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Biocooperation in rehabilitation robotics of upper extremities

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Abstract—**Multimodal rehabilitation environment including haptic, visual and audio pathways is, among other, also influencing the physiological state of the subject. Heart rate, skin conductance, respiratory rate and skin temperature were measured in 30 healthy subjects during a control task, a purely mental task, a task with minor physical load and a task with major physical load. All physical activity was performed using haptic robots. This paper presents an analysis of psycho physiological responses to these different tasks. Physiological responses were interpreted using the arousal-valence emotion model, which describes a person's mental state with two variables: arousal and valence. This model was expanded with a third variable, physical load. Psycho physiological measurements yield results even in the presence of physical load and can thus potentially be useful for rehabilitation robotics.**

I. INTRODUCTION

CEREBROVASCULAR accident (stroke), cerebral palsy (CP), multiple sclerosis (MS), SCI and Parkinson's disease (PD) are disorders where rehabilitation robotics could prove very useful.

A number of platforms have been designed specifically for rehabilitation robotics. Two types of devices exist: the exoskeleton and the end effector. L-Exos is a tendon driven wearable haptic interface with 5 DoF. Neural control of an upper limb Powered exoskeleton system has 8 DoF. ARMin (I, II and III) represents an interesting later design that currently allows movements with 6 DoF.

Examples of end-effector upper extremity devices include MIT Manus, Assisted Rehabilitation and Measurement (ARM) Guide, Mirror Image Motion Enabler (MIME), Bi-Manu-Track, GENTLE/S, Neurorehabiltation (NeReBot), REHAROB, Arm Coordinating Training 3-D (ACT3D), Braccio di Ferro and the NEDO project device.

The haptic rehabilitation robots that challenge exercised person in complete way from sensory, cortical, brain, motor path and muscle activity seem to offer evidence that robotics can be used as a general tool to harness brain plasticity and promote recovery at least for stroke in the long run for both subacute and chronic cases [4].

In order for treatment to be effective, a therapy regime must be intensive [5], of long duration [6], repetitive [7] and task-oriented [8]. Prange et al. pooled short-term mean changes in Fugl-Meyer scores before and after robot-aided therapy for four of the trials [9]. This systematic review indicates that robot-aided therapy of the proximal upper limb can improve short and long-term motor control of the paretic shoulder and elbow.

Another recent comparative study by Mehrholz et al. included 11 clinical trials with a total of 328 participants. It found no evidence that the use of electromechanical assistive devices in rehabilitation settings improves activities of daily living [10].

Finally, rehabilitation robotics is frequently supported by Virtual Reality (VR). An increasing number of groups are using visual, acoustic or tactile clues as biofeedback in order to challenge or motivate the patient during physical therapy exercises. Recorded signals (kinematic, static and physiological signals) are processed and fed back to the patients via visual, acoustic, vibrotactile or electrical stimulation displays.

In order to optimally integrate various sensory cues (haptic, acoustic, audio) and to adequately "dose" the sense of presence, a sensory system for assessing presence is required. There are several off-line measures that can estimate the level of presence, including off-line analysis of questionnaires, numerical scoring of task parameters, motor behavior parameters or physiological signals.

Acquisition of physiological signals and the use of these signals in adaptive systems in real time is not a new idea. Physiology has been used to assess responses to many types of virtual environments. For instance, physiological responses can be used to monitor patient progress in therapeutic VR (e.g. [11]). In addition to use in virtual environments, evidence has shown that emotions experienced while playing computer games are reflected in physiological responses and that this could be used to determine a person's level of enjoyment or frustration while playing [12]. If we can identify a person's emotions while they are engaged in an artificial environment, the logical next step is to use that information to modify the environment and make the experience more pleasant or more complex for the user. General system architectures have been proposed for emotion-aware VR systems, and basic systems have successfully shown an ability to affect the subject's attention level [13].

In order to meaningfully estimate emotions from signals, a model of emotions must first be chosen. In the field of

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human-computer interaction, the two-dimensional arousal-valence model originally developed by Russell [14] has recently been suggested as a relatively simple, yet effective model of emotions suitable for designing emotion-aware systems [15]. In this model, an emotion is represented by two independent variables. Arousal represents a person's general level of mental activity (with sleepy at one extreme and focused on the other) while valence indicates whether the person's feelings are positive or negative (with, for example, miserable at one extreme and happy at the other).

