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Adaptive Strategy for Multi-User Robotic Rehabilitation Games

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Abstract—**In this paper, we discuss a strategy for the adaptation of the "difficulty level" in games intended to include motor planning during robotic rehabilitation. We consider concurrently the motivation of the user and his/her performance in a Pong game. User motivation is classified in three levels (not motivated, well motivated and overloaded). User performance is measured as a combination of knowledge of results--achieved goals and score points in the game-- and knowledge of performance-- joint displacement, speed, aiming, user work, etc. Initial results of a pilot test with unimpaired healthy young volunteers are also presented showing a tendency for individualization of the parameter values.**

I. Introduction

REHABILITATION robotic devices are efficient in delivering certain routine physical and occupational therapy activities. Additionally they provide a richer data stream that improves patient analysis and diagnosis, customization of the therapy, and maintenance of patient records. Results are quite promising with the 2010 American Heart Association guidelines for stroke care strongly endorsing the use of rehabilitation robotics for the upper extremity [1] and likewise the 2010 Veterans Affairs/Department of Defense guidelines providing similar endorsement [2]. At least for stroke, outcomes were positive only when robotic systems employed interactive approaches, such as our performance-based progressive scheme [3].

Our 2003 performance-based algorithm explores concepts of motor learning during arm reaching movements, including knowledge of results (e.g., hitting the targets) and knowledge of performance (e.g., every fifth repetition of the game, performance is provided in terms of initiation, aiming, deviation, power, smoothness, etc.). However, in its present implementation it is not applicable when motor planning is required. We are expanding the adaptive concepts for other limb segments, such as gait training with the MIT-Skywalker [4] and motor-plan training for arm movement. Here we describe on-going work involving the latter while incorporating our gaming approach with the end goal being to increase users' motivation to perform therapy, perhaps augmenting the commitment of the patient to therapy [5][6]. The strategy proposed in this paper is to adapt the games during a robotic rehabilitation session taking into account the user's motor performance, motor planning, and his/her motivation to perform the exercise. Of notice, whenever entertainment is not the primary goal of gaming, it is referred to as "serious games" [7].

Recently, efforts have been made to model serious games and also to develop a sound scientific methodological basis for their design and customization, especially in the context of rehabilitation [8]. Our goal in this instance is to re-examine concepts described in our 2003 clinically-tested performance-based algorithm for reaching [3][5][9] and to consider whether we could afford more effective therapies by supplementing that approach and explicitly considering motor planning.

II. Adaptive Model

In this section, adaptation indexes are presented that describe the motivation and the performance of the user. For optimization purposes, it is assumed that better overall performance during the games will translate into better therapy outcomes. While previously we considered only motor execution, we will now expand that area to clearly consider motor planning. The presence of motor planning is directly associated with the choice of the game. We selected a classical game Pong, which requires not only motor execution--to move the hand to hit the ball--but also requires motor planning--to move the hand to where the ball will be in a few seconds. Furthermore, it was employed in past studies addressing game adaptation for an application not related to the rehabilitation context [10]. Assuming that the neuromotor system presents a hierarchical structure, predicting the future position of the ball demands a motion planning strategy and its subsequent execution.

We will constrain motivation (or engagement) between two states: low motivation (boredom) and over-demand (stress). Motivation is accessed via a logistic type Linkert scale, where patient/subject impression of the previous game session is evaluated with nominal values ranging from 1 to 5 with level (1) indicating boredom, level (3) indicating good motivation, and level (5) indicating an overload/stress condition.

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Figure 1 shows a variation of the Pong game screenshot that was implemented for the MIT robots [12][13]-[16] or University of Sao Paulo wrist robot shown in Figure 3. The game purpose is to hit the ball with the racket (vertical bar) and throw it to the opposite court, scoring a point when the ball cannot be reached by the opponent's racket. Here subjects' movement in flexion and extension of the wrist moves the bar at the left side of the screen up and down, whereas the right bar is controlled by the computer or another player. The challenge level (difficulty) for this Pong game was defined as a percentage increase in the initial measurement of user range of motion (ROM). The available range of movement for the bar is defined during the initial measurement of the user ROM with the challenging area added at the edges of the screen.

Figure 1: Pong game screenshot

The overall performance of the user is measured as a weighted value composed of three partial indexes. The first index represents knowledge of results and it is expressed as a direct function of the player's performance (points defended by user - Pu) in relation to the number of total points possible (points total - Pt). The second index also falls under the realm of knowledge of results and is intended to challenge the subject further and attempt to extend his/her ROM. It is expressed as the ratio between the number of hits in the extended challenging region (Na) and the number of challenges presented to the user (Nd). The number of challenges presented (Nd) is the number of times the ball is directed beyond the normal range ROM into the challenging areas. The number of hits in the game (Na) is the number of times the user hits the ball inside the challenging area. The last index is a function of the distance traveled by the user wrist (E). This factor attempts to penalize excessive mechanical work due to involuntary movements or lack of motor control by the user. We selected a quadratic format for this index to consider movements in arbitrary directions. Performance (*Perf*) is then presented by the following equation (1):

$$Perf = \left(\frac{2}{\sum_{i=1n} k_i} \left[k_1 \left(\frac{Na}{Nd} \right) + k_2 (g(E^2)) + k_3 \left(\frac{Pu}{Pt} \right) \right] - 1 \right) \quad (1)$$

where k_1, k_2 and k_3 are weights selected in accordance to their contribution building the overall performance.

