite number of emotion sets.

From this conclusion, a question arises : what components an affective architecture generating behaviours labelled as "emotional" must have ? Our hypothesis is that the theory of conservation of resources by psychologist S.E. Hobfoll [13] offers an interesting lead. In this theory, the drive for the acquisition and protection of resources is at the core of the dynamics which explains the stress or well-being of an individual, and is even able to predict it. But at first it should be understood that in this theory, the notion of resource refers to many types of objects : social ones such as self esteem or caring for others, material ones such as a car, or physiological ones such as energy. The main principle is that individuals strive to protect their resources, and to acquire new ones. This model has been developped originally for psychotherapeutic purposes, and resources considered are the ones which are critical in the life of an individual. But we believe that it can be adapted for the context of realistic simulations. This framework is generic to every computational environment where a description of available resources is provided, along with the behaviours associated with the acquisition or protection of these resources.

3 Proposed Model

3.1 Principle of the Model

The model is based on the following principles : (a) an agent strives to acquire resources that it desires (b) once a resource is acquired, an agent tries to protect it (c) an agent's well-being depends on its capacity to acquire or protect resources (d) an agent's well-being regulates the tendency for acquisition or protection of resources.

A desired resource triggers acquisition behaviours, and a threatened resource triggers protective behaviours. Each resource type is associated with a particular set of acquisition and protective behaviours. For example an acquisition behaviour for a resource "Position" in a waiting line could be "move forward", and an acquisition behaviour for a resource "Social Interaction" could be "talk to somebody". A protective behaviour for an acquired "Position" could be "move forward just behind next agent", and a protective behaviour for an ongoing "Social Interaction" could be "speak loud" in order not to be interrupted by other agents.

A need value for a resource represents the level to which an agent wants the resource. This need level is dynamic and can change over time as a consequence of agents' behaviour or environment events. For example a fire will trigger a high need level for security, and a long waiting time in a front of a ticket counter before a train departure will increase the need for the resource "Train Ticket".

3.2 Architecture

An agent's affective architecture is composed of five affective sets which constitute the base of the model. The presence of a resource in one of these sets is a key factor influencing an agent's behaviour. A distinction is made between a *type* of resource and an *instance* of resource. For example a type "TicketCounter" could have several instances in the simulation environment, e.g. ticket counters situated on the map with a location and effectively usable by an agent.

Let A the set of agents and R the set of resources in a simulation world S, with $A \subset R$. $\forall i \in A$ at time t, we denote the four following affective sets :

- $N_i(t)$, the resource types that i needs;
- $DR_i(t)$, the resource instances desired by i;
- $AR_i(t)$, the acquired resource instances of i;
- $TR_i(t)$, the threatened resource instances of i;
- $LR_i(t)$, the resource instances that i has lost.

Let $V \in \mathbb{N}$ be a finite set of values. $\forall r \in DR_i(t)$, we denote $\mu_i^r(t) \in V$ the level of desire that i has for a resource r at time t. This value depends on the need value for the resource type of r denoted as $\mu_i^{type(r)}(t)$, and the properties of r. For example if an agent i needs a resource of type "Ticket Counter" in order to buy a resource of type "Train Ticket", its desire for two instances tc_1 and tc_2 with $type(tc_1) = type(tc_2) = TicketCounter$ depends on : (i) $\mu_i^{TicketCounter}(t)$ (ii) the location properties of $tc1$ and $tc2$, since the closest is a ticket counter to i, the more it is interesting for i. Of course other factors are related to this situation, like the length of the waiting line to access a ticket counter instance, but we simplified this situation for explanation purpose.

Affective sets are initialized before the start of a simulation. It is possible to set them empty, to generate random desired resources, or to set them with specific resources in order to run a given scenario. Some needs for resource types like "Food", "Drink", "Social Image" or "Physical Integrity" should always be added for a realistic behaviour, unless no resource and no behaviour in the simulation environment allow to acquire or protect these resources. An example for a default setting could be : $\forall i \in A$, $N_i(t) = \{Food, Drink\}$, with $\mu_i^{Food}(0) = \mu_i^{Drink}(0) = x$, where x corresponds to a need value. An example for a setting related to a scenario where an agent $i \in A$ has to buy a train ticket could be : $N_i(t) = N_i(t) \cup \{TrainTicket\}$, with $\mu_i^{TrainTicket}(0) =$

$f(TrainDepartureTime)$, where the more train departure time is close, the more the need for a train ticket is increased.

It is possible to set an agent's personality in refining its need set. For example an agent could have a strong need for type as "Luxuous Car", "Uncrowded Place", "Social Interaction" or "Candy".

$\forall r \in R$, there is compensation degree $C_i^r(t) \in [-V, V]$ which is the level to which a resource r can decrease or increase $\mu_i^{type(r)}(t)$. Two instances of type "Food" may not compensate agent's need for food at the same level. Given two instances of type "Food" in the simulation environment which are $hamburger$ and $carrot$, it is possible to set $C_i^{hamburger}(t) > C_i^{carrot}(t) > 0$. This means that the instance hamburger decreases $\mu_i^{Food}(t)$ with a higher degree than the instance carrot. It is possible to set individual characteristics for some agents in order that they react to the same instance in a different manner : some may satisfy their need for "Food" with the instance $carrot$ whereas others may not.

During the simulation, addition and removal of resources in affective sets, as well as behaviour selection, are handled by the Affective Controller. This module takes into account resources perceived in agent's environment, behaviours executed by other agents, and agent's needs level. Each behaviour selected by this module has the purpose to acquire or protect a resource.

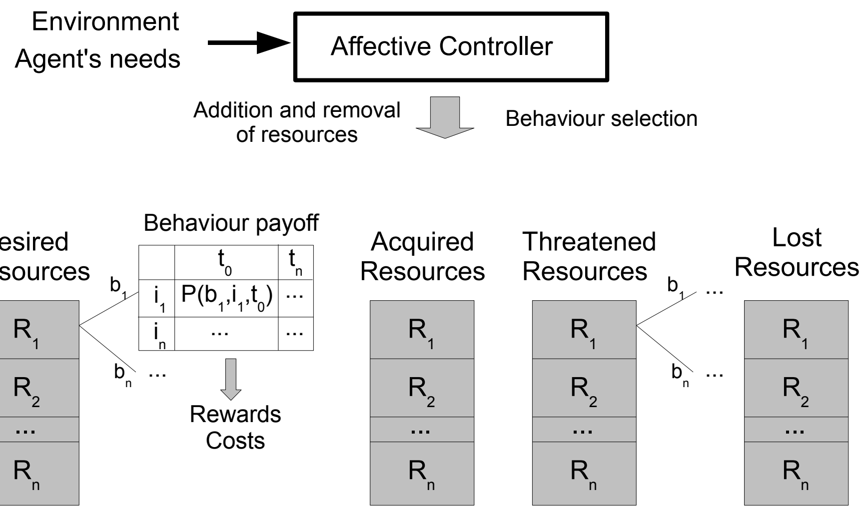

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Fig. 1. General Architecture

3.3 Behaviour Realization

The set of behaviours that can be performed by an agent i includes the acquisition behaviours corresponding to the agent's desired resources, and the protective behaviours corresponding to the agent's threatened resources. Let $B_i(t)$ the set of behaviours that can be performed by an agent i at time t. A behaviour $b \in B_i(t)$ has effects over resources during and after its realization for a given set of agents denoted as $patients(b)$. For example, if an agent i performs the behaviour "insult" towards an agent j during a verbal confrontation in a waiting line, the consequences of this behaviour is that j's "Social Image" resource will be threatened, and this will trigger protective behaviours from j in order to protect this resource.

$\forall b \in B_i(t)$, $\forall j \in patients(b)$, we denote :

- $R_b^+(j,t)$: resource instances acquired by j at time t;
- $R_b^\sim(j,t)$: resource instances of j threatened at time t;
- $R_b^o(j,t)$: resource instances of j protected at time t;
- $R_b^-(j,t)$: resource instances lost by j at time t;

These effects represent the agents' knowledge upon the consequences of their behaviours. However these effects are not guaranteed, because each agent doesn't know how other agents will react to a given behaviour. That means that if an agent j engages in a protective action for its resource "Social Image", this may lead to an agressive physical reaction from the other agent, and this will have consequences for j that are worse than the loss of its resource "Physical Integrity".

To perform behaviour selection, a utility value is computed for each behaviour $b \in B_i(t)$, taking into account the behaviour's effects described above. This value is computed with the compensation value of a resource upon an agent's need level : a decrease of a need level is considered as a reward, and an increase is considered as a cost. Hence the loss of a resource like "Physical integrity" is a cost, since it causes an increase in agent's need level for "Physical Integrity" : the agent no longer possesses the resource satisfying its need. The behaviour selected by an agent i corresponds to the behaviour with the maximum positive utility for i.

See figure 1 for an overwiew of the general architecture of the model.

3.4 Individual Parameters

An agent knows its needs, the behaviours that it could realize in its environment on perceived resources, and the typical effects of these behaviours. It can therefore anticipate gains and costs. These raw values can be modified by individual factors such as agent's well-being and egoism/altruism. The well-being of an agent acts as a sensor that guides an agent towards appropriate behaviours to readjust the state of its affectives sets. For example an agent that has endured too many losses has a low well-being that pushes it to acquire new resources. That means that if an agent has lost an important resource such as its job, it may try to readjust its well-being with easy resource acquisitions like resource instances of "Food" type. Egoistic agents give more importance to their own payoff, and altruistic agents give more importance to other agents' payoff.

4 Example

We consider a situation where agents have to buy train tickets provided by ticket counters in the simulation environment. Hence the provided resources are train tickets and ticket counters. Agents know that when a counter is occupied by another agent a, if they go to the waiting line it isn't costly for a, whereas if they go directly to the counter it is costly for a. Indeed, when an agent is in front of a counter it considers that it has acquired the counter resource, which allows it to purchase a ticket resource. When another agent b comes at the same time in front of a ticket counter, the counter acquired by a is threatened. a may choose to execute a protective behaviour in order to protect its resource, like telling b to go away. When agents are in a waiting line, they each possess a position resource attached to this waiting line. The acquisition of positions in waiting lines in real life, as well as many other resources, are regulated by FIFO rule (First In, First Out)[12]. When an agent b ignores this rule so as to gain positons, it is costly for all agents between the current and previous position of b. If agent's b need for a train ticket is very strong and if b is egoistic, it gives a great importance to the reward brought by a ticket acquisition, and a small importance to the positions lost for other agents. So b can choose the behaviour of ignoring waiting line's rule.

5 Discussion and Future Work

We presented in this paper an architecture aimed at providing virtual agents with affective behaviours in an urban simulation. Our hypothesis is that simulating behaviours that can be labelled as "emotional" do not necessarily requires an architecture grounded on emotional categories. Instead, we think that such behaviours are strongly motivated by resources. For example, even if behaviours in a waiting line are assumed to be driven by emotions, we tend to favor theories that considers a waiting line as a small social system regulated by the principles of property, that human beings are able to adopt naturally while not knowing the legal tenants of property [12]. Our hypothesis is that the processes of resource acquisition and protection are the basis of affective behaviours. Actually, this idea applies in various contexts : in case we run from a fire, we try to protect our primary resource which is our body, in case we become friends with someone, it is because we find useful resources in this friendship (see the "social exchange theory" by Thibaut and Kelley [15]), and so on. We believe that the architecture presented in this paper is generic, can account for several principles in social science and psychology theory, and is adaptable to many simulation contexts.

On another hand, the absence of emotional categories brings limitations. Our view is that emotions are concepts, and as concepts they are necessary for communication and reasoning. There are cultural patterns of facial expressions [3] which are not currently mapped in the model of conservation of resources, and the emotional vocabulary is a large part human langage. A necessary work has to be done on how the model of conservation of resources can be associated with concepts.

The model is currently under implementation for the context of a waiting line in front of a ticket counter. More contexts will have to be implemented in order to validate the genericity of the model. The evaluation will inlvolve two procedures. First, agents' behaviours in the simulation will be compared to behaviours described in psychological and sociological studies. Second, the credibility of agents' behaviour will be rated by users after they have watched a simulation video. Finally once the evaluation protocol is completed, we plan to extend our model to groups and crowds, in order to use it for simulations with a large amount of agents.

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Socially-aware emergent narrative

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Abstract. In agent research, *emergent narrative* aims for practical solutions to the *narrative paradox* problem in both drama and interactive scenarios. At the same time, *organisational frameworks* can be used in games to provide flexibility, adaptiveness, or social-awareness. In this paper, we propose an extension of our cONCIENS framework to support emergent narrative in games with two objectives: 1) provide social-awareness in emergent narrative by means of an organisational model, and 2) create convincing dynamic and flexible storytelling in games.

1 Introduction

The main objective of the use of Artificial Intelligence (AI) in both fun and serious games is to deliver the illusion of "intelligence" in the non-player characters' (NPCs) behaviour. While some aspects – e.g., pathfinding – have evolved to a mature state in both the industry and academic research, it is not the case with some important ones such as individual behaviour or strategical reasoning.

Current challenges deal with high-level concepts of gaming such as realistic virtual actors, automatic content and storyline generation, dynamic learning, or social behavior. Tackling these issues could represent a qualitative improvement on gaming experience from the player perspective and academic research on AI has good opportunities to provide solutions to these challenges [10].

Solutions taken by the industry are mainly based on domain-dependent low-level approaches. These solutions arise some obvious issues [3]: lack of flexibility and adaptation to environmental change, predictable or strange behaviour, low reusability, or blind specifications of NPCs – i.e. the NPCs always know *how* to act, few times they know *what* they are doing, but very rarely they know *why*.

One important factor that leads to these problems is the need for a plot or storyline. NPCs are usually mere enactors of a story previously designed, and their main use is to help advancing the story rather than *acting on their own*. It is well known that there is a compromise between narrative control and character autonomy [11]. This has been a topic of interest from the agent community in what has usually been called *emergent narrative*: stories can emerge through simulation of a virtual world inhabited by virtual characters.

As a result of research on *emergent narrative*, some theoretical frameworks and implementations have appeared, focusing on both plot and characters. In this paper we add a social aspect to this formula by linking our previous work on organisational frameworks for games.

2 Emergent narrative

Emergent narrative tries to break the common conception of linear narrative being the only possible product of human authorship over a story: human authorship can also be applied to the creation of a more open narrative by balancing character models, event sequences, and narrative landmarks. Furthermore, research on this topic tries to tackle the problem of the *narrative paradox*: virtual environments – such as games – and narratives exist on different ontological levels, and thus there is a fundamental conflict between free-form interactivity provided by the virtual environment and the level of satisfaction produced by a man-made narrative structure [11]. The main hypothesis of emergent narrative is that this problem cannot be solved by treating both issues as separate and combining them, but by treating narrative as a direct result of the actions of the characters [5].

In *FearNot!* and its agent architecture FAtiMA [6], narrative control is achieved by organising the story in episodes at design-time and sequencing them at run-time. Each episode defines pre- and post-conditions, as well as sets of possible locations, objects, choices, and goals available. However, as discussed in [11], such a strong episodic design is limiting, as a global sense of time – and what happens during scenes, or what happens between them in the "world"– or emotional residue after each scene are not accounted for.

One way to reduce rigidness in narrative control is *distributed drama management*, combined with *double appraisal* [9]. The main idea is that characters take responsibility in managing the drama, including in their plan selection mechanism a bias towards choices that have the greatest impact on the emotions of other characters. This idea of distributed drama management has been adopted by the *Virtual Storyteller* [11], the architecture of which is depicted in Figure 1. Character agents are based on the FAtiMA agent architecture and the world agent is the interface to a simulation layer. The plot agent acts as an intermediary, setting up the simulation and sending perceptions to, and receiving actions from the character agents. Stories are stored using *Fabula* [11], a formal model based on causal network theory to represent events already occurred with respect to the story. Events are linked to other narrative concepts such as goals, actions, or perceptions, via causal relationships – e.g., physical or psychological. The resultant graph is then used by both the presentation and simulation layers, and can be used for further analysis.

In this framework, characters enact two highly coupled roles: in-character (IC) and out-of-character (OOC) [4]. The former refers to the character behaviour and is driven by individual motivations, as normal agents. The latter, however, constrains the behaviour by trying to increase narrative impact – e.g., adopting goals that will probably cause conflict with other characters, looking for a modification on the relationship with them, or making sure that there are always goals to pursue. The action pursued by a story character will then be a function [11] upon believability (IC role), dramatic opportunity and variability (OOC role).

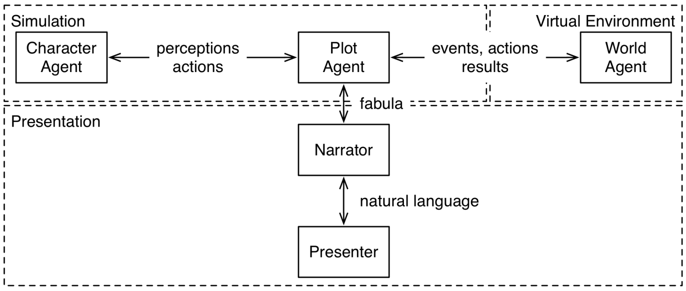

Fig. 1. *Virtual Storyteller* architecture

In *Virtual Storyteller*, emergent narrative is achieved by influencing the event sequence in order to *create* choices for the IC role while giving more chances to achieve the OOC role. This can be done in two ways, taken from drama improvisation techniques. *Making events happen* consists in creating an event that will likely enforce an advancement in the plot, e.g., the Princess has been kidnapped by a dragon, thus *forcing* those characters looking for brave actions to go and save her. *Late commitment* is based on the assumption that parts of the initial state of the world do not need to be fixed at authoring time, but dynamically determined at run time when it is purposeful for narrative purposes. In late commitment, OOC roles look for feasible and consistent properties to be added to the initial state and which will provide opportunities to advance the plot towards the storyline objectives, e.g., the story could advance by suddenly discovering that the governor is, in fact, a spy of the enemy.

Although the *Virtual Storyteller* presents a sound architecture for emergent narrative, it is strongly focused on non-interactive storytelling. This has already been noted in [11], stating that games allow for more radical applications of narrative control techniques such as late commitment. Also, from our point of view, the social aspect of multi-agent systems is somehow ignored by keeping character agents as a separate component from the simulation layer.

3 Organizational frameworks and games

As discussed on [3], our hypothesis is that it is possible to create elaborate solutions for the issues of both individual behavior control and collective strategy techniques by integrating models based on Organization Theoretical methods to control NPCs' behavior. This theory contributes to the systematic study of how actors behave within organizations. Hence, the actors in a game are described as an organization the behaviour of which is based on specific roles, norms, dependencies, and capabilities.

In fact, organizational frameworks such as OperA are already being explored for their use in *serious games*. In [12], organizational specifications are used to create a distributed intelligent task selection system that adapts to the player skill level and models the storyline.

cONCIENS [2] advances on this line of work by generalizing the use of organizational models for *fun games*, more focused on the realism of gaming experience, rather than on user modeling and learning. cONCIENS adapts the ALIVE framework [1] to its use in games and allows Game AI developers to think in terms of *why-what-how* when defining the decision-making actions for NPCs. That is, at the Organizational level, the developer defines "why to do something" by describing the elements of the organizational structure in terms of organization objectives, roles, norms, and restrictions. At the Coordination level, the developer defines "what to do" based on possible solutions and tasks to realize in specific situations; finally, at the Game Enacting level, the developer defines "how to do it" in terms of which actual, game-specific actions to perform in order to realize those tasks.

The set of tools and methods of cONCIENS provides inherent support to the development of complex, re-usable Game AI solutions, extending the ALIVE environment by providing:

1. A practical solution to couple agents to the Game Engine, by defining the Game Enactor programming interface.
2. A tool to describe the Organization Ontology, which contains a representation of agent structures.
3. The elements to describe game actors' behavior via social structures based on norms, roles and their enactment, promoting the balance between autonomy and story direction.

The research aim of cONCIENS is to provide solutions to the issues presented in Section 1 by representing the interactions between players and NPCs as compliant to an organisational structure. This approach provides extended flexibility to the elements that imply intelligent behavior, e.g. actors and characters, teams of individuals, and narrative storylines. In addition, it provides a methodology and metrics that can be applied to evaluate the organizational behavior using the games' environments as simulation scenarios. Hence, it would be possible to compare, learn, and improve NPC's behavior with an approach based on organization theoretical solutions for Game AI, contributing to overall flexibility and adaptiveness.

cONCIENS has already been used to implement automatic and flexible team direction in real-time strategy games [2], and to showcase an improved method to detect and enforce traffic violations in free roaming games [3]. The next goal in our research is to test adaptive storytelling in multiplayer games by using narrative emergence, and we will show in Section 4 how we intend to achieve it.

4 Our proposal

In this section we present our proposal, an extension of cONCIENS to adopt the architecture and some mechanisms of *Virtual Storyteller* to enable emergent narrative in games.