However, as new biocooperative rehabilitation robotic systems are designed, a question arises: Can psychophysiological measurements be used in situations with physical activity? Or would physiological changes due to physical activity mask any physiological signal changes caused by emotional changes? To answer this question, we designed a two-phase study. In the first phase, we verified our hardware setup by examining psychophysiological relationships that have been previously confirmed by other studies in situations with a complete absence of physical activity. In the second phase, we examined how much physical activity the subject can perform before psycho physiological measures become useless for identification of emotions.

II. METHODS

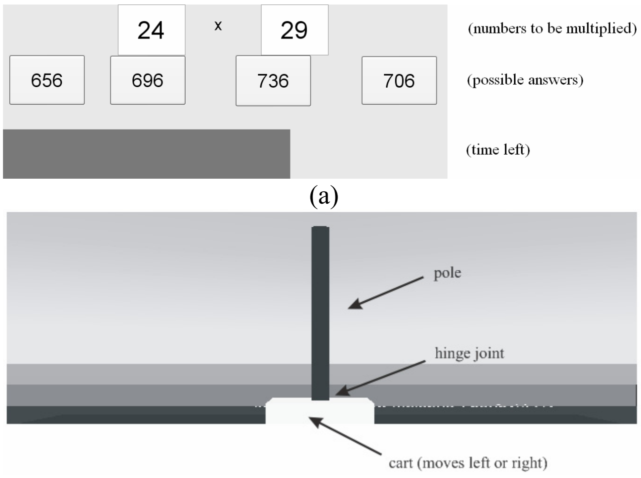
A. Experimental tasks

The first (I) task, which was not related to rehabilitation robotics, was a timed mental arithmetic task where the subject had to multiply two numbers and speak out loudly one of the suggested results. This situation required significant cognitive effort but only a verbal response and little interaction with the environment.

The second (II) task was a hand-eye coordination task where the subject had to constantly balance a virtual inverted pendulum shown on the screen using small movements of a Phantom haptic interface. This was a situation that required both mental and small physical effort as well as constant interaction with the environment.

During the third (III) task, the subject had to perform both previous tasks at once. This allowed us to study the effects of divided attention and possible mental overload.

In the fourth (IV) task, the subject was again presented with the inverted pendulum from the second task. However, a larger screen and a much more physically demanding haptic device (the HapticMaster) were used. All tasks other than the first one provided the subject with information about forces resulting from the movement of the cart via haptic feedback. Task screenshots are shown in Figure 1.



(a)

(b)

Fig. 1. (a) Computer display for cognitive task I., (b) for small II and larger movement task IV. Task III. has a combined display.

Task IV consisted of eight subtasks. There were three difficulty levels: moderately challenging (the original from task II), difficult to the point of frustration (with a second delay in robot control and higher gravity) and relatively easy (weaker gravity, with the pole more responsive to the movement of the cart). Each of the three difficulty levels was performed with two different levels of physical load for a total of six subtasks. For low physical load, the HapticMaster offered no resistance to the subject's actions. For high physical load, the HapticMaster divided the force applied by the subjects by five, forcing them to apply more force to achieve the desired effects.

In addition to the six subtasks with the inverted pendulum, a control task was introduced to evaluate the effect of physical load in the absence of mental load. In this control task, participants moved the HapticMaster left and right at an even, moderate speed with no information of the screen and no force feedback. The control task was also performed with two different levels of physical load, resulting in eight total subtasks: six pendulum subtasks and two control subtasks. Each subtask lasted five minutes. After each period (including rest), the participant was presented with a self-report questionnaire.

B. Hardware and software

The experimental hardware consisted of three major parts: the visualization system, the haptic interface and the signal recording system. In tasks I-III, a personal computer with a 22-inch display was used for visualization. In task IV, a 2 m x 1,5 m screen with back-projection was used for visualization (PC#1).

