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Difficulty Adaptation in a Competitive Arm Rehabilitation Game using Real-Time Control of Arm Electromyogram and Respiration

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Abstract— **Rehabilitation robots are often combined with serious games that motivate patients and keep them exercising at high intensities. A promising type of game are competitive rehabilitation games, but few difficulty adaptation algorithms have been presented for them. This paper thus presents the adaptation of difficulty in a competitive arm rehabilitation game based on two physiological signals: respiration and electromyography of the posterior deltoid. It consists of three smaller studies: an open-loop respiration study, a closed-loop respiration study (where a controller attempts to maintain respiration rate at preset levels), and a closed-loop electromyogram study (where a controller attempts to keep the electromyogram at preset levels). The studies control two difficulty parameters based on the physiological responses of one of the two exercising participants, though the ultimate goal is to control the physiological responses of both participants. Furthermore, all three studies are done with unimpaired participants. The closed-loop controllers achieved high correlation coefficients between desired and measured levels of respiration rate (r = 0.83) and electromyogram (r = 0.89), demonstrating that it is possible to control the physiological responses of unimpaired participants in a competitive arm rehabilitation game, thus controlling their level of workload and exercise intensity. In the future, the proposed method will be tested with patients undergoing rehabilitation.**

I. INTRODUCTION

Rehabilitation robots are frequently combined with game-like virtual environments meant to increase patient motivation [1]. One type of such virtual environments are interpersonal rehabilitation games, which motivate patients by allowing them to interact with another person: another patient, a therapist, or an unimpaired friend or relative. First proposed by Flores et al. [2] and Johnson et al. [3], interpersonal games have experienced a resurgence in recent years, with several studies demonstrating high motivation and exercise intensity in single-session evaluations [4,5,6,7]. However, to date, no multisession evaluations have been performed.

Before interpersonal rehabilitation games can be used in long-term studies, they must be equipped with difficulty adaptation algorithms that optimize exercise intensity by keeping the game difficulty at a level appropriate for the patient. Such algorithms are common in rehabilitation games played by a single patient [8, 9], and several algorithms have been proposed for interpersonal games [10,11], but practically no evaluations have been performed with actual human subjects in interpersonal games.

In this paper, we propose two methods of adapting the difficulty of a competitive arm rehabilitation game based on the respiration and electromyogram (EMG) of the two players. Both respiration [12] and EMG of skeletal muscles [13] have been widely used to assess human workload in many studies. By controlling EMG and respiration rate during a rehabilitation exercise, we would thus be able to control patient workload, [14], similarly to what has previously been done for rehabilitation games played by a single patient [15]. Respiration was selected since it is a common measure of overall metabolic workload while EMG was selected since it reacts much more quickly than respiration and reacts specifically to work done with the selected arm muscle.

Our ultimate goal is to adapt the difficulty of a competitive arm rehabilitation game based on physiological signals of both participants. However, as a first step, this paper is limited to measuring the EMG or respiration rate (RR) of one player and adapting game difficulty accordingly. The paper consists of three smaller studies. The first study conducts an open-loop evaluation of the effects of game difficulty on respiration. The second study then uses data from the first study to implement and test a closed-loop controller that adapts game difficulty in real time to keep respiration at a desired level. Finally, the third study presents a closed-loop controller that adapts game difficulty to keep EMG at a desired level.

II. METHODOLOGY

This section is divided into four parts as follows. Part A describes the robot and competitive arm rehabilitation game used for all experiments in this paper. Part B presents the open-loop experiment used as a basis for control of respiration while part C presents the closed-loop experiment on control of respiration during the competitive rehabilitation game. Finally, part D demonstrates the closed-loop control of EMG.

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A. Robot and competitive game

The competitive arm rehabilitation game (Figure 1) was taken from a previous study on interpersonal arm rehabilitation games [4]. It is an air hockey game consisting on two paddles and a puck on a board. The puck constantly moves across the board. Each player controls one paddle and must move it left or right to block the puck and keep it from reaching that player's goal. If the puck is deflected by a paddle, it bounces off it and moves toward the opposite side of the board. If the puck hits the player's goal, the other player scores a point and the puck is instantly moved to the middle of the board, where it remains stationary for a second before moving in a random direction.