4.1 Mapping *Virtual Storyteller* components to cOncienS

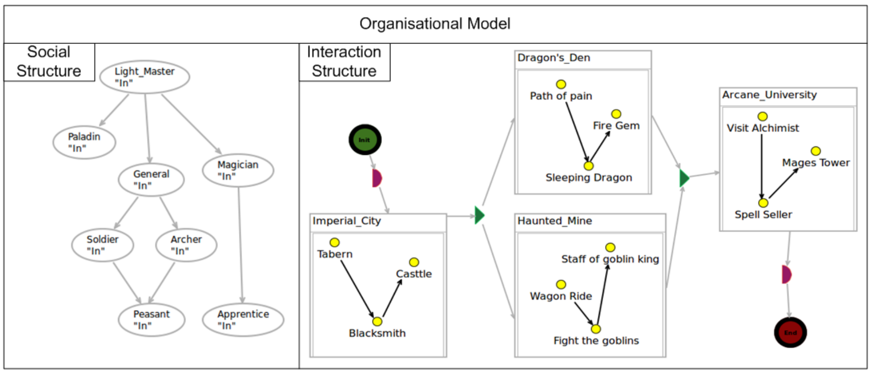

Fig. 2. Organisational Model Example

In cOncienS, everything starts from the organisational description (Figure 2), instanced as OperA documents. OperA consists of two main components, the Social Structure and the Interaction Structure. The Social Structure assigns roles to human players based on their preferences, and can be adapted to meet player's needs, for instance, *Apprentice* role can be removed if there is no player willing to play it. The Interaction Structure shows a set of *scenes* important to the overall plot. Each *scene* contains a set of *landmarks* that are important states of the world regarding the *scene*. Both *scenes* and *landmarks* are connected via *transition arcs* that allow navigating through them. Therefore, agents representing NPCs and players, by using these organisational constructs, become social-aware: they will be able to reason about their relationship with each other in terms of joint objectives, social rules and common interaction patterns.

We intend to incorporate the components of the *Virtual Storyteller* (see Figure 1) as an adaptation of the cOncienS framework as depicted in Figure 3. The components that enable emergent narrative are: the Character Agents, which support both NPCs and players and are represented in cOncienS by the already existing agents of the agent layer; the World Agent, represented by the Global Monitor; the Narrator layer, implemented by the Game Enactor – i.e., converting the world state into generic game concepts such as movement orders or player quests –; and the Presenter layer, in our case the Game Engine. The only new component required is the Plot Agent.

4.2 Constructing the plot

The Plot Agent will receive a storyline from the story designer. This storyline is implemented as a set of scenes and landmark patterns: the minimal set of states that conform the story and that *have* to be fulfilled in its proper order, from the beginning to the end of the gameplay time. This agent will continuously observe the state of the world and dynamically plan an order of the scenes needed to get to the next storyline landmark. The roles in each scene are assigned to specific Character Agents.

The story designer can decide, in this way, how rigid / flexible the story should be by adding more or less landmarks, and by declaring stronger or weaker conditions as landmarks. The designer will also design the set of possible late commitments and non-causal related events (see Section 2) in the form of framing operators [11], that is, sets of preconditions and a set of effects on these operators that can be done if the change in a specific case is consistent with the history of events – by the use of *Fabula* [11].

4.3 Character conflicts and personality

The Character Agent is a BDI agent implemented inside each agent of the cONCIENS agent level. Every NPC, as well as every player, has a representation as a Character Agent. The IC role (as seen in Section 2) is already implemented at the cONCIENS framework. Egoistic motivations, aims, capabilities, individual behaviour and organisational constraints (social objectives and norms acting as constraints to its behaviour or capabilities) are taken into account by the agent in an autonomous decision making process that produces an appropriate plan. This plan fulfills the agent's personal specifications bringing its own ways into the organisational society as well.

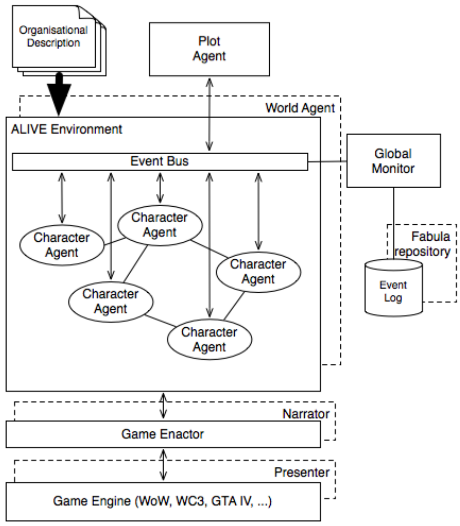

Fig. 3. Adapted cONCIENS architecture

On the other hand, as seen earlier, the agent receives from the Plot Agent a set of landmarks that is processed by the OOC role to help advancing the story. Due to this dual nature of the Character Agents, conflicts between the IC and the OOC can – and probably will – arise. This can be solved by applying negotiation processes, such as argumentation, and will be one of the main focuses of research on this project.

In order to apply personality to the characters – including players –, we will characterise them by using stereotypes or *play styles*. There are two main taxonomies to identify play styles: DGD1 [7] (*Conqueror*, *Manager*, *Wanderer*, *Participant*), and interaction between players: Interest Model [8] (*Achievers*, *Explorers*, *Socialisers*, *Killers*). During gameplay, players' behaviour – actions, chat logs, temporal evolution – will be monitored and analysed offline to identify them into an stereotype. Actions and states will be tagged in order to influence both the behaviour of NPCs and the way player goals should be completed. Each Character Agent's planner will identify the appropriate actions to fulfill a given landmark: two characters can fulfill the same landmark in different ways, creating the illusion of personality.

4.4 Adding interactivity to narrative

Interactivity is achieved by giving enough choices to the player to give an illusion of free will. The actions planned by the Character Agents representing actual players will be enforced in the form of missions or quests offered to the correspondent player taking into account both the IC and the OOC roles. The player, however, will be free to choose; if the player gets too far from the story line, its Character Agent can negotiate (as seen above) changes to the environment to keep the action in the boundaries of the storyline.

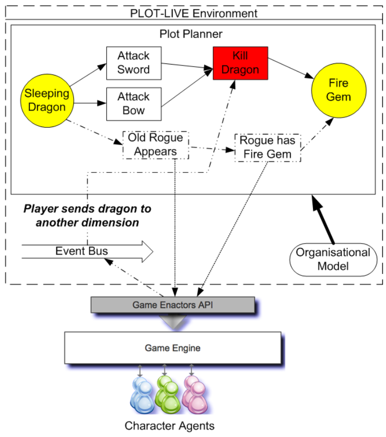

Fig. 4. System Architecture and usage of *late commitment* and *make events happen*

However, if the OOC role of a player's Character Agent predicts that the story plans incoming from the Plot Agent are not feasible or too incompatible with the individual plan, framing operators will be checked and studied, and there will be a negotiation process with the Plot Agent to propose and apply them, resulting in applications of *making events happen* or *late commitment*.

In the example shown in Figure 4, the player is supposed to kill the dragon (either with a sword or a bow) in order to obtain the fire gem from it. However, instead of performing the attack, the player decides to cast a spell on the dragon, sending it to another dimension. As the dragon and the player are in different dimensions, the player cannot obtain the fire gem, and thus, the plot cannot advance. The Plot Agent is able to recover the plot from this deviation by: 1) receiving the event that the player has sent the dragon to another dimension, 2) reacting by introducing an event (*make events happen*) on the game via the game enactor, e.g., an old rogue appears, as he *was hiding* in the shadows of the dragon cave, and 3) introducing a *late commitment* in the plot, via the game enactor, e.g. it comes out that the old rogue has the fire gem, as he had stolen it from the dragon before, and decides to give it to the player.

5 Conclusions

In this paper we have proposed an adaptation of an already existing organisational framework for games for its use in scenarios where the *narrative paradox* can be tested. The purpose is two-fold. First, we want to test storyline dynamic adaptation in cONCIENS applied to free-roaming games such as multiplayer role-playing games. Second, we want to explore if emergent narrative can improve with the use of organisational models, strongly focusing on the compromise between character freedom and plot design.

We use cONCIENS as a sandbox for applying the research of our agents group. By combining emergent narrative to the framework, we want to do research not only on narrative in itself but also applied to social aspects, both in-game (NPCs behaving as part of a society), and out-of-game (studying the interaction between players and between a player and the NPCs), from different perspectives: organisational, normative, emotion representation and detection, user profiling, gamification, and so on.

In order to provide empirical results, we have already connected cONCIENS to an open-source World of Warcraft server. Our immediate plan is to test the dynamic generation of missions by using the techniques described in Section 4.

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Organizing Scalable Adaptation in Serious games

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Abstract. Serious games and other training applications have the requirement that they should be suitable for trainees with different skill levels. Current approaches either use human experts or a completely centralized approach for this adaptation. These centralized approaches become very impractical and will not scale if the complexity of the game increases. Agents can be used in serious game implementations as a means to reduce complexity and increase believability but without some centralized coordination it becomes practically impossible to follow the intended storyline of the game and select suitable difficulties for the trainee. In this paper we show that using agent organizations to coordinate the agents is scalable and allows adaptation in very complex scenarios while making sure the storyline is preserved the right difficulty level for the trainee is preserved.

1 Introduction

In serious games, quality is measured in terms of how well the components in the game are composed, how they encourage the player (or trainee) to take certain actions, the extent to which they motivate the player, i.e. the level of immersiveness the game provides, and how well the gaming experience contributes to the learning goals of the trainee [3]. Thus believability is a main driver of game development. The search for enhanced believability has increasingly led game developers to exploit agent technology in games [11] in order to preserve believable storylines.

Dynamic difficulty adjustment is an important aspect in training applications that need to be suitable for a large variety of users with different skill levels. Having the correct difficulty level ensures that the game will contribute to the learning goals of the trainee. Current approaches of dynamic difficulty adjustment in games use a purely centralized approach for this adaptation [21, 9]. This becomes impractical if the complexity increases and especially if past actions of the non player characters (NPC's) need to be taken into account while trying to adapt to the skill level of the trainee (as is needed for serious games [18, 20]). The use of software agents has also been advocated as a means to deal with the complexity of serious games [11]. Distributing the responsibility of staying

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believable and adjusting to game progress, over the different non player characters creates a much more manageable situation, but this might lead to unwanted situations if their adaptation is not well coordinated.

Current agent approaches have no coordination over the adaptation at all. We argue that a system without any coordination will not result in good adaptation if the complexity of the game and the number of different adaptable elements increases. Multiple elements could adapt in the same direction and will overshoot the desired target difficulty for the trainee. Or the agents all adapt in a very similar way, resulting in state where the NPC's are not performing all the tasks required by the scenario. We will also show in this paper that a nave centralized approach will become too slow if the numbers of tasks that NPC's can perform becomes too big. While this might not be problematic with the current entertainment games yet where adaptation to the user is very limited, it will be a problem with more complex serious games. In this paper we propose to use agent organizations plus a related adaptation engine to manage the control of the coordination and adaptation of the agents, while leaving them enough autonomy to determine their next actions. We will show that this gives the right balance between distributing decision making (leading to scalability) and keeping the game believable and immersive.

The paper is organized as follows. In the next section we will look at the requirements for the adaptive serious games we are investigating. In section 3 we will look at the current approaches that are used in games. In section 4 we further explain the agent organization based framework we are using. We show how this framework can be used to create scalable serious in section 5. In section 6 we will show the order of magnitude of a resulting design compared to a nave centralized approach. Conclusions are discussed in the last section.

2 Adaptation

The type of adaptive serious games we are investigating have certain requirements and properties that are usually not found in current entertainment games. The biggest difference is that the NPC's in these games can perform a lot of different types of actions. In most commercial games that do adapt to the user, the NPC's can only perform a very limited number of different tasks and the adaptation isn't done on the task type level but only by adjusting certain simple parameters within the same task definition. In most serious games we want to expose the trainee to a much larger variety of different tasks. This is partly caused by the fact that the trainee needs to learn separate skills and different combinations of these skills. For example, the trainee needs to learn to extinguish fire while making sure the victims are safely extracted from the building. For each skill we also want to expose the trainee to a larger variety of challenges that do not only differ in simply tunable parameters but require a substantially different response from the trainee. For example the trainee should learn to extinguish basic home fires but also chemical fires at a chemical plant. Even within the basic home fire category we want the trainee to be able to cope with fire that started on the ground floor and fires that started on the higher floors.

Also if current games progress each character type will keep performing very similar throughout the game. In serious games we want the NPC to exhibit different behaviors throughout the game. This is required because we want to expose the trainee to significantly different scenarios with different skill combinations to allow the trainee to learn to handle a larger variation of different situations. The behavior of the NPC's also has very big influence on the difficulty level for the trainee. Because we want these serious games to be suitable for a large variation of trainees with different skill levels and different learning rates we want the game to continuously adapt. This also requires a much larger number of plans that can be performed by the agent (while keeping an overall goal) because they do not only need to operate in varying scenarios but also to operate in these scenarios with different difficulty levels.

Without a clear organization structure, adaptation can quickly lead to a disturbed storyline and the believability of the game will be diminished and will lead to an explosion of possible combinations. Furthermore, characters in serious games are usually active for relatively long periods. This poses an extra burden on the believability of the game, namely coherence of long-term behavior [13]. When there are multiple NPC's that all have their own preferences and can all adapt to the trainee independently, it becomes almost impossible to create a coherent game that has a natural progression of the game and is the right difficulty for the user. The game progression is much more controllable if there is a monitoring system in the application where the desired progression (could have different paths) is specified. We propose a system where we do not only have a monitoring system that specifies the desired storyline but that also tracks the current progression within the storyline. The NPC's are still programmed with their own preferences but they receive updates of the game progression. The agents can then easily be programmed to perform different plans, not only dependent on their own beliefs but also dependent on the game progression.

Coordination of agent actions (that are still autonomous most of the time) also becomes a lot more manageable if there is a central control system that allows the designer to put restrictions on the possible plans performed by the agents. A very simple example is that the designer can specify that at a certain point in the game, one of the NPC's should always check the left hallway. A possibility would be that all the agents are programmed with this restriction in mind and that they communicate directly with each other to make sure that one goes left. We propose an efficient coordination system where all the agents propose multiple actions with preference weights corresponding to each of these proposals. From these proposals the adaptation engine will select the optimal solution that also keeps the restrictions of the designer and the preferences of the agents in mind. In this example, this means that at least one agent prefers to check the left hallway but it puts a lot less burden on the designer to allow autonomy within the agents while making sure that certain critical criteria are always met.

An added challenge for user adaptation in games is that it can only be done while the user is playing the game [2, 5]. Online adaptation requires that the algorithm adapts quicker with a lot less episodes and learning data. Because the game is adapting while the user is participating in the game, it is also important that no unwanted and unpredictable situations are introduced by the adaptation. This means that the adaptation should only try promising and believable solutions while exploring different options.

Another important aspect of adaptation in (serious) games is the distinction between direct and indirect adaptation. Direct adaptation occurs when the designer specifies possible behavior of the agents in advance and specifies how and when to change this behavior. The designer also specifies what input information should be used. Direct adaptation only allows adaptation to aspects that the designer has foreseen. No unexpected behavior can emerge when using direct adaptation. On the other hand, in indirect adaptation performance is optimized by an algorithm that uses feedback from the game world. This requires a fitness function and usually takes many trials to optimize. If indirect optimization is used the algorithm also needs to be able to cope with the inherent randomness of most computer games.

In previous work [23, 22] we proposed the use of multi-agent organizations to define a storyline (defining coordination restrictions on the agents) in such a way that there is room for adaptation while making sure that believability of the game is preserved. This approach has the benefits of direct adaptation without the need for the designer to directly specify how the adaptation should be done. The designer is able to specify certain conditions on the adaptation to guarantee the game flow but does not have to specify which implementations are chosen after each state. In this paper we show how the agents are implemented and show the coordination of tasks and proof that it is scalable enough and works in practice

3 Current approaches

Even though many commercial games do not use any dynamic difficulty adaptation [15], already some research has been done on difficulty adaptation in games. Most of this research focuses on adaptation of certain simple quantitative elements in the game that do not influence the storyline of the game. For example better aiming by opponents or adding more or a stronger type of opponents.

Current research on online adaptation in games is mostly based on a centralized approach [21, 10]. Centralized approaches define the difficulty of all the subtasks from the top down. This is only feasible if the number of adaptable elements is small enough and if the separate adaptable elements have no separate time lines that need to be taken into account. In shooting games, for example, these requirements are not problematic. The games only adapt to the shooting skill of the trainee and most characters only exist for a very limited amount of time. In the type of adaptable serious games we are researching, completely centralized approaches will not be scalable enough.

Research has been done on using reinforcement learning in combination with adaptation to the user [21, 1]. Most of these algorithms rely on learning relatively simple subtasks. Moreover, the aim of these adaptation approaches is learning the optimal policy (i.e. making it as difficult as possible for the user). In order to avoid that the game becomes too difficult for the user, some approaches filter out the best actions to adjust the level of difficulty to the user. This results in unrealistic behavior where characters that are too successful suddenly start behaving worse again.

Little attention is paid to preserving the storyline in present online adaptation mechanisms, because they only adjust simple subtasks that do not influence the storyline of the game. Typical adjustments are, for example, changing the aiming accuracy of the opponents or adding more enemies.

Some work has been done on preserving the storyline with adapting agents [12, 4] but they focus on preserving the plot, not on adapting to the trainee. Other work [16] has also been done on interaction between the agents and the storyline while adjusting to the trainee. This framework adjusts to the trainee to preserve and repair the plot of the game, this is very different from adapting the difficulty level for the trainee. Some work has been done [19] on adjusting the goals of the agents to facilitate learning of the trainee, but they also do not take skill levels of the trainee into account.

4 Framework

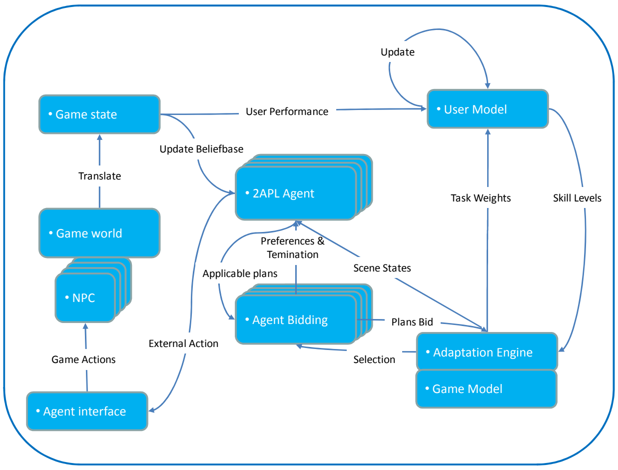

Fig. 1. Framework overview

To get a better understanding of the different elements of the whole framework we first briefly describe the different elements and the information that is passed between them. Figure 1 shows a schematic overview of all the different elements of the framework. We are currently using a custom Java environment as our *game world*, but our approach is also applicable to other games. The *NPC's* and other dynamic game elements in the game are controlled by *2APL agents*. The agents in the game have the capability to perform basic actions, like walking to a certain location or opening a door. The higher level behaviors are specified in the *2APL agents* which sent the basic *external actions* to the *agent interface* which translates these commands to basic game actions.

The *game state* is used to update the beliefs of the agents, update the progression of the game and pass the performance of the trainee to the user model. The *user model* uses this information and the *task weights* from the adaptation engine to update the estimated skill level for each state. These updated *skill levels* can then be used again to find better matching agent behaviors.

The 2APL agents can perform different actions depending on their beliefs and dependent on the scene states. The *game model* contains information about the desired storyline of the game and keeps track of how far the game has progressed in the storyline. This information is passed to the *2APL agents* to influence the possible actions they can perform. The *agent bidding* module specifies the agent preferences for all the *applicable plans*. The *adaptation engine* uses this information and the information from the *user model* to find the plan assignment for the agents that best serves the situation for the trainee. The bidding module of the agent uses this information to control the plans that are selected by the agents.

4.1 Agent organizations

Adapting the game to the trainee for complex learning applications requires both learning capabilities and decentralized control. However, in order to guarantee successful flow of the game and the fulfillment of the learning objectives, the system needs to be able to describe global objectives and rules. Although many applications with learning agents exist, multi-agent systems with learning agents are usually very unpredictable [14]. In order to limit unpredictability in MAS, organization-oriented approaches have been advocated such as OperA [7] and MOISE+ [8]. In this framework it is possible to define conditions when certain plans are allowed or not. The ordering of the different possible plans can also be defined in this framework. This allows the designer to make sure that the users are not exposed to tasks that are not suitable yet or would ruin the storyline. In previous work we have shown how to use agent organizations to specify the boundaries of the game [22, 23].

The OperA model for agent organizations enables the specification of organizational requirements and objectives, and at the same time allows participants to have the freedom to act according to their own capabilities and demands. In OperA, the designer is able to specify the flow of the game by using landmarks. The different sub-storyline definitions of the game are represented by scenes which are partially ordered without the need to explicitly fix the duration and real time ordering of all activities. That is, OperA enables different scenes of the game to progress in parallel. In the scenes, the results of the interaction are specified and how and in what order the different agents should interact.

4.2 Adaptation engine

The adaptation engine consists of two different parts. One part selects the best combination of plans for all the different agents. The other part keeps track of the game progress and is responsible for checking if the combinations of plans are currently valid depending on the state of the game. The adaptation engine has to optimize on two possibly conflicting objectives. On the one hand we want to optimize on the preferences of the agents while on the other hand we want to select the combination which is the optimal difficulty for the user. Because we focus on adapting to the trainee, we give the highest priority to finding the best match for the trainee. Remember that we optimize on different skills of the trainee. Slight variations in difficulty level are not problematic but we do want to prevent large deviations from the desired skill levels for each separate skill. This means that we rather have deviations that are a bit larger for each skill than have multiple skill levels that are perfectly chosen but a large deviation in one remaining skill.

