# Challenges in biocooperative rehabilitation robotics

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*Abstract*—**Psychological states such as mood, motivation and engagement are known to be critical for the success of rehabilitation, and encouraging unmotivated stroke patients improves the likelihood of their eventual recovery. Psychological factors can be incorporated into the closed-loop control of biocooperative rehabilitation systems, augmenting the device with critical information about the patient state. However, in rehabilitation robotics, interpretation of psychophysiological measurements is made complex by the multi-task environment, the presence of strenuous physical activity and patient's damage to the central and autonomic nervous systems. The study examines these challenges and proposes possible solutions for implementation in biocooperative control of rehabilitation robots.**

*Index Terms*—**Rehabilitation robotics, psychophysiology, biocooperative control, sensory fusion.**

## I. INTRODUCTION

Robotic systems for rehabilitation allow objective estimation of the patient's motor performance and functional improvement. However, they do not offer insight into patients' psychological states: mood, motivation, engagement, etc. Such factors are known to be positive to the success of rehabilitation, and encouraging unmotivated stroke patients improves the likelihood of their recovery [1]. The idea of incorporating psychological factors into closed-loop control of biocooperative rehabilitation systems is summarized in [2]. An extended version of the proposed biocooperative controller is shown in Fig. 1. It consists of a fast feedback loop for robot control and a slow feedback loop to adapt the training parameters to each individual patient. The adaptation is done based on real-time estimation of the user state consisting of performance, biomechanical, physiological and psychological features.

Rehabilitation robotics concepts such as *patient-cooperative* and *assist as needed* have extensively focused on performance and biomechanical parameters [3], [4]. These are state-of-the-art systems and the main problems related to their implementation are well-understood. On the other hand, biocooperative robotics additionally relies on psychological data, where no commonly accepted quantitative method of measuring patients' states during rehabilitation exists.

Psychophysiological responses, defined as body's responses (changes in heart rate, skin conductance, breathing frequency, skin temperature, etc.) to psychological stimuli, can be measured constantly without the subject's active cooperation or
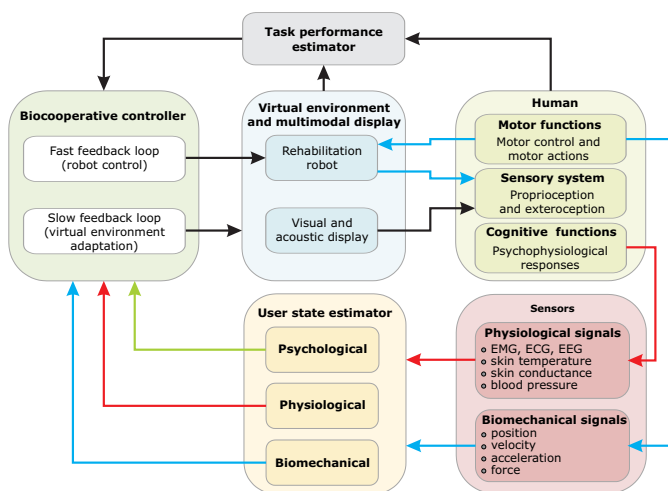
Figure 1.   The biocooperative feedback loop.

even awareness, which makes them ideal for use in biocooperative motor rehabilitation. Researchers have often been using physiological data to try to identify user's psychological states. However, there is no universally accepted set of rules that would translate physiological data to psychological states, which makes the implementation of biocooperative control a major challenge. Aside from theoretical limitations to inferring significance from psychophysiological data [5], there are entirely practical disagreements among psychologists, such as whether psychological states can be classified into discrete, specific emotions [6] or whether they exist among multiple axes in a multidimensional space [7].

Interpretation of psychophysiological responses becomes even more difficult when a person is engaged in a multi-task environment. Tasks that are apparently dissimilar can strongly interfere with each other [8] and in rehabilitation, patients are often faced with a multi-task problem requiring attention for limb motor control while at the same time they are engaged in a more or less complex virtual scenario representing the task.

