DYNAMIC DIFFICULTY ADJUSTMENT OF REHABILITATION TASKS THROUGH REAL-TIME EMOTION FEEDBACK AND PERFORMANCE

by

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Submitted to Graduate School of Nature and Applied Sciences

in Partial Fulfillment of the Requirements

for the Degree of Doctor of Philosophy in

Electrical and Electronics Engineering

Yeditepe University

2019

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ACKNOWLEDGMENTS

I would like to express my tremendous gratitude to my advisor Professor Duygun Erol Barkana, for her continuous support and help in all the time of research and writing of this thesis. Her wise supervision has been an encouraging experience which provided a broad scientific vision and guided me through the pleasure of learning.

I would like to thank all my family for their support during my education and research period. Especially I am grateful to my dear wife Dr. Seda Arslan Özkul for her endless love and patience.

This study is supported by the Scientific and Technological Research Council of Turkey (TUBITAK) under Grant 114E614.

ABSTRACT

DYNAMIC DIFFICULTY ADJUSTMENT OF REHABILITATION TASKS THROUGH REAL-TIME EMOTION FEEDBACK AND PERFORMANCE

The decision of proper difficulty level for patients in robot-assisted rehabilitation while keeping them engaged is still an open challenge. We develop an adaptive robot-assisted rehabilitation therapy to challenge the subjects by changing the difficulty level of the rehabilitation task considering their performance (score) (Performance Feedback Based Adjustment (PFBA)), their emotions through physiological signals (skin conductance) (Physiological Feedback Based Adjustment (PHFBA)), and both performance and emotions at the same time (Performance and Physiological Feedback Based Adjustment (PPFBA)). The concept is evaluated in 20 healthy subjects performing the tasks with an upper-extremity exoskeleton RehabRoby. The system adapts difficulty levels of the tasks by maintaining the subject's performance, and skin conductance at a moderate level to balance the engagement, and challenge for each subject. The mean difficulty level distribution showed that PHFBA on the average suggests slightly easier difficulty levels (2.62±0.43, mean±std) to the subjects than PFBA (5.93±0.88, mean±std) and PPFBA (3.99±0.38, mean±std). Easier difficulty level adjustment resulted in less engaged subjects and correspondingly lower subjects' skin conductance response (SCR) (9.35±8.9, mean±std) and heart rate (HR) (89.27±9.35, mean±std) values in PHFBA compared to PFBA and PPFBA. Additionally, easier difficulty level adjustment resulted in lower valence value (5.7±0.95, mean±std), arousal (5.45±1.6, mean±std) and dominance (5.9±1.5, mean±std) subjective ratings in PHFBA compared to PFBA and PPFBA. It was also noted that the difficulty variance of PPFBA (4.97±2.06, mean±std) was higher than PFBA (1.48±0.49, mean±std) and PHFBA (3.52±1.41, mean±std) which meant that PPFBA offered wider levels to each subject. A wider variety of difficulty level suggestions might increase the amazement experienced by the subject, and the subject might become more engaged in the rehabilitation task, and consequently, $Mean_{temp}$ value in PPFBA (1.33±1.5, mean±std) was lower than the PFBA (2.39±1.78, mean±std) and PHFBA (2.03±1.58, mean±std).

ÖZET

DUYGU DURUMU VE PERFORMANSIN GERÇEK ZAMANLI GERİBİLDİRİMİ ARACILIĞIYLA REHABİLİTASYON EGZERSİZLERİNİN ZORLUK DÜZEYİNİN DİNAMİK OLARAK AYARLANMASI

Robot destekli rehabilitasyonda hasta motivasyonunu yüksek seviyede tutacak uygun zorluk düzeyinin belirlenmesi hala ilerlemeye açık bir araştırma konusudur. Üç farklı geribildirim yöntemi ile rehabilitasyon egzersizinin zorluk düzeyini değiştirerek denek motivasyonunu yüksek seviyede tutmayı amaçlayan robot destekli bir rehabilitasyon sistemi geliştirilmiştir. Yöntemlerden ilkinde deneklerin performansına (skor) göre (Performans Geribildirim Tabanlı Ayarlama (PGTA)), ikincisinde fizyolojik sinyaller yoluyla (deri iletkenliği) duygu durumuna göre (Fizyolojik Geribildirim Tabanlı Ayarlama (FGTA)), sonuncusunda ise aynı anda hem performans hem de duygu durumuna göre (PFGTA) bir değerlendirme yapılmaktadır. Konsept bir üst ekstremite eksoskeleton robotu olan RehabRoby üzerinde egzersizleri gerçekleştiren 20 sağlıklı denek ile değerlendirildi. Sistem, motivasyon durumunu dengelemek ve aynı zamanda kişiye özgü zorlayıcı olabilmek için deneklerin performans ve deri iletkenliği değerlerini orta seviyelerde tutacak şekilde egzersiz zorluk düzeylerini adapte etmektedir. Ortalama zorluk seviyesi dağılımına bakıldığında FGTA' da deneklere sunulan zorluk seviyelerinin (2.62±0.43, ortalama+standart sapma), PGTA (5.93±0.88) ve PFGTA' ya (3.99±0.38) göre biraz daha kolay olduğu görülmektedir. Deneklere daha kolay zorluk seviyesi sunulmasıyla FGTA' da PGTA ve PFGTA' ya göre daha düşük deri iletkenliği cevabı (9.35±8.9) ve daha düşük kalp atış hızı (89.27±9.35) değerleri, buna bağlı olarak da deneklerin daha az motive olduğu gözlemlenmiştir. Ayrıca daha kolay zorluk seviyesi ayarının bir sonucu olarak FGTA' da PGTA ve PFGTA' ya kıyasla daha düşük değerlik (5.7±0.95), uyarılma (5.45±1.6) ve baskınlık (5.9±1.5) öznel derecelendirmeleri görülmüştür. PFGTA' nın zorluk düzeyi varyansının (4.97±2.06), PGTA (1.48±0.49) ve FGTA' ya (3.52±1.41) göre yüksek olduğu görülmektedir. Zorluk düzeyinde daha geniş bir aralıktaki çeşitlilik deneğin yaşadığı şaşkınlık durumunu arttırarak daha motive bir rehabilitasyon süreci sağlayabilmektedir. Buna bağlı olarak PFGTA' daki Mean_{temp} değeri (1.33±1.5), PGTA (2.39±1.78) ve FGTA' ya (2.03±1.58) oranla daha düşük olarak saptanmıştır.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS/ABBREVIATIONS

A_i, B_i, C_i, E_i	State-space model matrices
A_t	Belief for all difficulty levels that are difficult than the current level
b	Damping parameter of admittance filter
B_t	Belief for all difficulty levels that are easier than the current level
$b(\dot{q})$	Friction
BVP_{tp}	Blood volume pulse total power
d'	Disturbance vector
$Deriv_{bvp}$	First derivative of blood volume pulse
$Deriv_{sc}$	First derivative of skin conductance
$Deriv_{temp}$	First derivative of temperature
G(q)	Gravity
HF_{norm}	High frequency norm
I	Inertia parameter of admittance filter
i_{ci}	Feedforward compensating signal
i_{di}	Disturbance
k_{di}	Derivative gain
K_i	State-feedback gain matrix
LF_{norm}	Low frequency norm
L_i	Current difficulty level
L_{new}	New difficulty level
$m[n]$	Backward difference between the adjacent elements of $x[n]$
$\hat{m}[n]$	Backward difference between the adjacent elements of $\hat{x}[n]$
M(q)	Inertia tensor
$Mean_{bvp}$	Mean blood volume pulse
$Mean_{IBI}$	Mean inter-beat interval
$Mean_{sc}$	Mean skin conductance
$Mean_{temp}$	Mean temperature
per_{HF}	Percentage ratio of high frequency
per_{LF}	Percentage ratio of low frequency
per_{VLF}	Percentage ratio of very low frequency

P_i	Current performance score rate
q	Joint position
$\dot{q}$	Joint velocity
$\ddot{q}$	Joint acceleration
std	Standard deviation
Std_{IBI}	Standard deviation of inter-beat interval
τ	Joint torque
τ_{ext}	Torque (unknown external effects)
$\tau[n]$	Applied torque
T_s	Sampling time
u_{di}	Equivalent disturbance
u_i	Control input
$V(q, \dot{q})$	Coriolis and centrifugal
Var_{bvp}	Variance of blood volume pulse
Var_{sc}	Variance of skin conductance
Var_{temp}	Variance of temperature
v_i	Measurement noise
w_t	Belief about the correctness of each difficulty setting
x_i	State vector
$x[n]$	Actual angular position
$\hat{x}[n]$	Reference angular position
y_i	Measured output
$\triangle SCH$	Difference between high threshold and calculated values of $Mean_{sc}$
$\triangle SCL$	Difference between low threshold and calculated values of $Mean_{sc}$
$\triangle SH$	Difference between high threshold and calculated values of score
$\triangle SL$	Difference between low threshold and calculated values of score
θ_i	Joint angle of RehabRoby
ε	Motion range
BVP	Blood volume pulse
BDAPS	Biofeedback data acquisition and processing software
CP	Cerebral palsy

FFT	Fast Fourier Transform
FIS	Fuzzy inference system
FMRL	Fuzzy model reference learning
FS1	Force sensor 1
FS2	Force sensor 2
HF	High frequency
HR	Heart rate
HRV	Heart rate variability
LF	Low frequency
LKF	linear Kalman filter
PFBA	Performance feedback based adjustment
PHFBA	Physiological feedback based adjustment
POSM	Partially ordered set master
PPFBA	Performance and physiological feedback based adjustment
SAM	Self-assessment manikin
SC	Skin conductance
SCR	Skin conductance response
ST	Skin temperature
VLF	Very low frequency

1. INTRODUCTION

This section firstly presents the problem statement. After, the aim, research contribution, and the outline of the dissertation are given, respectively.

1.1. PROBLEM STATEMENT

The participation of the patients actively is shown to improve the rehabilitation outcome [1], [2], [3]. Designing rehabilitation tasks that are neither simple nor too difficult are important to increase the engagement of the patients [4]. The selection of the difficulty level of the rehabilitation and changing this level during the therapy are generally made by the experienced therapist in the clinical environments [5]. Robot-assisted rehabilitation systems decide the proper difficulty level by looking at the performance of the patients. Robot-assisted rehabilitation systems have shown to monitor the performance of the patients continuously, and adapt the rehabilitation task intensity and difficulty at each session or trial to optimally challenge them [6].

Various approaches had previously been proposed to adjust the difficulty of the rehabilitation task considering the patient's abilities during robot-assisted rehabilitation. A well-known approach is the assist-as-needed in where the assistance given to the patients is decreased progressively; thus, the task difficulty increases to engage, and challenge these patients [7]. The modulation of the assistance is decided considering the active participation of the patients, and the performance which is measured using muscle activity or interaction forces. The spatiotemporal parameters of the rehabilitation task such as increment of reaching positions [6], [8], increment of the complexity of the movement [6], or a decrement of time to complete the rehabilitation task [9] had also been modified without changing the level of the support given by the robot-assisted rehabilitation system to adjust the difficulty.