While optimizing on the skills of the trainee we also want to optimize on the preferences of the agents to keep their preferences into account to keep the game as believable as possible. This process uses a form of a combinatorial auction [17]. This needs to be a combinatorial auction because the agents can give a higher score for performing a certain action depending on which plans the other agents will perform. This preference dependence is only used for tasks that require coordination between the agents. For example, it is more believable for a fireman to lift a heavy object if another agent helps him. We try to limit the amount of preference dependencies because it is much more labor intensive for the game designer to specify the preferences of the agents and it is also more computationally expensive to find the best solution. Similar to finding the best match for the skill level we also want to avoid large deviations from the preferences. This means that we do not optimize on the highest combination of preferences from the agents but on the smallest squared deviations from the preferred proposal. The deviation in the skill levels are combined with the deviation of the agent preferences, giving more influence to the skill deviation.

In the game model we do not only allow the designer to specify the progress of the game but we also allow the designer to specify different difficulties corresponding to certain phases in the storyline. We also allow the designer to specify an absolute difficulty level, which can be a desired option especially for serious games because one would like to be able to know that if the trainee finishes the training that the skill level of the trainee is high enough. Updating the user model can be done in different ways. Our proposed user model update function is beyond the scope of this paper but is described in [22].

Selecting the best combination of plans from the different agents is easiest if they all terminate at the same moment. If all plans are terminated and started at the same time the optimal combination for the trainee can be selected. However, the time to execute the different plans by the agents is not always the same, and to keep the storyline flowing, it is not always a possibility to terminate plans of all the agents when a few agents have completed their task. In our framework we specify different subtasks of the game application by using scenes. The scenes usually begin when certain agents start interacting and end when that group of agents end their interaction or an organizational objective has been reached. The end of a scene usually is a natural time for all the participating agents to terminate or change their behavior. This gives enough control to make the necessary changes both for the gameflow and to optimize learning for the user.

Because multiple scenes can be active at the same time, it also does not mean that if a scene is finished all agents have terminated their plans. The goal is to have the most suitable task combination for the trainee during the whole game. Our solution is to assume that all plans that have not terminated are fixed and that newly created plan combinations keep these active plans into account. This results in a good combination for the trainee when the new plans are started. If plans are terminated the difficulty of the task changes again (becomes easier most of the time), but this can usually be compensated very quickly with new plans from the same agents (instant correction) or new plans from other agents. This results in a system that adapts quickly while keeping the behavior of the agents realistic.

4.3 Agent implementation

The high level actions of the NPC's are implemented using the 2APL [6] language. This allows modeling of the NPC's using the BDI architecture. Using BDI agents is a suitable implementation because it allows us to create intelligent characters that are goal directed and able to deliberate on their actions. 2APL is an effective integration of programming constructs that support the implementation of declarative concepts such as belief and goals with imperative style programming such as events and plans. Like most BDI-based programming languages, different types of actions such as belief and goal update actions, test actions, external actions, and communication actions are distinguished. These actions are composed by conditional choice operator, iteration operator, and sequence operator. The composed actions constitute the plans of the agents. The agents are created with the game model structure in mind. This is done in such a way that the applicable plans are not only dependent on the game state and the internal state of the agent but also on the scenes that are currently active. This process makes it a lot easier for the developer to ensure the certain behaviors are only performed at the right moment in the game progress. The 2APL agents are created in such a way that multiple plans are applicable at the same time. These applicable plans can vary in difficulty for the trainee but they can also have the NPC perform substantially different tasks in the game.

When the agents receive a request to perform a new behavior they reply with a number of different applicable plans according to the game state, the active scenes and the internal state of the agent. This bidding process is not part of the normal 2APL deliberation cycle but is a separate part of the agent. We separated these tasks because it would be very inefficient and unnecessarily complex if the agents use the BDI reasoning process to decide why they want to perform a certain plan. This separate bidding part of the agent is also responsible for estimating the believability of each action. One important factor in estimating the believability of a new plan is dependent on the difference compared to the previous plan.

5 Designing scalable AI

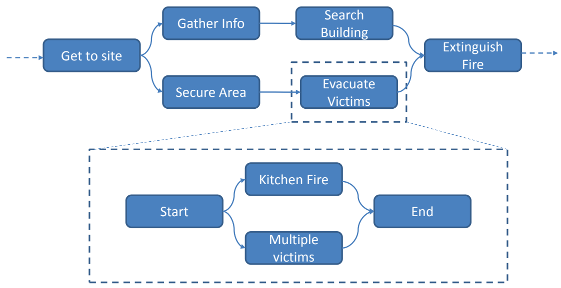

Fig. 2. Interaction structure

In this section we will show how our design approach can be used and why it gives a natural and effective implementation. One simple example is used throughout this section to show how the different aspects of the framework function. Figure 2 shows part of an interaction structure of a possible game. In the same figure we also display the partial ordering of the *Evacuate Victims* scene. On the interaction structure level we only define the ordering of the scenes and when it is allowed to transition to the next scene. The scenes are defined by scene scripts that specify which roles participate and how they interact with each other. The definition of the organization can be so strict that it almost completely defines the strategy. But it is also possible to specify the organization in such a way that all the agents in the game work towards achieving the goals of the game but are still able to do this using different strategies. In these scenes the results of the entire scene is specified and how and in what order the different agents should interact. It is also possible to defines norms in the scene description. This makes it possible to put extra restriction on the behavior of the agents. The agents can be programmed to break the norms. Agents that do not follow norms can be an essential part of the training. In a scene script is also possible to define certain time constraints to make sure that the game progresses fast enough.

When scripting languages or hard coding of NPC behavior is used, it will become very difficult to read and understand the intended behavior if the project becomes more complex. In our approach we use NPC's that are based on BDI agents. This means that agent behavior is specified using high level goals and act according to their internal believes. This makes it much easier to identify why a NPC why an agent performs a certain plan. We specially use the term "high level" goals because some of the lower level behaviors can better by specified by other approaches then BDI. For example path planning can much better be handled by an A* algorithm then to incorporate this into the BDI part of the NPC. The BDI part still selects where to go but the lower level behavior handles exactly how this is done. This also results in a nice and modular approach. Using a combination of BDI agents with an agent organization architecture, results in very natural agent objectives. The whole storyline of the game is build from a collection of partially ordered different scenes. In each scene we specify the scene objective and the roles that are being played in this scene. Each participating agent plays one of these roles and therefore helps to complete the scene objective. This results in agents goals and plans that are very natural and relevant to the scene and therefore relevant to the storyline.

An obvious danger of coordinating actions between agents is that, if all possibilities are always sent to a central point which finds the best the combination, we can run into scaling problems and you might as well use completely central control instead of an agent based approach. One of the differences between a completely centralized approach and our approach is that the agents make a pre-selection of the plans that are applicable in regards to their internal state and the current game state.

5.1 Scenes

As discussed earlier the rough outline of the game is specified in the interaction structure. This interaction structure is build up from the scenes where the action required behavior of the participating agents is outlined. Only a limited number of scenes can be active at the same time. Each arrow in the interaction structure defines a scene transition with its corresponding transitions requirement. A transition always means that the old scene is no longer active (a scene transition could spawn multiple new scenes). From Figure 2, where we show a small part of an interaction structure, it can be seen that in this specific case only one or two scenes can be active at the same time. The scene *get to site* has two outgoing arrows, this type of arrow is used for situations where both transition are valid at the same time. In our framework the agents are always informed which scenes are currently active. The agents are designed in such a way that they know which plans are applicable in which scene. This allows the agents to make a very fast selection on all the plans. They do not have to check the applicability of these plans according to their believes. Because the kind of serious games we investigate have a lot of specialized plans for each scene this filtering has a very big influence on the performance of the whole system. Every scene is also build of a partial ordered collection of sub-scenes. This allows the agents to make an even more fine grained pre-selection.

Technically it functions as follows. As can be seen in Figure 1 the *adaptation engine* updates every 2APL agent with the most current *scene states*. Each 2APL agent extends a basic *GameCharacter* agent. From this definition every agent

Example 1.

```
Include: GameCharacter.2apl
//handles scene transition messages
//and characters movement

BeliefUpdates:
[...]

Beliefs:
 SubScene(MultipleVictims)
 Subscene(KitchenFire)

Goals:
    ExtractVictims(disasterArea)
  StoveOff(disasterArae)

Plans:
  @disasterArea( enter( 8, 8, red ), _ )

PG-rules:
true<-SubScene(MultipleVictims)//init sub-scene
 |{[...]}

true<-Scene(KitchenFire)//init sub-scene
 |{[...]}

ExtractVictims(disasterArea)<-SubScene(MultipleVictims)
//easy
 |{[...]}

ExtractVictims(disasterArea)<-SubScene(MultipleVictims
)//hard
 |{[...]}

StoveOff(disasterArae)<-Scene(KitchenFire)//easy
 |{[...]}

StoveOff(disasterArae)<-Scene(KitchenFire)//hard
 |{[...]}

PC-rules:
[...]
```

will inherit the standard ability to update its believes according to the *scene states update*. This specific 2APL plan adds the current active sub-scene to the beliefbase of the agent.

Example 1 shows a simplified version of the code of a fireman agent. In this example only the *Evacuate victims* scene is active. As can be seen the agent has the current active sub-scene available as beliefs. These beliefs are used as conditions for the PG-rules of the agents. A planning goal rule (PG-rule) specifies that an agent should generate a plan if it has certain goals and beliefs. This means that these plans are only generated if the sub-scene conditions is true. Some generic plans can be used in multiple scenes. This can easily be achieved because the conditions check is a belief query that can also include the logical OR.

For every sub-scene we use a special rule that will be applicable when the corresponding belief is added to the belief base. These specific rules will be applicable independent of the agents current goals (it could have no goal at all). In this plan we specify which goals should be added to the added goals base (and which should be removed). These goals that are added to goal base match the goals that should be fulfilled in the scene. For example in the *evacuate victims* scene each victim agent will have the goal to play a victim in that specific scenario while a fireman agent could have a goal to locate the victims and a goal protect them from harm. In Example 1 it can be seen that the scenes are already initialized because the corresponding goals are already active.

Most of the time when a sub-scene is finished the participating agents are finished with their sub-scene specific goals and plans. However this is not always true. In some cases a different agent satisfies the requirements to move to the next sub-goal while a different agent is in the middle of a task. The agent will now have more applicable plans then just the new plans corresponding to the new sub-scene. In other systems it would be very difficult to manage these kinds of situations. In our system the agent would just propose the applicable from the old task and from the new sub-scene. The agent can also give a much higher believability rating to the old plan if terminating the plan would disrupt the flow of the game.

An important thing to note is that the scenes start and end in natural situations in the games, it is not just split up into arbitrary pieces. Scenes correspond to natural occurring phases in the training game. The scene *Get to site* in Figure 2 for example is clearly a separate and phase in the progress of the game. The goals of the agents that are active during this scene will correspond to the goal of the scene and will usually be fulfilled when the termination criteria of the scene are reached. This also makes the transition between scenes a very natural moment to adapt to the trainee and to coordinate this adaptation with the participating agents.

5.2 Believability

Besides the pre-selection on the scene level we also prune the number of suggested plans that the agent can suggest by using their believability preferences. This means that the agents will estimate the believability for all the remaining and exclude the plans that have a believability below the set threshold. In quite a number of cases there will be plans that have a believability that is very low or even zero. This is mainly caused by past events that are already observed by the trainee. It could happen for example, that the agent is currently playing a victim with a broken leg because that was the best fit with the current skill levels of the trainee. It would then be completely unbelievable if the agent suddenly switches to a plan where he runs away.

The believability filtering will have a larger influence if the characters are interacting for a larger part of the game. The trainee will have more knowledge about the NPC and the numbers of believable actions will be more limited. A factor that is frequently limited because of this is the intelligence or autonomy of the NPC. It is possible for an NPC to perform a task a bit more intelligent (as if the NPC would have learned) but it would be very strange if the NPC suddenly becomes much more intelligent or very stupid.

On the implementations level it works as follows. 2APL builds a list of all the applicable plans exactly in the same way as the default 2APL implementation. This list is already quite limited because of the scene restrictions we discussed earlier. For all these we calculate the believability number. This is always between zero and one. The actual calculation of the believability is domain dependent. For example, a fire agent can only increase or decrease the fire expansion rate within certain limits. NPC's that simulate humans will have very different limitations in order to make sure the agent does not appear schizophrenic while adapting to the trainee.

The calculation of the believability is done in a separate module in our intended 2APL implementation. The believability is usually dependent on past actions and believes from the agent. The agents for example need to keep track of the level of intelligence of its past actions to make sure it will stay consistent from the perspective of the trainee. We also store this data in the belief base of the agent. This means that not only the extra believability module has access to this but that the reasoning part of the agent is also able to use this data. This means that the agent can reason that it cannot run away because it is aware that it has a broken leg. This allows the designer to implement these dependencies on the past more naturally. It also helps to make the framework to scale better because more plans are excluded in an earlier phase. The believability calculations are allowed to be a bit more computationally expensive then some of the calculations in the framework because they only have to be performed on a relatively small number of plans. A cutoff threshold is set and all the plans that fall below this level will be excluded from the agent proposal. The threshold level for a part defines the tradeoff between accurate adaptation and believability. Only filtering out plans with believability zero will already help a lot in solving the disruptive changes that can be observed in some more traditional adaptive games.

5.3 Combinations

After all the agents have finished selecting the possible plans that possible fit in the current situation they send this proposal to the adaptation which checks the tasks that are currently performed by agents and then checks all the new proposals from possibly different agents (remember that the agents can use the coordination asynchronously). The adaptation engine uses the specifications from the game model of the scenes that are currently active (for example only the *extract victims* scene could be active). This means that number of plan combinations is not only limited by the number of plans proposed by the agents but also by checking the validity of the combinations before they are evaluated on skill difficulties. In some cases this pruning can have a big influence. If we for example assume that the (sub)scene defines that at least fireman should explore the left corridor and that there is currently only one fireman active then we can very quickly throw away all the combinations that contain the fireman performing a different plan than exploring the left corridor. In most cases however this pruning is little less efficient because most requirements require to really check the plans of multiple agents. For example, if the (sub)scene specifies that a stretcher needs to be carried by at least two agents then we need to check each combination until from all the corresponding plans there are at least two agents that perform the carry stretcher plan.

The agents also do not use the adaptation engine for all their plan selections. If there is no need for adaptation, then the agents will keep running their normal 2APL program with the current preferences. The adaptation engine will request a new bidding round if the deviation from the intended difficulty becomes too large. The bidding process is also started at fixed points in the game scenario where it is logical for the agents to start performing different actions. Updated preferences also do not mean that the agents have to stop performing their current plan but the selection of the first new plan is influenced. A third way of managing the scaling problem is that multiple scenes can be active at the same time and not all agents are part every scene. This splits the optimization problem into smaller subtasks which makes it more efficient to optimize.

6 Scalability analysis

In this section we will analyze the scaling difference between a naïve centralized approach and our coordinated distributed approach. Both approaches will have a very similar approach of combining the actions of the NPC's but the main difference will be in the remaining number of plans proposed by the agents. We aim to use reasonable assumptions that correspond to the type of serious games we have encountered during our research. The example in Figure2 shows a part an interaction structure of a game. This part of the interaction structure shows six scenes. A reasonable assumption is that a whole game can be split into 30 different scenes of which on average two scenes are active at the same time. Because the scenes are independent of each other, the total number of scenes hardly influences the execution time if our distributed approach is used. In Figure 2 only one or two scenes can be active at the same time. In practice most interaction structures are very similar and it hardly ever happens that more than two scenes can be active at the same time. Using an average of two scenes at the same time will therefore give a pessimistic estimation of the performance. The ability of the agents to filter the possible actions depending on the active scenes makes a huge difference in the number of possible actions that can be proposed by the agents. In this example the agent will filter out more than 93% ((30-2)/30) from its complete plan base. In the same figure we also see an example of scene with different sub-scenes. In this case there are only two sub-scenes but an average of four will give a more realistic estimation. We again pessimistically assume that on average two sub-scenes are active at the same time (per scene). We assume that every agent has 6 unique plans for each sub-scene. The ability to also select plans according to the sub-scenes will cut the remaining number of plan in half again (2 of 4 sub-scenes are active for each scene). As explained in section 5 the agents can also filter out some of the remaining plans by cutting out the plan that are not believable enough. In some cases this filtering percentage will be very low but in the kind of serious games where the NPC also cooperate with the trainee a reasonable assuming will be that 50% of the remaining plans are filtered out. We will leave out the optimization on the invalid combinations because it is very difficult to give accurate estimations for this and it will also make it more difficult to compare to the nave approach. This means that we will compare the number of combinations that can be made from the actions proposed by the agents. For each of these combinations the difficulties for the different skill levels needs to be calculated. Even though this calculation itself is not very time consuming the exponential nature of making these combinations will really become a factor in complex scenarios.

The purely nave approach will have 720 (30 scenes * 4 sub-scenes * 6 actions per sub-scene) different plans for each agent active at the same time. Our approach will have 12 (6 actions per sub-scene *2 sub-scenes active per scene * 2 active scenes /2 for believability filtering) In figure 3 we plotted the out the number of combinations for both approaches depending on the number of agents. As can be seen the number of combinations already add up very quickly with our distributed filtering but it is much more manageable then without the filtering. Even with four agents the filtered approach is already 12960000 times as slow. With more than four agents the nave approach becomes completely impractical.

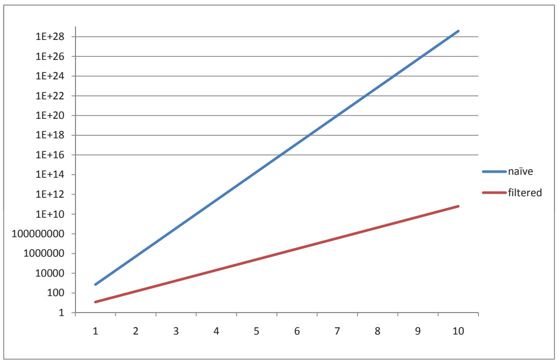

Fig. 3. Number of possible action combinations

Keep in mind that in practice our distributed approach will be much faster because we are also efficiently filtering out impossible combinations. This means that in practice the number of combinations that will be evaluated will be much lower than the estimations from our graph. We, however, also realize that the term scaling is relative. The coordination is fast enough by using our distributed approach for the type of games we are investigating and is much faster than the nave approach. But because of the exponential nature of the remaining coordination it will not scale to games with massive numbers of NPC's.

7 Conclusion

In this paper we discussed online adaptation in serious games. The adaptation is based on the use of learning agents. In order to coordinate the adaption of the agents we use an organizational framework that specifies the boundaries of the adaptation in each context. We argue that an agent based approach for adapting complex tasks is more practical than a centralized approach. It is much more natural when the different elements are implemented by separate software agents that are responsible for their own believability.

We mainly concentrated on the different phases of plan selection performed on the agent level. However, we also have shown that by using an agent organization framework we can segment the game in scenes in a natural way to describe which of the possible actions of the agents are relevant at the current moment. Every selection phases reduces the number of plans that need to be coordinated. This greatly reduces the scaling problems when coordination multiple agent with a large variety of possible actions.

The system is implemented using 2APL for the agents and tested with artificial trainees on the fire fighting example also used in this paper. The next step is to couple the system to a game engine and test it with real trainees.

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Inferring Pragmatics from Dialogue Contexts in Simulated Virtual Agent Games

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Abstract. In emergent narrative for virtual agents or human machine interactions, the pragmatics hidden in the dialogue cannot easily be inferred based on the Grice's maxims alone. We model the speech acts in terms of the change of unobservable mental states of agents including in several dialogue contexts such as emotion state, social relation, social norm, social commitment, personality and preference. With the speech act model virtual addressee agents could infer the pragmatics of the addresser agents from the dialogue contexts and vice versus using probabilistic reasoning of Dynamic Bayesian Networks. We adopt a scene in the famous movie Doubt that has 53 dialogue sentences as the test corpus and implement 21 types of speech acts in the experiments to show that agents with dialogue context awareness ability can infer indirect speech acts from given direct speech acts.

Keywords: Speech act theory, Bayesian networks, Pragmatics, Context awareness, Agent dialogue, Virtual games

1 Introduction

While computer entertainment and education games have become a big industry in recent years, they have brought us into a new era full of imagination and creativity. Computer games today could be simulated in more believable than before and could allow people immerse their cognition and feelings in the virtual worlds. Various techniques including 3D graphics and sound effects have been implemented in the latest games to make them more vividly and lively in the virtual worlds. We can act as a virtual character role and interact with non-player characters (NPCs) and the virtual environment in the virtual games for entertainment or education. Therefore, in virtual world, we need to enrich the NPCs ability in their reasoning, dialogues and context awareness. NPCs are usually treated as intelligent automatic agents and the game engine as a multi-agent system (MAS).