Psychophysiological measurements in rehabilitation are made additionally complex by two problems that most psychophysiological studies do not need to contend with. The first problem is the presence of strenuous physical activity. Most psychophysiological studies have focused on tasks and situations that require little physical activity. This has been primarily because it is difficult to separate the physiological effects of physical and psychological activity [9]. Although a number

of studies have examined psychophysiological responses to a combination of physical and psychological activity, they have mainly focused on the effects of a mentally demanding task superimposed onto a physically demanding task [10]. Subjects in these studies were thus performing several unrelated tasks at once. In haptic human-robot interaction such as that used in rehabilitation robotics, however, the same task is usually both physically demanding and evokes emotions such as frustration or boredom. This interplay between psychological and physical activity may result in different psychophysiological responses.

The second problem is that motor rehabilitation is often performed with patients who have suffered damage to the central and autonomic nervous systems, and this damage also affects psychophysiological responses. Stroke patients, for instance, show long-lasting abnormalities in sweating and heart rate variability [11]. These differences need to be carefully analyzed and taken into consideration when developing biocooperative rehabilitation systems.

Seeing the challenges originating from the biocooperative robotics approach, the following issues are addressed in the paper: analysis of physiological responses in multi-task environments, analysis of effects of interplay between mental and physical activity on physiological responses and analysis of differences in psychophysiological responses between healthy subjects and hemiparetic patients in a clinical rehabilitation setting. Finally, general concepts for dealing with these challenges are proposed.

## II. METHODS

### A. Experimental setup

The Phantom Premium device (Sensable, Inc.) and HapticMaster robot (Moog FCS) were used as haptic interfaces. The end-point of the HapticMaster was equipped with a force sensor and a two-axis gimbal with a two-degree-of-freedom passive grasping module instrumented with force cells [12]. The subject's arm was additionally supported by two cuffs fastened above and below the elbow in order to compensate for the gravity acting on the subject's arm. Subjects sat in front of the screen, where the task was displayed, with the haptic interface situated between the seat and the screen (Fig. 2).

Physiological signals were sampled at 2.4 kHz using a g.USBamp signal amplifier (g.tec Medical Engineering GmbH). The electrocardiogram (ECG) was recorded using four surface electrodes placed on the torso. Skin conductance was measured using a g.GSR sensor. The electrodes were placed on the medial phalanxes of the second and third fingers of the unaffected hand. Respiratory rate was obtained using a thermistor-based SleepSense Flow sensor placed beneath the nose. Peripheral skin temperature was measured using a g.TEMP sensor attached to the distal phalanx of the fifth finger of the unaffected hand.

A questionnaire in the form of Self-Assessment Manikin [13] was used for comparison of physiological responses to subjects' subjective observations of their psychological state.

### B. Measurement scenarios

Two different virtual scenarios were designed in order to investigate the feasibility of biocooperative approach in robot supported motor rehabilitation. The first scenario requires balancing a virtual version of an inverted pendulum while the second scenario requires catching and placing virtual objects.

*1) Inverted pendulum scenario (IPS):* Subjects were presented with a virtual version of a classic control theory problem, the inverted pendulum attached at its bottom to a moving cart (Fig. 2 above). The cart was moved either using the Phantom or HapticMaster robot, with the goal of keeping the pole from falling. The cart moved in the same direction and with the same velocity as the robot end-effector. Force feedback was also implemented, allowing the subjects to feel the reaction forces resulting from the movement of the cart.

In order to investigate the interplay between cognitive and physical workloads, different levels of cognitive workload were achieved using three different task difficulty levels: underchallenging, challenging and overchallenging. In the underchallenging version, the pendulum was not affected by gravity and thus never fell. The subject was simply asked to move the cart left and right at a moderate speed. In the challenging version, the model dynamics were balanced in such a way as to make the balancing of the pendulum moderately challenging. In the overchallenging version, a half-second delay was introduced between the time the cart was moved and the time the cart's movement affected the pole. This made the task extremely difficult to perform successfully. All the three difficulty levels were implemented in low and high physical load versions. The versions were identical except for one factor: in the high physical load versions, five times more physical force was required to move the robot. Combinations of different levels of cognitive and physical load totaled in six task conditions.