The game is played by two players using a large projection screen (Figure 2) and a 17-inch monitor. One uses a Haptic Master (Moog FCS, Netherlands – Figure 2) haptic robot, and moves the robot's end-effector left and right to move his or her paddle. The other player uses a standard commercial joystick, and tilts it left and right to move the other paddle. Such a combination of rehabilitation device and joystick was previously used in our research [7] and is appropriate for an unimpaired and impaired person exercising together, though a final implementation with two patients would ideally use two robots.

The game has two difficulty parameters: the speed with which the puck moves across the screen (from very slow to very fast) and the resistance with which the Haptic Master resists the player's movements (from very low to very high). Notably, the speed parameter affects both participants directly while the resistance only affects one player. In the future, using two haptic robots would allow us to vary the resistance parameter independently for each player.

B. First study: Open-loop study of respiration rate

Before designing a closed-loop controller, we first evaluated how different difficulty settings affect respiration rate in the competitive game. Twelve healthy university students (23.6 ± 4.2 years old, 2 females) participated in the open-loop study together with self-selected friends (who played against the participants, but did not have their RR measured). Participants were relaxed at the beginning of the experiment. Figure 3 shows the protocol of this study, which starts with a 3-minute baseline recording of RR using a thermistor-based sensor (Respiration airflow sensor, g.tec, Austria) placed in front of the nose and mouth. The main part of study then consists of four test periods separated by1-minute rest periods to "wash out" the effects of the previous test.

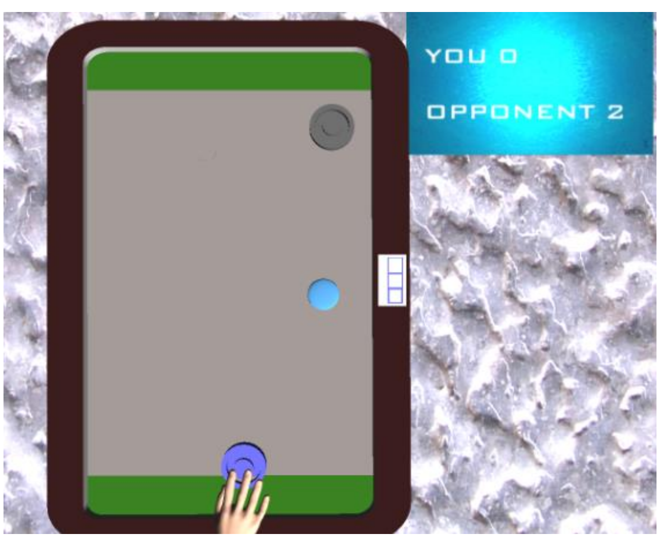

Figure 1. The air hockey competitive arm rehabilitation game. It consists of a puck, two paddles that are controlled by the haptic robot and joystick, and a score board.

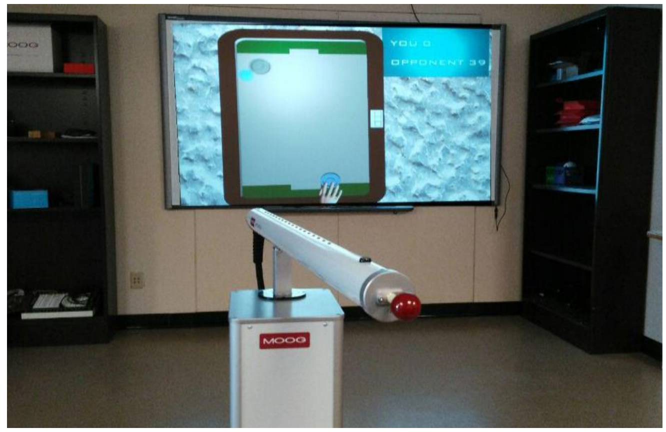

Figure 2. Hardware setup. A combination of haptic robot and projection screen, used by the first participant. A 17-inch monitor and a commercial joystick are used by the second participant.