In tasks II and III, the Phantom Premium 1.5 from Sensable Technologies, Inc (PC#2) was used as the haptic interface. This device provided a range of motion approximating hand movement pivoting at the wrist. Speech was recorded using a headset connected to the visualization PC. For task IV, the HapticMaster, a high-performance force-controlled robot developed by Moog FCS, was used as the haptic interface. The subject's upper and lower arms were linked to two gravity compensators suspended from the ceiling. The participant sat approximately 1.5 meters in front of the screen, with the HapticMaster situated between the seat and the screen.

For the psychological signal measurement, the electrocardiogram was recorded using pre-gelled, disposable surface electrodes affixed to the chest and abdomen. Skin conductance was measured using a g.GSR sensor (g.tec Medical Engineering GmbH). The sensor, originally designed for use on completely stationary subjects, was modified in order to decrease sensitivity and make it suitable for use in situations where the subject is moving the dominant hand. The electrodes were placed on the medial phalanxes of the second and third fingers of the non-dominant hand using Velcro™ straps. Respiratory rate was obtained using a thermistor-based SleepSense Flow sensor. This sensor is placed beneath the nose and can measure respiration both, through the nose and through the mouth. The peripheral skin temperature was acquired with a g.TEMP sensor attached to the distal phalanx of the fifth finger using medical adhesive tape. All the signals were amplified and sampled at 2.4 kHz using a g.USBamp amplifier linked via USB to PC#3.

The visualization was implemented in Matlab's Virtual Reality toolbox while physiological signals were imported directly into Simulink using drivers and Simulink blocks provided by the manufacturer of the signal amplifier. Samples were recorded raw, then filtered and analyzed offline. xPC Target 3.3 was used to control the Phantom as well as HapticMaster. The three PCs used for visualization, signal recording and haptic interface control were synchronized via UDP.

C. *Physiological and biomechanical measures*

The subjects' psychophysiological state was evaluated using physiological signals recorded during the experiment. Analysis of the ECG began by extracting the R-peaks, manually removing any ectopic beats or noise that had not been removed by filtering. The times between two normal heartbeats (NN intervals) were calculated from the R-peaks and converted into heart rate. Mean heart rates were calculated for each section of the recording. Standard deviation of NN intervals was derived from heart rate and used as a measure of heart rate variability (HRV) [16]. The skin conductance signal can be divided into two components: the skin conductance level (SCL) and skin conductance responses (SCRs). The SCL is the baseline level of skin conductance in the absence of any particular discrete environmental event. Its mean value was calculated for each period. The absolute value of skin conductance could not be measured with our instrument, which records only changes from an initial offset, so the value of skin conductance at the beginning of the experiment was considered to be the zero value. SCRs are temporary increases in skin conductance followed by a return to the tonic level. Every increase in skin conductance was classified as a SCR if its amplitude exceeded 0.05 µS and the peak occurred less than five seconds after the beginning of the increase. In addition to the number of SCRs that occurred during each section, we calculated the mean amplitude of all SCRs.

Mean respiratory rate was calculated in breaths per minute for each section of the recording. Additionally, respiratory rate variability was estimated by calculating the standard deviation of respiratory rates.

Peripheral skin temperature was recorded at the end of each section of the recording by averaging temperature during the last five seconds to remove the effect of noise.

The position, velocity and acceleration as well as the force exerted by participants on the haptic devices were continuously recorded. From this data, six parameters were extracted for each time period: the mean absolute force, the standard deviation of the force signal, the mean frequency of the force signal, the mean frequency of the position signal, the mean frequency of the velocity signal and the mean frequency of the acceleration signal.

D. *Subjects and experimental procedure*

Twenty students and staff members of the University of Ljubljana (age: 20-46, mean 28.6, std 7 years) participated for tasks I to III, and thirty persons (age: 19-46, mean 26.2, std 5.8 years) participated in the experiment IV. All were without any known major cognitive or physical defects. Each signed an informed consent form before participating.

The experiment was conducted in a dedicated area of the laboratory with no external disturbances. Tasks I to III were performed in random order among subjects. After arrival and description of procedures, each subject had a chance to practice the tasks for a few minutes. The measurement equipment was then attached and baseline measurements were taken. Self-evaluation questionnaires were filled out after each task. Each task lasted five minutes. There was also a five-minute rest period before each task. After completion of the tasks, the subjects rested for another five minutes while final baseline measurements were taken.