In order to investigate physiological responses in a multi-task environment, an additional task was introduced as a standalone test or simultaneously with the IPS. This was a timed mental arithmetic task with a visual display and verbal user response. The mental arithmetic task presented the participants with two numbers that had to be multiplied. These numbers were randomly generated between zero and thirty for each subject. Four different possible answers were shown. Using speech recognition, the participants verbally chose the answer they believed was correct. The participants had 15 s to answer each question. The time remaining was displayed using a large bar next to the numbers. In the multi-task environment, the difficulty of inverted pendulum balancing was challenging and the physical load was low.

The HapticMaster robot was used as the input device for the task that combined different levels of physical and mental workloads. However, in order to completely eliminate the effect of physical load, the Phantom device was used in place of the HapticMaster robot for the study performed in multi-task environment. Other settings remained unchanged.

*2) Catch and place scenario (CPS):* The scenario combines reaching and grasping exercise (Fig. 2 below). In the center of

the screen, there is a table sloped toward the subject. A ball appears at the top of the slope and starts rolling downward. The subject's goal is to catch the ball before it reaches the lower end of the table. Once the ball is grasped, a basket appears above the table. The subject must then hold the ball and place it in the basket. Once the ball is dropped into the basket or falls off the table, another ball appears at the top of the table and the task continues. The robot allows the subject to feel each virtual item and enables various modes of support. If a subject is unable to perform any or all of the following, the robot will actively guide his or her arm in order to move left or right and reach the ball, squeeze the grasping device in order to grasp the ball, and/or lift the ball into the basket.

A second, harder version of the scenario (henceforth referred to as the harder CPS) was also designed. Meant to be more mentally demanding but equally physically demanding, the harder CPS had inverted left-right controls. If the subject moved his or her arm to the left, the virtual hand on the screen moved right (and vice-versa). In order to investigate the effect of physical activity on physiological responses, a physical control task (CT) was introduced that required movement of the robot end effector with similar velocity and force as during the CPS.

After the completion of the CPS based task, subjects were presented with a task designed for evaluation purposes that required only cognitive effort. A variant of the Stroop word-color interference task [14] was used. Subjects were shown a word on the screen. The word was either *red*, *blue*, or *green*. The color of the letters was also red, blue or green - but the word and the color of the letters did not always match. Subjects were given a keypad with the words *red*, *blue*, and *green* written above the buttons. They were told to ignore the meaning of the word and, as quickly as possible, press the button corresponding to the color with which the word was written.

### C. Signal Processing

The features used in signal processing and user state estimation were divided into three groups:

*a) Biomechanical:* Biomechanical features describe the forces and movements applied by the subjects and include mean absolute force, mean absolute velocity, mean absolute acceleration, total work, mean frequency of the position signal, mean frequency of the velocity signal, mean frequency of the acceleration signal, and mean frequency of the force signal.

*b) Performance:* Performance features are task specific and describe how well a subject performed the task. For the mental arithmetic task and the Stroop test percentage of correct answers was used. In the IPS the performance criterium was the frequency of pendulum falls, while in the CPS the criteria were the percentage of balls successfully caught and the percentage of balls successfully placed into the basket.