The four test periods differ according to the levels of the game's two difficulty parameters: puck speed and robot resistance. In this study, each parameter has two possible levels (low and high), leading to four possible combinations. The test period with low puck speed and low robot resistance can be assumed to be the least demanding test and should thus result in the lowest increase in respiration rate while the period with high puck speed and high resistance should result in the highest increase in respiration rate. To validate that the difficulty changes indeed affected participant workload, the NASA-TLX questionnaire [16] was also filled out after each test period. It assesses six aspects of workload: mental demand, physical demand, temporal demand, performance, effort and frustration.

The four tests were conducted in order to establish each difficulty parameter's effect on respiration rate. This served as the basis for the closed-loop study in the next section.

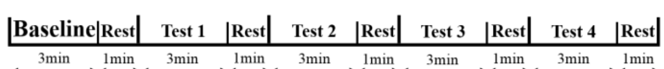

Figure 3. Protocol of the first, open-loop study on respiration.

All RR values obtained from 4 tests are normalized by subtracting the mean RR value of baseline period. The normalized data are presented in next section to indicate different levels of RR during different difficulty levels.

C. Second study: Closed-loop control of respiration rate

The closed-loop respiration rate controller was designed based on the results of the previous study, which identified (as described in more detail later) the amplitude of changes in respiration rate that should be expected in young, unimpaired participants. In the most difficult test (high puck speed, high resistance), RR showed, on average, an increase of 6 breaths per minute compared to baseline values (ΔRR_{MAX}). Thus, that is the maximum we can expect our controller to be able to achieve.

The closed-loop study was conducted with nine healthy participants (age 26.44 ± 3.04, 2 females) and their self-selected friends (who played against the participants, but their RR was not measured), none of which had participated in the open-loop study. It began with a 3-minute baseline period, during which the participant's baseline RR (RR_{BASE}) was calculated over the entire period. After the baseline period, there were three 3-minute test periods. During each test period, the closed-loop respiration rate controller aimed to maintain the participant's RR at a different reference level:

- Reference 1: $RR_{BASE} + 0.5\ \Delta RR_{MAX}$
- Reference 2: $RR_{BASE} + 0.8\ \Delta RR_{MAX}$
- Reference 3: $RR_{BASE} + 0.3\ \Delta RR_{MAX}$

Figure 4 shows the protocol of this study. There were no breaks between the four periods. Every 15 seconds, the controller calculated the mean RR over the last 15 second-period and compared it to the reference value, then changed the puck speed and robot resistance in order to reduce the difference between actual and reference values of RR.

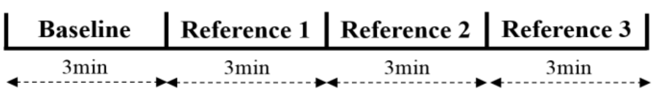

Figure 4. Study protocol for closed-loop control of respiration rate.

Control of difficulty is done using a few simple proportional rules. Each interval, the difference between measured and reference values of RR is calculated. The puck speed is then increased by 0.1 times the difference between measured and reference RR values; simultaneously, the robot resistance is increased by 5 times the difference between measured and reference RR values. As game speed can be adjusted between 0 and 1 while robot resistance can be adjusted between 0 and 50, a difference of 1 cycles/min between desired and actual RR results in a 10% change in speed and resistance. Thus, if the measured RR is lower than the reference value, both puck speed and robot resistance are increased (or vice versa).

D. *Third study: Closed-loop control of EMG*

Unlike respiration, closed-loop control of arm EMG was done in a single study, without first conducting open-loop experiments. Five healthy participants (27.3 ± 4.2 years old, all male) and their self-selected friends, none of which had participated in the first two studies, were recruited. The EMG activity of their posterior deltoid muscle was recorded using a g.USBamp biosignal amplifier (g.tec Medical Engineering GmbH, Austria). The posterior deltoid was selected as it is the muscle that exhibited the strongest contractions during the left-right Haptic Master movements required to play the competitive game. Its EMG was recorded with a combination of four leads (Figure 6) – a ground lead on the spine, a reference lead on the acromion process, and two leads on the posterior deltoid (with a 20-millimeter distance between the two). The mean absolute (MABS) value of EMG signal amplitude was used as an indicator of muscle activity level.

