A two party haptic guidance controller via a hard rein

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State dependent full discrete linear controller for guiding the human with impaired visual and auditory perceptions

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Abstract— **In the case of human intervention in disaster response operations like indoor firefighting, thick smoke, noise in the Oxygen masks, and clutter, not only impair the environmental perception of the human responders, but also causes distress. An intelligent agent (man/machine) with full environment perceptual capabilities is an alternative to enhance navigation in such unfavorable environments. Since haptic communication is the least affected mode of communication in such cases, we consider human demonstrations to use a hard rein to guide blindfolded followers with auditory distraction to be a good paradigm to extract salient features of guiding using hard reins. Based on experimental systems identification and numerical simulations on demonstrations from eight pairs of human participants, we show that, the relationship between the state of the follower and the lateral swing patterns of the hard rein by the guider can be explained by a novel 3rd order auto regressive predictive controller. Moreover, by modeling the follower's dynamics using a virtual damped inertial model, we were able to model the confidence level of the impaired follower. In the future, the novel controller extracted based on human demonstrations can be tested on a human-robot interaction scenario to guide a visually impaired person in various applications like fire fighting, search and rescue, medical surgery, etc.**

I. INTRODUCTION

The need for advanced Human Robot Interaction (HRI) algorithms that are responsive to real time variations in the physical and psychological states in a human counterpart in an uncalibrated environment has been felt in many applications like fire-fighting, disaster response, and search and rescue operations [1]. There have been some studies on guiding people with visual and auditory impairments using intelligent agents in cases such as fire fighting [2] and guiding blind people using guide dogs [3]. In this context detailed characterization of the bi-directional communication for guiding the person with an impaired perception in a hazard environment is a pressing need.In the case of fire fighting, fire fighters have to work in low visibility conditions due to smoke or dust and high auditory distractions due to their Oxygen masks and other sounds in a typical firefighting environment. At present, they depend on touch sensation of walls for localizing and ropes for finding the direction [2]. In [2], the authors propose a swarm robotic approach with ad-hoc network communication to direct the fire fighters. The main disadvantage of this approach is lack of bi-directional communication estimate the behavioral and psychological state of the firefighters. Personal navigation system using Global Positioning System (GPS) and magnetic sensor were used to guide blind people by Marston [3]. One major drawback with this approach is, upon arriving at a decision making point, the user has to depend on gesture based visual communication with the navigation support system, which may not work in low visibility conditions. Moreover, the acoustic signals used by the navigation support system may not suit noisy environments.

Another robot called Rovi, with environment perception capability has been developed to replace a guide dog [4]. Rovi had digital encoders based on retro-reflective type infra red light that recorded errors with ambient light changes. Though Rovi could avoid obstacles and reach a target on a smooth indoor floor, it suffers from disadvantages in uncertain environments. An auditory navigation support system for the blind is discussed in [5], where, visually impaired human participants (blind folded participants) were given verbal commands by a speech synthesizer. However, speech synthesis is not a good choice to command a visually impaired person in a stressful situation like a real fire. A guide cane without acoustic feedback was developed by Ulrich in 2001 [6]. The guide cane analyzes the situation and determines appropriate direction to avoid the obstacle, and steers the wheels without requiring any conscious effort [6]. Perhaps the most serious disadvantage of this study is that it does not take feedback from the visually impaired follower. To the best of our knowledge, there has been no detailed characterization of the bi-directional communication for guiding the person with an impaired perception in a hazard environment.

Any robotic assistant to a person with impaired perception of the environment should monitor the level of confidence of the person in the robot for it to be relevant to the psychological context of the person being assisted. In a simulated game of fire-fighting, Stormont *et al* [7] showed that the the fire-fighters become increasingly dependent upon robotic agents when the fire starts to spread along randomly changing wind directions. Freedy [8] has discussed how self confidence correlates with trust of automation in human robot collaboration. So far, however, there has been little discussion about human confidence on robots in unstructured environments. Therefore, in HRI, it is increasingly becoming

*This research was supported by the UK Engineering and Physical Sciences Research Council (EPSRC) grant no. EP/I028765/1, and the Guy's and St Thomas' Charity grant on developing clinician-scientific interfaces in robotic assisted surgery: translating technical innovation into improved clinical care (grant no. R090705)