*c) Psychophysiological:* From the ECG, eight features were extracted: 1) mean heart rate, 2) the difference between the longest and shortest NN interval (defined as the period of time between two successive normal R-peaks), 3) standard
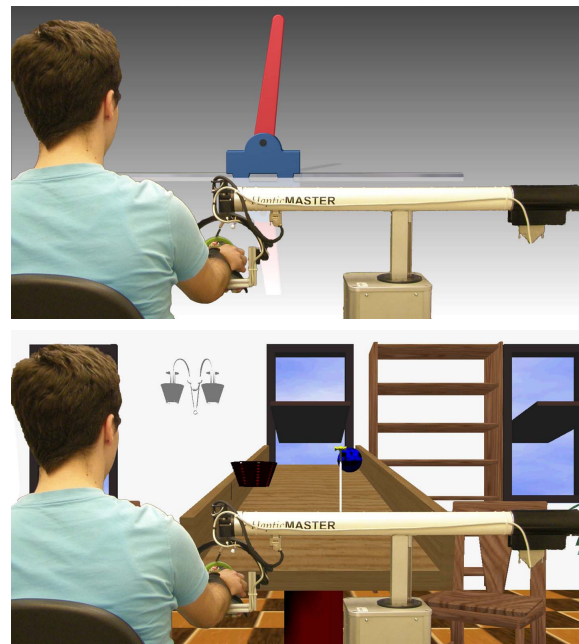


Figure 2. Pendulum balancing scenario (above) and ball catching and placing scenario (below). In multi-task environment the HapticMaster was replaced with the Phantom robot.

deviation of NN intervals (SDNN), 4) square root of the mean square differences of successive NN intervals (RMSSD), 5) the percentage of interval differences of successive NN intervals greater than 50 ms (pNN50), 6) total power in the high-frequency (HF – 0.15 Hz to 0.4 Hz) band of the heart rate signal, 7) total power in the low-frequency (LF – 0.04 Hz to 0.15 Hz) band of the heart rate signal, and 8) the ratio of the two above variables (LF/HF ratio). From the skin conductance signal, three features were extracted: 1) mean skin conductance level (SCL), 2) skin conductance response (SCR, transient increases in skin conductance with amplitude exceeding 0.05 $\mu s$ and peak occurring less than five seconds after the beginning of the increase) frequency, and 3) mean skin conductance response amplitude. From the respiration signal, two features were extracted: mean respiratory rate and standard deviation of respiratory rate. From the skin temperature signal, temperature at the end of the period was extracted.

### D. Participants

Volunteers were recruited for each specific task. Twenty-four healthy male subjects (age range 20-46, mean age 28.0, standard deviation 6.6 years) participated in multi-task experiment. Thirty healthy subjects (age range: 19-46 years, mean 26.2, standard deviation 5.8, seven were female) participated in the experiment trying to identify influence of physical activity on physiological responses. In a study comparing physiological responses of patients and healthy subjects the stroke group consisted of 23 subjects (age $51.0 \pm 13.3$ years, age range 23-69 years, 16 males, 7 females). They were diagnosed with subarachnoid hemorrhage (4 subjects), intrac-

erebral hemorrhage (9 subjects) or cerebral infarction (10 subjects). The control group consisted of 23 subjects (age $50.5 \pm 12.6$ years, age range 24-68 years, 16 males, 7 females) with no major physical or cognitive defects.

## III. RESULTS AND DISCUSSION

Due to the large number of features being observed, not all are presented in this section. Presentation of results emphasizes challenges related to biocooperative robotics.

### A. Subjects' responses in multi-task environments

During the mental arithmetic task, participants correctly answered 80.4% of questions. The time needed to answer a question was $7.7 \pm 3.9$ s. When performing both tasks simultaneously, participants correctly answered 73.3% of questions. The time needed to answer a question was $8.5 \pm 4.8$ s. Without participant input, the inverted pendulum fell every 6.0 s. When balanced by participants, it fell every $19.2 \pm 5.4$ s. When the participants performed both tasks simultaneously, the pendulum fell every $13.5 \pm 7.6$ s.