There are little research going on robot-assisted rehabilitation that considers the emotions of patients by looking at their physiological signals to adjust the difficulty level of the rehabilitation task [10]. The human-in-the-loop approach had previously shown to find the suitable challenging level that increases the engagement of the subjects [11]. Motor learning and thereby, the training efficiency had also shown to increase when human emotions had been used in the closed-loop [12], [13]. The facial expression, electroencephalogram, voice, body gestures or physiological signals had previously been used to understand the emotions of the individuals [10], [14], [15], [16], [17] during human-robot interaction.

We develop an adaptive robot-assisted rehabilitation therapy to challenge the subjects by changing the difficulty level of the rehabilitation task considering their performance (score) (Performance Feedback Based Adjustment (PFBA)), their emotions through physiological signals (skin conductance) (Physiological Feedback Based Adjustment (PHFBA)), and both performance and emotions at the same time (Performance and Physiological Feedback Based Adjustment (PPFBA)) when they are performing the rehabilitation task using an upper-extremity exoskeleton RehabRoby.

1.2. AIM OF THE DISSERTATION

The aim of this dissertation is first to develop an adaptive robot-assisted rehabilitation therapy to challenge the subjects by changing the difficulty level of the rehabilitation task considering performance, emotion feedback through physiological signal (skin conductance), and both performance and emotion at the same time, and then evaluate the adjustment for each feedback by looking at the performance (score), emotions through physiological signals (skin conductance, blood volume pulse and skin temperature), and subjective ratings (arousal, valence and dominance).

1.3. RESEARCH CONTRIBUTION OF THE DISSERTATION

All in all, research on robot-assisted systems that are capable of not only detecting the patient’s performance but also inferring patient’s internal state, and then dynamically adjusting the difficulty level of the rehabilitation task to better suit the patients' feelings and performance have gained momentum in the recent years. We develop a dynamic difficulty adjustment mechanism for upper limb exoskeleton RehabRoby that can dynamically find the suitable challenge level while keeping the patients engaged throughout the entire duration of the rehabilitation task with this dissertation. Such an adjustment mechanism can be used for other robot-assisted rehabilitation systems within the limits of device capabilities, and can easily be integrated into other rehabilitation tasks. The main contributions of this dissertation are: 1) augmenting a robotic rehabilitation system that can provide dynamic difficulty adjustment mechanism to potentially enhance engagement in a subject, and 2) testing how this augmented system works, and how one can explore the impact of different dynamic difficulty adjustment algorithms using this augmented system using physiological signals, performance and survey ratings. We believe that such a comparison will pave the way for an optimal approach to robot-assisted rehabilitation.

1.4. OUTLINE OF THE DISSERTATION

The introduction of the thesis is given in Section 1. The literature review of the upper limb robot-assisted rehabilitation systems, difficulty level adjustment methods used for rehabilitation purposes, and physiological sensory feedback types are presented in Section 2. The methodology of the study is explained in Section 3. The details of the mechanical design, electrical design, and control architecture of RehabRoby are given in Section 3.1. The physiological data collection, feature extraction, and feature selection are presented in Section 3.2. The rehabilitation task called fruit picker game, which has been used to evaluate the proposed adjustment mechanism, is described in Section 3.3. The dynamic difficulty adjustment mechanism details are presented in Section 3.4. In Section 4 experimental set-up, the subjects and the experimental procedure are provided. The results of the experiments and discussion are given in Section 5. The conclusions of the proposed study are presented in Section 6. In Section 7, the limitations and future work of the study are provided.

2. BACKGROUND

In this section background information about robotic devices for rehabilitation, difficulty level adjustment methods for rehabilitation games, and physiological sensory feedback is presented.

2.1. ROBOTIC DEVICES FOR UPPER LIMB REHABILITATION

Use of robotic devices for upper limb rehabilitation has shown to improve the movements of the patients [18], [19]. Various robotic systems have been developed to only assist shoulder movement [20] or elbow movement [21], [22] or both should and elbow movement movements [23], [24], [25], [26], [27], [28], [29], [30] and [31] or shoulder, elbow and forearm movements [32], [33], [34]. Additionally, robotics devices have been developed to provide assistance to movements of shoulder, elbow, forearm and wrist together [35], [36], [37], and whole arm [38], [39], [40]. A survey on robot-assisted upper limb rehabilitation systems has been given in [41].

The developed robotic devices can be grouped as end-effector based or exoskeleton based considering their mechanical design. Patient's extremity is contacted to the robotic device only at its most distal part in the end-effector based robotic device. This makes the structure of the robotic device simpler, and as a result, less complicated control algorithms are needed to control the robotic device. However, it is hard to segregate definite movements of a specific joint because end-effector based devices produce combined joint movements. The end-effector-based systems consist of serial manipulators such as MIT-Manus [42] (Figure 2.1), ACRE [43], and parallel manipulators such as CRAMER [44], and cable-driven robots such as NeReBot [30] (Figure 2.2), MACARM [45], RehabExos [34], MEMOS [29], PLEMO [46], ARM Guide [24] and ARC-MIME [23]. MIT- MANUS [42] is one of the well-known end-effector based robotic devices which can provide assistance to shoulder and elbow movement in a horizontal plane, and patients can do repetitive reaching exercises (Figure 2.1). Another end-effector based robotic device NeReBot [30] provides assistance for flexion and extension, pronation and supination, adduction and abduction, circular movements of shoulder and elbow exercises (Figure 2.2). ARM Guide [24] uses graphical feedback of the hand position to provide feedback on the amount of motor assistance (Figure 2.3).

Figure 2.1. MIT-MANUS [42]

Figure 2.2. NeReBot [30]

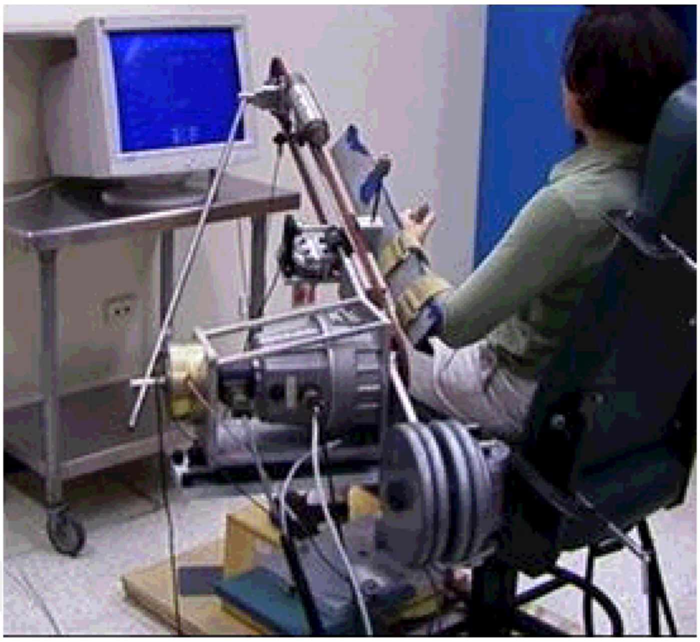


Figure 2.3. ARM Guide [24]

It is also possible to control the movements of each joint separately in exoskeleton based robotic devices. Note that the mechanical design of an exoskeleton based devices is more complicated than an end-effector based devices. There is a need to adjust the lengths of each link of the related joint considering the length of the related link of the user arm in the exoskeleton based device to avoid patient injury. Additionally, the position of the center rotation of the human body joints can change significantly during movement (especially the shoulder joint movement [20]). IntelliArm [47] (Figure 2.4) are one of the exoskeleton based devices that have a higher number of degrees of freedom. ARMin V is one of the well-known exoskeleton robotic devices that has been widely used in hospitals (Figure 2.5) [48].

Some of the end-effector based robotic devices are integrated with the wrist mechanism to increase the movement capabilities of the robotic devices. MIME-RiceWrist device [49] and MIME (end-effector based device) [50] are integrated with a parallel wrist mechanism (Figure 2.6).

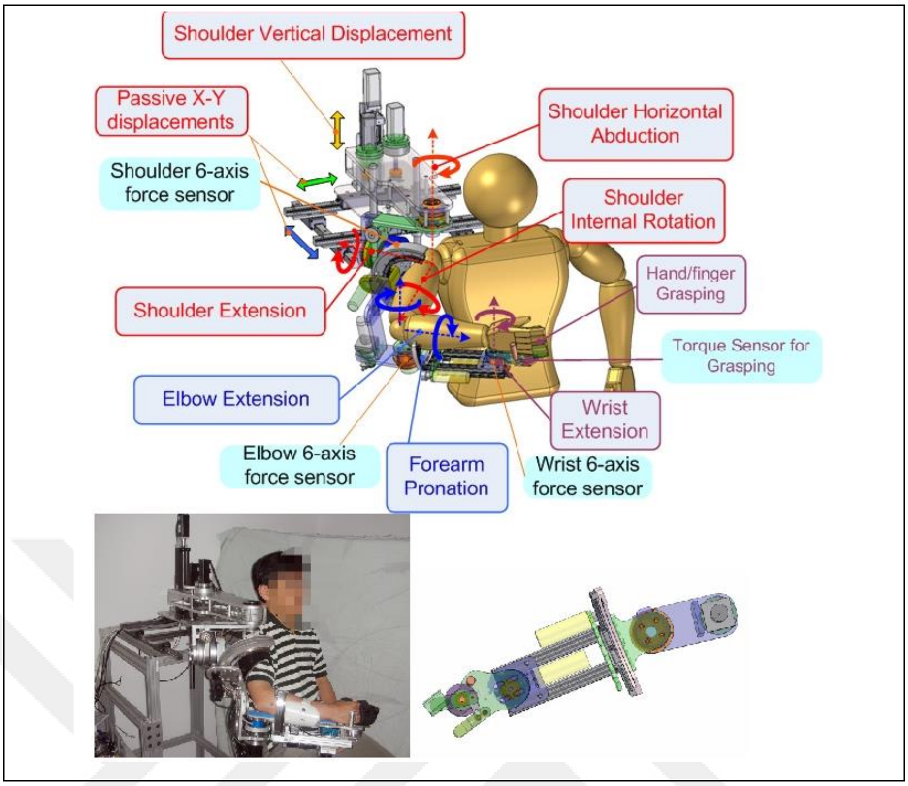


Figure 2.4. IntelliArm [47]

Figure 2.5. ARMin V [48]