In MAS, either rational or non-rational agents rely on communication to solve problems, resolve the conflicts, argue about disagreements, form teams for cooperation, come up with a joint plan, and conduct social activities, etc. Different modes of communication for agents have been developed in different platforms for a MAS. In 1993, DARPA KES defined a standard of agent communication language (ACL) called Knowledge Query Manipulation Language (KQML) that was based on the speech act theory for intelligent agents [6]. FIPA-ACL extended KQML and defined 22 performatives for agents to communicate. Both KQML and FIPA-ACL [7] basically pre-suppose that agent's dialogue pragmatics must to some extent follow Grice's maxims [9] in order to achieve effective communication and avoid ambiguity and misunderstanding. However, in computer games, the ability for NPCs to accurately interpret the semantics and pragmatics in a dialogue can be restricted merely under the sanction of Grice's maxims. To interact with intelligent agents, the indirect speech acts such as metaphors, jokes, ironies, or even lies can easily violate the Grice's maxims. Therefore if we insist an ACL of agents to follow strictly to Grice's maxims, it would be impossible for agents to infer different pragmatics from its semantic in the dialogue context.

Our research objective is to establish a dialogue context awareness model for virtual agents who play as a NPC in a computer game so that they can "understand" the dialogue context to some extent and infer the true intentions of other agents in the dialogue conversation in an emergent narrative. From our point of view, a virtual agent who can conduct dialogue properly with other agents must have at least the following capabilities: 1. be aware of the situations in the dialogue including the observable environment and dialogue history; 2. be able to reason about other agent's mental states; 3. be able to predict possible consequence or other agent's possible reactions at current dialogue situations; 4. be able to explain what might have possibly happened based on current dialogue context situations. We consider these abilities all relate to the dialogue context awareness that is needed for a dialogue agent to be able to infer semantics of a dialogue to its pragmatic under various dialogue contexts. On the other hand, for an agent to conduct dialogue properly, it implies the agent can select a proper speech act at the proper dialogue context. Therefore we must be able to model speech acts well so that the virtual agent can base upon to select a speech act properly not only by considering its preconditions but also by projecting its post-conditions and effects in a dialogue. However, unlike physical actions, speech acts normally involve contexts that are related to human mental states and social situations and are difficult to specify. We need to clarify these context models first before we could model the speech act well. Besides, since mental states of agents and dialogue pragmatics are in general unobservable and uncertain, we need a probabilistic reasoning model to support the uncertain reasoning both forward and backward between the dialogue pragmatics and dialogue contexts. We adopt dynamic Bayesian networks [12] (DBN) as the framework to support the simulation of the context awareness reasoning based on a sequence of dialogue sentences in the dialogue.

This paper focuses on how to model the speech acts so that they can facilitate agents to be aware of dialogue contexts by mapping from the dialogue semantics to its pragmatics. In section 2, we survey some related works. In section 3 we describe our method of modeling speech acts and various dialogue contexts, the computation models of DBN for context awareness. In section 4, we describe the simulation experiments against a test dialogue corpus from a movie script and we show our results and discuss their significance. In section 5, we make conclusions.

2 Related Works

In traditional context-awareness domains, researches focused on extracting and abstracting information from the low-level signals in real world [14]. For example, emotion detection from texts, speeches or videos is a kind of context awareness in human-machine interactions [10][11]. Dey [5] gave a definition of a context as any relevant information for interactions between users and applications, or themselves. For multi-agents application domains, the MAS can process every low-level signal from internet, I/Os and other applications and then deliver the events or other high-level concepts to intelligent agents. To make agents interact reasonably and appropriately, modeling an abstract context is necessary in a complex virtual environment.

Agent communication is a complex problem domain for knowledge querying, delivering and exchanging between various agents and applications. For the efficiency of knowledge exchange, researchers designed various protocols in terms of Agent Communication Languages (ACLs) for agents to follow. Jamal [3] designed a logical model called Commitment and Argument Network, to make agents reason about the communicative acts and the states in the conversation. However, we assume agents might not follow the Grace's maxims in the virtual drama or in emergent narrative approach. So we adopt a probability model instead of a logical one to describe the dialogue context.

Stolcke et al. [15] use 42 dialogue acts to tag 1,155 Switchboard conversations with a probability model to recognize the conversation speech act. They used hidden Markov model (HMM) as Bayesian network to compute the likelihoods $P(U|E)$ (E for evidence of complete speech signal and U for sequence of dialogue act labels) and reached high accuracy on speech act recognition. We differ from Stolcke et al. in that we attempt to relate pragmatics with various dialogue contexts which is important for virtual agents to achieve context awareness in many virtual simulated games. In this paper, we focus on inferring the pragmatic speech act from a semantic-tagged sentence and various dialogue context information. Galley [8] demonstrated a statistical approach for modeling agreements and disagreements in interactions. They ranked maximum entropy based on several observable features to identify participants in conversation. Besides the observable contexts, we modeled several unobservable dialogue contexts to infer speech acts. In contrast to previous work, our approach could be applied to emergent narratives and virtual interactive drama.

3 Methods

In speech act theory, all speech acts must accompany some context to become meaningful. We illustrate possible contexts involved to dialogue in figure 1. Agents can obtain part of dialogue context information through the observation on the environment such as the physical states of location, room arrangement, temperature, brightness and etc. In additional, agents can also memorize all previous dialogues as contextual information. The kind of context information can be obtained via agent sensors as evidence and can become more reliable and refined as the sensor technologies available to the agents are improved and diversified.

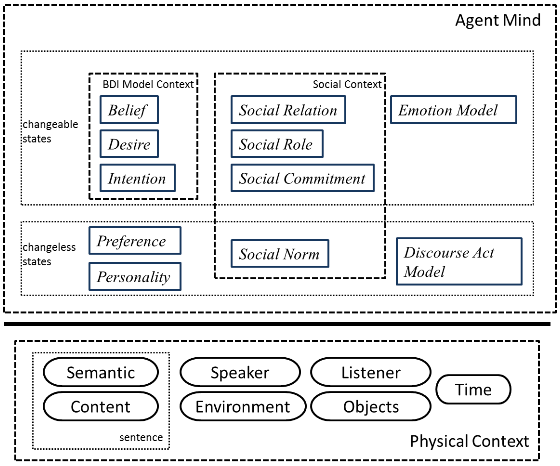

Fig. 1. Agents mental states and physical context.

Another part of context information is unobservable and agents must obtain by reasoning based on prior knowledge and evidence gathered from the environment. The mental states of other agents including their emotions, cognition of social relations, personalities, beliefs, goals, intentions or even atmosphere of dialogue are usually hidden and unobservable context information. Even reasoning with sound logic, agents cannot one hundred percent sure that the context information inferred is correct. Since no Grices maxims can be assumed, the agents cannot believe that other agents are not lying. Although there is uncertainty in unobservable context information, most agents must rely on it to make decision. Therefore its importance is no less than the directly observable context information. We call the two kinds of context information as dialogue context in the speech act model and use them to define speech acts. This will be described in detail in section 3.1.2. To design the reasoning of contextual information based on the observable evidence and unobservable information we adopt dynamic Bayesian networks which are described in details in section 4.

In a dialogue, agents could directly obtain contextual information from not only tones of speech, facial expressions of other agents, but also the dialogue content of a sentence. The dialogue content of a sentence could in general be obtained from complicated natural language processing steps. To simplify the discussions and focus on the theme of the paper, we assume the content semantics of a dialogue have been extracted to the speech act and we only do experiments with speech acts.

3.1 Models of Speech Acts and Dialogue Context

Speech Acts. In traditional planning, each action must satisfy some physical states called as pre-conditions to be executed and after its execution it can cause the change of the world states as effects or post-conditions. These states are in general observable to ensure the action be executed or successfully carried out.

In dialogue speech act, it is similar except that a speech act only changes the mental states of agents that cannot be verified via direct observation without some mode of reasoning. Therefore we must define first what dialogue contexts a particular speech act can affect and how and to what degree it affects a dialogue context.

An action can only be applied when all pre-conditions are matched in the action model. However, the speech act model is more relax than the action model. Although there are many related dialogue contexts can trigger a speech act, we think a speech act can be fired by partially match with related dialogue contexts. For example, emotion contexts *anger* and *reproach* are related to the speech act *blame*, but an angry agent might still blame someone even if he/she didnt have the *reproach* emotion. Its a major difference between the speech act model and action model. In our speech act model, a speech act affects not only speakers mind but also listeners mind. The reason that we cant combine all agent mental contexts into a big one is that we use the dynamic Bayesian network to model each agents mental model, and the DBN models are independent between dialogue agents. We will explain this in more details in section 3.2.

In figure 2, we show that a speech act is modeled as the change of various contexts, in which (1) indicates mental states of an agent can affect the selection of a speech act, (2) indicates a speech act can affect the mental states of agents own and others, based on the observation from current dialogue contexts.

As discussed above if we believe all agents dialogues obey Grices maxims then we could convert the dialogue content semantics directly in some way to pragmatics, namely, infer speech acts from the their dialogue content semantics directly. However, in emergent narratives, we have relaxed the assumption of Grice maxims for agent communication so we could not directly obtain the pragmatics, or speech acts, from the dialogue content semantics. Since the agent mental states are essentially unobservable, we cannot confirm for sure whether the inferred speaker agents pragmatics in a dialogue sequence are indeed the true intentions (or speech acts) of the speakers. Therefore we distinguish two different dialogue sequences; a coherent semantic sequence which means that all the dialogue semantics of speech acts in the dialogue sequence can be treated

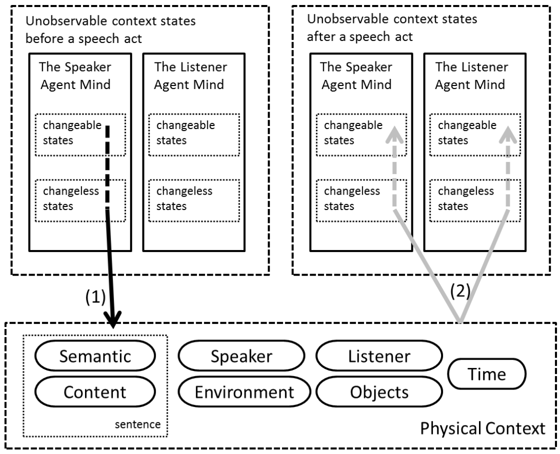

Fig. 2. A speech act affects both speakers and audiences mental contexts. The effects to audience are hard to know until the agent conduct some speech acts in conversation.

as pragmatics and no incompatible speech acts can be found in the sequence while an incoherent semantic sequence; which means if the dialogue semantics of speech acts are treated directly as pragmatics, there are some speech acts whose dialogue semantics might be in conflict with their true pragmatics. For most cases of dialogues in the emergent narratives, they are more or less incoherent semantic sequences and therefore we need to find an explanation as the most likely pragmatic speech act sequence for a given dialogue sequence.

Dialogue Context. In the work of speech act classification [1], 4800 speech acts and 600 categories are divided into four major layers: expression, appeal, interaction and discourse. Each speech act can be defined by changing or trigger by specific contexts. Surely, to list all possible applicable context conditions for a speech act is impossible as it falls into the frame problem that we could not possibly specify all contingent conditions involved. To make it worse, due to the unobservable property of the mental states of other agents, the ramification effects of a speech act on other agents mental states sometimes cannot be easily and clearly framed.

In designing the dialogue context model, we only aim at the major conditions and effects that a given speech act can achieve in a dialogue while ignore completeness of all possible contingent conditions. It seems to be somewhat ad-hoc, however, some principles and commonly encountered contexts and can still be adopted in the dialogue context modeling to make the context awareness feasible.

In describing the relations between the dialogue context and a speech act, in order to distinguish that an agent is more likely to choose some speech act rather than the others under certain context, or some speech act may have more likely to affect a given context than the others, we often encounter the matter of the degree of effect. Our solution is to divide the degree of effect in terms of five levels. Each level is mapping a probability in Bayesian network: Level 1: 15%, Level 2: 35%, Level 3: 50%, Level 4: 65% and Level 5: 85%. We then subjectively annotate such information in each speech act. Although at beginning, the subjective annotation can cause inaccurate predictions, we could dynamically adjust the degree of effect later at a separate learning stage based on the dialogue records when we find the inaccurate predictions. For example, when we find that all agents tend to have low estimation toward the *angry* emotion, we could raise the levels of the effects of all speech acts that have affected the *angry* emotion.

Emotion Context. The OCC emotion model [2] proposed an emotion model for 22 types of emotions according to their triggering conditions in terms of an agents appraisal on objects, agents and events with respect to his/her utility. Using OCC model to logically describe the emotion context for speech acts encounters not much difficulty. However, the strength of an emotion cannot have a common standard way to model. For example, if Peter *requests* Mary something, he will have emotions of *hope* if Mary accepts or have emotion of *fear* if Mary rejects. However, if there is no difference in the strength of emotions, it is hard to distinguish the emotional differences that could be brought from the use of three different speech acts: *request*, *beg*, and *order*. Intuitively speaking, speaker agents using *order* should have less *fear* and *hope* emotion than *beg* after using it. Table 1 shows an example of speech act models of *beg* and *order* respectively in their post-conditions to distinguish such a difference.

Table 1. The effects on speakers emotion of speech acts of *order* and *beg*.

· A *order* B · (effects on the speaker A only)

P(A_emotion_hope | order) = 0.15
P(A_emotion_fear | order) = 0.15

· A *beg* B · (effects on the speaker A only)

P(A_emotion_hope | beg) = 0.65
P(A_emotion_fear | beg) = 0.65

As discussed above, not only can a speech act affect an emotion at a different degree to an agent, but the strength of an emotion can also affect the selection of a speech act for an agent. In Ballmers speech act classification, 155 speech acts have been identified under Expression Layer that are used to express agents self-emotion. In other word, in dialogue context, expressing self-emotion can play a very important role in agent communication that can help an agent to make other agents understand his reactions to previous conversation or release his emotional pressure.

In Table 2, we show an example of possibility model to emotion expression speech act *blow-up* that is adopted by a speaker whose angry emotion has reached a higher degree than a specified threshold (according to his personality) in the precondition and that might also affect its listeners emotion toward negative in the post-condition.

Table 2. The emotion context of speech act blow up.

· A *blow_up* B ·	
P(blow_up | A_emotion_anger) = 0.85	trigger
P(B_emotion_NEGATIVE | blow_up) = 0.5	effect

Social Context. Besides emotion, a dialogue can be directed to different styles and directions according to different social relations among speakers and the listeners. After all, a dialogue can be conducted with more than one agent. To maintain a normal dialogue, agents will more or less respond with a proper speech act that follows some conventions or protocols. Random selection of speech acts among dialogue agents cannot possibly make the dialogue be pursued smoothly. Therefore under most situations, agents would choose certain speech acts according to the social context in the dialogue. For example, a subordinate rarely *yells* to his/her boss under a normal social context, while we would more than often see a warm greeting among friends. We therefore include social norms, agent social roles and social relations in the social context modeling for a speech act.

Social Relation. The social relations refer to organizational relations, friendship/enemy relations, or family relations. We focus on those relations in two aspects that need to be specified in the speech act: the relations that can be suggested or implied when a given speech act is adopted and the relations that can be affected by the speech act. Of course, the social relations can affect the speech act at different degrees of influence toward the emotions of listener agent.

Social Role. Some speech acts can only be used by the agents having certain social roles. The speech acts *Sentence* in court or *Diagnose* a disease must be adopted by a judge or a medical doctor respectively to be considered as the proper utilization of a speech act. On the other hand, when a speech act is adopted by an agent, it might be naturally to make other agents believe that the speaker agent actually plays the social role that is implied in the speech act.

Social Norm. The social norm refers to the rules or conventions that are usually the common knowledge for all agents and that in a dialogue context can usually specify whether a given speech act should be or should not be used under certain social contexts. However, social norms can also be violated. For example, take *greeting* as an example, someone can ignore the step of *greeting* and directly cut in the main topics of the dialogue. To deal with this, we would maintain a personality context of an agent and record the frequency of violation of norms in the speech act behaviors of the agent so that it could predict more accurately the pragmatics and dialogue context of the agent in the future dialogue.

Social Commitment. Agent may have social commitments in conversations. However, since we have not modeled in detail about the social commitment, so the agent cant realize when or how to comply with their social commitments. But we model the relation between social commitment and speech act. With *Social Commitment* context model, agent may or may not use certain kinds of speech acts in the conversation, and the conditional probability model could be the same model as *Social Relation* context model.

Personality Context. Personality context specifies the tendencies of the reactions of an agent toward certain emotions and social norms. Since personality is relatively fixed in dialogue, without affect the performance evaluation of other context models in this paper we could assume they are fixed at some prior constant for all dialogue agents.

Preference Context. In the preference context, we record the frequencies of speech acts used by a particular agent toward other agents under certain dialogue situations so that the tendency of choosing a particular speech act for the agent can be analyzed for future prediction. Similar to *Personality* context, we could assume preferences are also fixed at some prior constant for all dialogue agents.

Discourse Act Context. Discourse context refers to a sequence of speech acts that often appear together under certain patterns to achieve a particular social functions for the dialogue agents. For example, in a quarrel discourse context, the dialogue agents might interleave with such speech acts as *angry*, *disagreement*, *scolding*, *argue*, *attack*, etc. while negotiating discourse context there can be speech acts as *proposal*, *counter-offer*, *acceptance* or *rejection*.

3.2 Computational Model of Context Awareness Reasoning Using DBN

In DBN modeling and implementation [13], in general we need to specify the domain sensor model and the transition model in terms of conditional probabilities $P(E_t|X_t)$ and $P(X_{t+1}|X_t)$ respectively, where E_t represents the evidence collected from sensors at time t and X_{t+1} and X_t represent the domain states at time t+1 and t. With an assigned initial state $P(X_0)$, we can get the states of X at any t :

$$\mathrm{P}(X_{0:t}, E_{1:t}) = P(X_0) \prod_{i=1}^{t} P(X_i \mid X_{i-1}) P(E_i \mid X_i)$$

Since each speech act is modeled as the change of dialogue contexts, we could subjectively attach the probability of the possible change of context preconditions and post conditions in the speech act as a transition model. Basically the sensor model gathers evidence from the physical environment which includes the content semantics of the dialogue sentence and other information cues via observations such as tone of a speech, facial expression, gesture and object location, etc. In the figure 3, we used two DBN model for two participants, agent A and agent B, in conversation. A_t and B_t are unobservable dialogue contexts for their mental state in dialogue step t. The observable data (Ob_t) that includes the speech act (SA_t) is the sensor model that reflects states of observable dialogue contexts evidence E_t, and the speech act could also affects the dialogue context. The effects of speech act could cause the dialogue context to change with probability $P(X_t|X_{t-1}, SA_{t-1})$ in which SA_t is speech act at dialogue step t. Using DBN, we can infer context states we designed based on the observation in the conversation. So with the speech act model, we can get the states of X at dialogue step t:

$$\mathrm{P}(X_{0:t}, E_{1:t}) = P(X_0) \prod_{i=1}^{t} P(X_i \mid X_{i-1}, SA_{i-1}) P(Ob_i \mid X_i)$$

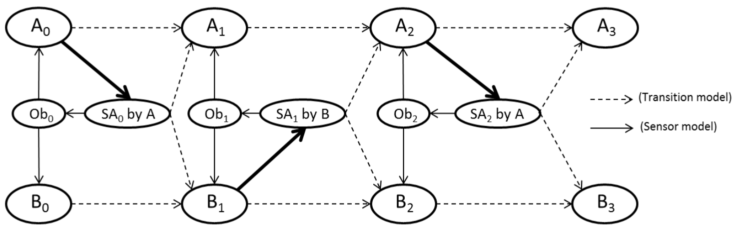

Fig. 3. Two DBN models for both the speakers and the listeners dialogue contexts. The speech act and observation information in the dialogue are treated as the sensor model in the DBNs.

Combine CPT with Noise-or Model. To combine those related conditional probability, we use noisy-or model under the assumption that all the contexts with conditional probabilities are independent. The idea of Noisy-OR [4] function is that a speech act SA with n precondition contexts C_i, then there are n probability values p_i where p_i is the probability that $\{SA = true\}$ on $\{C_i = true\}$ and $\{C_j = false\}$ for all j $\neq$ i.

$$\mathrm{p}(\mathrm{SA} = true \mid \mathrm{C1}_1, \ldots, \mathrm{C_n}) = 1 - \prod_{\mathrm{i:C_i}=true} (1 - \mathrm{p_i})$$

The limitation of using the noisy-or model to calculate the CPT is that we can only design triggers to fire a speech act. We cant describe the kind of condition that a context might reduce the possibility of firing a speech act with the noisy-or model. Moreover, in order to use the noisy-or model, the assumption that all dialogue contexts are independent could be too strong. However, using the noise-or model, we can simplify the computation complexity of calculating the conditional probabilities table (CPT) by reducing all 2^n combinations of true-false possible conditions to only n-item computation.

4 Experiments

We collected a dialogue sequence from a script in a famous movie Doubt [16] which is a 2008 film adapted from John Patrick Shanley's Pulitzer Prize winning fictional stage play Doubt: A Parable. In the movie there is a scene where three characters Father Flyn, Sister Aloysius and Sister James were having an argument dialogue. We adopt the scene that has 53 dialogue sentences as in Table 3 and annotated manually the dialogue sentence with observable evidence, possible mental states (such as emotions and other context) as well as correct speech acts as our test corpus. We modeled and implemented 21 types of speech acts according to the approaches discussed in section 3 among which 18 are actually appeared in the scene of the selected movie script.

Table 3. The dialogue sentences from a scene script from the file Doubt.