Two psychophysiological parameters that exhibit particularly significant differences between task types are shown as box plots (median value, box edges – 10th and 75th percentiles, whiskers – 25th and 90th percentile) in Figs. 3 (mean SCL) and 4 (final skin temperature). The first box plot in each figure presents the results of measurements obtained while the subject was only moving a robot without a task.
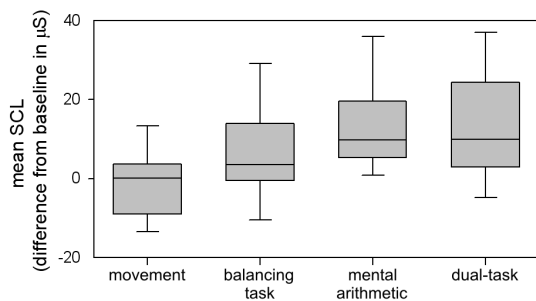


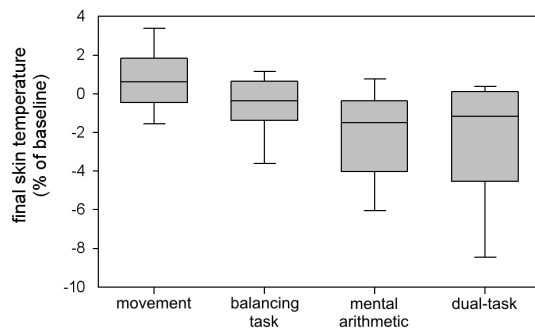Figure 3.  *Mean SCL* during different tasks as a percentage of baseline value.



Figure 4.  *Final skin temperature* during different tasks as a percentage of baseline value.

In multi-task environments performance, is clearly affected when performing two tasks at once. Performance can thus

provide an estimate of the subject's mental (over)load. In multimodal human-computer interaction, psychophysiological responses are sensitive not only to interindividual differences, but also exhibit significantly different responses to different tasks even though participants in questionnaires report no significant subjective differences (questionnaire results are not presented here). When participants do feel significant subjective differences, however, these may not be evident in psychophysiological responses. In multitasking situations, psychophysiological measures could fail altogether as some mental resources become overloaded. This complexity also suggests that simple interpretation rules may be insufficient to accurately identify psychophysiological states, since even small changes in task parameters result in significantly different responses. At the very least, a combination of multiple parameters (including performance as a non-physiological one) is likely to be necessary.

### B. Changes in subjects' responses due to variations in physical and cognitive workload

For low physical load, the pendulum was reset $3.2 \pm 1.3$ times per minute during the challenging condition and $5.6 \pm 1.0$ times per minute in the overchallenging condition. For high physical load, the pendulum was reset $2.8 \pm 0.9$ times per minute in the challenging condition and $5.4 \pm 1.2$ times per minute in the overchallenging condition. Differences between challenging and overchallenging conditions were significant (p < 0.001) for both levels of physical load. Differences between low and high physical load were not significant for either difficulty level.

Introduced primarily as a measure of physical load, mean absolute force was not equal for all the three difficulty levels. For low physical load, mean absolute force was $3.1 \pm 6.9$ N in underchallenging, $1.0 \pm 2.7$ N in challenging and $1.4 \pm 3.6$ N in overchallenging condition. For high physical load, it was $17.1 \pm 6.9$ N in underchallenging, $6.8 \pm 3.5$ N in challenging and $7.4 \pm 2.9$ N in overchallenging condition. For both levels of physical load, it was significantly higher in the underchallenging condition than in the other two conditions.

The physiological effects of physical load were evaluated by comparing relative values between the low and high physical load conditions for each difficulty level (the underchallenging task with low physical load was compared to the underchallenging task with high physical load and so on). Differences between difficulty levels are illustrated with relative values of two representative physiological parameters: mean heart rate (Fig. 5) and respiratory rate variability (Fig. 6). More detailed results can be found in [15].