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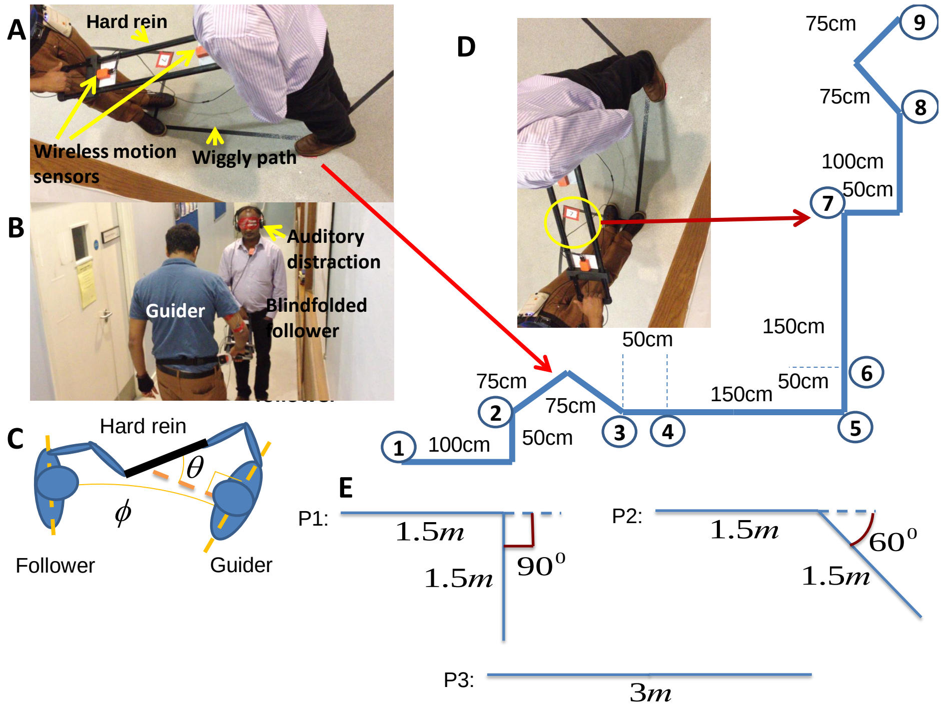

Fig. 1. The experimental setup: A) The hard rein with wireless MTx motion trackers. pushing/pulling in horizontal plane to guide the follower , B) Tracking the path by the duo, C) The hard rein with wireless MTx motion sensors attached to measure the state ϕ and the action θ, D)The detailed diagram of labeled wiggly path on a floor, E) The experimental apparatus of confidence studies of following subject in three different paths , additional Mini 40 6-axis force torque transducer at 1000Hz attached to the hard rein to measure pushing/pulling force P1: Ninety degree turn, P2: Sixty degree turn, and P3: Straight path.

important to consider confidence of the human on the robotic counterpart in uncertain environments like real fire. The paper attempts to show that optimal state dependent full controller for haptic based guiding an impaired mobility in unstructured environment.

Recent studies were conducted on complementary task specialization [9] between a human-human pair and a human-robot pair to achieve a cooperative goal. It suggested that complementary task specialization develops between the human-human haptic negotiation process but not in the human-robot haptic interaction process [10]. This indicates that there are subtle features that should be quantified in the closed loop haptic interaction process between a human pair in task sharing. Therefore, characterization of human-human interaction in a haptic communication scenario, where one partner is blindfolded (impaired perception of the environment) while the other human participant has fully perceptual capabilities, can provide a viable basis to design optimal human-robot interaction algorithms to serve humans working in many hazardous/uncertain environments.

It is very important to understand the mathematical properties of closed loop haptic guidance- that would in turn shed light on optimal robotic guidance of humans in low visibility conditions in a hazard or uncertain environments. Therefore, to the best of our knowledge, this is the first paper to characterize the closed loop state dependent haptic signaling policy of an agent with full perception capabilities to take a following impaired human in an arbitrary path.

The rest of the paper is organized as follows. Section II elaborates the experimental methodology to collect data of human-human interaction via a hard rein while tracking an arbitrary path. Section III describes the mathematical model of the guider's state dependent control policy in detail. Section IV gives the experimental results of human participants along with numerical simulation results to show the stability of the control policy identified through experiments on human participants. It also discusses the virtual time varying damped initial model to estimate the confidence of the visually impaired follower. Finally, section V gives a conclusion and future works.