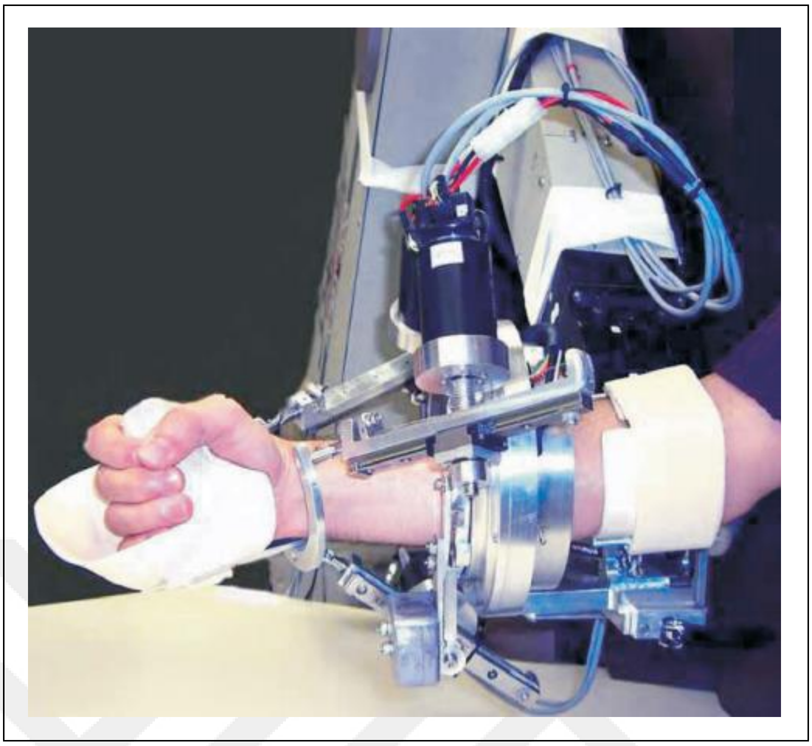


Figure 2.6. MIME-RiceWrist [49]

ArmeoSpring system (Hocoma AG), BONES [26] (Figure 2.7), 6 degrees of freedom Gentle/S [32] (Figure 2.8), 9 degrees of freedom Gentle/G [51], HEnRiE [52] are the other exoskeleton based robotic devices developed for upper limb rehabilitation. Dampace [27] (Figure 2.9), L-Exos [33], RUPERT IV [36], and ARMOR [39] are also well-known exoskeleton robot-assisted rehabilitation systems. Gentle/S [32] is an exoskeleton based robotic device that uses virtual reality and haptic interface as feedback, and patients can practice hand to mouth and reaching movements with this robot.

End-effector based and exoskeleton based approach have also been combined in some of the robotic devices. REHAROB [31], iPAM [53] and UMH [54] (Figure 2.10) are examples of these robotic devices. The patient executes the exercises slowly with constant velocity, and passive assistance is given to the patient when using REHAROB [31].

We have developed an exoskeleton based upper limb robotic device, which is called RehabRoby [55], [56] in Yeditepe University Robotics Research Laboratory (Figure 2.11). The details of RehabRoby will be given in Chapter 3.

Figure 2.7. ArmeoPower (Hocoma AG)

Figure 2.8. Gentle/S [32]

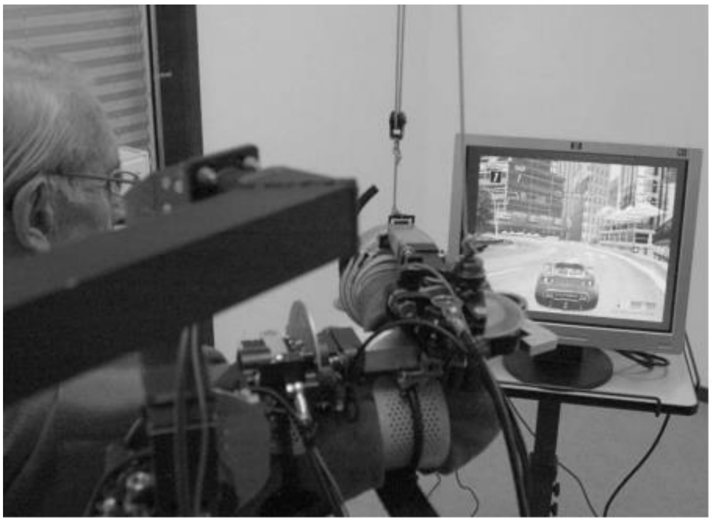


Figure 2.9. Dampace [27]

Figure 2.10. UMH [54]

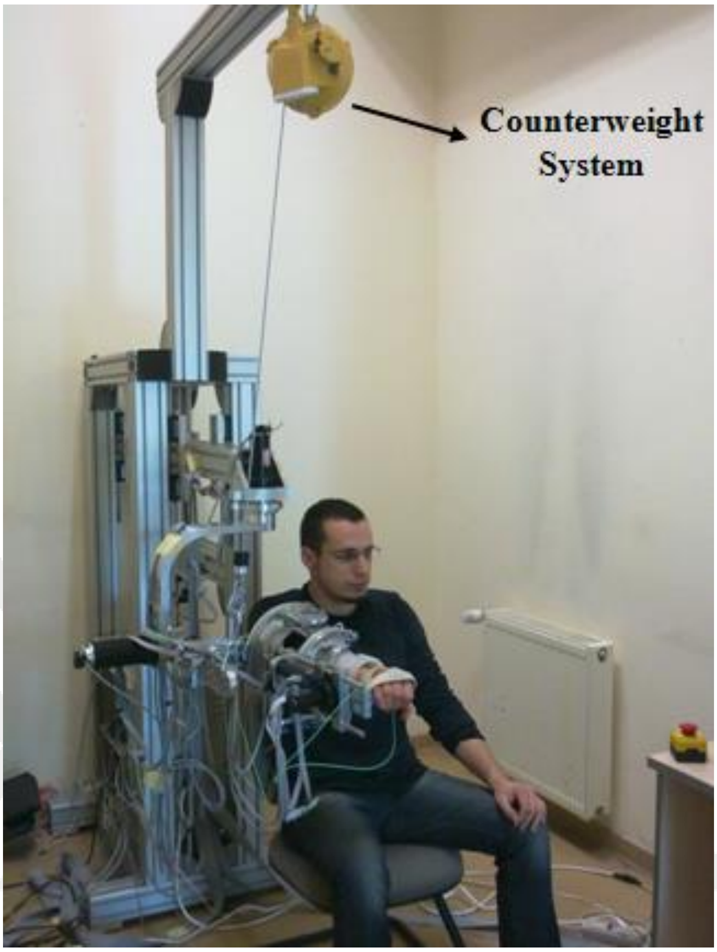


Figure 2.11. Robot-assisted rehabilitation system RehabRoby

2.2. DIFFICULTY LEVEL ADJUSTMENT FOR REHABILITATION THERAPY GAMES

Engagement and positive feelings of patients have shown to increase the outcome of the rehabilitation [2], [12], [13]. Games have been used to increase the engagement of the patients by encouraging them to get involved in the rehabilitation program [57], [58]. The patients' range of movements have previously been increased/decreased to raise the engagement of the patients when games are used in their rehabilitation [59]. The subjects' attention has shown to be longer than traditional and tracking exercises when games are used that resulted in engagement increment [60].

Various, principles have been extracted for an effective game design to increase user's engagement, and motivation such as reward, optimal challenge, feedback, etc. [61]. Challenging level of rehabilitation task in terms of games has been a good indicator for motor learning of the patients [62]. Additionally, it has been noticed that the learning rate of a motor task has been maximum when the difficulty level of the rehabilitation game is selected in such a way that it positively challenges the subject [63]. Thus, it is important to define the best challenging level of the rehabilitation task for each subject during the therapy.

Subjects can be kept at the upper limit of their ability by manipulating difficulty level in different ways (for example, making things faster if speed is the critical component) in games to avoid boredom and frustration. It is also possible that the subject may find the rehabilitation game difficult (his/her lacks of ability), then he/she can become frustrated and quit the rehabilitation task [64]. Likewise, the subject may find the game easy, and he/she can get bored and not interested in completing the rehabilitation task [64]. The performance (score), and the success rate of the subject can be used to understand if the defined difficulty level for the rehabilitation is appropriate for that subject.

A rehabilitation game difficulty level should balance the defined challenges with the skills of the subject to keep their engagement level high according to the flow theory [64]. Various offline difficulty level adjustment techniques proposed for rehabilitation games are used in upper limb robotic rehabilitation systems [65]. The difficulty levels are initially predefined at the beginning of the rehabilitation task and presented to the subject. Then, the challenges are presented with increasing difficulty to establish a correspondence with the subject's skill evolution. Subjects access new difficulty levels when their skills improve. For example, the distance to reach the goal points is gradually enlarged to increase the difficulty level of the rehabilitation task. The same difficulty increment level has generally been used for all subjects that which do not take into account subjects' performance. However, it is important to maintain a suitable rehabilitation game difficulty level for each subject, considering the subjects' game performance and abilities.

A reinforcement learning approach (Q-learning algorithm) has previously been used to dynamically model the subject skills and match the game difficulty during the use of a robotic rehabilitation system [66]. Q-learning algorithm has modified game parameter (i.e., fall down velocity and the appearing frequency of an object). This algorithm evaluates the skills of subjects by looking at their performance. The evolutionary algorithm has also been proposed to modify the game parameters (i.e., distance from the player and speed) dynamically during the use of a robot-assisted rehabilitation system [67]. An adaptive game technique, which is used to adjust the difficulty dynamically considering the patient's abilities and performance, has shown to increase the movement amplitude of patients [68]. An intelligent game engine, which has been based on a search Bayesian model established on patient's performance (i.e., the hit ratio), has been proposed for home rehabilitation [69]. Furthermore, the level of therapy difficulty has generally been adjusted using the increase by one level - decrease by one method by looking at the patients' performance [70]. Increase by one level - decrease by one method has been used for the I-TRAVLE robotic system to adjust the difficulty level of the rehabilitation game [71]. We use a partially ordered set master (POSM) algorithm of difficulty level adjustment of RehabRoby in this dissertation. The details of the POSM algorithm will be given in Chapter 3.

2.3. PHYSIOLOGICAL SENSORY FEEDBACK

Various physiological sensors have previously been used to understand the emotions and feelings of people. Skin Conductance (SC) has commonly been used to serve as an indication of affect and emotion in psychology and related disciplines [72]. SC has also been used in controlled experiments to measure arousal while subjects experienced a variety of emotions such as stress, excitement, boredom, and anger [73]. Additionally, SC measurements have been used to differentiate anger and fear emotions [74]. A linear relationship between skin conductance response (SCR) and the emotional feature of arousal has been found [75]. The emotion strain has shown to be changed based on the number of SCR [76], [77]. The stress level of people has also been detected using SC when people are performing various tasks [76]. Furthermore, the SC value has shown to increase when the difficulty level of the task changed from low to medium [78]. Heart rate (HR) is the other physiological sensors commonly used to understand the feeling of the subjects. HR is extracted from the Blood Volume Pulse (BVP) physiological sensor. An increment in arousal and valence has been noticed when HR has shown to increase [79]. HR has also shown to have a positive correlation with valence [72]. Heart Rate Variability (HRV) signal has also been shown to understand the feelings of the people [80]. Skin Temperature (ST) is the other commonly used physiological sensor that has shown to fall when stress, excitement, tension, or other sensations arise [81]. An increase in ST has been noticed when people watch film clips that have a happy effect in itself [82]. Thus, in this dissertation, we extract various features from the raw SC, BVP, and ST physiological signals to understand the feelings of the subjects when they are performing the rehabilitation task with RehabRoby. Mean and standard deviation methods are generally used to extraction features from ST. Power spectral density calculation, filtering, and peak detection are the other commonly used methods used to extract features from BVP. SC is generally characterized by the amplitude, and SCR [83]. A list of commonly used features is available in [84]. The details of the features used in this dissertation are given in Chapter 3.