Task IV was performed in two separate time blocks (due to experiment length). The first time block included an initial baseline period, the three difficulty levels of the inverted pendulum task and the control task performed at one level of physical load. The order of the difficulty levels and the control task was chosen randomly for each subject. The second block was identical, except that all subtasks were performed at the other level of physical load. The order of the two levels of physical load was also chosen randomly. Subjects were not informed at all about existence of difficulty levels in task IV. During the task, subjects were told not to speak. However, if any asked about changes in task difficulty, the experiment supervisor claimed that difficulty was constant.

A. Self-report questionnaires

After each task, participants were presented with a questionnaire that gauged their feelings during the task. They were asked to rate their level of satisfaction, frustration and concentration on a six-point scale. They were also asked to rate the difficulty of the task on a five-point scale. Finally, participants had to estimate their level of concentration and mental state on a two-dimensional graph similar to the arousal-valence model described earlier.

III. RESULTS

When comparing sets of data, gathered as explained in previous section, a statistical significance of differences was calculated using a One-way Repeated Measures ANOVA followed by the Tukey test in post-hoc analysis. If the assumptions for regular ANOVA were not met, ANOVA on Ranks was used instead. Table 1 provides a summary of how each physiological parameter increased or decreased from baseline during tasks I-IV. The arrow ↑ means that the parameter significantly increased from baseline to task while ↓ means that the parameter significantly decreased from baseline to task. Bigger arrows ↑ are used when $p < 0.01$ while smaller arrows ↑ are used when $p < 0.05$. No arrow is shown for $p > 0.05$.

If we wish to study the effects of arousal and valence, it is not sufficient to only test for significant differences from baseline. To exclude the effects of physical effort, relative values of measured and calculated variables from the inverted pendulum task were compared to the relative values of variables from the control task. The relative value is defined as the value of a physiological parameter during a task in percentage of baseline (rest) value.

In order to gain a better understanding of physiological differences between different task difficulty levels, we also compared relative values between the two difficulty levels in the I, II and III experiments with the HapticMaster experiment IV. Only two physiological parameters showed significant differences between difficulty levels: respiratory rate variability was significantly lower during the normal task than during the hard task ($p < 0.001$) while final skin temperature was significantly higher during the normal task than during the hard task ($p = 0.011$).

Mean absolute force during the experiment with the HapticMaster was 17.1 N (std 6.9 N) during the control task, 6.8 N (std. 3.5 N) during the normal inverted pendulum task and 7.4 N (std 2.9 N) during the hard inverted pendulum task. It was significantly higher ($p < 0.001$) during the control task than during either version of the inverted pendulum task. It was also significantly higher during the hard task than during the normal task ($p = 0.025$).

Figure 2 shows a sketch of how arousal, valence and physical effort affect the physiological parameters. Please note that this sketch represents a general summary of our assessments and would require further measurements with different environments and stimuli in order to more accurately describe the general relationships between emotions, physical effort and physiological responses.

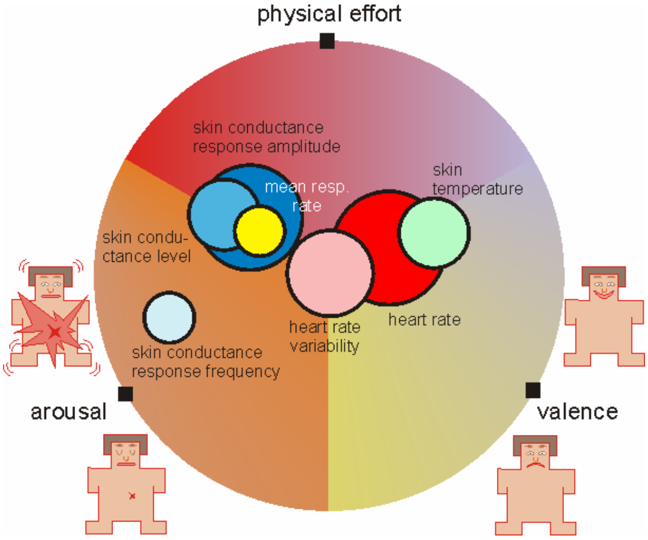


Fig. 2. Influence of arousal, valence and physical effort on various physiological parameters. Each parameter is represented by a circle. The distance of a circle's centre from each of the three black squares represents the effect that square has on it; the shorter the distance, the greater the effect. The radius of a circle represents variability between subjects;

IV. DISCUSSION

A. Force measurements

Participants were significantly more physically active when using the HapticMaster during the control task than the inverted pendulum task. Physiological changes thus may not be caused only by changes in psychological state, but also by differences in physical workload.