II. Experimental Methodology

Figure 1(A) shows how the guider and the follower held both ends of hard rein to track the wiggly path so that the hard rein. We conducted two separate experiments to understand: 1) The guider's state dependent control policy in an arbitrary complex path, 2) The coefficients of the follower's time varying virtual damped inertial system over different paths.

In the first experiment, eight pairs of subjects participated in the experiment after giving informed consent. They were healthy and in the age group of 23 - 43 years. One of the subjects (an agent with full perceptual capabilities) lead the other (a person with visual and auditory impairment) using a hard rein as shown in figure 1(B). Visual feedback to the follower was cut off by blindfolding, while the auditory feedback was cut off by playing a sound track of less than 70dB as shown in figure 1(B). figure 1(C) shows the relative orientation difference between the guider and the follower (referred to as state hereafter), and angle of the rein relative to the agent (referred to as action hereafter). MTx motion capture sensors (3-axis acceleration, 3-axis magnetic field strengths, 4-quaternions, 3-axis Gyroscope readings) were used to measure the states ϕ and actions θ of the duo. Two MTx sensors were attached on the chest of the guider and the follower to measure the rate of change of the orientation difference between them (state of the duo). Another two motion trackers were attached on the hard rein to measure the angle of the rein relative to the sensor on the chest of the guider (action from the agent). Since we used four MTx sensors, we sampled data at 25Hz to stay within hardware design limits. For clarity, the detailed wiggly path is shown in figure 1(D). The path of total length 9m was divided into nine milestones as shown in figure 1(D).

In any given trial, the guider was asked to take the follower from one milestone to another at six milestones up or down (ex. 1-7, 2-8, 3-9, 9-3, 8-2, and 7-1). The starting milestone was pseudo-randomly changed from trial to trial in order to eliminate the effect of any memory of the path. Moreover, the guider was disoriented before starting every trial. The guider was instructed to move the handle of the hard rein only on the horizontal plane to generate left and right turn commands. Furthermore, the guider was instructed to use push and pull commands for forwards and backwards movements. The follower was instructed to pay attention to the commands via hard rein to follow the guider. The follower started to follow the guider once a gentle tug was given via the rein.

A second experiment was conducted to study the follower confidence in the guider by 10 trials each for three different paths as shown in figure 1(E). ATI Mini40 6-axis force torque transducer was attached to the hard rein to measure tug force sampled at 1000Hz along the horizontal plane to guide the impaired follower. The acceleration of the follower was measured by MTx sensors as shown in figure 1(B).

The experimental protocol was approved by the King's College London Biomedical Sciences, Medicine, Dentistry and Natural & Mathematical Sciences research ethics committee.

III. Modeling

A. The guider's closed loop control policy

We model the guider's control policy as an N-th order state dependent discrete linear controller. The order N depends on the number of past states used to calculate the current action.

Let the state be the relative orientation between the guider and the follower given by ϕ, and the action be the angle of the rein relative to the sensor on the chest of the guider given by θ as shown in figure 1(C).

Then the linear discrete control policy of the guider is given by

$$\theta(k) = \sum_{r=0}^{N-1} a_r^{Re} \phi(k-r) + c^{Re} \tag{1}$$

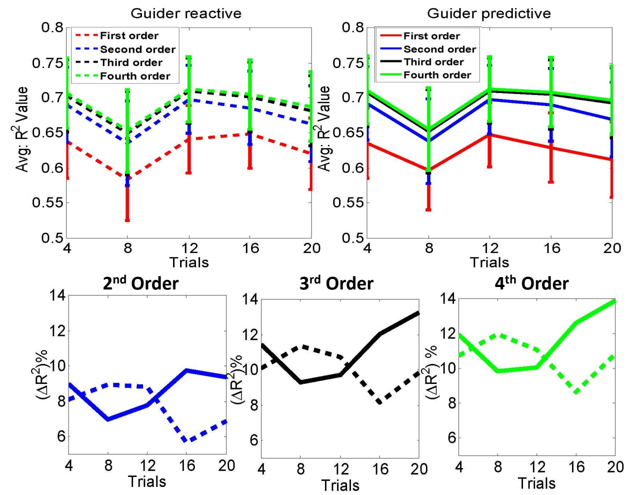

Fig. 2. Control policy model orders over the guider reactive (dashed line) and predictive (straight line): (A) The R^2 value variation of the guider reactive and predictive model order from 1 to 4 over trials. (B) The % differences of R^2 values of model order 2nd to 4th polynomials relative to the 1st order polynomial: model order 2 and 1 (blue), model order 3 and 1 (black), model order 4 and 1 (green). The guider reactive and predictive are marked by dashed and straight respectively