An initial adaptation strategy was developed by combining two competing characteristics, namely Performance (*Perf*) and Motivation (*Mot*) to change the game difficulty. Conceptually this combination can be optimized automatically through different schemes. For simplicity, we first selected a heuristic approach as shown in Table 1, where the inputs were normalized for training purposes. We changed the ball speed as the means to adapt the Pong game. By changing ball speed, the game's difficulty level changes. This effect may be directly observed in the performance of the healthy subject. Subject moves the racket at higher speeds as the speed of the ball increases, potentially requiring more corrections (higher E) and leading to smaller numbers of hits (Na).

TABLE I
HEURISTIC STRATEGY TO MODIFY BALL VELOCITY (ΔV) FOR THE PONG GAME

		Motivation Level		
		Not Motivated (Mot = -1)	Well motivated (Mot = 0)	Overloaded (Mot = 1)
Performance	Good (Perf = 1)	ΔV > 0	ΔV > 0	ΔV < 0
	Acceptable (Perf = 0)	ΔV > 0	ΔV = 0	ΔV < 0
	Bad (Perf = -1)	ΔV > 0	ΔV < 0	ΔV < 0

To convert this discrete heuristic look-up table into a continuous function that allows measures with intermediate values and that can be used to combine user performances and motivation after each game, a neural network was trained with feed forward architecture and a back propagation learning algorithm.

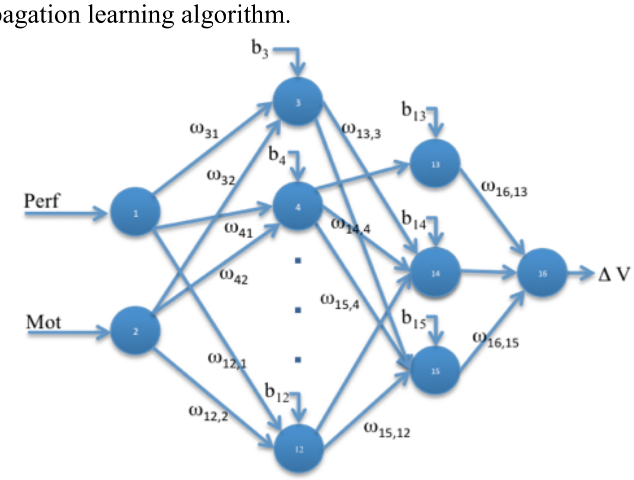

Figure 2 – Feed forward neural network structure

The neural net has two neurons in the input layer, a first hidden layer with ten neurons and a second hidden layer with three neurons. There is a single neuron at the network output. The approximation function generated and implemented in the game is shown in the equation (2) below:

$$\Delta V = \sum_{j=13}^{15} \omega_{16,j} \cdot f\left(\sum_{i=3}^{12} f\left(\omega_{i,1} \cdot Perf + \omega_{i,2} \cdot Mot + b_i\right) + b_j\right) \qquad (2)$$

where w_{ij} are the weights of the network, b_{ij} are the bias in the hidden layers neurons. A logistic function f(.) was adopted in the hidden layers and a linear activation function in the output layer. The network was trained using a Levenberg-Marquardt algorithm to determine changes in ball speed.

III. EVALUATION

The adaptive strategy is intended to be evaluated clinically with the MIT robots which have been extensively employed during clinical trials [9][19]. For development purposes, we are evaluating the algorithm using University of São Paulo interactive robot shown in Figure 3. As with MIT wrist robot, this device has three degrees of freedom - flexion/extension of the wrist (used in this work), ulnar/radial deviation and pronation/supination of the forearm, which also allows the measurement of system parameters such as joint position, joint velocity and motor current.

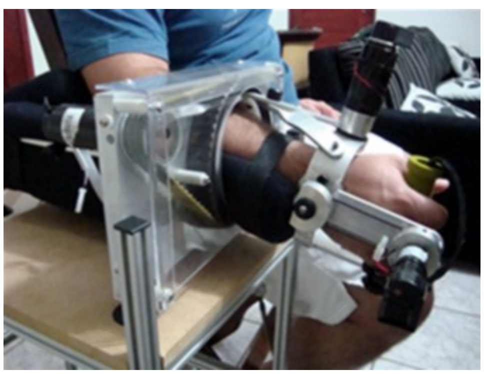

Figure 3: Wrist Rehabilitation System

The Pong game was developed in XNA/C# platform and has the purpose of motivating the user during the exercise. The RobRehab library is responsible for interfacing the Pong game with the EPOS controllers of the Wrist Orthosis. The functions available in the framework are end-user ready so that the developers do not need to care about any issue related to communication (for more details see [17]).