Investigation of differences between difficulty levels shows that many psychophysiological parameters differentiate between baseline and task, but only three parameters showed significant differences between difficulty levels regardless of the level of physical load. For both low and high physical load, mean respiratory rate showed a significant difference between underchallenging and the other two conditions while final skin temperature and respiratory rate variability showed a signifi-
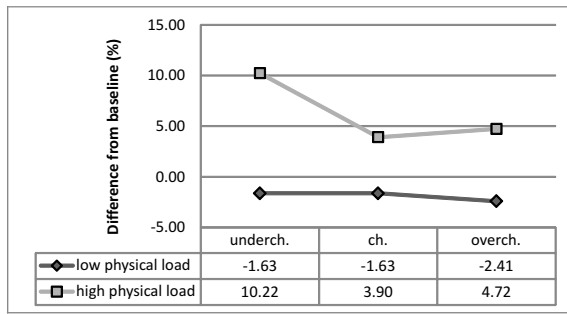
Figure 5. Mean relative values of *mean heart rate* as a function of task difficulty. Underch. = underchallenging, ch. = challenging, overch. = overchallenging.
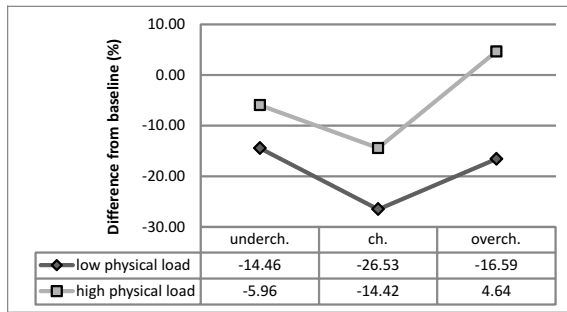


Figure 6. Mean relative values of *respiratory rate variability* as a function of task difficulty. Underch. = underchallenging, ch. = challenging, overch. = overchallenging.

cant difference between the challenging and overchallenging conditions.

Investigation of differences influenced by physical workload shows that skin temperature, in particular, seems the least affected by physical load. While respiration does not show significant differences between low and high physical load, non-significant differences are clearly visible in the corresponding figure. Though heart rate has been used as a psychophysiological indicator in many studies, our results suggest that, in haptic interaction, it is primarily influenced by physical load. By far the greatest increase in mean heart rate was during the underchallenging condition (Fig. 5), where the exerted force was the greatest. In all conditions with high physical load, mean heart rate was significantly higher than in the corresponding conditions with low physical load. Thus, it appears that the increase in heart rate due to physical workload can completely overshadow any psychological effects. Heart rate could at least be used as a measure of physical effort.

## C. Differences between healthy subjects and stroke patients

Damage to the central and autonomic nervous systems is known to affect psychophysiological responses. Two examples are shown to illustrate the issue. Analysis of mean SCL (Fig. 7) found significant differences between physical control task, CPS and harder CPS tasks ($p < 0.05$ for all three pairwise comparisons). There were no significant differences between healthy subjects' and patients' responses. Analysis of final skin temperature (Fig. 8) found an effect of task type ($p = 0.01$).

In the stroke group, temperature in the normal CPS task was lower than in both the physical control task and the harder CPS task. In the control group, temperature in the harder CPS task was lower than in the physical control task and the normal CPS task, indicating an opposite response with regard to the stroke patients. As evidenced also by the results from the Stroop task, the mean SCL responds similarly in healthy subjects and stroke patients, while final skin temperature shows just opposite trends. More detailed results can be found in [16].
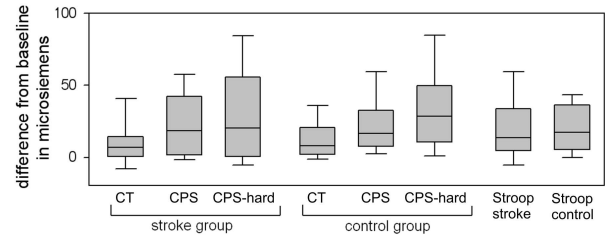


Figure 7. Changes in *mean SCL* as a response to different tasks. CT = physical control task, CPS = normal catch and place task, CPS-hard = harder catch and place task.
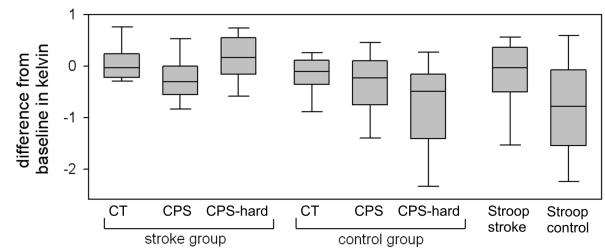


Figure 8. Changes in *final skin temperature* as a response to different tasks. CT = physical control task, CPS = normal catch and place task, CPS-hard = harder catch and place task.