if it is a reactive controller, and

$$\theta(k) = \sum_{r=0}^{N-1} a_r^{Pre} \phi(k+r) + c^{Pre} \tag{2}$$

if it is a predictive controller, where, k denotes the sampling step, N is the order of the polynomial, $a_r^{Re}, a_r^{Pre}, r = 1, 2, \cdots, N$ is the polynomial coefficient corresponding to the r-th state in the reactive and predictive model respectively, and c^{Re}, c^{Pre} are corresponding scalars. These linear controllers can be regressed with the experimental data obtained in the guider-follower experiments above to obtain the behavior of the polynomial coefficients across trials. The behavior of these coefficients for all human participants across the learning trials will give us useful insights as to the predictive/reactive nature, variability, and stability of the control policy learned by human guiders. Furthermore, a linear control policy given in equations 1 and 2 would make it easy to transfer the fully learned control policy to a robotic guider in a low visibility condition.

B. Virtual time varying damped initial system reflecting confidence of the follower

In order to study how the above control policy would interact with the follower in an arbitrary path tracking task, we model the blindfolded human participant (follower) as a damped inertial system, where a force $F(k)$ applied along an angle $\phi(k) = \sum_{i=0}^{k} \theta(i)$ relative to the follower's heading direction at sampling step k would result in a transition of position given by $F(k) = M\ddot{P}_f(k) + \zeta \dot{P}_f(k)$, where M is the virtual mass, $P_(f)$ is the position vector in the horizontal plane, and ζ is the virtual damping coefficient. It should be noted that the virtual mass and damping coefficients are not those real coefficients of the follower's stationary body, but the mass and damping coefficients felt by the guider while the duo is in voluntary movement.This dynamic equation can be approximated by a discrete state-space equation given by

$$x(k) = Ax(k-1) + Bu(k) \tag{3}$$

where , $x(k) = \begin{bmatrix} P_f(k) \\ P_f(k-1) \end{bmatrix}$,$x(k-1) = \begin{bmatrix} P_f(k-1) \\ P_f(k-2) \end{bmatrix}$,
$A = \begin{bmatrix} (2M+T\zeta)/(M+T\zeta) & -M/(M+T\zeta) \\ 1 & 0 \end{bmatrix}$,

B = $\begin{bmatrix} T^2/(M+T\zeta) \\ 0 \end{bmatrix}$, $u(k) = F(k)$,

k is the sampling step & T is the sampling time.

Given the updated position of the follower $P_f(k)$, the new position of the guider $P_g(k)$ can be easily calculated by imposing the constraint $\|P_f(k) - P_g(k)\| = L$, where L is the length of the hard rein.

IV. Experimental results

A. Determination of the salient features of the guider's control policy

We conducted experiments with human participants to understand how the coefficients of the control policy relating states ϕ and action θ given in equations 1 and 2 settle down across learning trials. In order to have a deeper insight into how the coefficients in the discrete linear controller in equations 1 and 2 change across learning trials, we ask 1) whether the guider and the follower tend to learn a predictive/reactive controllers across trials, 2) whether the order of the control policy in equations 1 and 2 change over trials, and if so, what its steady state order would be.

First, we used experimental data for action θ and state ϕ in equations 1 and 2, to find regression coefficients. Since the raw motion data was contaminated with noise, we use the 4th decomposition level of Daubechies wave family in Wavelet Toolbox (The Math Works, Inc) for the state and the action profiles for regression analysis. Since the guider generates swinging actions in the horizontal plane, the Daubechies wave family best suits such continuous swing movements [11].

Once the coefficients of the polynomial in equations 1 and 2 are estimated, the best control policy (equations 1 or 2), and the corresponding best order of the polynomial should give the best R^2 value for a given trial across all subjects. To select best fit policies, coefficients of (equations 1 are 2) were estimated for 1^{st} order to 4^{th} order as shown in figure 2 (A). Twenty trials were binned to five for clarity. From figure 2 (A), we can notice that the R^2 values corresponding to the 1^{st} order model in both equations 1 and 2 are the lowest. The relatively high R^2 values of the higher order models suggest that the control policy is of order > 1. Therefore, we take the % differences of R^2 values of higher order polynomials relative to the 1st order polynomial for both equations 1 and 2 to assess the fitness of the predictive control policy given in equation 2 relative to the reactive policy given in equation 2. Figure 2 (B) shows that the marginal % gain in R^2 value of 2^{nd}, 3^{rd}, and 4^{th} order polynomials in equation 2 (predictive control policy) grows compared to those of the reactive control policy in equation 1. Therefore, we conclude that the guider gradually gives more emphasis on a predictive control policy than a reactive one. However, at this stage, we do not quantify the relative mixing of the two policies across learning trials if at all.