We tested the procedure with five healthy young volunteers. They were instructed to play the game during 10 sessions lasting 1 minute each. To minimize fatigue, we included a 2-minute rest between blocks, when we evaluated subject's motivation using the single multiple-choice questionnaire described earlier. The resulting values as well as the previous performance measures are used to adapt the ball velocity according to Equation (2).

IV. EXPERIMENTAL RESULTS

In this section, we present the experimental results obtained for the application of the strategy to Pong in the five healthy young volunteers. Figure 4 shows the ball speed variation over the 10 sessions for the five volunteers. Despite the limited number of sessions, we can observe the interesting tendency of each user to present a different ball speed variation over the sessions. This result confirms the goal of this research in producing a customized rehabilitation procedure.

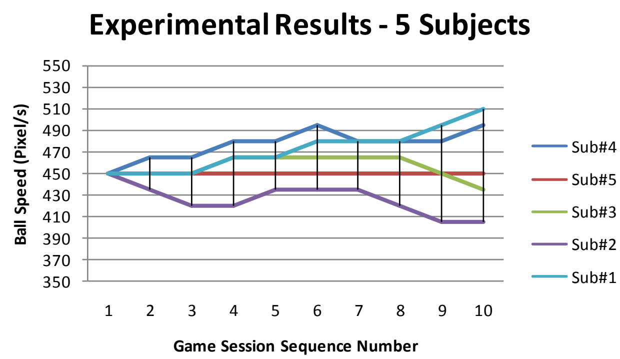

Figure 4. Experimental results showing ball speed for all subjects.

Figure 5 shows the results for Subject #2, including performance, motivation and ball speed. It can be observed that the output of the neural network, associated with the ball speed variation, corresponds to the adaptation strategy presented in Table 1. For example, after session 4 the subject was not motivated and presented a satisfactory performance; as a result, the ball speed was increased.

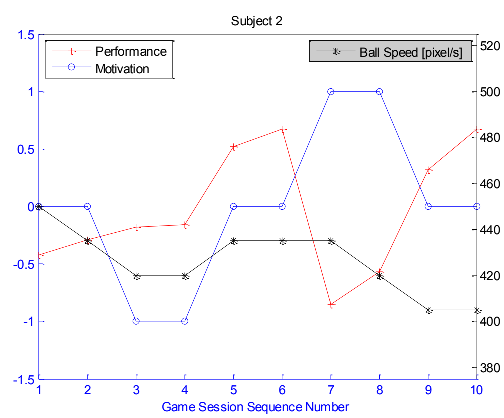

Figure 5. Performance, motivation and ball speed for Subject #2.

We can also associate the ball speed variation and the relation between the number of hits of the patient per number of challenges demanded (Na/Nd), Figure 6. For \Subject #2 we have seen that the performance relation Na/Nd increases every time the velocity is adjusted.

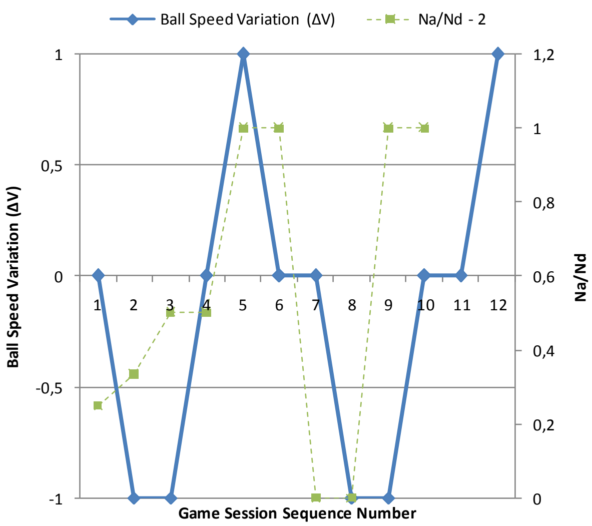

Figure 6. Ball speed variation and Na/Nd ratio during different game sessions for Subject #2.

V. Conclusion

This paper describes our on-going effort to build a combined adaptive strategy that takes into consideration the user's motivation and performance, while affording motor planning. Defining a model for increasing motivation and performance is a complex challenge, and this work represents one of our attempts in this direction for the case of a simple Pong game environment. We will next deal with the automatic acquisition of motivation measures, the statistical validation of the performance parameters (k_1, k_2, k_3, Na/Nd, E and Pu/Pt). The integration of motor planning aspect to rehabilitation robotics may open a way to making the therapeutic process more attractive and challenging for the patients and encouraging compliance. The implemented neural network was able to follow the proposed adaptive strategy without compromises. More experiments will be performed in the near future to analyze tendencies and eventual strategy correction or improvement requirements.

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