#1 Aloysius: "The boy's well-being is my responsibility."
#2 Flynn: "His well-being is not a issue."
#3 Aloysius: "I'm not satisfied that that is true."
...
#50 Aloysius: "Intolerance"
#51 Flynn: "That's right. I'm not pleased with how you handled this."
#52 Flynn: "Sister"
#53 Flynn: "Sister"

4.1 Speech Act Model with Multiple Contexts

Speech Act Classification. In the Doubt scenarios, the pragmatic speech acts: ask and interrogations are frequently used in the conversation. Lack of well-designed domain ontology for the dialogue semantic content in the communication language, the two pragmatic speech acts are hard to be distinguished. It is because both of them belong to semantic speech act *ask*. However, the pragmatic speech act *ask* affects the listeners emotion merely in general sense. In table 4, we defined four kinds of semantic speech act classification and each can be elaborated or interpreted as three to six pragmatic speech acts according to its context. Some of the speech acts can change the emotion context, and some of them need to have special social roles or social relations involved. To distinguish speech acts in such speech act classifications can show that the agent has the ability to identify a proper pragmatic speech act under different context states.

Table 4. Four semantic speech acts and their elaborated pragmatic speech acts in Doubts scene.

Request	*Recount*
· Request	· Recount
· Order	· Censure
· Propose	· Accuse
Ask	*Reply*
· Ask	· Reply
· Interrogate	· Reject
· Interpellate	· Accept
· Threaten	· Controvert
	· Threaten
	· Not-intimidated

Dialogue Context Scheme. Although we describe a lot of dialogue contexts in section 3, due to the limited effort and computation as well as the test bed domain for obtaining the full performance, we only focus on 7 negative emotions and one positive emotion (*Shame, remorse, fear-confirmed, reproach, disappointment, anger, fear and hope*) from OCC emotion model into emotion context. The rationale to choose more negative emotions than positive is that the agent in the chosen domain will tend to show more negative emotional speech acts than positive. And we use emotions *fear* and *hope* to model speech acts *ask* and *request* that can have some effects due to the *accept* or *reject* speech acts for the dialogue agent.

In addition to emotion context, we also model several social relation contexts such as *friend* to model the positive relation,*be_authority_to* and *be_subordinate_to* to model the precondition of a pragmatic speech act *order*, and et al.

4.2 Experiment 1: Pragmatic Prediction with Dialogue Contexts

In experiment 1, we intend to show that a dialogue agent can predict the correct pragmatic speech act to some extent from its semantic speech act of a dialogue sentence in the agent dialogue conversation given the dialogue contexts of the speech act model.

In Table 5, we showed 21 speech acts occurred in the conversation, all 21 semantic and pragmatic speech acts used in the Doubt script of 53 dialogue sentences and are labeled with a symbol from a to u in which a: *Announce*, b: *Controvert*, c: *Dissatisfied*, d: *Recount*, e: *Ask*, f: *Reply*, g: *Interrogate*, h: *Reject*, i: *Censure*, j: *Rebut* , k: *Say-goodbye*, l:*Accuse*, m: *Agree-with*, n: *Request*, o:

Propose, p: *Be-glad*, q: *Threaten*; r: *Not-intimidated*, s: *Pride*, t: *Praise*, and u: *Grumble*. The annotations of semantic speech act sequence and pragmatic speech act sequence corresponding to the 53 dialogue sentences in the dialogue script are annotated in A and B respectively. Each dialogue character is labeled with a number: 1. Father Flynn, 2. Sister Aloysius, 3. Sister James and each dialogue sentence can be abbreviated as (speaker + audience + speech act). For example Sister Aloysius makes an announcement speech act (a) to Father Flynn that will be annotated as (21a) as in the semantic speech act sequence. And the pragmatic speech act is the same as its semantic speech act in this dialogue context and therefore it is annotated as the same (21a) in the pragmatic speech act sequence.

Table 5. 21 Semantic and pragmatic speech act sequences in Doubt scenario.

A. Semantic speech acts input sequence:

(21a)(12b)(21c)(21d)(13e)(31f)(21e)(12e)(21f)(12f)(21e)
(12f)(21e)(32e)(23f)(12i)(21j)(12e)(21f)(21e)(12e)(21f)
(21e)(12h)(12k)(13k)(21d)(12e)(31f)(21e)(12n)(21h)
(31n)(12n)(21h)(12f)(31p)(21e)(12f)(12f)(31t)(13s)(31t)
(32e)(23f)(12m)(12e)(21f)(12d)(21u)(12l)(12k)(12k)

B. Pragmatic speech acts input sequence:

(21a)(12b)(21c)(21b)(13e)(31f)(21g)(12e)(21f)(12h)(21g)
(12h)(21g)(32e)(23f)(12i)(21j)(12e)(21f)(21g)(12e)(21f)
(21g)(12h)(12k)(13k)(21l)(12e)(31m)(21g)(12n)(21h)
(31n)(12n)(21h)(12b)(31p)(21q)(12r)(12q)(31t)(13s)(31t)
(32e)(23f)(12m)(12e)(21f)(12d)(21u)(12l)(12k)(12k)

We assume the correct pragmatic speech acts in the first half of the speech acts in the script are given as known, and then each dialogue sentence is input one by one by continuing the second half of the dialogue. We model two different agents as a test. The first agent will be given the preloaded context information in the first half part of dialogue log. By the pre-loaded context information, we mean all the pragmatic speech acts in the dialogue sequence that have been conducted so far. We observe it prediction ability on the pragmatics on every dialogue sentence in the dialogue sentences at the second half. The second agent will not be given any preloaded context information, so he/she is the third party agent and join in the conversation in the middle. Of course, we expect the second agent to have a lower accuracy for prediction than the first one as a contrast. In the Table 6, the first row is the pragmatic speech act sequence for the second half part in the scenario. The second row is the predicted results of the first agent with pre-loaded context information. The third row is the predicted result from the second agent without pre-loaded context information. The third column in row 2 and 3, we calculated the accuracy ratios of precition of the two agent respectively. All the mismatchs are indicated in grey shade.

Table 6. The accuracy of pragmatic speech act prediction with/without preloaded context.

Correct data	lemgnfnnhbpqrqtstefmefdulkk	Accuracy
Results with context info.	lemgnfnnhbpefftstefmefdudkk	15/19
Results w/o context info.	demenfnnffpefftstefmefdudkk	11/19

We only calculate the accuracy with the predicted result for the speech act classification. There are 16 classified speech acts, and 5 speech acts are not classified. It means that if a semantic speech act is not classified, the pragmatic speech act will be equivalent to the semantic speech act. In this experiment, only 19 of 26 sentences have classified semantic speech acts.

The first result in the experiment 1 with preloaded context knowledge has four error predictions with accuracy rate 15/19. The reason of error is due to, in the end of the conversation, emotion intensity is at normal level, so agent cant easily distinguish the pragmatic speech acts using *Emotion* context.

The second result shows a worse performance of an agent without context information. However, it still has an accuracy rate of 11/19. Its because the *Discourse Act* context used to predict the speech act pair *ask-reply* actually make effects.

In the experiment 1, we show that the accuracy with preloaded context knowledge (namely, the accumulated context information during dialogue) helps in predicting the pragmatic speech act from a semantic one.

4.3 Experiment 2: The Most Likely Pragmatic Speech Acts Sequence

In experiment 2, we assume only semantics of dialogue sentences are given as known, we attempt to assess if the speech act model could find out the most likely explanation of the dialogue context. Since most dialogue sentences are ask/reply speech acts, but sometimes emotions of dialogue agents can become incompatible with the contexts, we wish to know to what extent the model could find an explanation of pragmatic context (as *interrogation* in this case) for each dialogue speech act (as *ask* in this case) sentence. With the same reason mentioned in section 4.2, we calculate the accuracy based on the classified speech acts.

Using DBN, we calculate a most likely pragmatic speech act sequence from it corresponding semantic sequence whose overall probability is 6.792e-11 with 29 correct pragmatic speech acts matching out of 40 semantic speech acts as shown in Table 7. We reason that the error could be due to the peaceful conversation at the beginning of the scenario that provides little emotional context. So the prediction of the pragmatic speech act interrogate from semantic speech act ask is incorrect at the beginning for about the first one third of conversation.

Table 7. The probability and accuracy of the most likely pragmatic speech act sequence.

Correct data	abcbefgefhghgefijefgefghkk lemgnfnnhbpqrqtstefmefdulkk	Probability Accuracy
Result	adcdefeeffghgefijefeefehkk lgmgnhnnhbpefftstefmefdudkk	6.792e-11 29/40

5 Conclusion

We have established a speech act model to serve as a bridge for virtual agents to reason about multiple sophisticated dialogue contexts that include norms, social relations, emotion, personality, intention or goals among agents in a dialogue scene. We have relaxed the traditional agent communication assumption of ACL that assumes speech acts used by virtual agents be modeled as precisely and as sincerely possible as suggested by the Grice maxims to avoid ambiguity in communication. By proper modeling the preconditions and post conditions of these contexts in speech acts of various types, and adopt DBN to conduct the uncertain reasoning and inference among the contexts, it provides a powerful and flexible method to support complicated context awareness reasoning. We illustrate with a scenario using the dialogue script in a movie as a test bed and show the performance feasibility of this approach. We show that with proper model of speech acts in terms of change of dialogue contexts, it could support agent reasoning about pragmatics of other agents in the dialogue. This is important in supporting virtual agents toward more context awareness in various simulated virtual games.

DBN model is adopted and the probabilities are devised based on evidences from the domain and data corpus. We implemented it with customizing subjective conditional probabilities that are reconciled under various constraints to show the feasibilities. It could possibly lead to poor accuracy and some bias in rigorous evaluation. However, after the implementation when an agent detects mass error predictions or encounters misunderstandings of a particular semantic speech act with high frequency, it has a space for incorporating some learning mechanism to automatically refine the parameters in the speech act model.

Therefore the study has not only shed some light on the context awareness for virtual agents to conduct dialogue but also points out many interesting research directions. The future work includes more elaborated design of the speech acts in various types as well as the automated acquisitions of proper parameters in supporting DBN reasoning. Since we have simplified the semantics of an entire dialogue sentence into a dialogue semantic label (*speaker-audience-speechact*) by ignoring its actual dialogue content semantic, we are aware that in some situations, context awareness does require the content semantics of a dialogue sentence as well as its background context knowledge to resolve semantic ambiguities. The refined content semantics and background knowledge can not only improve the accuracy of the awareness but also lead to deeper context awareness in dialogue. For this aim, we need to augment not only the speech act model but also augment the domain content ontology and sentence parsing and understand. Another direction of future research is to integrate with various signal sensor technologies to collect more evidence cues from environment and other agents that can support DBN to achieve a full-fledge context awareness model for the virtual agents to conduct various believable conversations in dialogue.

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Dialog Designs in Virtual Drama: Balancing Agency and Scripted Dialogs

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Abstract. With a story generator, scripts would be automatically generated and then played by virtual agents. While scripts for actors consist of two parts: movements and dialogs, the latter is little addressed in current research of story generation, and hence limiting the generated stories. Therefore, our initial goal is to enable story generators to generate dialogs as sets of character-based actions integrated with original story plots. This paper firstly presents a speech-act-based dialog generation framework to define the relationship between dialogs and story plots. Secondly, we introduce how agents may improvise scripted dialogs by selecting different courses of actions. Finally, a sample scenario is generated according to this framework and demonstrated by virtual agents with Unreal Development Kit. Our initial results indicate that this framework strikes at a balance between agency and scripted dialogs; that improvised dialogs of virtual agents would not break the consistency of stories.

Keywords: speech act theory, dialog generation, virtual drama

1 Introduction

The rise of intelligent virtual agents has formed a new interdisciplinary research community spanning across artificial intelligence, computer graphics, cognitive science, natural language processing, and narrative theories.

While the future direction of virtual agents may vary according to the major domain of researchers, a significant one would be virtual drama, as it takes place in existing applications such as computer games, emotion counseling and simulation-based training. Here, we identify virtual drama as a play with the following characteristics:

1. Virtual environments: rendering computer graphics with either realistic or cartoon-style pictures as the scenes in the play, the virtual environments often serve as the engine that integrates other components such as camera controllers and physics.
2. Virtual actors: virtual agents may be implemented in different methods from virtual environments, yet intended to act as characters in the play, equipped with the abilities to make believable gestures, facial expressions, synthesize voice, and other interactions.

3. Play scripts: actions of virtual actors and virtual environments are described in the play scripts, either manually written or automatically generated. While different from movie scripts intended for human actors and directors, play scripts in virtual drama are often defined with formalisms and/or markup languages, e.g. PDDL [14] in planning domain, and BML [29] to describe the action timing of virtual actors.

While the first and the second parts remain important research issues in virtual agents, we focus on the generation of the third part, which is identified as story generation or narrative generation in academic terms.

The potential need of automated story generation exists as the speed of consuming stories by audience is greatly larger than that of writing stories by human authors. With a story generator, scripts would be automatically generated and then played by virtual actors situated in virtual environments. Thereby we argue that story generation is the starting point for virtual drama to become completely automated and on-demand digital contents.

However, while recent research in story generation applies various types of planning [8][25] and theories in narrative analysis to generate plots, these plots contains only high level actions containing physical actions only , and the dialogs between characters are often left unattended or vastly hand-crafted, resulting in speechless or very domain-specific scenarios. While the former require human authors to fill in the dialogs, the dialogs of the latter are confined in current storylines, difficult to be re-applied to other generated stories.

To fill the gap, the primary purpose of our research is to model a generative framework of dialogs, so that it would be able to generate dialogs for different stories and actors without losing its generality. Since the whole domain of natural language generation is way beyond our research problem, our framework is based on a simplified yet well-structured form of language, which is known as speech acts and treated as ordinary actions in the planning domain, so the state-of-the-art techniques of story planning may utilize them during the planning process without many modifications.

In particular, this novel dialog framework is flexible to both virtual actors and story plots: allowing virtual agents to choose more detailed dialogs based on internal character profiles and the play scripts, while it also allows human authors to specify constraints at the level of story discourse.

The remainder of this paper is described as follows. First, section 2 reviews related literatures in the domains of agent communication and story generation, situating our work and identifying its scope. In section 3, we describe our desiderata and explain why we choose hierarchical speech acts as the foundation of our framework. Within this context, section 4 gives a formal representation of virtual drama and our dialog framework in Z notation. Next, section 5 applies this framework to an abstract scenario to evaluate how our model can be used to generate balanced dialogs between characters and plots. We conclude in section 6 by summarizing our main findings and future work.

2 Related Work

2.1 Narrative Generation

In general, research of narrative generation is rooted in literary structuralism. Based on their work, a narrative world is described by a series of events, which are known as fabula. Pieces of fabula chosen by storytellers to retell the audience are identified as sujet. Since story discourse (the sequence of sujet) may be different from fabula in temporal order and appearance (e.g. not every piece of fabula will appear in sujet), different stories may be generated even based on the same fabula.

Formulated as actions, fabula and sujet may be generated with POP-based planning. Whereas structuralists [7][24] analyzed stories as a set of specific patterns of sujet, the goal of narrative generation is to generate stories according to these patterns. Further decompositions of these overall story patterns lead to the formulation of causal constraints in planning. On the other hand, the continuity of character intention expressed in sujet is also an important factor to stories and identified as intentional constraints by Riedl et al. and utilized by their story planner IPOCL [25].

POP-based narrative planning yield sound results of stories, which can be further processed into different styles of sujet such as suspense. Besides, Riedl further extended his method with incorporating vignettes [27], which are considered good scenarios and used as existing plan fragments during planning process, making story reuse possible. Nevertheless, the actions used by planners are defined as major events, rather at the level of overall fabula than at the level of sujet, which consists of lines of dialogs between characters.

2.2 Interactive Narratives

A parallel trend of research in narrative intelligence is interactive narratives, which focus on interactions between human users and virtual actors. In I-Storytelling system [4] and its following, each virtual actor interacts with users and other virtual actors based on a pre-scripted HTN plan, allowing others to change its behavior based on the actual interactions on-stage. Without definite fabula, the sujet emerges from real-time interactions and thus this method is also identified as emergent narratives. The method of emergent narratives lead to multiple possible fabula, as it may generate inconsistent stories with the same set of HTN plans.

Intuitively, the formulation of interactive narratives should be more suitable describe dialogs since dialogs are a type of interaction. As the number of pre-scripted interactions increase, users may experience more different dialogs. In most applications, defining story directions at different levels is still desired, avoiding virtual actors to become completely random chat bots and lose the grip of intended stories. Therefore, a drama manager is needed to pick up appropriate interactions according to current development of stories. With fine-grained interaction segments, such systems can yield highly interactive stories with good quality, exemplified by Façade [19]. However, contrary to those actions which are general events in POP-based story planning, all the dialogs and other interactions in interactive narratives are domain (story) specific. As a result, recent development about dialog generation in interactive narratives leads to demonstrate differences among characters respect to different forms of expressions [5], character archetype [28], personality [18], culture [11], and multi-modal dialogs [22]. These dialogs require significant time to build and polish, yet the lack of explicit notations related to high level plots makes them difficult to reuse in new stories since they intertwine with implicit and possibly multiple fabula.

2.3 Simulation-based Training

On the other hand, negotiation formalisms from agent communication languages are introduced into applications of simulation-based training [30]. As their goal is to train human users with virtual agents in virtual environments, the virtual actors also need to interact with users through protocols of normal coordination and communication. While actual lines of dialogs are pre-recorded, virtual actors reason about their communication with users and evaluate it as different states, based on explicit task models of standard operation procedures. To allow users negotiate with virtual actors, a set of negotiation-related speech acts are adopted, and either actors or the user interact each other via speech acts and related parameters defined in the task models, while users speech acts are identified automatically with voice recognition and further natural language processing. If negotiated properly, virtual actors would take different courses of actions and hence change the following story.

This method is applied in several related training projects [10][31]. In our point of view, task models and speech acts are defined explicitly within interactions, the gestures, facial expressions, and other movements of virtual actors are configured independently in the visualization process, making this dialog model modularized and plausible to stories. Inspired by this research, our work introduces a speech act classification system to serve as the foundation of dialog framework shown in the next section, and further integrate it with the narrative generation process.

3 Dialog Framework

In this section, we attempt to clarify the purpose and the definition of dialogs with formalisms.

Dialogs, either ones monologue or conversation involving multiple participants, can be conducted in any part of narratives, describing a part of the story from the point of view from particular characters. The presented story may even become different, depending on different characters point of view [23]. However, as Austin pointed out that the purpose of statements is not only to describe, but also to do things with words [1], the purpose of dialogs in narratives is not just to describe the story, but also to represent characters actions toward the narrative world. To model these actions, we adopt the theory of speech acts and view dialogs as sequences of different speech acts.

While the model of domain knowledge in dialog contents are conducted in recent research [17], speech acts in interactive narratives are usually tailor made according to the tasks in stories [6][19][30] in an ad-hoc fashion without certain hierarchy or relations among different speech acts, making them hard to be utilized by either story planners or virtual actors intending to emerge narratives. Against this background, in the following we progressively introduce what we believe to be the essential classification of speech acts, and how we apply it to build a consistent schema that captures the dialogs in narratives.

While we only intend to allow virtual actors to adopt and mimic the structures of human dialogs to generate similar sentences, first we need to categorize and identify the relations among numerous speech acts used by human. Our approach is inspired by Ballmer and Brennenstuhls speech act classification [2] as it provides explicit relationship among different groups of speech acts. Their classification indicates there are four major groups of speech activities as hierarchical linguistic functions. Though a semantic verb may appear in different categories, the functional effect of each category of speech acts does not overlap. In this way, we believe it is possible for story generators to select based on the effects of speech acts. Here we explain them in the context of narratives:

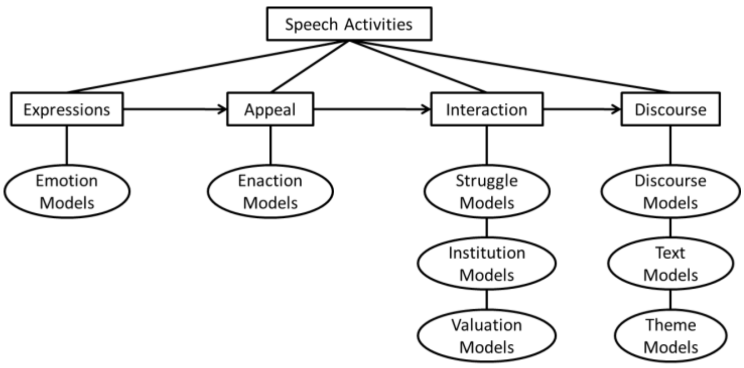

Fig. 1. Speech Act Classification from [2].

- Level1-Expression: including all emotional reactions, Expression has the most primitive and direct speech acts that present characters profiles, such as angry, afraid, grateful, and etc.
- Level2-Appeal: Appeal represents speech acts in a narrower sense, where the speaker tries to influence and control the hearer (e.g. order, threaten, encourage).

– Level3-Interaction: similar to Appeal, yet the hearer has the ability to influence the speaker, whereas the speaker may try to avoid, which forms a series of Appeals in different directions.
– Level4-Discourse: Better-behaved and more rigidly organized Interaction(s), which implies these Interactions have certain order and appearance according to the definition of this Discourse.