Our next attempt is to understand how the polynomial parameters of a linear state dependent controller would evolve across learning trials of the guider along an arbitrarily complex path. We notice in figure 3 that the history of the polynomial coefficients fluctuate within bounds. This could come from the variability across participants and variability of the parameters across trials itself. Therefore, we estimate the above control policy as a bounded stochastic decision making process. However, the white noise(c) is lowest. Therefore, c plotted by black with different scale.

B. Modeling the follower's confidence level in different contexts

Then we address the question of how the follower's confidence towards the guider should be accounted for in designing a closed loop controller. Our intension is to incorporate the instantaneous confidence level of the follower in the state-space of the closed loop controller. Here, we suspect that the confidence of the follower in any given context should be reflected in the compliance of his/her voluntary movements to follow the instructions of the guider. By modeling the impedance of the voluntary movement of the follower using a time varying virtual damped inertial system, we observe the variability of the impedance parameters - virtual mass and damping coefficients - in paths with different complexities (context). The three paths are shown in figure 1(E). The experimental results of eight pairs of subjects in three types

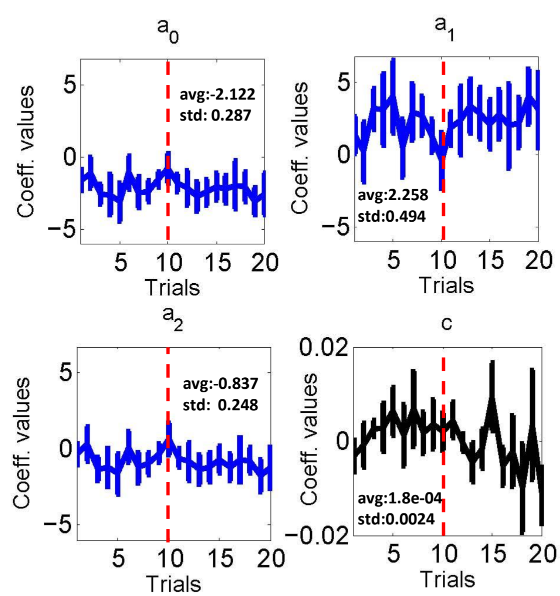

Fig. 3. The evolution of coefficients of the discrete dynamic controller of the guider (for eight guider-follower pairs). 10th trial is shown by horizontal dashed red line. The average & S.D values of the coefficients are marked.

of paths - 90° turn, 60° turn, and a straight - are shown in figure 4. Here we extracted motion data within a window of 10 seconds around the 90 and 60 degree turns, and for fairness of comparison, we took the same window for the straight path for our regression analysis to observe the virtual damping coefficient and the virtual mass in three different paths. figure 4(A) shows the variability of the virtual damping coefficient, and figure 4(B) shows that of the virtual mass for the above three contexts. We can notice from figure 4(A) that the variability of the virtual damping coefficient is highest in the path with a 90° turn, with relatively less variability in that with a 60° turn, and least variability in the straight path. However, we do not notice a significant variability in the virtual mass across the three contexts.

Two-sided t-test showed that the virtual damping coefficient in 90° turn was significantly different from that in straight path ($p < 0.01$). Moreover, virtual damping coefficient in 60° turn was also significantly different from that in straight path ($p < 0.02$). There was no statistically significant difference between the virtual damping coefficient in path 90° turn and 60° turn ($p > 0.60$). Moreover, the virtual mass distribution in equation 4 in figure 4 (B) is as follows. Interestingly only straight path was statistically significantly different from 90° turn ($p < 0.01$). Furthermore, The t test in between 60° turn and straight path is not significantly different ($p > 0.70$). We assumed that, the follower has more confidence to follow the guider in a straight path than other two paths. If our argument is correct, the pushing/pulling force along the hard rein is low to track him in the path and it would be reflected from the virtual mass and the virtual confidence. In figure 4 the average values of the virtual mass distribution and the virtual damping coefficient in straight path are lowest. This shows that the confidence level of follower is greater in straight path.