Figure 5 presents the protocol of the study for closed-loop control of EMG. It begins with two 1-minute individualization periods – one with very low and one with very high task demand (TD). The low-TD period involves a very low puck speed and robot resistance while the high-TD period involves very high puck speed and robot resistance. These two periods provide us with each participant's minimum and maximum EMG MABS values ($MABS_{MIN}$ and $MABS_{MAX}$) that are realistically achievable in the competitive arm rehabilitation game. The difference in MABS values between these two individualization periods was calculated as ΔMABS.

Following the two 1-minute individualization periods, there were three 4-minute test periods. During each test period, the closed-loop EMG controller aimed to maintain the participant's EMG MABS value at a different reference value (similarly to the closed-loop respiration study):

- Reference 1: $MABS_{MIN} + 0.45\ \Delta MABS$
- Reference 2: $MABS_{MIN} + 0.7\ \Delta MABS$
- Reference 3: $MABS_{MIN} + 0.2\ \Delta MABS$

As in the closed-loop respiration study, the closed-loop controller aimed to reduce the difference between reference and actual values of MABS by adjusting the puck speed and robot resistance. To keep the changes smooth, each 4-minute period was divided into twelve 20-second periods. At the end of each period, the mean MABS value of the EMG was calculated over the last 20 seconds and compared to the reference value.

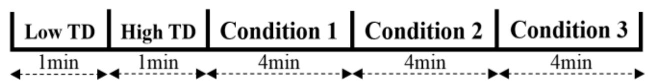

Figure 5. Protocol of EMG closed-loop study. Starts with low TD followed by high TD and three test conditions.

The decision of how to adapt game difficulty was made using a multiple linear regression model. Every 20-second interval of the test results in a vector of EMG MABS, speed and resistance values. Each vector forms a point in 3-dimensional (3D) solution space. By having at least three points in the solution space, a plane can be fitted using a multiple linear regression model. The model can be used to estimate

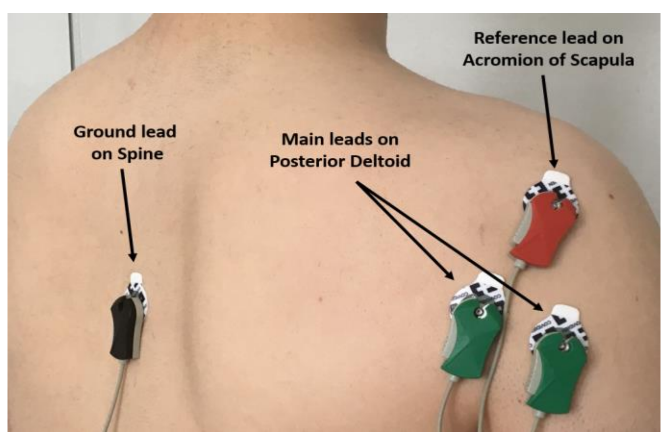

Figure 6. The placement of leads for recording EMG of posterior deltoid. The ground, references and main leads are shown by black, red and green colors, respectively.

the values of the two game parameters that will result in desired levels of EMG MABS. Equation (1) shows the function representing the relationship between speed (x), resistance (y), EMG MABS (z) and a constant (c). By taking speed and resistance parameters as inputs, the best regression model (best plane) can be fitted to the points in 3D solution space. This can be done by using Equation (2) and calculating 'a', 'b' and 'c' coefficients. After each 20-second interval, Equation 1 is then used to calculate the game parameters (speed and resistance) for the next interval based on desired EMG MABS values. Furthermore, after each 20-second interval, coefficients 'a', 'b' and 'c' are recalculated by adding the new data vector (from the last interval) to the training dataset. This results in a slight change to the coefficients after each interval and results in gradual individualization of the controller.

$$z = ax + by + c \tag{1}$$

$$\begin{bmatrix} \sum x_i^2 & \sum x_i y_i & \sum x_i \\ \sum x_i y_i & \sum y_i^2 & \sum y_i \\ \sum x_i & \sum y_i & n \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum x_i z_i \\ \sum y_i z_i \\ \sum z_i \end{bmatrix} \tag{2}$$

III. Results

A. Open-loop study of respiration rate

Table 1 presents the mean and standard deviation for six dimensions of NASA-TLX and mean RR during four different tests. An increase in all aspects of workload and a decrease in workload can be seen as a result of difficulty changes. Furthermore, mean RR increases when difficulty increases.