While currently we only use a subset of speech acts in our system, we argue that it is the relationship among these levels that link character dialogs (low levels) to narrative discourses (high levels). As indicated in the classification definition, there is an important property that allows us to utilize this speech act model in narratives.

Property 1. (Speech Act Hierarchy): Being the higher linguistic functions imply being the lower ones.

That is, if a Discourse is described between two actors, then it should contain one or more interactions, all leads to many Appeals in both directions. These Appeals occurs with different (emotional) Expressions.

With this property, any plot symbols in narrative structures can be expanded into one or more speech acts (which are later realized as dialogs) in addition to ordinary actions. For example, when two persons A and B start to argue over something in a play script (which its performance is sujet), if we describe this speech act as primitive actions in domain theory of planning, then this speech act can be shown as:

$$argue(A, B, sth) \tag{1}$$

During the process of argue, some forms of protocols must exist in the knowledge of both sides, such as rebut, undercut, negotiate, and etc. These protocols contain a series of speech acts designating verbal attacks and defenses toward each other, waiting to be chosen by both parties during run time. When A and B execute these speech acts, they may also express their current emotions.

In the previous example, argue itself belongs to Discourse (level-4); rebut, undercut, and negotiate are its associated Interaction (level-3). Those attacks, defend, evade, and etc. following Interaction protocols are Appeal (level-2), and their emotional behaviors are seen as Expression (level-1).

Inspired by this property, we further define a *dialog frame* based on *speech acts* within narratives.

Definition 1. *(Speech Act): There are four major groups of speech acts, which are Expression, Appeal, Interaction, and Discourse from lower level to higher level.*

A high level speech act may include speech acts in lower levels.

Definition 2. *(Dialog Frame): a dialog frame must contain more than one speech act.*

While these definitions do not give precise information to what kind of speech acts are included in each model, we merely point out that the rules among each groups. While our focus is not to re-examine whether speech acts in each model are appropriate in human language, we give several examples to demonstrate how to utilize these models as parameters for virtual drama, explaining the pros and cons with different approaches. It is up to users to customize their own sets of speech acts in each level, and the associated relations among these groups. Interested readers may refer to speech act classification for more details.

4 Virtual Drama

As we stated in section 1, an automated virtual drama system should has at least 3 components: story generators to generate play scripts, virtual actors to play according to the scripts, and virtual environment that integrates these components. While the mechanism of story generation is outside the scope of this paper, we assume the scripts are already generated as a sequence of high level actions such as those in [13][25]. Under this assumption, we specify how dialog frames can be elaborated in virtual drama as these high level actions, and how virtual actors may improvise during the play of dialog frames.

4.1 Virtual Actors

To specify without losing generality, we define schema of each component based on environment and autonomous agents of SMART Agent Framework [9] in Z notation.

Virtual Environmnent. The major difference between virtual drama systems and general agent systems is the existence of play scripts. These play scripts should be perceived by virtual actors to indicate the play, so they should be defined in virtual environment, on top of original environment schema Env.

Definition 3. *(Virtual Environment)*

VirEnv

Env

$virenv : VirtualEnvironment$

$socialcommitments, socialrelations :$
$AutonomousAgent \times AutonomousAgent \times Goals$

$script : Script = \langle s1, s2, \cdots \rangle$

$script \neq \{\}$

In the above definition, virtual environment includes not only play scripts, but also social commitments and social relations among virtual actors. All of these attributes may affect the play of virtual actors. As Karunatillake et al. point out that, *since most (social) relationships involve the related parties carrying out certain actions for each other, we can view a relationship as an encapsulation of social commitments between the associated roles.* 16 Here we omitted the notion of social roles and adopted this notion, as we only use them as parameters during the play, especially the play of dialog frames.

Character Profiles. Besides social relations, virtual actors should have certain internal parameters to maintain consistency between different states during the play, so they will not break the character believability proposed by Riedl and Young [26]. Nevertheless, besides intention of characters, we argue that the continuity of affective states also plays an important role on maintaining character believability, as a character suddenly laughs whereas it cries a few minute ago would bring unpredictable expressions to the audience. During a scene of dialogs, a virtual actor should be able to interact in different manners based on its affective states and the changes of them.

Here we define the affective states as *character profiles*, following the ALMA affective model [12]. The reason we adopt ALMA is its elegant notation, integrating emotions, mood, and personality in a single three-dimension space where axes are pleasure, arousal, and dominance, rather than defining each of them in a different model [3][20][21].

Definition 4. *(Character Profile)*

CharacterProfile

VirtualActor

p: *Pleuasure*

a: *Arousal*

d: *Dominance*

$affect = \langle p,a,d \rangle$

$p \in (-1,\ldots,1)$

$a \in (-1,\ldots,1)$

$d \in (-1,\ldots,1)$

Virtual Actors. The difference between virtual actors and autonomous agents is its definition of motivation, which is based on script and character profiles.

Scripts and character profiles are independent from each other, while their combination will determine the motivation of virtual actors. As we only define

VirtualActor

AutonomousAgent

---

motivation=$\{$ *script*$\times$*characterprofile*$\}$

motivation on terms of scripts and character profiles, the definitions of agent perceptions and actions may not need further modification from those in autonomous agents beside they percept and act upon virtual environments instead of environments. To keep clarity of this paper, we omitted the action and perception schema of virtual actors.

Based on previous definition, we may define virtual actor state as follows:

Definition 5. *(Virtual Actor State)*

VirtualActorState

AutonomousAgentState
VirtualActorPerception
VirtualActorAction

---

willact=actoractions motivation
goals actualpercepts virenv

There are three possible effects on virtual environments and virtual actors during the play:

1. Change of character profiles: which change the motivation of virtual actors, and lead to different choices of Interaction made in the case of dialogs.
2. Change of social commitments: it leads to change of available options in Interaction since social commitments serve as preconditions of Interaction.
3. Changes of scripts: since scripts are also a part of virtual environment, the result of speech acts may also change the scripts themselves, and cause replanning of scripts. While we acknowledge its importance and effects, this issue of story replanning is outside the scope of this paper.

Dialog Frame. Here we summarize the usage of dialog frames. First, as dialog frames are taken as high level actions in play script, the mapping of speech act models should also be specified in the script, giving virtual actors available courses of actions during the play. Second, character profiles of each virtual actor will determine its goal selection on the courses of actions. On the other hand, the effects of dialogs would not only change character profiles, but also change social commitments, which will alter available options of speech acts within given script. Last but not least, speech acts may also changes scripts in the Discourse level, will leads to replanning of scripts.

4.2 Improvisation of Dialog Frames

While dialog frames provide virtual actors different options to select during the play, yet sometimes these options are still insufficient to reflect character profiles of virtual actors because a script is a linear sequence of action events. Although each event may be decomposed into different sub events (speech acts in lower levels), these sub events are still limited to the script itself, and defining specialized mapping between speech act models for individual virtual actors would be ad-hoc and inflexible. Inspired by Gebhards justification to ALMA model [12], we propose an improvisation mechanism to achieve higher degree of believability. This improvisation allows virtual actors to use certain speech acts in Appeal and Expression level to reflect extreme cases of character profile values and changes.

It is important to notice that, the add-on of improvisation mechanisms still satisfy the previous specs of virtual actors. Since character profiles are one of the determinants of motivation, improvisation is defined in terms of affect thresholds and changes of $< p, a, d >$ vectors in virtual actors instead of virtual environments.

Furthermore, improvisation will be triggered despite of current script, so other virtual actors should be able to cope with improvisation in the time improvisation occurs; otherwise the following behaviors will be against audience prediction and sabotage character believability. These coping behaviors are limited to insert right after improvisation occurs, and thus need not to replan the whole play script. By defining coping behaviors in secondary scripts parallel to play scripts, virtual actors may conduct improvisation and coping speech acts by selecting different scripts to play, without replanning primary play scripts. The coping behaviors between improvised speech acts and coping ones can be defined as follows:

Definition 6. *(Script of Coping Behaviors)*

CopingBehavior

Script

ImprovisedAct

CopingAct

$copingbehaviors == Script : ImprovisedAct \rightarrow \mathbb{P}\ CopingAct$

$copingbehaviors \neq \{\}$

The overview of dialog frames is shown in fig. 2, with an intuitive script of detective story, which will be illustrated in section 6.

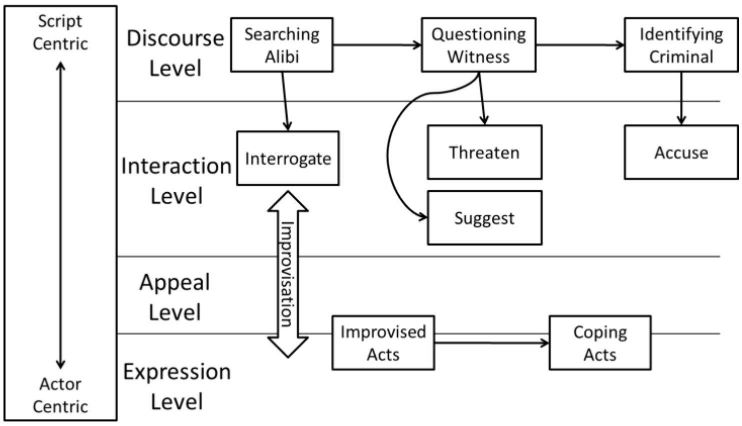

Fig. 2. Dialog Frames in Detective Scenario.

5 System Implementation

To demonstrate this dialog framework, we have a first-stage implementation of virtual drama system according to the specs. The system overview is shown in fig 3.

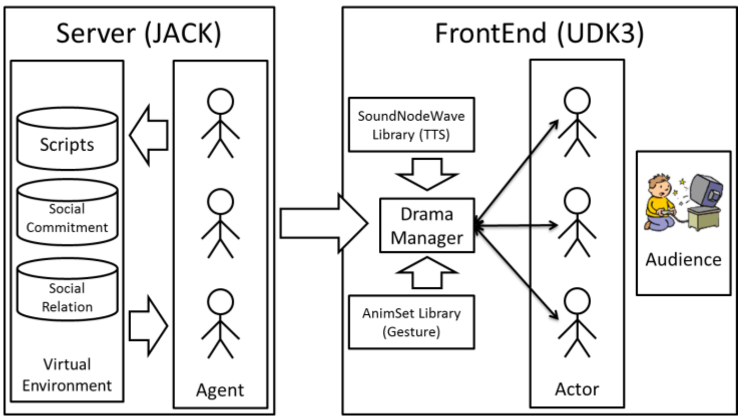

Fig. 3. System Implementation Overview.

The system can be divided into two main parts:

1. Virtual Drama Server: The server is implemented with JACK [15] agent platform for it supports in capacity, plan, and communication of autonomous

agents. The Virtual Environment is also implemented in JACK as named data set. As a result, the server alone may generate different sujet of play scripts in a plain-text fashion.
2. Visualization Frontend: The frontend is responsible for providing visual and audio experience for the audience of virtual drama. We choose UDK3 (Unreal Development Kit 3) [32] as our frontend platform, as it has built-in full functional GUI editor, and APIs written in Unreal Scripts that allow us to write drama manager within it. Once the server pass sujet of a play script, the drama manager allocates corresponding virtual actor, customized SoundNodeWave library corresponding to speech acts with built-in text-to-speech function, and gestures, treating all of them as parameters of matinee in cinematic mode.

At this stage of implementation, the purpose of virtual drama system is to attempt to achieve fully automation of sujet performance; thereby user interaction is not implemented to simplify the process.

6 Sample Scenarios

In this section, we provide a sample scenario to demonstrate the effect of dialog frames in our implemented system, which is shown in fig. 2.

This sample scenario is a typical detective story, as the play script only contains three high level speech actions in Discourse: search for alibi, question the witness, and identify the criminal. Assuming this play script is easy enough to be generated by state-of-the-art story planners; our system is able to demonstrate the following functionalities:

1. This sample scenario is a typical detective story, as the play script only contains three high level speech actions in Discourse: search for alibi, question the witness, and identify the criminal. Assuming this play script is easy enough to be generated by state-of-the-art story planners; our system is able to demonstrate the following functionalities:
2. Given these protocols as dialog options, each virtual actor choose protocols which preconditions match its character profiles while playing that part of the script.
3. Improvised dialogs may occur during the play, because each move in Interaction protocol has effects on the opponents character profiles, which will trigger improvisation in given thresholds. After improvisation, virtual actors return to former part of script and continue the main storyline.

7 Conclusion and Future Work

The development of story planning led to the possibility of automated drama system, in which play scripts are firstly generated by story generators, and then played by virtual actors, all on top of virtual environment with the ability of visual and audio expression. While few attempted to further generate dialogs based on given fabula, here we made a first step toward dialog generation in virtual drama based on speech act classification derived from empirical studies of speech act designating verbs. The contribution is threefold:

1. We propose a dialog framework with the ability to promote flexible dialog selection and to improvise character-based dialogs from given play scripts.
2. Core specs of virtual actors and virtual environment are specified in Z notation to elaborate the desiderata of virtual drama components without losing generality.
3. A first-stage virtual drama system is implemented to demonstrate the selection of dialogs during a sample scenario.

While the initial results are fruitful, there are several components remain as future work to achieve fully automated virtual drama system:

1. Generating natural from speech acts to advance the automation of dialogs.
2. Treating Discourse-level speech acts as vignettes [27] in story planning may lead to improvements in script generation. As Discourse-level speech acts are combinations of Interaction-level protocols, they may stand as a source of vignettes.
3. The domain knowledge of speech acts and their parameters may be further elaborated as more structured data, so virtual actors may reason with the play script rather than profile-based selection in available options.

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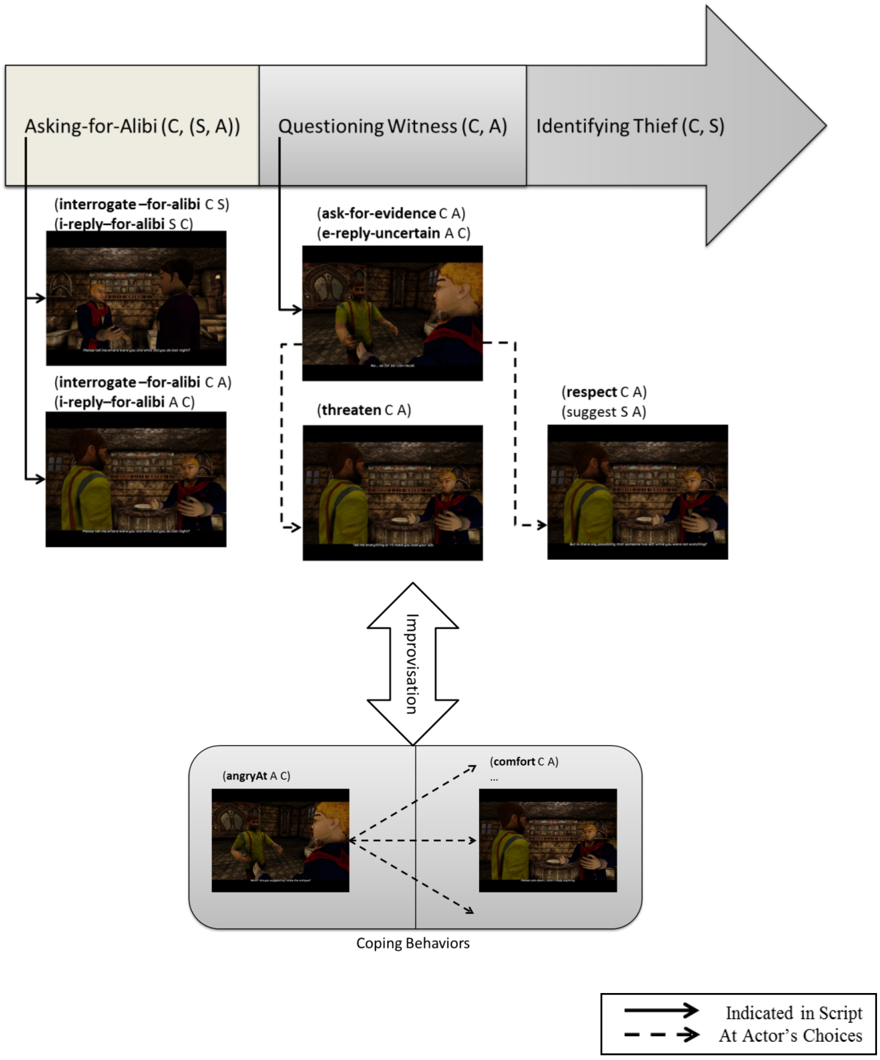
8 Appendix



Asking-for-Alibi (C, (S, A))
Questioning Witness (C, A)
Identifying Thief (C, S)
(interrogate –for-alibi C S)
(i-reply–for-alibi S C)
(interrogate –for-alibi C A)
(i-reply–for-alibi A C)
(ask-for-evidence C A)
(e-reply-uncertain A C)
(threaten C A)
(respect C A)
(suggest S A)
Improvisation
(angryAt A C)
(comfort C A)
...
Coping Behaviors
Indicated in Script
At Actor's Choices

Collection and Analysis of Multimodal Interaction in Direction Giving Dialogues: Towards an Automatic Gesture Selection Mechanism for Metaverse Avatars

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Abstract. With the goal of building a spatial gesture generation mechanism in Metaverse avatars, this paper reports an empirical study for multimodal direction giving dialogues. First, we conducted an experiment where a direction receiver asked the way to some places in a university campus, and the direction giver gave a direction to there. Then, using a machine learning technique, we annotated direction giver's right hand gestures automatically, and analyzed the distribution of the direction of their gestures. As the result, we proposed four types of proxemics, and found that the distribution of gesture directions is different depending on the type of proxemics between the conversational participants. In future work, we plan to establish a method for spatial gesture generation, and implement it into a Metaverse application.

Keywords: Gesture, Direction giving, Proxemics, Empirical study, Metaverse

1 Introduction

Online three-dimensional virtual worlds based on the Metaverse applications as typified by Second Life have been growing steadily in popularity. The communication method in such a virtual world is mainly an online chat using an avatar, which is a user's representation of himself/herself. However, the current avatar's chat has a limitation in its expressiveness in that it largely depends on speech balloons except for some extended systems that allow avatars to communicate based on speech and gesture.

On the other hand, many communication studies suggest that a large part of human face-to-face communication is dependent on non-verbal behavior, which can compensate for verbal information [1, 4, 5]. In particular, many spatial gestures are used in direction giving dialogues in order to illustrate directions and physical relationships of buildings and landmarks. Therefore, it is expected that a spatial gesture generation mechanism in multimodal direction giving dialogues between two avatars in a virtual world would facilitate their users' communication.

We thus report an empirical study for multimodal direction giving dialogues with the goal of building a spatial gesture generation mechanism in Metaverse avatars. First, we collected multimodal interaction data by conducting an experiment where a direction receiver asked the ways to some places in a university campus, and the direction giver gave him/her a direction to there. Then, using a machine learning technique, we annotated direction giver's right hand gestures automatically, and analyzed the distribution of the direction of their gestures. As a result, it is illustrated that the distribution of gesture directions differs depending on the proxemics of the conversational participants.

2 Related Work

Gestures frequently accompany speech, emphasizing its important points or coordinating its rhythm. McNeill [6] classifies speech-accompanying gestures, in view of function, into iconic gestures, metaphoric gestures, beats, and so on. Based on the classification, several automatic gesture generation systems have been developed. Nakano, et al. [7] implemented an embodied conversational agent system, which selects appropriate gestures and facial expressions based on the linguistic information, and calculates a time schedule for the set of agent actions. Breitfuss, et al. [3] builds a system that automatically adds different types of gestural behavior and eye gaze to a given dialogue script between two virtual embodied agents. Their gestures, generated based on the analysis of linguistic and contextual information of the input text, are generally limited to 'beat' gestures represented by the repetitive up-and-down motion of hands or arms.

However, these studies have not fully dealt with iconic or metaphoric gestures, the shape and motion of which should be decided according to their meaning. The difficulty of implementing these types of gestures lies in their differences among individuals, thus preventing the coherent sub-classification of them. It is nevertheless indispensable for achieving a genuine automatic gesture generation to precisely determine the shape and motion of gesture as well as the functional type.

In order to tackle this problem, Tepper, et al. [8] focused on direction-giving dialogues and proposed a new method for the generation of novel iconic gestures. They used spatial information about locations and shape of landmarks to represent concept of words with multi-dimensional properties. From a set of parameters, novel iconic gestures can be generated without relying on a lexicon of gesture shapes. Moreover, Bergmann & Kopp [2] represents the individual variation of gesture shape using the Bayesian network. Based on the transcription of spoken words and the segmentation and coding of coverbal gestures, they built an extensive corpus of multimodal behaviors in direction-giving and landmark description task, from which both general and personalized networks were built. As the result, they could simulate a variety of gestures of different speakers for the same referent in the same situation.

Fig. 1. Snapshot of experiment

We thus focus on the direction-giving situation, aiming at establishing an automatic gesture selection. Though the previous methods above were largely dependent upon the form of landmarks, we pay more attention to the relationship between the proxemics and the gesture distribution of interlocutors.

3 Experiment

To determine appropriate gesture shapes for direction giving utterances in Metaverse avatars, we conducted an experiment to collect direction giving conversations, and analyzed human gestures used in the conversations.

