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Cognitive Robotics for the Modelling of Cognitive Dysfunctions: A Study on Unilateral Spatial Neglect

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I. INTRODUCTION

Damage to the posterior parietal cortex (PPC) can cause patients to fail to orient toward, explore, and respond to stimuli on the contralesional side of the space. PPC is thought to play a crucial role in the computation of sensorimotor transformations that is in linking sensation to action. Indeed, this disorder, known as *Unilateral Spatial Neglect* (USN), can compromise visual, auditory, tactile, and olfactory modalities and may involve personal, extra-personal, and imaginal space [1], [2]. For this reason, USN describes a collection of behavioural symptoms in which patients appear to ignore, forget, or turn away from contralesional space [3]. Given the complexity of the disease and the difficulties to study human patients affected by USN, because of their impairments, several computer simulation studies were carried out via artificial neural networks in which damage to the connection weights was also found to yield neglect-related behaviour [4]–[6].

In this paper, we present preliminary results of a cognitive robotic approach to the computational modelling of human cognitive dysfunctions like USN. The purpose of the present study is to explore some of the possible advantages of using an artificial brain and a robotic platform to simulate cognitive dysfunctions. Indeed, we can show results of tests that are difficult to carry out with human subjects. As an example, it is impractical to find subjects with the lesion in the left hemisphere that can actually perform the proposed experiment, because other impairments associated with the damage of the left hemisphere (e.g. memory, speech, writing, and cognitive processing) can severely limit their capabilities. Another possibility given by the robotic simulation is to test the rehabilitation training, which can be unpractical with a human patient as it is unlikely that he can reliably perform the test after each therapy session.

II. EXPERIMENTS

A. Experimental setup

The aim of our experiment is to replicate a previous study with human subjects, which repeated a manipulation task in four different conditions for placing targets and for orienting longitudinal axes of the head and eyes [7]. To this end, we setup the four conditions as represented in Figure 1 using the simulated iCub platform [8].

The experimental task is to explore one by one the eight positions and to remove, with the right hand, the objects placed on a table, without visual control.

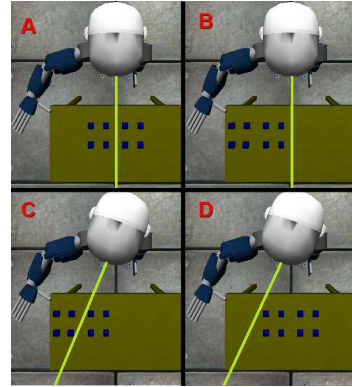


Figure 1. The four experimental conditions. The yellow lines highlight the head axes. In conditions A and B, they are right in front of the robot, while in conditions C and D the head is turned 20 degrees to the right.

The robot was first instructed to accomplish the task using a training algorithm to move the right hand. During the training, also torso was moved in order to allow the robot to reach the targets on the left with the right arm.

When the robot is trained, the vision input was used to calculate the relative position of the objects on the table from the eye cameras pictures. These positions were represented in polar coordinates and constitute the input of our artificial neural architecture (*target inputs*). The other input for the training is the neck joint angle. The goal of the training is to learn the spatial attentional focus that identifies a specific place in the table to explore.

In the experiment, we simulate damages between the artificial hemisphere by cutting neural links (i.e. assigning 0 to link weights), obtaining also intra-hemispheric disconnection between anterior (premotor cortex) and posterior (PPC) layers. During the experiment, the four conditions were run in the order from (a) to (d) and neural units activations were collected from the output and the layers n. 3 (left and right). The experiment was run 5 times with random weight initialization, we report the average results. Finally, we re-apply the backpropagation to simulate a rehabilitation therapy to recover after the damage. After each repetition of the backpropagation algorithm (epoch), we repeat the experiment and record the omissions. The

results are analyzed in terms of number of repetitions needed to recover.

The neural network model used in this work is schematically represented in Figure 2.

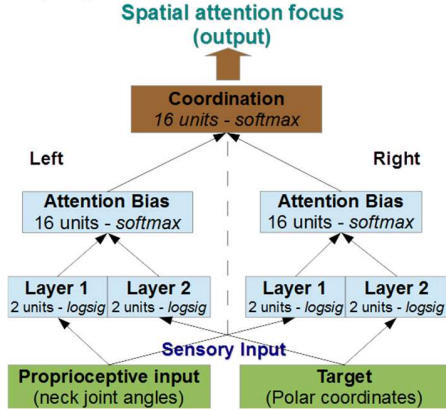


Figure 2. A neural network model for simulation of USN with right hemisphere “specialization”. The hidden layers (1,2 and Attention Bias) are divided into two regions to mimic the separation of the Cerebral hemispheres, while the right part is trained to be at least partially active for any input.

B. Results and Discussion

Here, we present the result two cases: (1) there is no specialization, left and right hemispheres activate the focus only when the target is in the contralateral area of the attention focus; (2) the right hemisphere is “specialized” and it is able to activate the focus in any area, while the left one can only activate the focus on the right.

In case 1, we simulated the damage of the right hemisphere and, as expected, the robot exhibits USN on the left side, as it is not able to focus all the targets on the left side of attentional space. Even if, in some cases, the likelihood is significantly lower than in the healthy status, no errors were observed.

In case 2, we simulated the damage of the “specialized” right and the “unspecialized” left hemispheres. In this case, we see that damaging the robot exhibits only when the right hemisphere is damaged, while just one error was observed in condition B and C when the left hemisphere is damaged. The results are exemplified in Table I, in which the green boxes indicate the successful removal of the object in the corresponding area, while red boxes indicate that the area was omitted (i.e. the object was not removed).

TABLE I. CASE 2: EXPERIMENTAL RESULTS WHEN THE “SPECIALIZED” RIGHT HEMISPHERE IS DAMAGED (GREEN = OK; RED = OMISSION)

Condition A	Condition B	Condition C	Condition D
Red	Green	Green	Red
Red	Green	Green	Red
Red	Green	Green	Red
Red	Green	Green	Red

Comparing the robot behaviour when the “specialized” right hemisphere is damaged we see that case 2 is more in line with the findings reported in the work that inspired our experiment. Indeed, in [7], authors report missing targets also in the same side of the brain lesion as shown in Table I in condition B and C.

When the “unspecialized” left hemisphere is damaged in case 2, we see that only the right side of the special attention

focus is affected, but the problems can be considered minor as only one error is registered in condition B and C, i.e. when the targets are placed on the right side of the table.

The results in condition A and B in are suggesting that there is a different effect between the two hemispheres and this is in line with the findings reported in the literature [9].

Finally, Figure 3 presents the result of the rehabilitation training. The condition B is the easiest to recuperate, as the robot is able to fully recover, i.e. remove all the targets from the table, after just 4 repetitions (epochs). As expected, condition D is the most difficult to recover, indeed, after 50 repetitions, the robot still omits to remove one of the targets.

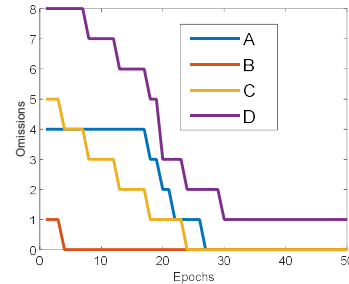


Figure 3. Rehabilitation training results. The network is retrained to recover from the damage (i.e. to re-learn the weights and biases) and omissions are presented with after each train repetition (epochs).

In future work, we will perform the experiment with the real iCub platform and the effort will focus also on the study of rehabilitation procedures, e.g. comparing different exercises to recover after the damage.

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