Table 2 shows the results of the repeated-measures analysis of variance (RM-ANOVA) for the different workload aspects of the NASA-TLX and different puck speed and robot resistance levels. Puck speed affects all six NASA-TLX dimensions while robot resistance primarily affects physical aspects. Therefore, the selected competitive rehabilitation game can induce different workload levels in players.

Table 1. Mean and standard deviation of six aspects of NASA-TLX (each aspect is in the range of 0-20) and mean RR (Normalized by subtracting baseline value) for 4 different tests.

	Slow & without resistance	**Slow & with resistance**	**Fast & without resistance**	**Fast & with resistance**
Mental demand	3.4 ± 2.6	3.8 ± 3.4	7.6 ± 4.3	7.8 ± 3.4
Physical demand	3.4 ± 2.9	7 ± 6.2	6.5 ± 5.6	10.5 ± 5.5
Temporal demands	2.8 ± 2.6	4.3 ± 5.1	10.4 ± 4.6	12.3 ± 5.3
Performance	16.5 ± 3.0	16.3 ± 3.4	11.6 ± 5.7	12.7 ± 4.9
Effort	3.1 ± 3.2	6.7 ± 6.1	8.4 ± 4.1	11.4 ± 5.3
Frustration	1.9 ± 1.4	1.8 ± 1	5.6 ± 4.4	4.5 ± 4.1
Mean RR (cycles/min)	4.6 ± 3.6	4.5 ± 4.4	7.5 ± 5.6	7.5 ± 5.2

Table 2. Significant differences in workload aspects (measured with the NASA-TLX) between the two levels of puck speed and robot resistance. Presented as p-value and effect size (calculated as η^2)

	Speed	**Resistance**
Mental	$p < 0.001, \eta^2 = 0.74$	n.s.
Physical	$p < 0.001, \eta^2 = 0.76$	$p < 0.001, \eta^2 = 0.62$
Temporal	$p < 0.001, \eta^2 = 0.82$	$p = 0.018, \eta^2 = 0.41$
Performance	$p = 0.005, \eta^2 = 0.53$	n.s.
Effort	$p < 0.001, \eta^2 = 0.78$	$p = 0.010, \eta^2 = 0.47$
Frustration	$p = 0.003, \eta^2 = 0.56$	n.s.

The RM-ANOVA is also exploited for assessing the effects of puck speed and robot resistance on mean RR (the physiological indicator of game difficulty). Puck speed shows P-value less than 0.001 and the effect size (calculated as η^2) is equal 0.72 which indicate significant effect on mean RR. Although resistance has effect on mean RR but the P-value is not less than 0.01 (the considered confidence level). Taking the results of Tables 2 and the significant effect of speed on mean RR, we can conclude that puck speed and robot resistance affect player workload. Thus, it should be possible to control player workload via closed-loop control of RR.

B. Closed-loop study of respiration rate

In the closed-loop study of respiration rate, game difficulty is adapted each 15 seconds over nine minutes of the test, resulting in 36 intervals (15 seconds each). Figure 7 presents the mean measured RR across participants as well as the desired reference pattern. The Pearson correlation coefficient between the measured RR and the preset reference is 0.833 while the Root mean square (RMS) of differences between them is 12.90 percent of maximum RR difference from baseline, showing that the proposed approach is capable of adapting difficulty to maintain respiration rate at desired levels.

C. Closed-loop study of electromyography

Figure 8 shows the average of EMG MABS across participants. In closed-loop control of EMG, game difficulty

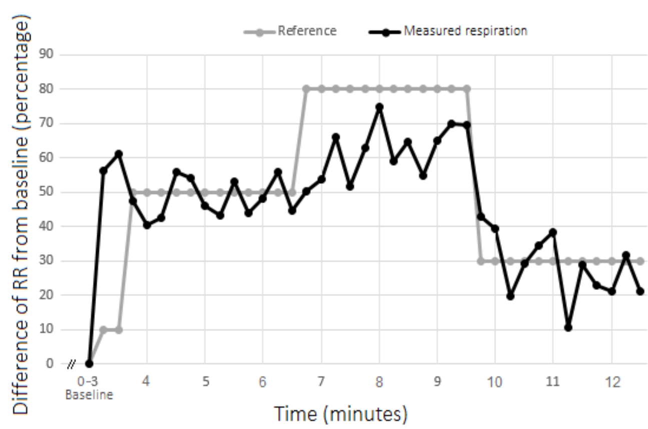

Figure 7. Respiration rate (normalized by subtracting the baseline value). It is averaged across all participants. Each dot represents a 15-second interval in the closed-loop control study. The RR mean value of the 3-minute baseline period is represented by a single point at zero.