3.1 Experimental Procedure

A student of Seikei University, who played as a direction giver (DG), stood in front of a big screen where a snap shot of a virtual university campus was displayed (Fig. 1). Direction givers were the students of that university, and they knew the directions to any place on campus. The other student playing as a direction receiver (DR) was approaching to the DG and asked a way to a specific building. Then, the DG explained how to get to the building.

Instruction: The DR was instructed to completely understand the direction to the goal through a conversation with the DG. On the other hand, the DG was instructed to make sure that the DR understood the direction correctly. To confirm the DR's understanding, the DG asked the DR to explain the way to the goal after the explanation from the DG was finished. If the explanation by the DR was not correct, the DG explained the direction again. In each session, the DG was requested to remember two landmarks to which the DG must refer during the conversation.

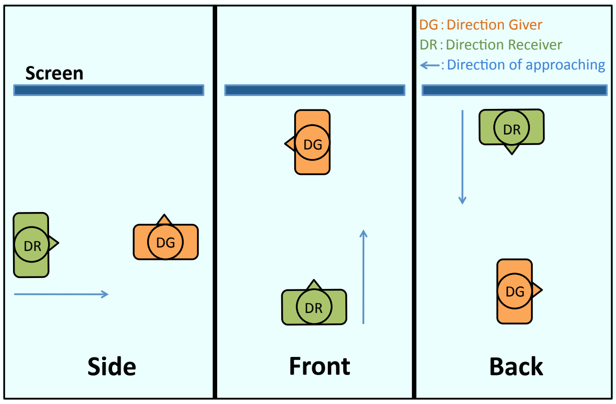


Fig. 2. Three experimental conditions

Experimental materials: As the experimental materials, 6 pictures were created by capturing the screen, and goal places, which were not visible in the picture, were assigned to each picture.

Experimental conditions: The following three types of initial positions of the DG were used as experimental conditions (Fig. 2).

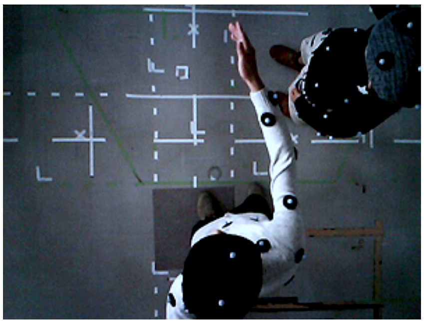
(a) Side: The screen was on the left hand side of the DR. The DG was facing toward the screen.
(b) Front: The screen was in front of the DR, and was on the right hand side of the DG.
(c) Back: The screen was on the back of the DR, and was on the left hand side of the DG.

Note that a 50cm square sheet was used to mark the position of the DG, and the DG was instructed to keep one of his legs on the sheet. By this procedure, the movement of the DG was restricted. Since we plan to implement a proxemics coordination system by guiding (or automatically moving) the DR avatar, we needed to collect human interaction data in a similar situation.

In all the conditions, the DR was approaching to the DG from her/his side, and initiated the conversation by asking a direction. Six scene pictures were randomly assigned to three conditions. Therefore, two conversations were recorded for each condition.

Equipments: Each subject used a wireless (Bluetooth) headset microphone to record her/his voice, and wore a cardigan on which motion capture markers were mounted. OptiTrack motion capture system with 10 cameras was used to capture the subject's upper body motions. The subject's interactions were video-recorded from their side and above. Fig. 3-(a) (side) and Fig. 3-(b) (overhead) are the pictures in the 'Back' experimental condition.

(a) Side camera



(b) Overhead camera

Fig. 3. Videos in 'Back' condition

Subject: 14 university students (7 male and 7 female) joined as DRs, and 14 male students of Seikei University joined as DGs. Thus, we had 14 pairs of subjects in this experiment.

3.2 Collected Data

We collected video data from two directions, speech audio of each subject, transcription of utterances, and motion capture data tracking each subject's upper body motions. Each subject's motion was tracked for her/his head, shoulder, back, right arm, and left arm in 100 fps.

We had 14 pairs of subjects, and each pair had 6 sessions. So, we collected 84 direction giving dialogues in all. The average length of conversation was 68.6 sec.

4 Analysis

Analyzing the collected data, this section investigates how DG's gesture directions for indicating the spatial information are different depending on the proxemics between DR and DG. We analyzed 30 dialogues collected from 10 pairs for further analysis.

4.1 Automatic Gesture Annotation

Since it is very time consuming to manually annotate nonverbal behaviors, we automatically annotated the gesture occurrence (start and end time of a gesture).

Since more than 77% of the gestures observed in this study were right hand gestures, we built a decision tree that judges the occurrence of right hand gestures using Weka J48. From the motion capture data of the DG's right arm and the right shoulder, 10 features were extracted: position (x, y, z), rotation (x, y, z), movement of z position, relative position of the right arm to the right shoulder

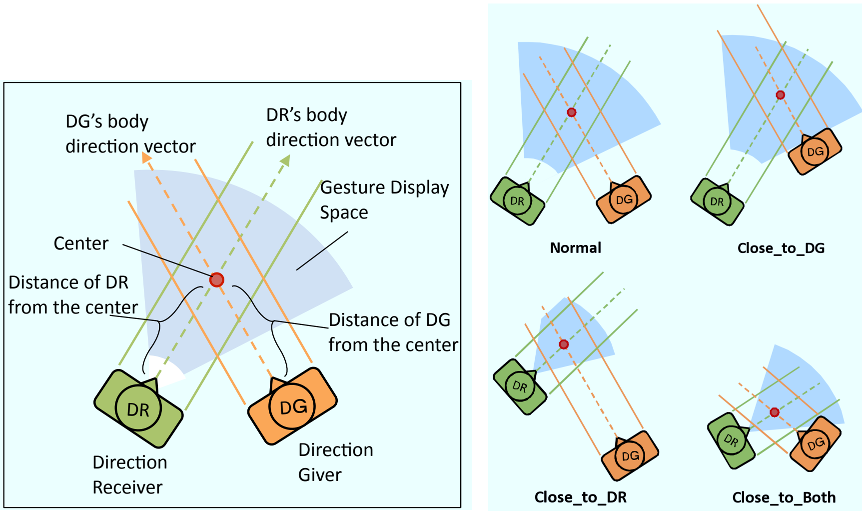


Fig. 4. Definition of proxemics

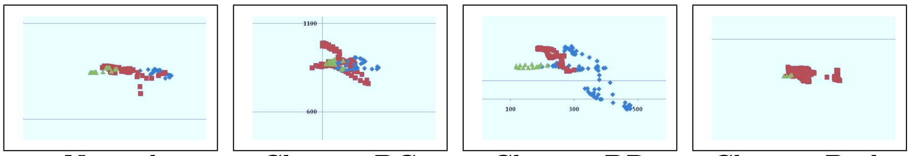
(x, y, z), and distance between the centroid of the right arm and that of the right shoulder. We annotated right hand gestures for two subjects for 6 sessions to create training data.

As the result of 10-fold cross validation, the accuracy of binary judge (gesturing or not gesturing) was 97.5%, which is accurate enough for automatic annotation. Thus, we applied the decision tree to the rest of the data, and automatically annotated right hand gestures. Through this process, we obtained 161 right hand gestures for further analysis.

4.2 Proxemics between the Direction Giver and the Direction Receiver

To characterize the proxemics between DG and DR, we defined a gesture display space. As illustrated in Fig. 4, the gesture display space is specified as the overlap between the DG's front area and the DR's front field of vision towards the screen. The width of the DG's front area is determined by the distance between the left shoulder and the right shoulder. Then, the center of the display space is calculated as follows. First, a shoulder vector is defined by connecting the left shoulder position and the right shoulder position. Then, another vector, which is orthogonal to the shoulder vector, is defined as a body direction vector. The intersection between the DG's body direction vector and the DR's body direction vector is defined as the center of the gesture display space.

Then, we categorized the pair's proxemics based on the distance from the center of the gesture display space. We assumed that if the gesture display space is far from the DG, s/he needs to stretch her/his arm to show her/his gestures to the DR. On the contrary, if the gesture display space is very close to both



Normal **Close_to_DG** **Close_to_DR** **Close_to_Both**

Fig. 5. Distribution of gestures WRT proxemics

participants, the DG, s/he does not need to use large motions, but small gestures are enough to communicate. Since human arm length is 60cm to 80cm, by adding 15cm margin we defined 450mm to 950mm as the standard distance from the center of the gesture display space. Based on this, we defined the following five categories of proxemics.

(i) Normal: Both participants are standing within the standard distance (450mm to 950mm) from the center of the gesture display space.
(ii) Close_to_DG: The DG is standing close (less than 450mm from the center) to the gesture display space, and the DR is keeping the standard distance.
(iii) Close_to_DR: The DR is standing close to the gesture display space, and the DG is keeping the standard distance.
(iv) Close_to_Both: Both participants are standing close to the gesture display space.
(v) Far_from_Both: Either of the participants is standing far (more than 950mm from the center) from the gesture display space.

As the result of analyzing the motion data for 30 sessions, 11 were categorized as Normal, 4 as Close_to_DG, 9 as Close_to_DR, 2 as Close_to_Both, and 4 as Far_from_Both. Far_from_Both is a very inconvenient proxemics because it is almost impossible for the DR to see the DG's gesture. For example, both participants were facing to the screen, or the DG was standing behind the DR. Thus, for gesture analysis in the next section, we will exclude the data classified as this category. Table 1 shows the average distances from the center of the gesture display space for each category.

4.3 Relationship between Proxemics and Gesture Distribution

To investigate the relationship between the proxemics and the DG's right hand gestures, we analyzed the distribution of gestures by plotting the DG's right arm position, which was the centroid of the right forearm calculated from four data points: one on the right elbow and three on the right wrist. Fig. 5 shows some examples. As shown in the plots, Normal and Close_to_DG are similar in gesture distribution range. In Close_to_Both, the range of gesture distribution is much smaller. This suggests that the DG uses smaller gestures because both participants were close to each other and the gesture display space was smaller than that in other proxemics. On the contrary, in Close_to_DR, the range of gesture distribution was much wider, specifically in z position. This suggests that the DG was little bit far from the display space, and tried to show her/his gestures by stretching her/his arm to the front.

To confirm this observation, we measured the area of the gesture distribution. Table 1 shows the average width, length, and the square measure for 4 types of proxemics.

Table 1. Gesture distribution area

	Normal	Close_to_DG	Close_to_DR	Close_to_Both
Dis DG (mm)	665.9	395.0	596.4	392.0
Dis DR (mm)	706.5	638.7	281.9	359.0
Width (mm)	197.2	214.0	237.6	189.5
Length (mm)	246.2	188.0	368.9	119.5
Area (mm^2)	48557.1	46388.0	91257.8	23218.0

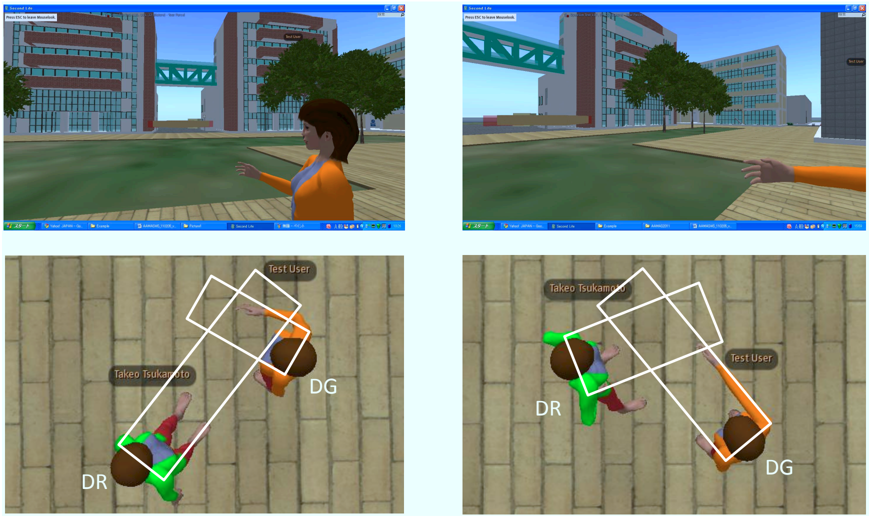
The data support our discussion above. The gesture distribution range (Area) is similar in Normal and Close_to_DG because in both categories, the gesture display space is not far from the DG and the DG can widely choose the directions of gestures. In Close_to_DR, the distribution range is much larger, specifically in length (z position) because the gesture display space is a little bit far from the DG and the DG needs to stretch her/his arm to make the gestures reach to the gesture display space. In Close_to_Both, the gesture space is not very wide because the participants are too close to each other and there is not enough space for gesturing.

4.4 Applying the Proxemics Model to a Metaverse Avatar

To test whether the findings in the previous sections are applicable to Metaverse environment, we created avatar gestures based on the proxemics model illustrated in Fig. 4. Fig. 6 shows the pictures from the DR's point of view and from a bird's eye view. Fig. 6(a) shows pictures for Close_to_DG proxemics. In this situation, the user as a DR can see the whole picture of DG avatar. As the gesture display space is close to the DG avatar, the avatar is doing a small gesture by bending her right arm. On the contrary, Fig. 6(b) shows the pictures for Close_to_DR proxemics. In this situation, DG avatar is not close to the gesture display space, the user as a DR cannot see the avatar's body but can only see her right arm. Therefore, the DG avatar needs to stretch her right arm to show her gestures in the gesture display place.

5 Conclusion and future work

With the goal of automatic generation of direction giving gestures in Metaverse avatars, this study conducted an empirical study to collect human gestures in



(a) Close_to_DG (b) Close_to_DR

Fig. 6. Creating avatar gestures based on the empirical results

direction giving dialogues. Then, we investigated the relationship between the proxemics and the gesture distribution. As the result, we proposed four types of proxemics characterized by the distance from the gesture display space.

As the future work, we need to investigate other factors that may influence the gesture shape. One important aspect is the relationship between the experimental conditions and the gesture distributions. We plan to analyze whether preferable proxemics is different depending on the direction from which the direction receiver is approaching. In addition to categorizing the proxemics, it is also important to investigate how two people approach and coordinate the position to each other as a process of determining the proxemics. Another important future direction is to establish a computational model of determining gesture direction, implement it into Metaverse avatars, and then examine the effectiveness of the model by testing whether the users perceive the avatar's gestures being appropriate and informative.

Acknowledgment

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Learning by Playing in Agent-oriented Virtual Learning Environment

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Abstract. Virtual environments have gained tremendous popularity among young generation in recent years. Learning in the virtual environment becomes a new learning perspective that helps to promote the learning interests of students. However, there is a lack of methodology to develop and deploy a virtual learning environment to various learning subjects that can be personalized and engaged. In our paper, we propose an *A*gent-oriented *VI*rtual *L*earning *E*nvironment (AVILE) as a new "learning by playing" paradigm, in which each learning object is built up as a *g*oal-*o*riented *l*earning *a*gent (GOLA). Students are able to conduct the personalized virtual experiments through the simulations and personalized role-playing games for knowledge acquisition by interacting with the intelligent *GOLAs*. Each *GOLA* provides proper instructions by analyzing the students' learning process, and stimulates the students to make the deeper learning by encouraging exploration and knowledge application on real problems in the virtual learning environment. We adopted this methodology to teach plant transportation for secondary school students and received very positive results.

Key words: Virtual Learning Environment, Agent, Virtual Experiment, Personalization

1 Introduction

Virtual environments have gained tremendous popularity among young users in recent years for its openness, convenience, and mobility. People are able to communicate with each other in the virtual community and share information easily and efficiently, which is limited in the real world. Learning in the virtual environment becomes a new learning perspective that helps to promote the learning interests of students in the new era. The potential for innovative and ground breaking research in virtual learning environments has been recognized by leading scientists [3] [5]. Preliminary studies on the use of virtual worlds as learning environments to promote highly immersive experiential learning have achieved encouraging results [1]. However, it is still a big challenge to make a personalized virtual learning experience based on the students' preferences and real-time interactions, due to a lack of systematic methodology. Agent-based learning environment has been studied by researchers as a research tool for investigating teaching and learning [6], which provides a new perspective to the future learning method in virtual environment.

In this paper, we propose an agent-oriented virtual learning environment (AVILE) as a "teaching by learning" paradigm targeting to the raised challenges. In our system, each learning object is modeled as a goal-oriented learning agent (GOLA). AVILE is constructed as a multi-agent system of *GOLAs*, which construct the virtual laboratory that students perform the virtual simulations, and a virtual environment that students can engage and interact with. *GOLAs* are created to percept the players' actions and provide customized laboratory simulation or playing experience in the virtual environment, which can be visible as non-player characters or invisible as observers or instructors. In order to model different learning objects with consequences, Fuzzy Cognitive Goal Net (FCGN) is used to model the hierarchical goals with alternatives, through which *GOLA* selects the goals and actions by reasoning the real-time interactions and context variables. Evolutionary Fuzzy Cognitive Maps (E-FCMs) is used as the reasoning model about the dynamic causal relationships among the user interactions, contexts and agent goals, thus *GOLA* can provide a personalized learning object.

The rest of the paper is organized as below. Section 2 will illustrate our agent oriented virtual learning environment system and the involved agents. Section 3 will focus on Fuzzy Cognitive Goal Net which models leaning objects as the goals and cognition model to provide personalized playing and learning. We will show a case study of using the paradigm to teach secondary school students plant transportation system and assessments in Section 4. Lastly we will draw the conclusions and future plan.

2 Agent-oriented Virtual Learning Environment (AVILE)

Agent-oriented virtual learning environment (AVILE) provides a new approach for students to learn by playing in the virtual environment, which might not be easy to achieve in the conventional classroom learning (CL) or the real-life experiments, due to the communication constraint, physical limitation, and building cost etc. Each student is unique, in terms of the learning curve of new knowledge and learning habit. A generic virtual learning environment or virtual laboratory might not suit the needs of all the students easily. Therefore, there is a need to find a way to customize the virtual learning experience for the learners with many alternatives.

In current agent-based virtual learning environment, the learning contents are mainly delivered by the non-player character agents [8–11], with limitations of the knowledge delivering. In our approach, agents are not only used to model non-player characters, but also to model any learning objects which can be visible or invisible.

2.1 Learning Structure

Providing a personalized learning experience is a key to promote the learning experience of the student at knowledge acquisition. Agent-oriented virtual learning environment (AVILE) augments the virtual learning environment with a number of intelligent goal-oriented learning agents (GOLAs), which provide personalized virtual learning for the students based on reasoning over the students' preferences and real-time interactions with the students.

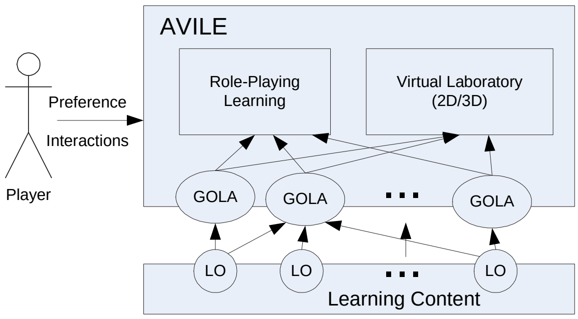

Fig. 1. Learning Structure in the Agent-oriented Virtual Learning Environment

Figure 2 shows the learning structure of agent based virtual learning environment. Learning content is decomposed to a series of learning objects (LO), e.g. diffusion and osmosis in plant transportation. Each LO is assigned to one or more *GOLAs* as their goals. For example, water molecules and plat root are two *GOLAs* to show the "diffusion" concept. The *GOLAs* are created in the role-playing learning virtual environment and virtual laboratory that the player can interact with and learn from.

In order to provide a fast-responsive and personalized learning experience, the user preferences are firstly gathered off-line for each student, e.g. age, gender, interests and prior knowledge. After that, the students play and learn in the agent mediated virtual learning environment, using two methods: virtual laboratory and role-playing learning. In the virtual laboratory, the students are able to conduct 2D or 3D simulations of learning objects, by acting as a "God". Moreover, the students are able to immerse though a role-playing learning by acting as a "Player", to verify the concepts they have learnt in the virtual laboratory. Stories are used to motivate the students in the role-playing learning by linking the learning objects seamlessly. Agents percept the real-time interactions of the students, reason about them and act back to the player, i.e. to provide a unique learning experience eventually.

There are three phases of learning in AVILE, which are carried out iteratively:

Experiment: The students conduct the virtual simulation in the virtual laboratory to study the basic concepts of learning objects.

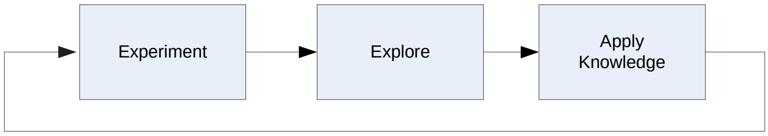

Fig. 2. Learning Model in AVILE

Explore: The students explore the virtual environment and interact with *GOLAs* to verify the concepts they have learnt in the virtual laboratory.

Apply Knowledge: The students transfer their knowledge they have learnt to solve real problems in the virtual world.

2.2 Goal Oriented Learning Agent (GOLA)

Different from other agent-based virtual environment, each learning object can be modeled as a goal-oriented learning agent (GOLA), which can be visible or invisible in the virtual environment. Visible *GOLAs* include the non-player characters (e.g. humans, animals, and context objects) that deliver the knowledge to students directly; while invisible *GOLAs* include the invisible contexts (e.g. temperature, weather, time and instructions) that deliver the knowledge indirectly.