B. Skin conductance

Two different components of the skin conductance signal were studied: tonic skin conductance level (SCL) and nonspecific skin conductance responses (SCRs). SCL did not change significantly from baseline on the Phantom, but increased significantly from baseline during the control task and both inverted pendulum tasks on the HapticMaster. There were no statistically significant differences in SCL between the control task and inverted pendulum task for either haptic interface, suggesting that

SCL is primarily affected by physical load and is thus unsuitable as a psycho physiological indicator in environments that require physical interaction. During the control task on the HapticMaster, the frequency of SCRs was significantly higher than during the baseline period, showing that physical activity also increases the frequency of SCRs. On the Phantom, frequency of SCRs was significantly higher during the inverted pendulum task than during the control task, showing a connection between the frequency of SCRs and general arousal. To sum up: the frequency of nonspecific skin conductance responses is a valid indicator of both mental arousal (estimated through questionnaires) and physical load, with both contributing significantly to it. However, if physical load becomes too high, it can completely overshadow the effects of mental arousal, rendering SCRs useless as a psychological indicator.

C. *Respiration*

Both, the control task and the inverted pendulum task showed an increase in mean respiratory rate from baseline for both haptic interfaces. On the HapticMaster, respiratory rate during the inverted pendulum task was significantly higher than during the control task despite the fact that mean absolute force was higher during the control task. Respiratory rate variability significantly decreased from baseline during both the control task and the inverted pendulum task on the Phantom. This suggests that respiratory rate variability decreases as arousal increases, but increases as valence decreases.

D. *Heart rate*

Heart rate increased significantly during the control and inverted pendulum tasks on the HapticMaster. By far the greatest increase was during the control task on the HapticMaster, where the exerted force was also the greatest. A significant increase in heart rate from baseline was observed during the control task on the Phantom, but not during the pendulum task. The only differences in mean heart rate observed in our study were due to physical load.

E. *Skin temperature*

The difference in skin temperature between baseline and task was significant only for the hard inverted pendulum task on the HapticMaster. It would appear that peripheral skin temperature decreases as emotional valence decreases.

V. CONCLUSIONS

We were able to demonstrate a significant influence of both mental arousal and emotional valence on physiological responses even in the presence of significant physical load. Mean respiratory rate and frequency of skin conductance responses are both indicators of arousal, but also both strongly influenced by physical load. Peripheral skin temperature appears to be independent of the level of physical load, and it might increase their potential usefulness in human-computer interaction. Very strenuous physical activity would most likely cause physiological responses that would completely overshadow the physiological responses caused by changes in psychological state. Future work includes studies of physiological parameters specifically in a rehabilitation robotics environment with normal subjects and then closing the biocooperation loop by making changes in the virtual environment based on physiological changes.

TABLE I.A

CHANGES FOR PHYSIOLOGICAL SIGNALS

Signal	Parameter	Mov. period	Cogn. Task (I)	Coord. Task (II)	Both tasks (III)
skin conductance	number of SCRs		↑	↑	↑
	final SCL (µS)	↑	↑	↑	↑
respiration	mean resp. rate	↑	↑	↑	↑
	st. dev. of resp. rate	↓		↓	
heart rate	mean HR	↑	↑		↑
	SDNN			↓	
skin temperature	final temperature		↓		↓

TABLE I.B

CHANGES FOR PHYSIOLOGICAL SIGNALS

Low physical load Medium Task IV	Low physical load High Task IV	High physical load High Task IV	Arousal	Increase d stress Valence	Increased physical
↑	↑	↑	↑		↑
		↑			↑
↑	↑	↑	↑		↑
↓	↓	↓	↓	↑	↓
	↓	↑		↓	↑
↓	↓	↓	↓		↓
	↓			↓	

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