3. METHODOLOGY

The control architecture of the proposed difficulty adjustment system with RehabRoby is given in Figure 3.1. RehabRoby is designed to provide assistance to the upper limb movements of the subjects (Figure 2.11) [55], [56], [85], [86]. RehabRoby is an exoskeleton-based robot. Physiological signals of the subjects are measured using biofeedback sensors during the execution of the tasks with RehabRoby (Figure 3.1). The distinctive features from these biofeedback signals and performance of the subjects are then used as a feedback to partially ordered set master (POSM) algorithm to dynamically change the difficulty level of the task for each subject (Figure 3.1).

3.1. REHABROBY

In this section, firstly the mechanical and electrical components of RehabRoby are briefly explained. Next, the control architecture of RehabRoby is presented.

3.1.1. Mechanical and Electrical Components of RehabRoby

RehabRoby is an exoskeleton-based upper limb robotic device developed in Robotics Research Laboratory in Yeditepe University [55], [85], [87], [88], [89]. It is possible to make the following movements with RehabRoby, i) abduction and adduction of shoulder rotation (θ_1), ii) shoulder flexion and extension elevation (θ_2), iii) internal and external rotation of shoulder (θ_3), iv) elbow flexion and extension (θ_4), v) lower arm elbow pronation and supination (θ_5), and vi) wrist flexion/extension (θ_6) (Figure 3.2). The range of motion, torque values, velocities and accelerations of joints (θ_1, θ_2, θ_3, θ_4, θ_5, θ_6) for RehabRoby have been taken from [90]. Specific brushed DC motors were selected for each joint of RehabRoby.

The details of motor selections of RehabRoby have previously been presented in [87] and [88]. RehabRoby can provide assistance to one movement (shoulder flexion/extension elevation) or any mixtures of more than one movement.

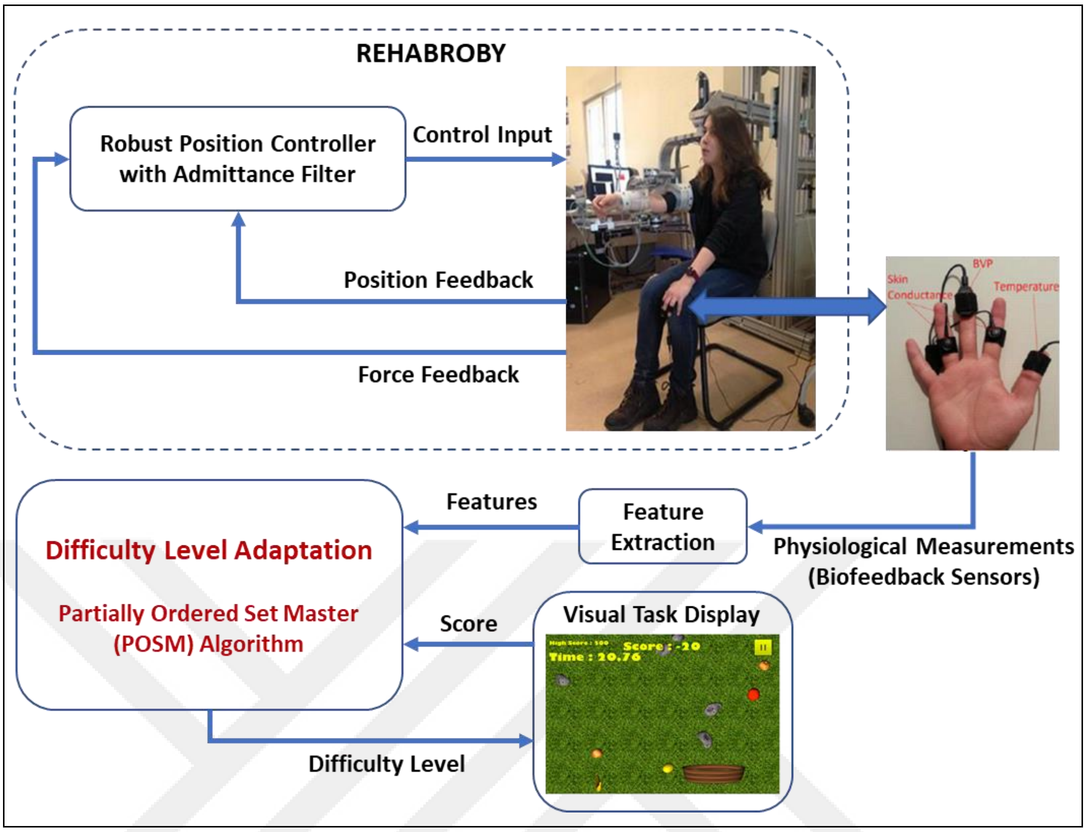


Figure 3.1. The general control architecture of the proposed system

The link lengths of RehabRoby has been selected as L_1:400 mm (vertical length of the first link), L_2: 261-401 mm (upper arm length - the distance between shoulder and elbow joints), and L_3: 205-302 mm (forearm length) (Figure 3.3). L_1, L_2, and L_3 values are decided using a report that provides arm lengths of people in Turkey [91]. It is possible to change the L_1, L_2, and L_3 for patients with different arm lengths and heights. RehabRoby can be easily attached to patients affected arm (left/right).

A thermoplastic arm splint has been involved in the design of the RehabRoby (Figure 3.4). Patients applied force (elbow flexion and elbow extension) is measured using Kistler (9313AA1; Kistler France, Les Ulis, France) force sensors (Figure 3.4-middle and right). An emergency button has been included to stop the RehabRoby immediately. The emergency button can be used by therapists. It is also possible to disable each joint of RehabRoby using buttons (Figure 3.4-left). A counterweight mechanism is integrated into RehabRoby to reduce the gravity effect (Figure 2.11). Thus, patients can easily flex his/her shoulder.

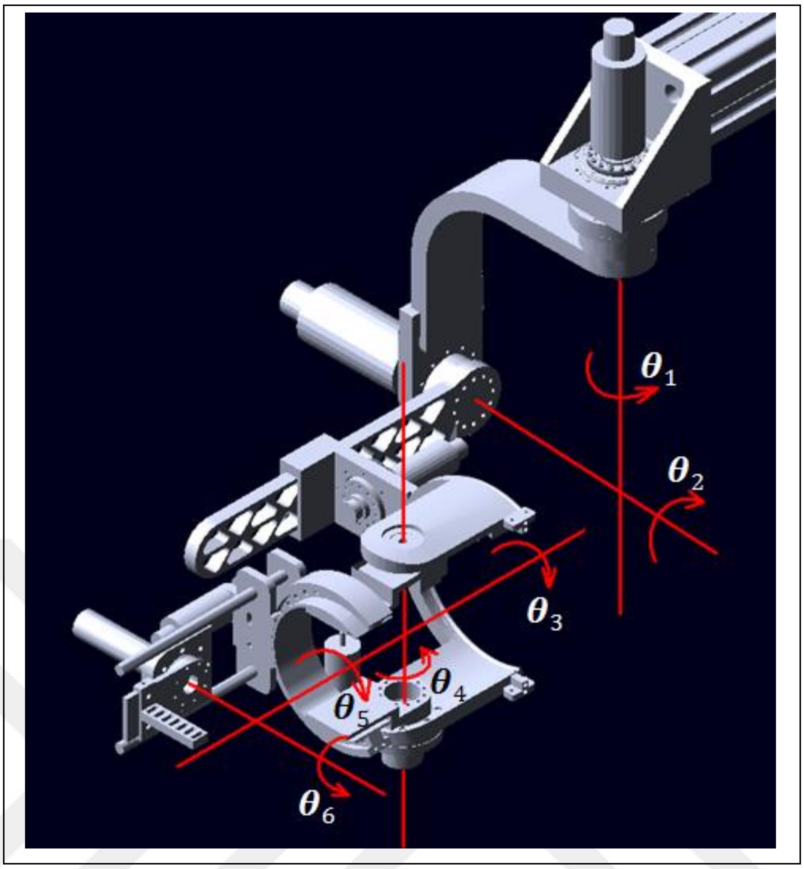


Figure 3.2. Joint angles of RehabRoby

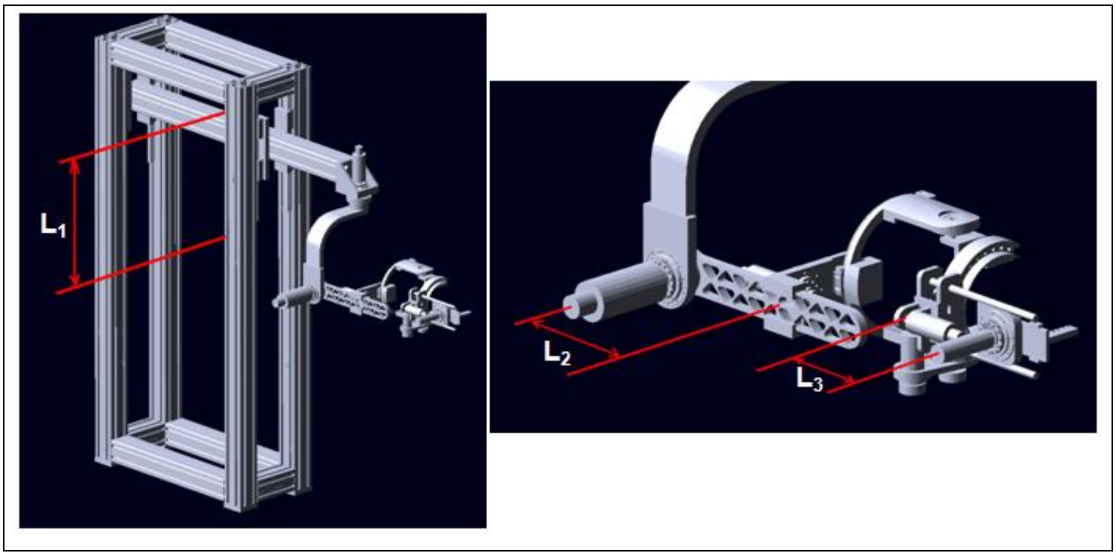


Figure 3.3. Arm lengths of RehabRoby

Figure 3.4. Arm splint and force sensors of RehabRoby

Humusoft Mf624 model data acquisition board is used for the communication between the software and hardware of RehabRoby. The encoders of the DC motors are used to measure the position. A sampling rate of 500Hz is used while recording the force and encoder data from the sensors. The electrical design details of RehabRoby is given in our previously published papers ([87], [88]).

3.1.2. Control Architecture of RehabRoby

A robust position controller with an admittance filter is developed for RehabRoby (Figure 3.5) [85], [87], [88]. The subjects' applied force is measured, and applied torque is calculated using Jacobian. Later, the torque is then given as an input to the admittance filter [92]. The characteristics of motion RehabRoby is defined using admittance filter. The output of the admittance filter is the reference motion that is defined for the position controller.