Of the examined psychophysiological measures, skin conductance appears to be the most useful for patient state assessment. Skin conductance level differentiated between the physical control task, the normal CPS task and the harder CPS task while skin conductance response frequency was correlated with self-reported arousal for both the stroke group and the control group. Additionally, skin conductance sensors are very easy to use. Skin temperature, which is also simple to use, shows different responses in the stroke and control groups. It also responds to stimuli much more slowly than skin conductance.

## IV. SUMMARY AND CONCLUSIONS

The paper summarizes main issues related to psychophysiology that need to be considered properly when designing biocooperative controllers for motor rehabilitation. Challenges are such that cannot be simply avoided and have to be dealt with. However, there are no general guidelines applicable in all cases. Namely, psychophysiological responses are significantly affected by the type of motor activity, parameters of training scenario (task), patient's pathology, environmental conditions

and many other factors. Nevertheless, some practical considerations could be summarized as follows.

Due to theoretical limitations to inferring significance from psychophysiological data and challenges presented in this study, mapping from physiological measurements to quantitative description of user's psychological state should be avoided when possible. Nonexistence of standardized procedures for inferring psychological state from physiological data affected by *noise* inherent to rehabilitation setting results in unreliable observations that are not suitable for biocooperative control. Mapping from physiological measurements, in combination with biomechanical and performance data, to task related user's state observations should be considered instead. This would enable direct estimation of task appropriateness for a specific patient without first estimating his or her psychological state. Unfortunately, this makes mapping task specific (desired overfitting), but due to complex psychophysiological interactions a general solution is probably not feasible anyway.

In robot-supported rehabilitation, patients are usually challenged by at least two factors. The first is the attention a patient needs to address to motor control of the affected limb. Due to a central nervous system lesion, the movement cannot be performed unconsciously anymore. The second factor is the virtual task that is used to engage the patient in training. Due to different motor and cognitive abilities of patients, the interplay between the two factors causes different psychophysiological responses of individual subjects. The issue is inherent to robot-supported therapy and cannot be avoided. Partial solution would consist of fitting the user state estimator to the specific task being used for motor rehabilitation. However, in order to address intersubject differences, an adaptive version of the estimator algorithm should be considered.

During motor rehabilitation, the patient's physical activity is very much desired and stimulated by the system. The level of physical effort differs in relation to the body part being exercised. For upper extremity rehabilitation, physical effort is generally lower than during lower extremity training. Such are also effects of physical activity on physiological measurements. These effects often cannot be neglected and have to be taken into consideration when developing biocooperative control strategies. In order to compensate for the effect of physical activity on heart rate during training of walking, a model-based approach has been proposed in [17].

Differences in physiological responses of healthy subjects and stroke patients were observed in response to similar motor and cognitive challenges. This means that the biocooperative controller cannot be designed and validated on healthy subjects and then transferred to patients. In the patient group, large intersubject differences can also be expected, due to different central and autonomous nervous system lesions. Consequently, performance of a biocooperative controller designed for a specific patient would likely be unsatisfactory when used with a different person. If psychophysiological measurements are to be implemented in a biocooperative controller, an adaptive approach would most likely be necessary.

Seeing the complexity of processing and classification of psychophysiological measurements, it is evident that a combination of various features, such as biomechanical measurements and performance indices in combination with psychophysiology, is likely to produce the most reliable results. Kalman adaptive linear discriminant analysis was proposed in [18] as a patient-specific solution for combining multiple features into a patient state estimate. However, the value of each individual feature in a specific rehabilitation scenario needs to be assessed first and only used if its contribution outweighs the complexity of its use. Psychophysiology is relevant, but also cumbersome for use and its inclusion in biocooperative control should be well justified.

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