Therefore, we conclude that the virtual damping coefficient can be a good indicator to control the push/pull behaviors of an intelligent guider using a feedback controller of the form given in equation 4, where F(k) is the pushing and /pulling tug force along the rein from the human guider at kth sampling step, M is the time varying virtual mass, M_0

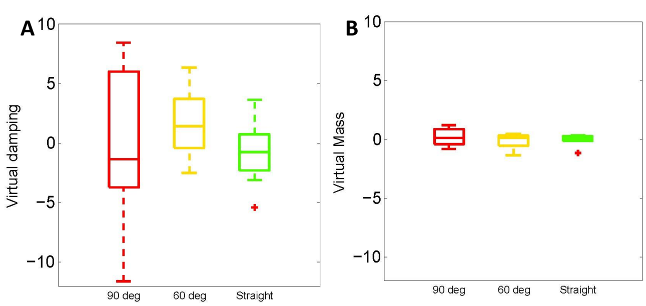

Fig. 4. Regression coefficients in equation 4 of different paths : (A) Virtual damping coefficient for paths: 90° turn (red), 60° (yellow) turn, and straight path (green).The average values are 3.055, 1.605 & -0.586 for 90° turn, 60° turn & straight path respectively. (B) Virtual mass coefficient for paths: 90° turn (red), 60° turn (yellow), and straight path (green). The average values are 2.066, -0.083 & 0.002 for 90° turn, 60° turn & straight path respectively.

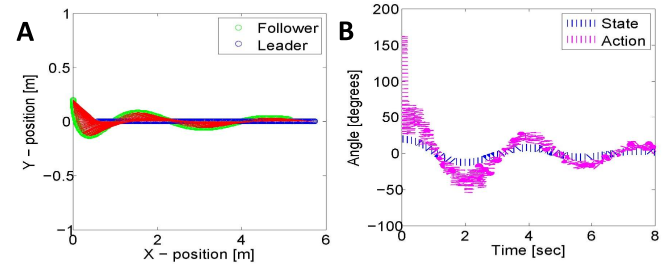

Fig. 5. Simulation results: (A) Stable behavior of trajectories of the follower (green) for where the guider tries to get the follower to move along a straight line from a different initial location. The control policy was based on the coefficients extracted from the experiments on human participants. (B)The behavior of the state and the action for the simulated guider-follower scenario. The control policy was based on the coefficients extracted from the experiments on human participants.

is its desired value, ζ is the time varying virtual damping coefficient, k is the sampling step, and ζ_0 is its desired value.

$$F(k+1) = F(k) - (M - M_0)\ddot{P}_f(k) - (\zeta - \zeta_0)\dot{P}_f(k) \qquad (4)$$

C. Developing a closed loop path tracking controller incorporating the follower's confidence level

Back to our main problem is to guide a person with visually and auditory impaired perception of the environment by using another (human or machine) who with full perceptual capabilities. Our 3^{rd} order auto regressive control policy explains more human behavior. However, our confidence analysis results show human confidence over different paths. Furthermore, if we could combine our experimental results with a simulator, it would be a complete solution for our problem.

We use the last 10 trials coefficients values as marked on figure 3 by red dashed line to calculate the statistical features of the regression coefficients in order to make sure the model reflects the behavior of the human participants at a mature learning stage. The model parameters were then found to be: $a_0 = N(-2.3152, 0.2933^2)$, $a_1 = N(2.6474, 0.5098^2)$, $a_2 = N(2.6474, 0.5098^2)$ and $c = N(1.0604e-04, 0.2543^2)$.

In order to ascertain whether the control policy obtained by this systems identification process is stable for an arbitrarily different scenario, we conducted numerical simulation studies forming a closed loop dynamic control system of the guider and the follower using the control policy given in equation 2 together with the discrete state space equation of the follower dynamics given in equation 3. The length of the hard rein $L = 0.5$m, the follower's position $P_f(0)$ was given an initial error of 0.2m at $\phi(0) = 45°$, the mass of the follower $M = 10$[kg] with the damping coefficient $\zeta = 4$[Nsec/m], the magnitude of the force exerted along the rein was 5N, and the sampling step $T = 0.02$.