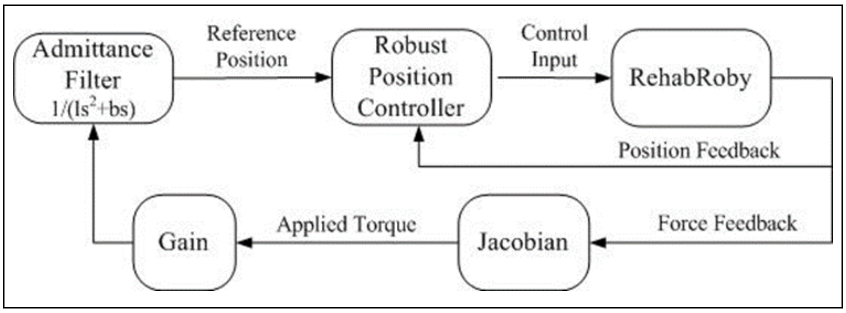


Figure 3.5. Robust position controller of RehabRoby with admittance filter

The applied torque is found using the admittance filter equation as:

$$\tau_a = M_d\ddot{q}_r + B_d\dot{q}_r + K_d q_r \tag{3.1}$$

where, τ_a is the torque applied by the patient. Desired values of inertia, stiffness and viscosity matrices are defined as M_d, K_d and B_d, respectively. Desired joint angle, angular velocity, and angular acceleration are also defined as q_r, $\dot{q}_r$ and $\ddot{q}_r$, respectively. The dynamic equation of a robotic system is known as $\tau = M(q)\ddot{q} + V(q,\dot{q}) + b(\dot{q}) + G(q) + \tau_{ext}$ and the definition of each parameter in this dynamic equation is given in Table 3.1. The details of how $M(q)$ and $b(\dot{q})$ are defined given in [85], [87] and [88].

Table 3.1. Definition of each parameter of the dynamic equation

Parameter	**Definition**
τ	Joint torque
$M(q)$	Inertia tensor
q	Joint position
$\dot{q}$	Joint velocity
$\ddot{q}$	Joint acceleration
$V(q,\dot{q})$	Coriolis and centrifugal
$b(\dot{q})$	Friction
$G(q)$	Gravity
τ_{ext}	Torque (unknown external effects)

All Coriolis, centrifugal, friction and gravity forces, parameter variations and unknown external effects are included in the disturbance vector d'. Then, the dynamic equation of RehabRoby becomes $\tau = \bar{M}\ddot{q} + B_v\dot{q} + d'$. B_v is the viscous friction coefficient. State-space model of the dynamic equation is written as:

$$\dot{x}_i(t) = A_i x_i(t) + B_i u_i(t) + E_i u_{di}(t) \tag{3.2}$$

$$y_i(t) = C_i x_i(t) + v_i(t) \tag{3.3}$$

$\dot{x}_i(t)$ consists of $q_i(t)$ (joint angle) and $\dot{q}_i(t)$ (joint velocity) where i is the joint index from 1 to 6. The control input is selected as $u_i(t)$. The equivalent disturbance is described as $u_{di}(t)$. The measured output of the system is $y_i(t)$. Finally, the measurement noise is shown as $v_i(t)$. The matrices in Equation (3.2) and (3.3) are defined as $A_i = \begin{bmatrix} 0 & 1 \\ 0 & -\frac{B_{vi}}{\bar{M}_i} \end{bmatrix}$, $B_i = \begin{bmatrix} 0 \\ \frac{K_{tri}}{\bar{M}_i} \end{bmatrix}$, $E_i = \begin{bmatrix} 0 \\ -\frac{1}{\bar{M}_i} \end{bmatrix}$, and $C_i = [1 \quad 0]$. The details of how A_i, B_i, C_i and E_i matrices can be found in [85], [87] and [88]. Motor torque constant and the gear ratio of the actuator are multiplied to find K_{tri}. $u_i(t) = -K_i x_i(t) + r_i(t)$ is selected where K_i is the state-feedback gain matrix. $r_i(t)$ includes the summation of the multiplication of proportional gain with the reference joint angle ($k_{pi}q_{ri}(t)$), compensating signals to eliminate the disturbance ($i_{di}(t)$) and feedforward compensating signal ($i_{ci}(t)$). When all these definitions are included in Equation (3.2), then the state-feedback equation becomes as:

$$\dot{x}_i(t) = (A_i - B_i K_i) x_i(t) + B_i r_i(t) + E_i u_{di}(t) \tag{3.4}$$

Equation (3.4) can be represented as a general second order system. The control gains for the state-feedback control can be found by defining anticipated damping ratio and natural frequency values [85], [87], [88]. The discrete state space model is described in Equation

(3.5) and (3.6). The equivalent disturbances are estimated using a discrete linear Kalman filter (LKF) method [92].

$$x_i(k+1) = (A_{ki} - B_{ki}K_i)x_i(k) + B_{ki}r_i(k) \tag{3.5}$$

$$y_i(k) = C_{ki}x_i(k) + v_i(k) \tag{3.6}$$

where $A_{ki} - B_{ki}K_i = \left(I + T_s \begin{bmatrix} 0 & 1 & 0 \\ -\frac{K_{tri}k_{pi}}{\bar{M}_i} & -\frac{B_{vi}}{\bar{M}_i} - \frac{K_{tri}k_{di}}{\bar{M}_i} & -\frac{1}{\bar{M}_i} \\ 0 & 0 & 0 \end{bmatrix} \right)$, $B_{ki}T_s$, $\quad C_{ki} = [1 \quad 0 \quad 0]$

and T_s is the sampling time, and k_{di} is the derivative gain. The position controller with disturbance estimator is shown in Figure 3.6.

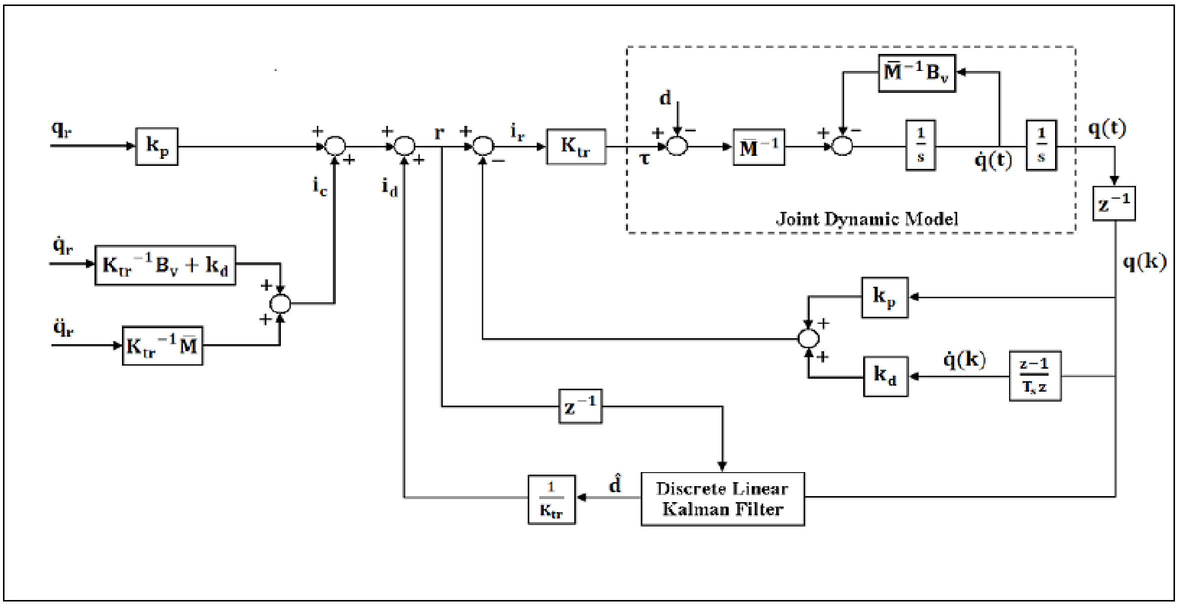


Figure 3.6. Robust position controller of RehabRoby

3.1.3. Adaptive Admittance Controller of Rehabroby

The admittance control with an inner robust position control loop, which is used as the low-level controller of RehabRoby is shown in Figure 3.5. Each force axes has independent parameters (Gain, I (inertia), b (damping)) that are needed to be calculated. The forces that are applied by the subject, which are measured using Force Sensor 1 (FS1) and Force Sensor 2 (FS2), are converted into torque values (one for each force sensor) using the robot Jacobian matrix. The torque values are then passed through an admittance filter, which is used to define the characteristics of the motion of RehabRoby against the applied forces, to generate the reference motion for the position controller. The applied force/torque is the input and reference position is the output of the admittance filter. Subjects are asked to perform 90^o elbow flexion and extension movement three times continuously while RehabRoby is kept passive to determine the proper admittance filter parameters (I and b), and the gain (Gain) for each subject.

A suitable adaptive control scheme, which adapts the admittance parameters dynamically, has previously been obtained with a trained frequency domain classifier using adaptive boosting algorithm [93]. Furthermore, a method has been proposed to achieve an optimal variable control scheme by combining human decision making process emulated using an on-line fuzzy inference system (FIS) with a fuzzy model reference learning (FMRL) controller [94]. FRML controller has also been used to adapt the FIS according to the minimum jerk trajectory model. The heuristically created FIS assists both rapid movements of the human and the accurate positioning during lower velocities by determining the desired damping of the admittance controller. An FMRL controller adapts the FIS for optimal cooperation towards the minimum jerk trajectory model. Online Fast Fourier transform (FFT) of the manipulator end-effector forces are used to detect oscillations that disturb the haptic experience.

The algorithm (Algorithm 3.1), which is used to find the suitable parameters in the admittance filter, was executed for 15 subjects using MATLAB/Simulink. The details of the experimental procedure can be found in [86] and [87]. The results for the each subject are given in Table 3.2. The mean values of the admittance parameters calculated for 15 subjects (Table 3.2) were used for the proposed system in this dissertation.

Algorithm 3.1. Algorithm for finding suitable admittance filter parameters

- Each subject performs 90^{o} elbow flexion and extension movement 3 times while RehabRoby is passive. The actual angular position $x[n]$, and applied torque $\tau[n]$ during this passive motion are recorded.

- The parameter Gain is used to scale the measured torque data during real-time experiments and found as Gain=6/max$\{\tau[n]\}$, where max$\{\tau[n]\}$ is the maximum value of the measured torque data during passive motion. A threshold is applied to the measured torque data during real-time experiments because of the noise in the measurement data. This value is chosen as 2 Nm, which is one third of the maximum applicable torque value (6 Nm).

- We are interested in the velocity characteristics of the reference motion. The slopes of $x[n]$ and $\hat{x}[n]$ are defined as $m[n] = x[n] - x[n-1]$ and $\widehat{m}[n] = \hat{x}[n] - \hat{x}[n-1]$, respectively. $\hat{x}[n]$ is the reference angular position calculated using the modified admittance parameters. $m[n]$ and $\widehat{m}[n]$ are the backward differences between the adjacent elements of $x[n]$ and $\hat{x}[n]$.