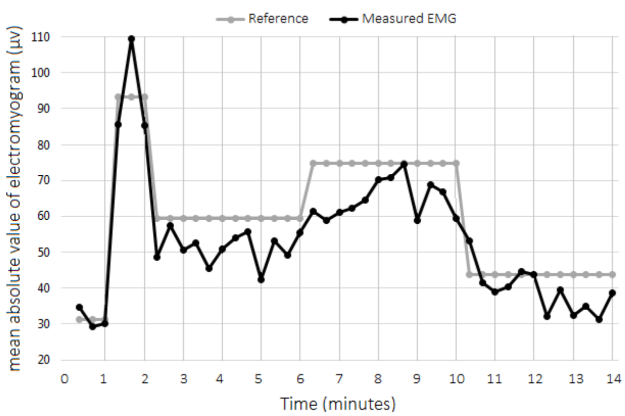

Figure 8. Mean absolute value of electromyogram activity during the test. The gray line represents the preset reference and black line is the measured electromyogram signal. The test consists of two 1-minute individualization periods followed by three 4-minute test periods with different references. Results are averaged across all participants.

is adapted each 20 seconds over twelve minutes of the test, resulting in 42 intervals. The Pearson correlation coefficient between reference and measured EMG values is 0.896 while the RMS of differences between them is 9.22 µV, indicating that it is possible to control EMG by adapting game difficulty in real time. The correlation coefficient may be higher for EMG than for respiration since EMG reacts more quickly to changes in task difficulty.

IV. Discussion

The obtained results show that it is possible to control a player's respiration rate or EMG during a competitive arm rehabilitation game with a reasonable accuracy by adapting game difficulty. As both respiration rate and EMG are indicators of workload, this means that it should be possible to control patient workload during a competitive arm rehabilitation exercise using the proposed methods.

The presented results are, of course, preliminary: in a final implementation, we would aim to control the respiration and/or EMG of two patients while they exercise in the competitive arm rehabilitation game; in the current implementation, we only control the respiration or EMG of a single unimpaired person while he or she exercises together with a second unimpaired person. Nonetheless, our work lays the foundation for real-time control of physiological signals in competitive and cooperative rehabilitation exercises.

Aside from expanding the work to actual patients and to controlling the physiological responses of both players, multiple other improvements could be made to the system. For example, other physiological signals connected to workload and engagement could be added to make the controllers more robust and accurate, and additional game difficulty parameters could be introduced to the model. By analyzing the effect of each parameter in the game, we could, for example, control different aspects of the patient's workload (e.g. physical and mental). Finally, patient-specific factors such as familiarity with the game, mood, fatigue, and personality could be taken into account to create patient-tailored controllers. However, we must also be careful not to make the model overly complex – given low patient sample sizes generally available in rehabilitation robotics research, we must carefully balance increased accuracy with the risk of overfitting the control model.

V. Conclusion

We present two preliminary prototypes of control systems that adapt the difficulty of a competitive arm rehabilitation game in order to keep the player's respiration rate or arm EMG at a desired level. The controllers achieved a high correlation coefficient between desired and actual respiration rate and EMG, demonstrating that such control can be done with good accuracy.

As the next steps, the demonstrated controllers need to be tested with actual patients as well as expanded to take both players' physiological responses into account. In the long term, however, they have the potential to be used to adapt the difficulty of competitive and cooperative rehabilitation exercises, keeping patients at an appropriate level of engagement that allows them to exercise intensely for a good amount of time without becoming tired, bored or frustrated. They could also be transferred to other fields of human-machine interaction, keeping the workload of computer users at an appropriate level that maximizes performance.

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