From figure 5(A) we notice that the follower asymptotically converges to the guider's path within a reasonable distance. The corresponding behavior of the state and the resulting control action shown in figure 5 (B)further illustrates that the above control policy can generate bounded control actions given an arbitrary error in the states. Next, we set

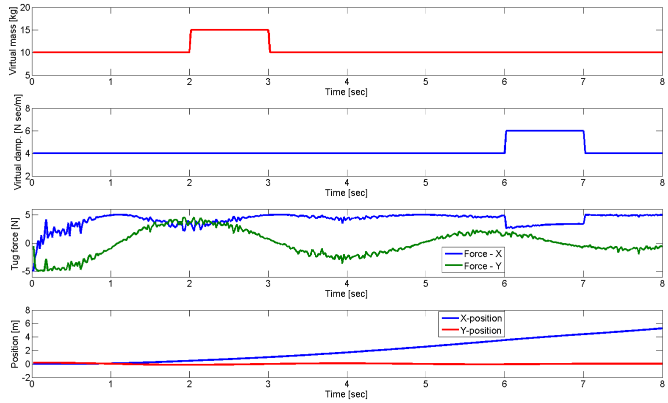

Fig. 6. Simulation results: The tug force and position variation of the follower in order to sudden change of the virtual mass $M = 15$[kg] from $t = 2$s to $t = 3$s and the virtual damping coefficient $\zeta = 6$[Nsec/m] from $t = 6$s to $t = 7$s.

the the virtual mass $M = 15$[kg] from $t = 2$s to $t = 3$s and the virtual damping coefficient $\zeta = 6$[Nsec/m] from $t = 6$s to $t = 7$s to observe tug force variation in equation 3 as shown in figure 6. The tug force variation figure 6 shows that, the virtual damping coefficient more influenced to vary the tug force than the virtual mass.

Combining the 3^{rd} order autoregressive model for swinging the hard rein on the lateral plane to make path corrections, with tug force modulation in response to the varying confidence level of the follower, we can now compose the combined controller given by

$$\begin{aligned}\begin{bmatrix} F(k+1) \\ \theta(k+1) \end{bmatrix} &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} F(k) \\ \theta(k) \end{bmatrix} \\ &+ \begin{bmatrix} (M-M_0)\ddot{P}_f(k) - (\zeta-\zeta_0)\dot{P}_f(k) \\ \sum_{r=0}^{N-1} a_r^{Pre}\phi(k+r) + C^{Pre} \end{bmatrix}\end{aligned} \tag{5}$$

V. Conclusions and Future Works

In this study we could understand three major features in the haptic communication between a guider and a follower described in figure 1: 1) the control policy of the guider can be approximated by a 3^{rd} order auto-regressive model without loss of generality, 2) when the duo learns to track a path, the guider gradually develops a predictive controller across learning trials, 3) the varying confidence level of the follower with visual and auditory impairment can be estimated by the variation of a virtual damping coefficient of a virtual damped inertial model that relates the tug force along the hard rein to the voluntary movement of the follower.

A novel state dependent controller developed based on the above findings. To the best of the author's knowledge, this is the first publication that shows how to combine the confidence level of an impaired follower in the context of being guided, is incorporated into a state dependent predictive controller based on a hard rein. The transient and steady state properties of the controller and its responsiveness to sudden changes in the voluntary movement of the impaired follower was demonstrated using numerical simulations, demonstrating that it is ready to be exported to a mobile robot to guide an impaired follower along an arbitrarily complex path using a hard rein.

In the future, we plan to uncover the cost functions that are minimized by the duo, during learning to track a path. This would help us to develop a reward based learning algorithm to enable a mobile robot to continuously improve the controller while interacting with a human follower. Moreover, we plan to have a closer look at how the guider maybe adaptively combining a reactive controller with a predictive one, in order to stabilize learning. It will also be interesting to explore for broader factors affecting the confidence level of a follower, so that predictive action can be taken to maintain a good confidence level within the impaired follower in the context of guiding.

In addition to applications in robotic guidance of a person in a low visibility environment, our findings shed light on human-robot interaction applications in other areas like robot-assisted minimally invasive surgery (RMIS). Surgical tele-manipulation robot could use better predictive algorithms to estimate the parameters of remote environment for the surgeon with more accurate adaption of control parameters by constructing internal models of interaction dynamics between tools and tissues in order to improve clinical outcomes [12]. Therefore, we will continue to discover a generic robotic learning strategy/algorithm that can be generalized across RMIS as well as robotic assisted guidance in low visibility environments.

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