- Set j = 0, set b^0, I^0 to their default values, and set $T_{iterations}$ = 2000

- WHILE $j \leq T_{iterations}$

  (Step 1) $f_{sum} = \sum_{n=0}^{N-1}(m[n] - \widehat{m}[n])^2$

  (Step 2) $\{b^{j+1}, I^{j+1}\} = \arg\min_{b,I} f_{sum}$

  $\mathrm{j = j + 1}$

  END WHILE

  where N is the number of samples.

- Above in Step 2, optimization is performed using the *fminsearch* function of MATLAB. For the one motion region, Figure 3.7 shows that the sum of the square differences f_{sum} converge to minimum while the iteration number increases. The final values of the parameters *b* and *I* are obtained by taking the mean of the parameter values calculated in each of three active motion regions.

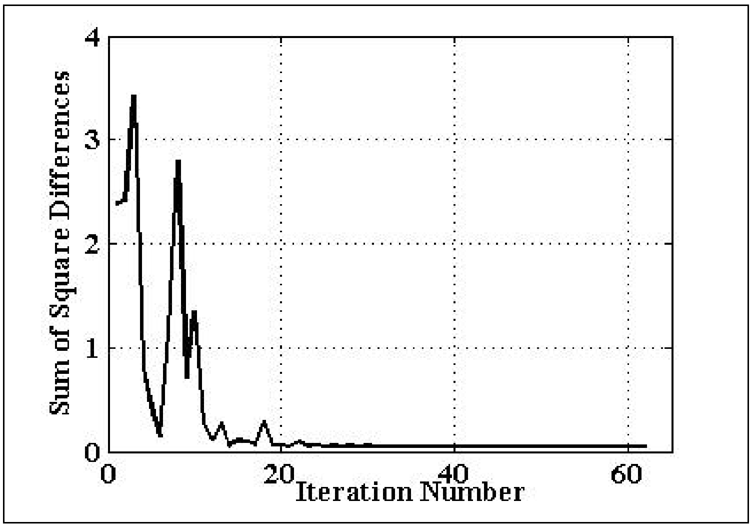


Figure 3.7. Sum of the square differences at each iteration

Table 3.2. Calculated admittance parameters for each subject (I_1, b_1 and $Gain_1$ for FS1, I_2, b_2 and $Gain_2$ for FS2)

Subject	**I_1**	**b_1**	**$Gain_1$**	**I_2**	**b_2**	**$Gain_2$**
S1	1.25	6.00	0.73	0.68	6.00	1.62
S2	1.35	10.67	0.89	0.84	6.00	1.21
S3	1.73	6.00	1.55	0.81	6.00	1.02
S4	1.50	10.67	1.15	0.92	6.00	0.80
S5	1.10	6.00	0.80	0.60	6.00	2.19
S6	1.07	6.31	1.19	0.78	6.00	1.32
S7	1.13	6.64	1.13	0.60	6.00	1.07
S8	1.75	6.10	0.98	1.30	6.00	0.95
S9	1.40	6.00	1.22	0.67	6.51	1.13
S10	1.44	6.00	1.16	0.65	6.00	0.78
S11	1.13	6.00	0.95	0.60	6.00	1.09
S12	1.01	6.00	0.90	0.83	6.00	0.71
S13	1.54	6.00	1.54	1.07	6.00	1.75
S14	1.26	6.00	1.37	1.85	6.00	1.50
S15	0.60	6.00	1.02	0.60	6.00	0.92
Mean	**1.28**	**6.69**	**1.10**	**0.85**	**6.03**	**1.20**

3.2. PHYSIOLOGICAL MEASUREMENTS

The details of the physiological measurements used in the dynamic difficulty adjustment mechanism are presented in this chapter.

3.2.1. Physiological Data Collection

Lightweight and wearable biofeedback sensors from Thought Technology [95] are used to record the physiological data from the subjects in this dissertation. Skin conductance (SC), blood volume pulse (BVP), and skin temperature (ST) biofeedback sensors from Thought Technology [95] are selected. The sensor placement on the fingers is shown in Figure 3.8. The BVP sensor is positioned on the middle finger. SC sensors , on the index and ring fingers. ST sensor is positioned on the thumb finger. The physiological signals from these biofeedback sensors are sampled at 100 Hz using Procomp Infiniti Encoder.

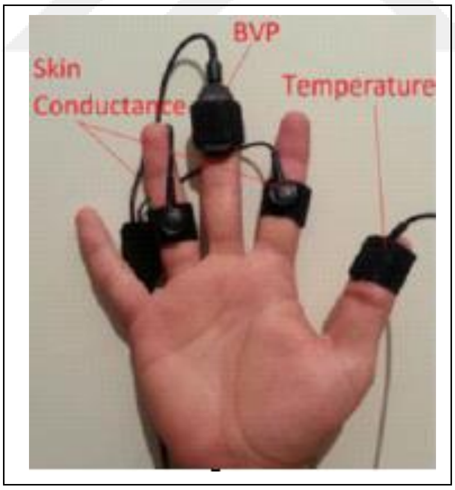


Figure 3.8. Placement of biofeedback sensors on the subject

3.2.2. Feature from Physiological Data

There is a need to extract the feature from the raw SC, BVP, and ST raw signals. Mean and the first derivative of the raw signals are generally used as the features of the raw signal [83]. However, the mean and first derivative may not be enough for some raw data; thus, some other methods such as filtering, peak detection are also used for feature extraction [83]. A list of features that are generally used is given in [84]. Furthermore, the previously proposed signal processing methods used to calculate the features from the raw physiological raw data can be found in [96] and [97]. Normalization and dimension reduction are also used to extract the features. Since features display changeability, thus, normalization can be used to reduce the effect of this changeability. Various normalization methods have been proposed to derive the features, and a detailed survey about these methods are presented in [79] and [83]. In this dissertation, the normalization method in where the mean value of baseline is subtracted from the feature vector, and the result is divided by the maximum absolute value of subtraction from feature vector from the mean value of baseline is used [79].

The list of extracted features from the SC, BVP, and ST raw data are given in Table 3.3. The first feature heart rate (HR) is calculated from the BVP data. Mean ($Mean_{IBI}$) and standard deviation (Std_{IBI}) of inter-beat intervals are found from the BVP raw data. Mean BVP ($Mean_{bvp}$), the first derivative of the BVP ($Deriv_{bvp}$) and the variance of the BVP (Var_{bvp}) have been obtained from the BVP sensor. Then, Heart Rate Variability (HRV) signal [98] has been found [99], and the Fourier transform of this signal is found to find the frequency intervals [100]. 0-0:05 Hz interval, 0:05-0:15 Hz interval and 0:15-0:4 Hz interval which correspond to very low frequency (VLF), low frequency (LF) and high frequency (HF) interval, respectively. LF/HF ratio has also been selected as one of the features [99], [101]. The ratio of total frequencies (VLF+LF) to HF has also been calculated as one of the features of the BVP sensor. The BVP total power (BVP_{tp}) is divided by VLF total power to find the percentage ratio of the very low frequency (per_{VLF}). The percentage ratio of the low frequency (per_{LF}), and high frequency (per_{HF}) are also obtained using the same procedure as in (per_{VLF}). Low frequency norm (LF_{norm}), and high frequency norm (HF_{norm}) has also been calculated [102]. Skin conductance response (SCR) is obtained as the total number of temporary increases in the skin conductivity signal [103]. The details of how SCR been found are explained in [102]. Mean conductance ($Mean_{sc}$), the variance of the conductance (Var_{sc}), and mean the first derivative of skin conductance ($Deriv_{sc}$) are also calculated as features from SC sensor. Finally, mean temperature ($Mean_{temp}$), the first derivative of the temperature ($Deriv_{temp}$) and the variance of the temperature (Var_{temp}) have been obtained from the ST sensor. The details of calculation methods for each feature had been given in [102].

Table 3.3. Biofeedback sensors and features

Physiological Indices		
Physiological signals	**Features derived**	**Label used**
Blood volume pulse sensor	Heart rate	HR
	Mean IBI	$Mean_{IBI}$
	Standard deviation of IBI	Std_{IBI}
	Mean BVP	$Mean_{bvp}$
	Variance of BVP	Var_{bvp}
	First derivative of BVP	$Deriv_{bvp}$
	Very low frequency	VLF
	Low frequency	LF
	High frequency	HF
	BVP total power	BVP_{tp}
	Ratio of low frequency to high frequency	LF/HF
	Ratio of frequencies	(VLF+LF)/HF
	Percentage ratio of the very low frequency	Per_{VLF}
	Percentage ratio of the low frequency	Per_{LF}
	Percentage ratio of the high frequency	Per_{HF}
	Low frequency norm	LF_{norm}
	High frequency norm	HF_{norm}
Skin conductance sensor	Mean skin conductance	$Mean_{sc}$
	Skin conductance response	SCR
	First derivative of skin conductance	$Deriv_{sc}$
	Variance of skin conductance	Var_{sc}
Temperature	Mean temperature	$Mean_{temp}$
	Variance of temperature	Var_{temp}
	First derivative of temperature	$Deriv_{temp}$

3.3. REHABILITATION TASK – FRUIT PICKER GAME

A single player fruit picker game, which provides elbow flexion/extension game with various difficulty levels is selected as the rehabilitation task in this dissertation. The fruit picker game contains a basket, fruits, and rocks (Figure 3.9). Various parameters of the fruit picker game such as basket speed, basket size, level time (sec), fruit number, fruit speed, rock number, rock speed, spawn wait time (sec), wave wait time (sec) are manipulated systematically to produce different difficulty levels. The score of the subjects is also shown to the subjects during the execution of this game to motivate them.

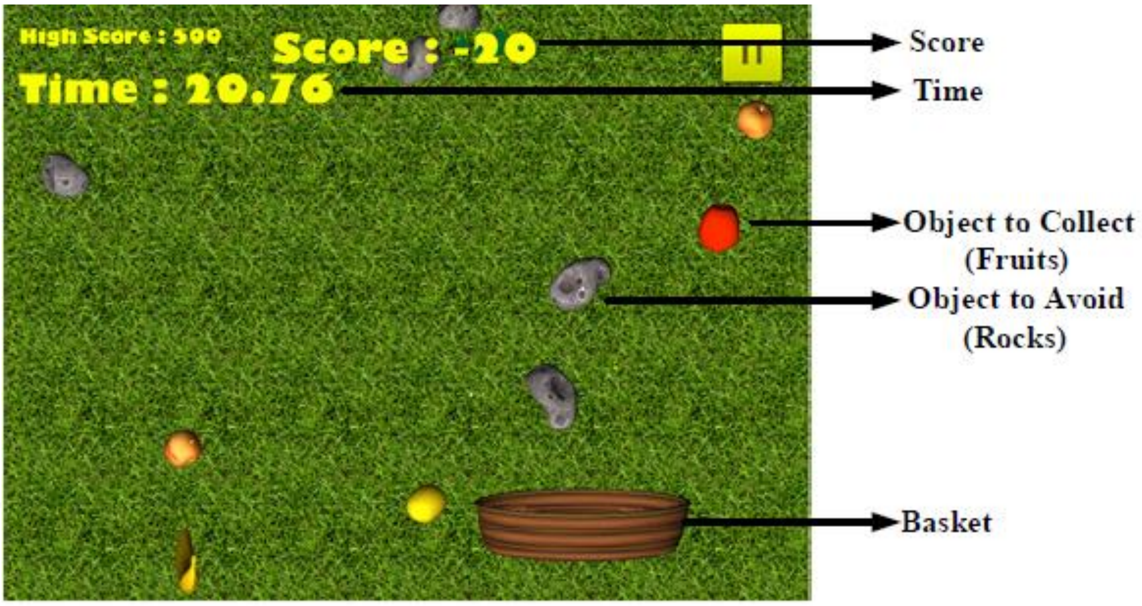


Figure 3.9. Fruit picker game

The subjects who participate in the experiments are asked to collect the fruits when these fruits are falling uninterruptedly. The subjects are also asked not to collect the rocks (Figure 3.9). The aim is to collect as many fruits as possible and escape from the rocks by moving the basket from left to right and right to left. The subjects earn 10 points when they collect fruit, and they lose 20 points when they collect rock. This fruit picker game forces subjects to accomplish elbow flexion/ extension movements with the RehabRoby. The subject is required to move the basket to the left for elbow flexion, and he/she is required to move the basket to the right for elbow extension. The fruit picker game mimics elbow flexion/extension exercises which are often needed in patients with cerebral palsy, stroke, or traumatic brain injury. The game performance score of the subject is also shown to the subjects during the execution of the game to motivate them. Every subject starts the game at 90^o elbow extension. The basket is kept on the right side at the beginning. Subjects have a chance to move their elbow from 0^o to $90^{o,}$ which is suitable for human anatomy. The game is developed using the Unity game engine [104]. The details of the fruit picker game can be found in our previous publications [105].