A capable agent is able to percept, reason and act in the virtual environment by defining the goals and cognitive variables initially. Fuzzy Cognitive Goal Net is used as the goal model for *GOLAs* to act in the agent-oriented virtual learning environment, which is explained in details in next section.

In the AVILE, the following agents interact with students, help the students and analyze the learning process in real-time:

– **Instructor Agent** Each instructor agent is capable to provide instructions to the students. By monitoring the learning process of the students, the agent is able to tune the instructions in terms of difficulty level and instruction details.
– **Assessment Agent** An assessment agent evaluates the learning progress of the students, in order to master the learning efficiency of the students. Then it will send feedbacks to the instructor agent to adjust the virtual learning, in terms of speed and difficulties.
– **Inhabitant Agent** Inhabitant agents are the believable non-player characters to deliver the learning contents in the virtual learning environments, which could be a human or a tree, etc.

In order to provide an engaging learning experience, each *GOLA* presents the following properties:

Interactive: The agents are able to interact with the students in real-time.

Intelligent: The agents are able to "percept, reason and act" in real-time, which enables to create intelligent interactions.

Adaptive: The agents are able to learn from the players' behaviors and context changes, in order to provide "believable" interactions to the players.
Emotional: The agents are emotional to the interactions with students as a feedback to user interactions.

As a result, the students are able to be immersive in the virtual learning environment.

2.3 Virtual Laboratory

3D virtual laboratory allows students to do the experiments immersively. In our AVILE, both 2D and 3D virtual experiments are designed as simulations in the virtual laboratory.
2D or 3D virtual simulations have their own strengths and limitations. Table 1 shows a brief comparison between the two kinds of simulations. 3D simulation

	2D Experiment	3D Experiment
Implementation	Easy	Hard
Immersion	Low	High
Player Role	"God"	"Player"
Collaboration	No	Yes
Suitable Contents	Intuitive	Explorative

Table 1. Comparison of 2D and 3D Simulations

provides a better immersive experience to the players, and allows the interactions and collaborations of students at the learning. It is more suitable for students to explore and induct in the science learning. However, the implementation of 3D simulation is more expensive at the implementation. On the other hand, 2D simulation is more suitable to present the intuitive concept, e.g. a specific science term. In our real implementation, we use a hybrid of 2D and 3D simulations as a balance of production cost and user experience.
Virtual laboratory provides a basis for the students to learn through the simulation. Thus, the students are able to recall the simulation when they are exploring the virtual learning environment.

2.4 Role-playing learning

In AVILE, role-playing learning is a main concept that the student can immerse into the virtual environment to learn. Inhabitant agents are distributed in the learning environments to provide the related learning objects. Thus, the students need to compare, evaluate and induct the knowledge which are gathered in different places at various times, which might help the students to achieve the deeper learning. Moreover, students are encouraged to apply the knowledge they have learnt in the virtual experiments or exploration to solve real problems in the virtual learning environment. Stories are incorporated in the virtual learning environment to motivate the students at acquiring the new knowledge step by step.

3 Fuzzy Cognitive Goal Net

How to model a number of learning objects in an organized way is a big challenge. Fuzzy Cognitive Goal Net is a computational model to simulate the goals that *GOLA* pursuits in the virtual environment. As shown in Figure 3, *goals*,

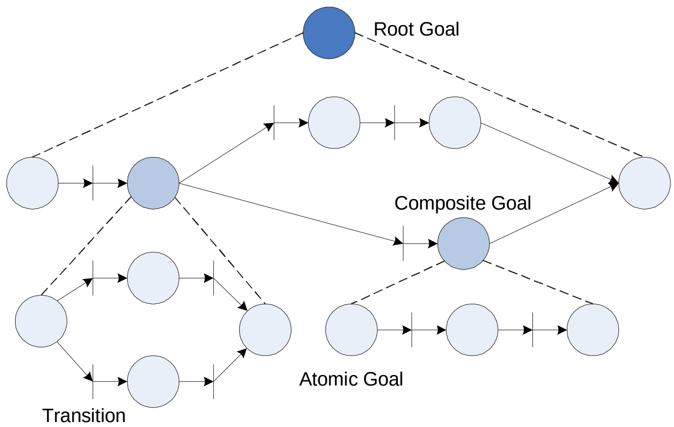

Fig. 3. A Sample Fuzzy Cognitive Goal Net which is composed of goals and transitions

denoted as circles, are used to represent the goals that an agent pursues. *Transitions*, represented by arcs and vertical bars, connecting from the input goal to the output goal, specify the relationship between the two goals. Each transition is associated with a task list which defines the possible tasks that an agent needs to perform in order to transit from the input goal to the output goal. This is the key of our personalized virtual learning environment. Here, each learning object is modeled as a goal of *GOLA*. A simple learning object (e.g. diffusion concept) is modeled as an atomic goal; while a complex learning object is modeled as a composite goal, which can be separated to "diffusion" goal and other goals.
As an extension to generic Goal Net model [4], Fuzzy Cognitive Goal Net percepts the goal-related variables/events and reasons to choose the suitable goals [2]. With the "choice" transition, different goals can be achieved based on user preferences or real-time interactions. For example, in our virtual learning environment, the agent can present different learning contents to different learners based on the learners' levels, past activities etc.
The pseudo code of running fuzzy cognitive goal net is shown as below.
By modeling the learning objects as goal net in a hierarchical way, the students

Algorithm 1 $RunningofFuzzyCognitiveGoalNet$

```
Require: Root Goal G
Push G into Goal Queue Q
while Q is not empty do
    Pop goal g from Q
    Percept Environment e
    if g requires e then
        if g is Atomic then
            Get action A from g
            Execute action A
        else
            Get Sub-goals g1, g2, ...
            Push Sub-goals g1, g2, ... into Goal Queue Q
        end if
    end if
end while
```

are able to take a learning curve systematically, from the easy learning object to difficult learning object, and from learning object piece to learning object cluster.

In the "learning by playing" paradigm, a personalized learning is achieved by the goal selection mechanism of *GOLAs*. *GOLA* can use different goal selection mechanisms to choose an appropriate goal in order to handle user interactions correctly at playing. Evolutionary Fuzzy Cognition Map is a soft computing model to simulate the dynamic context variables and to conduct real-time reasoning [7]. It is adopted as the reasoning and simulation tool in the Fuzzy Cognitive Goal Net for goal selection. It models two main components: *concepts* S_i and *causal relationships* R_i. *Concept* can be input (context variables, user interaction variables), intermediate (i.e. variables that connect input and output), or output (agent goals, states etc). *Causal relationship* represents the interconnection from one concept to another. In the virtual learning, the concepts includes students' preference (i.e. gender, age, interests), students' activities in the learning environment and learning objects. By studying the causal relationships among the students and the learning objects, *GOLA* is capable to select a most appropriate learning curve to each student in real-time. The details of the model and its inference process can be found in [7].

4 Case Study: Plant Transportation in Banana Tree

4.1 Learning Content

The agent-oriented virtual learning environment is adopted for secondary level science learning about plant transportation in Catholic High Secondary School, Singapore. The learning content of the virtual learning environment is the plant transportation system. The related learning concepts (LO)include:

Xylem and Phloem of Root, Stem and Leaf: the cross section and functionalities of xylem and phloem inside the plant.

Osmosis and Diffusion: different movement methodologies of the water and mineral molecules.

Photosynthesis: how the energy and oxygen are generated inside the leaf with water, light and carbon-dioxide.

4.2 Implementation

In order to motivate the students to learn the concepts in the plant transportation, we generate a story scenario, namely "saving the dying banana tree".

> "The banana trees in Singapura town are quite sick. The farmer "Uncle Ben" asks the investigators to explore the whole plant transportation system of the tree, in order to find how to save them."

We have implemented our agent-oriented virtual learning environment with Torque 3D Game Engine.

4.3 Sample GOLAs

There are a set of agents involved in the virtual learning environment to facilitate the students at the learning of plant transportation system as investigators. Three main *GOLAs* that provide the personalized learning are illustrated here.

Lab Supervisor Lab supervisor "Miss Lee" is a tutor in the virtual laboratory, who determines the learning objects of the student based on the student's current level and preferences.

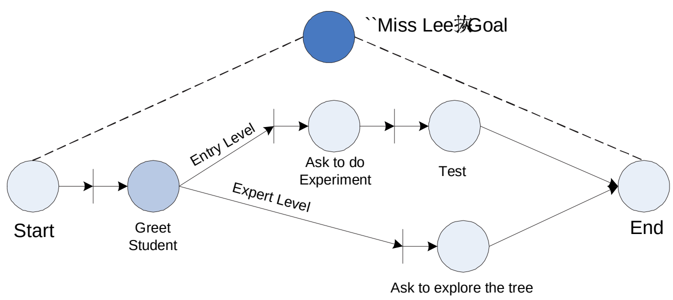

Fig. 4. Fuzzy Cognitive Goal Net of Lab Supervisor Agent to Choose the Learning Content

The goal net used by the supervisor agent is shown as Figure 4. If the student is in the entry level, she will lead the student to do the virtual experiment, e.g.

diffusion or osmosis; otherwise, she will recommend the student to enter into the banana tree to watch the diffusion or osmosis process of water molecules at the root.

Fig. 5. Lab Supervisor "Miss Lee" greets students with an introduction ('Greet student' goal in Figure 4)

Figure 5 shows the snapshot that the lab supervisor "Miss Lee" greets the student with some introductions by pursuing "greet student" goal (Figure 4).
Figure 6 illustrates a 2D diffusion simulation that the student can play. Through this observation, the students are able to learn the diffusion concept by checking how the ink molecules move in the water and the variables that might affect the diffusion process.

Director Agent Besides the simulations in the virtual laboratory, the students can watch the diffusion or osmosis at plant root immersively, which is impossible in the real experiments. Director agent is a background agent that directs the whole role-playing learning. It provides hints and analyzes the students' behaviors at the students' playing.
The goal net used by the director agent is shown as Figure 7. It can schedule the students to talk to different non-player characters to find the sick banana tree to start the plant transportation journey. The "visit plant transportation" is a composite goal. When the director agent pursues this goal, it will load the sub-goals of it, which is shown as Figure 8.
Here are some screenshots of the students at the playing when the goals of the director agent are executed.

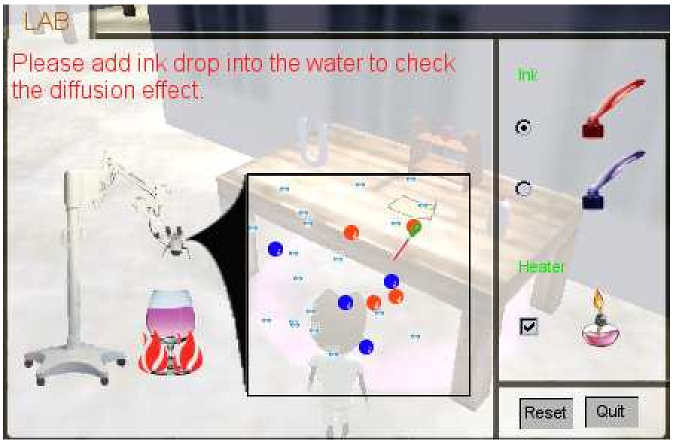

Fig. 6. Diffusion Experiment with 2D Simulation: add ink drops to observe the movements of molecules of diffusion ('Experiment' goal in Figure 4)

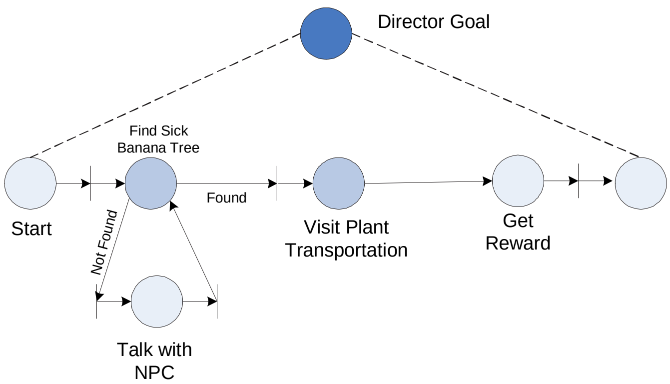

Fig. 7. Fuzzy Cognitive Goal Net of Director Agent to Control the Role-playing of Students

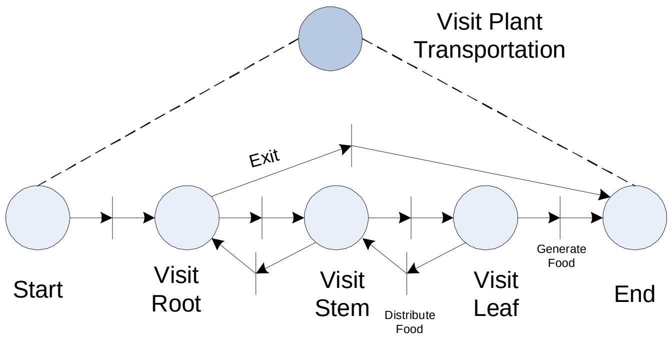

Fig. 8. Sub-goal of Director Agent to visit plant transportation

Fig. 9. Student is flying upwards inside of stem xylem ('Visit stem' Goal in Figure 7)

Figure 9 shows that the student is exploring the stem xylem through flying upward. Through this, the students are able to observe the inner structure of the stem xylem and the molecules that flow in it.
Figure 10 shows the cross section of the leaf, in which xylem is on top of the phloem. This is different from the cross section at the root or at the stem. Figure 11 shows that the student pushes the water molecule to carbon-dioxide molecule to generate food in the leaf. Through this process, the students are able to learn the photosynthesis intuitively.

Water Molecule Water molecule is an inhabitant *GOLA* in the learning adventure, who asks for help from the student to take them into the leaf where the photosynthesis is carried out.
The goal net used by the water molecule agent is shown as Figure 12.
Depending on the learning scenario, the water molecule's goal is composed of a series of goals linearly.

4.4 Assessments

We conduct the agent-oriented virtual learning environment in the Catholic High School to evaluate the students' performance in the agent oriented virtual learning environment. One group of 36 students (Group 1) use the agent-mediated virtual learning environment to learn and another group of 34 students (Group 2) use the formal classroom learning as a comparison. Group 1 uses a same learning time as group 2, around 2 hours. After the learning, both groups are given a MCQ test about the plant transportation.

Fig. 10. Cross Section of Leaf: Xylem on top and Phloem at bottom ('Visit leaf' Goal in Figure 7)

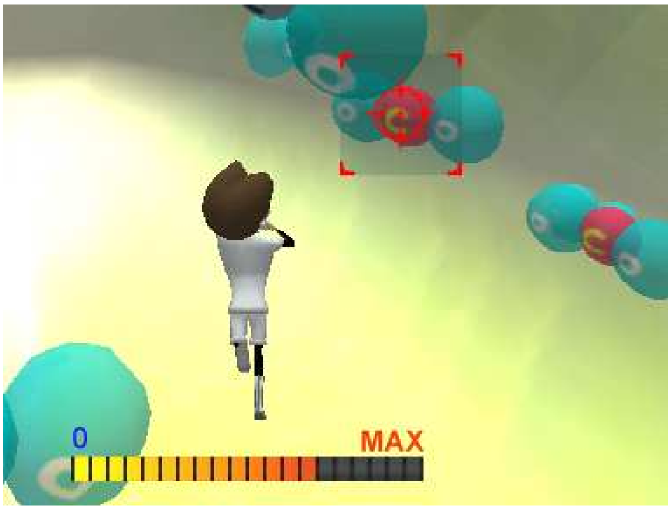

Fig. 11. The player pushes the water molecule to carbon-dioxide molecule to generate food ('Generate food' Goal in Figure 7)

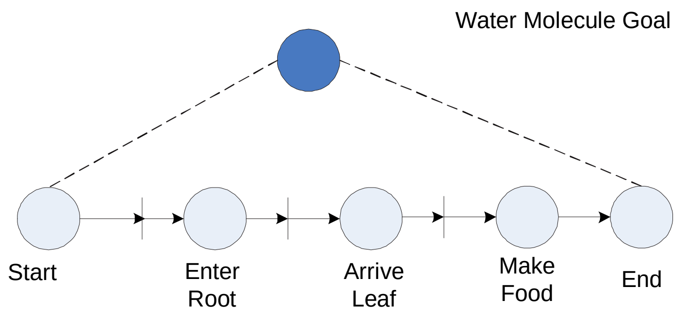

Fig. 12. Fuzzy Cognitive Goal Net of Water Molecule Agent to Go through root, stem, leaf and generate the food

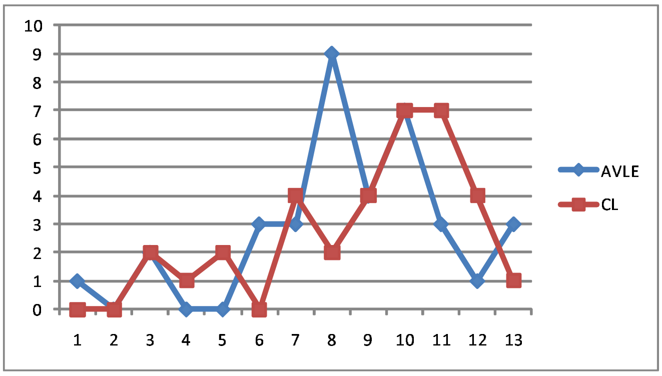

Fig. 13. Distribution of scores in agent-oriented virtual learning environment group (AVILE) and classroom learning (CL) group (horizontal axis: score; vertical axis: student number)

Exam Results

The group using AVILE has a mean score of 13.55 and the group using CL has a mean score of 14.05. As shown in Figure 13, AVILE group's learning result is close to that of CL. Considering that the students need to use around 1 hour to be familiar with the virtual learning environment, AVILE students still learn quite well. Moreover, more students got highest score (13 scores) in AVILE than those in CL. Because MCQ questions include some open questions that require the reasoning of concepts, the students perform well in AVILE which stimulates the exploration and thinking at the learning process, rather than memorizing the knowledge.

Figure 14 shows the average score of each question in both AVILE group and CL group. It is found that, students of the two groups perform well in different questions.

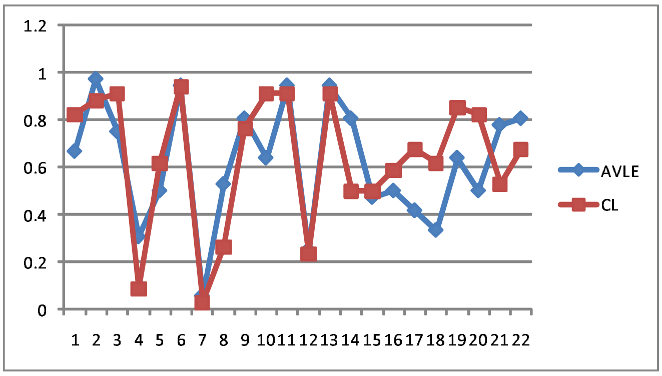

Fig. 14. Average of each question in agent-oriented virtual learning environment (AVILE) and classroom learning CL Horizontal axis: MCQ number; Vertical axis: average score

Some questions require the students to make the reasoning based on what they know, e.g. question 21.

Suppose you killed the plant cell in the Figure of question 14A with poison (that does not destroy the cell membrane) and immediately placed the dead cell in a 25% saltwater solution. 1. Osmosis and diffusion would not occur. 2. Osmosis and diffusion would continue. 3. Only diffusion would continue. 4. Only osmosis would continue.

In this case, students in AVILE perform better. On the other hand, students in CL perform better in the questions about concepts memorizing. The students in AVILE might focus on the exploration process with less concept memorization, as agents help them at all the memorizing.

4.5 Discussions

Through the test results, we found that agent-oriented virtual learning environment helps the students at deep learning by encouraging them gain knowledge through thinking and reasoning. The students can also transfer their knowledge easily, e.g. they apply the "osmosis" knowledge learnt in the virtual laboratory to help molecules enter into the root.
According to our observation and interview, the students are very engaged and motivated in the learning in the virtual environment. With the similar computer game experience, they adapt to the virtual learning environment very fast. The students are excited to experience in the virtual world differently with their

classmates, and assisted well by the learning agents.
However, the test results are not as good as expected, which might be due to the following reasons:

1. The students have little training time to be familiar with the virtual learning environment. They need more time to be comfortable with the learning method.
2. AIVLE is a good compensation but not a replacement to the classroom learning. Especially when we conduct the virtual learning with the teachers supervised, the students are easy to be panic.
3. We choose the students who have very good academic performance as the test groups, which might not be very sensitive of the different learning methods.

In the future, it will be used an informal learning method as a testbed to prove the concepts which are learnt in the classroom, rather than replacing the whole classroom teaching.

5 Conclusion

In the paper, we propose an agent-oriented virtual learning environment (AVILE) with a mixture of 3D virtual laboratory and role-playing learning. The learning objects are modeled as goals of goal-oriented learning agents (GOLAs), which provide personalized learning experiences through real-time goal selection. The results prove the learning efficiency and students' interests improve over that of the classic classroom learning.
Currently, mouse and keyboard are the main interaction methods for students to conduct the virtual experiments. In the future, we expect to have a more intuitive user-computer interfaces to increase the engaging experience. Moreover, we will improve the learning ability of the agent to study the players' behaviors, in order to provide a better personalization of learning contents.

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