A pilot study [105] had been first conducted to choose the difficulty levels for the experiments. The difficulty level had been increased from Level 1 (L1) to Level 7 (L7). Level 1 was easy (under-challenged), Level 4 was the medium (challenged), and Level 7 was the difficult (over-challenged) (Figure 3.11). Selection of adjustment game parameters depended on the objective of the rehabilitation program. The goal of the rehabilitation program with RehabRoby was to improve the interval between the appearance/dispersion of targets. The falling rates of fruits and rocks had been increased to make the game challenging, and subjects had been required to move in a broader range to collect fruits and to avoid rocks. Additionally, rock number and rock speed had been raised to increase the difficulty level of the game. Fruit number, fruit speed, and basket size were kept the same for all seven difficulty levels. 31 unimpaired subjects (8 female and 23 male), 23-36 years of age, participated. Initially, the subjects had been given some practice opportunity to familiarize them with the RehabRoby. Later, three arbitrarily selected difficulty levels of the game had been given to the subjects. The duration of each game was 60 seconds. The subjects did not know the difficulty level of the game. Then, subjects were asked to complete a self-assessment manikin (SAM) survey after each game (Figure 3.10). SAM has a 9-point scale. 1 represented the lowest valence (”unpleasant”), arousal (”inactive”) and dominance (”helpless”), and 9 represented the highest valence (”very happy”), arousal (”excited”) and dominance (”in control everything”) in SAM.

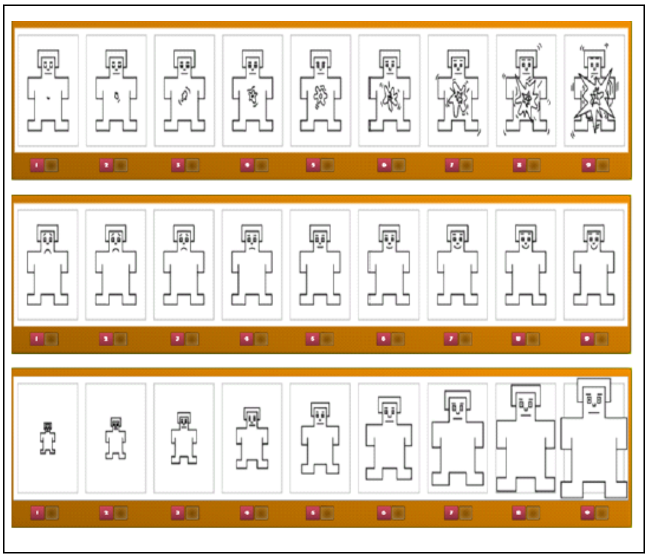


Figure 3.10. Self-assessment manikin (SAM) (arousal (top), valence (middle), and dominance (bottom))

Figure 3.11. Difficulty levels of the fruit picker game

The mean and standard deviations of the subject scores for each of the difficulty levels are shown in Figure 3.12. It was noticed that the subjects were generally pleased when their valence score was above the average. It was also observed that the level of arousal had increased when the difficulty level of the game increased. Similarly, as the difficulty level increased the subjects tended to lose their control on the game, which could be seen from the decrement of the dominance rating.

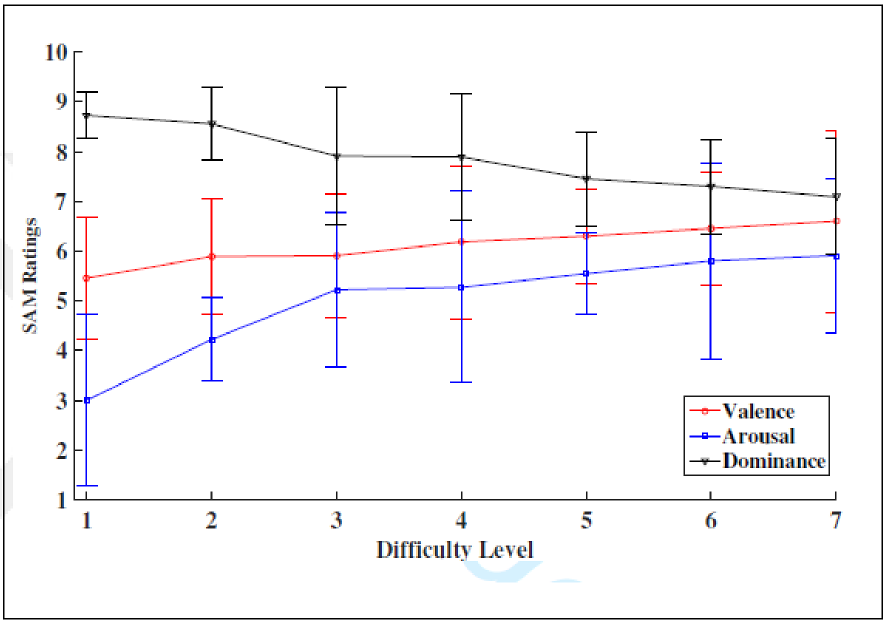


Figure 3.12. SAM ratings for difficulty levels

3.4. DYNAMIC DIFFICULTY ADJUSTMENT MECHANISM FOR REHABROBY

This chapter presents the details of the developed dynamic difficulty adjustment mechanism for RehabRoby.

3.4.1. Partially Ordered Set Master (POSM) Algorithm

In this study, a partially ordered set master (POSM) algorithm is used for difficulty level adjustment of the fruit picker game during the performance of the rehabilitation task with RehabRoby. POSM algorithm predicts the difficulty level by learning from the observations.

POSM has three main advantages compared to other approaches:

- POSM requires no offline training and no background knowledge about the behavior of the subject is needed,
- The algorithm can be easily ported between games and game genres,
- There are theoretical guarantees on the maximum number of mistakes POSM makes before learning the appropriate setting.

The input to the dynamic difficulty adjustment algorithm is the user's performance (e.g., score), and physiological data that represents the feelings of the subject. Initially, the master predicts a difficulty setting and the subject performs the task with the defined difficulty setting for a specific period of time. Later, one of the following feedbacks is received:

- "Under-challenged" if the predicted difficulty setting is not difficult enough for the subject.
- "Challenged" if the predicted difficulty setting is for the subject.
- "Over-challenged" if the predicted difficulty setting is above the capability of the subject.

The difficulty of the task is changed frequently to determine the proper difficulty level for each subject. POSM algorithm predicts proper difficulty level from a fixed partly ordered set of all potential levels. The order is such that $\forall i, j \in K$ if i is more challenging than j. The settings can be:

- +1 if the difficulty level is under-challenged,
- 0 if it is challenged,
- -1 if it is over-challenged.

POSM algorithm keeps the belief w_t about the correctness of each difficulty setting. Later, this algorithm keeps on updating the level when the task is found to be under-challenged or over-challenged. The steps of POSM algorithm are given in Algorithm 3.2 [106].

Algorithm 3.2. Steps of POSM algorithm

Require: $\beta \in (0, 1)$, K difficulty settings, a partial order $\geq$ on K, a sequence of observations $o_1, o_2, \ldots$

1. $\forall k \in K$: let $w_1(k) = 1$
2. for t = 1, 2... do
3. $\quad \forall k \in K$: let $A_t(k) = \sum_{x \in K,\ x \geq k} w_t(x)$
4. $\quad \forall k \in K$: let $B_t(k) = \sum_{x \in K,\ x \leq k} w_t(x)$
5. $\quad$ Predict $k_t = \mathrm{argmax}_{k \in K} \min\{B_t(k), A_t(k)\}$
6. $\quad$ Observe $o_t \in \{-1, 0, 1\}$
7. $\quad$ if $o_t = +1$ then
8. $\quad\quad \forall k \in K$: let $w_{t+1}(k) = \begin{cases} \beta w_t(k), & k \leq k_t \\ w_t(k), & otherwise \end{cases}$
9. $\quad$ end if
10. $\quad$ if $o_t = -1$ then
11. $\quad\quad \forall k \in K$: let $w_{t+1}(k) = \begin{cases} \beta w_t(k), & k \geq k_t \\ w_t(k), & otherwise \end{cases}$
12. $\quad$ end if
13. end for

Belief for all difficulty levels that are difficult than the current level at the current time step is collected by A_t. Belief for all difficulty levels that are easier than the current level is collected by B_t. k represents the difficulty level. The following actions are taken by looking at the observation output. The details of how the POSM algorithm is used for RehabRoby is given in our previously published paper [107].

- If the observation output is under-challenged, then it means that the difficulty level must be increased, and the belief of the proposed level as well as all levels are easier than the proposed one are updated.

- If the observation output is over-challenged, then it means that the difficulty level must be decreased, and the belief of the proposed level as well as all levels are difficult than the proposed one are updated.

3.4.2. Difficulty Level Adjustment in POSM

POSM algorithm uses three feedbacks, which are score, physiological signal, and score and physiological signal together for difficulty level adjustment of the rehabilitation task. Observations from these three feedbacks are evaluated to find the new difficulty level of the rehabilitation task.

3.4.2.1. Performance Feedback Based Adjustment (PFBA)

The difficulty adjustment is based solely on the subject's performance (score) in performance feedback based adjustment (PFBA) mechanism. POSM algorithm decides the difficulty level considering the score change rate in a given period. Two threshold levels are defined that are high threshold level (50%), and low threshold level (20%). The PFBA tries to keep the performance percentage between 20% and 50%. These ranges are chosen as initial best estimate but can be changed at any time considering the requirements of the rehabilitation program, and the capabilities of the patients. For example, if the patient is low-functioning, then the performance cannot be a high value, on the other hand, if the patient is high-functioning, the performance can be high to keep the patient engaged. Maintaining performance rate at 50% had previously been shown as an optimal balance between engagement and challenging [4], [108], [109].

The performance feedback based adjustment (PFBA) is shown in Figure 3.13. If the performance score rate (P_i) is higher than the high threshold level (50%) ($P_i \geq 50\%$), then the observation result is +1 which means the difficulty level is easy (under-challenging) for the subject. If the P_i is lower than the low threshold level (20%) ($P_i \leq 20\%$), then the observation result becomes -1 which means the difficulty level is hard (over challenging) for the subject. If the subject's performance is between 20% and 50%, then the observation result is 0, which means that the current difficulty level is appropriate for the subject. The observation result obtained from one of these three conditions is used for finding the new difficulty level (L_{new}) by the POSM algorithm.

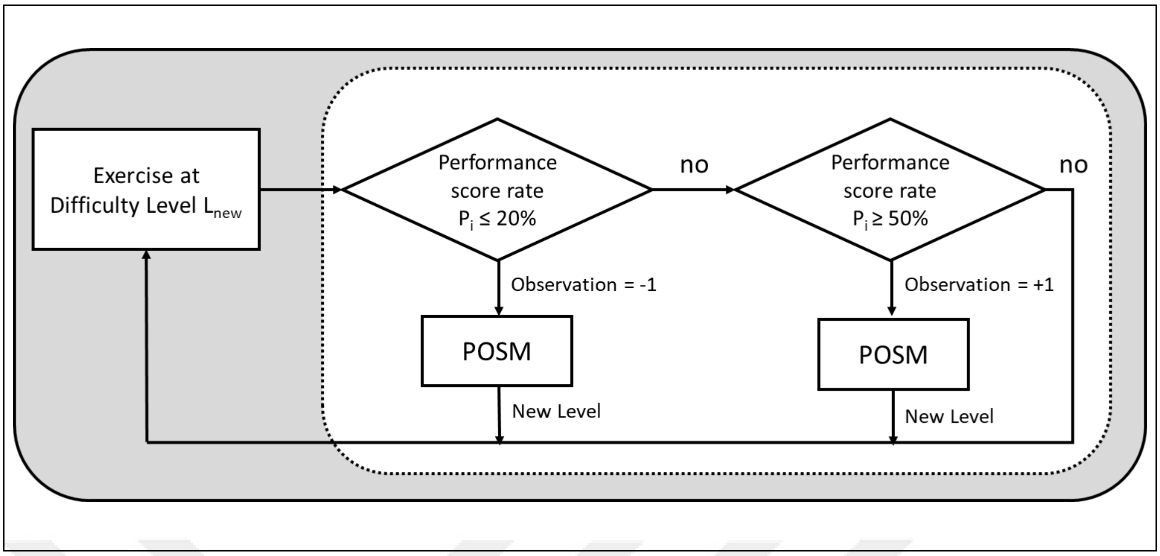


Figure 3.13. Performance feedback based adjustment (PFBA) mechanism

3.4.2.2. Physiological Feedback Based Adjustment (PHFBA)

It is important to integrate the human in the loop using physiological signals. Thus, physiological signal $Mean_{sc}$ is used as a feedback to the POSM algorithm in physiological feedback based adjustment (PFBA) mechanism to adjust the difficulty level. $Mean_{sc}$ feature is selected as a new feedback in the closed loop decision-making mechanism since it gives a relatively fast, and significant information about the subject in terms of challenged, overwhelmed, or bored [73].

The overall architecture, which includes the real-time feedback of the score and the $Mean_{sc}$ feature is given in Figure 3.14. The main controller which runs on MATLAB coordinates the signal flow and time synchronization of the integrated real-time system and also updates the difficulty level. Biofeedback data acquisition and processing software (BDAPS) developed with C++, records, and processes physiological data that comes from the biofeedback sensors. In every 10 seconds, $Mean_{sc}$ is calculated by BDAPS with the start signal from the main controller. The communication between BDAPS and the main controller is provided through files. Low-level control of RehabRoby is implemented in Simulink where the position data is transmitted to the main controller in real-time. The main controller updates the position value of the fruit picker game at every 50 milliseconds. The main controller and the fruit picker game communicate through a virtual serial port. The main controller decides the new difficulty level at every 10 seconds evaluating the score and/or the $Mean_{sc}$ feature using the POSM algorithm.

Two threshold levels, which are high threshold level (70%), and low threshold level (30%) are defined. These threshold values are decided by looking at the $Mean_{sc}$ value ranges that subjects are overwhelmed or bored from our previous experiments. Note that if $Mean_{sc}$ is too high, the subject may be overwhelmed because the subject may found the task more demanding [78] and if $Mean_{sc}$ is too low, then the subject may get bored.

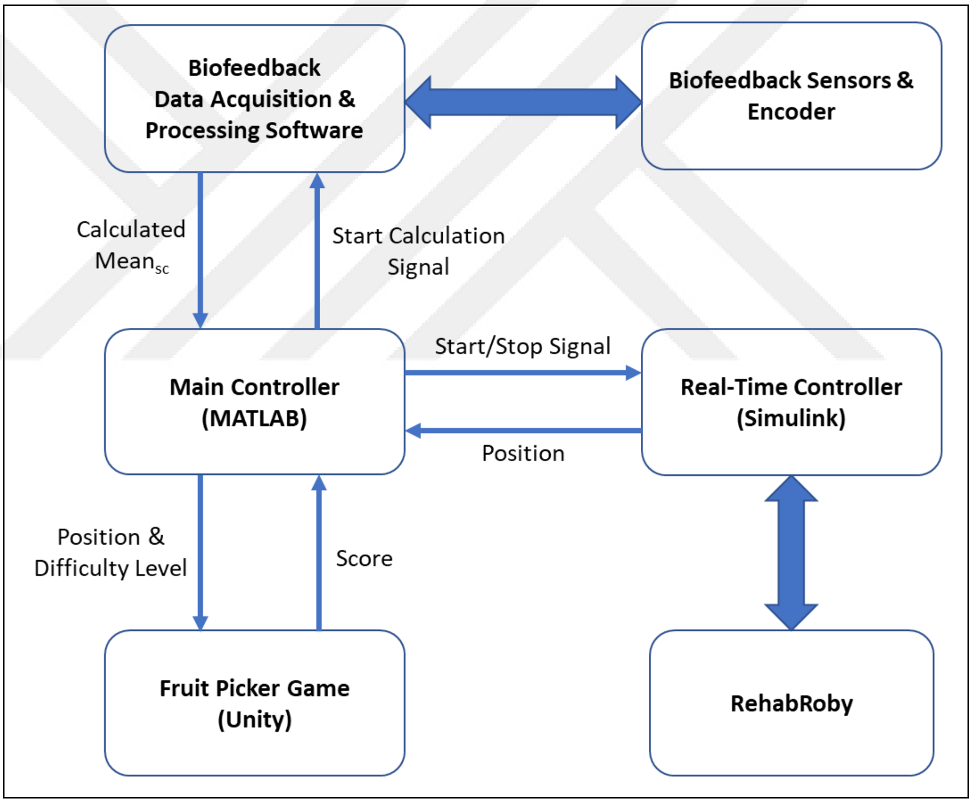


Figure 3.14. Integration of real-time feedback of both the score and the physiological signal to the RehabRoby

The physiological feedback based adjustment (PHFBA) mechanism is shown in Figure 3.15. If the $Mean_{sc}$ increase rate is higher than the high threshold value ($MSC_i \geq 70\%$), which means the difficulty level is over-challenging for the subject, then the observation result is -1. Note that MSC_i is the current $Mean_{sc}$ increase rate. If the $Mean_{sc}$ increase rate is lower than the low threshold level ($MSC_i \leq 30\%$), then the observation result becomes +1, which means the difficulty level is easy for the subject. If the $Mean_{sc}$ increase rate is between 30% and 70%, then the observation result is 0, which means that the current difficulty level is appropriate for the subject. The observation result obtained from one of these three conditions is used for finding the new difficulty level (L_{new}) by the POSM algorithm.

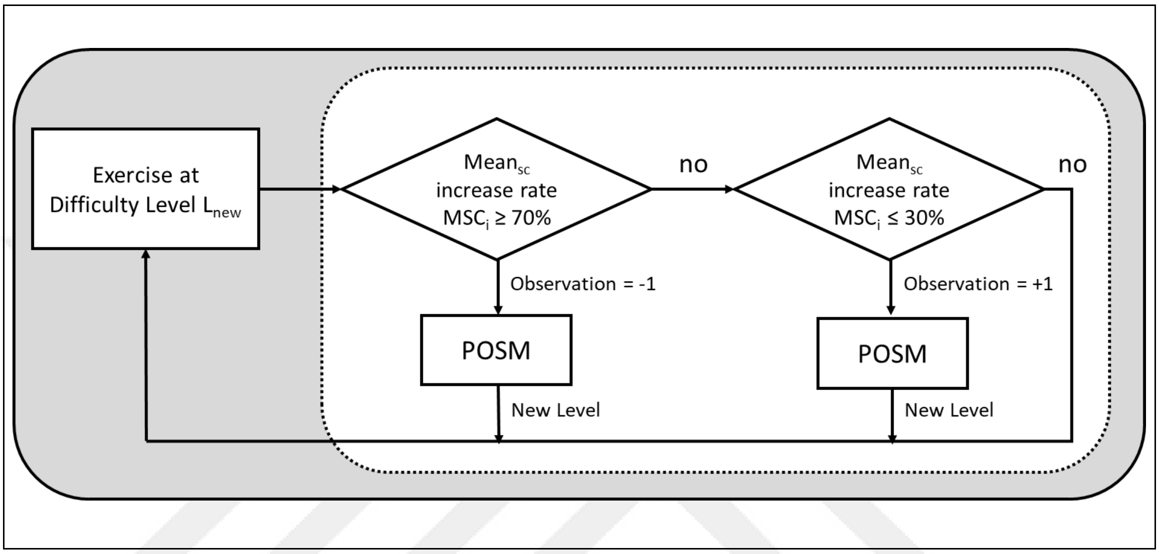


Figure 3.15. Physiological feedback based adjustment (PHFBA) mechanism

3.4.2.3. Performance and Physiological Feedback Based Adjustment (PPFBA)

Finally, POSM algorithm uses both performance (score rate) and physiological signal ($Mean_{sc}$ increase rate) (PPFBA) as feedback to find the appropriate difficulty level of the rehabilitation task. Estimated difficulty regions for score and $Mean_{sc}$ parameters are given in Figure 3.16. A new rule set is defined by comparing the differences ($\triangle SH$, $\triangle SL$, $\triangle SCH$, $\triangle SCL$) between the corresponding threshold and calculated values of score rate and $Mean_{sc}$ increase rate (Table 3.4). Green cross marks are the representations for any values of the score rate and $Mean_{sc}$ increase rate (Figure 3.16). Red cross marks shows the example values of the score rate and $Mean_{sc}$ increase rate for the condition in which the score rate result is easy (under-challenging), and $Mean_{sc}$ increase rate result is hard (over-challenging). If the difference between the score rate value and the high threshold ($\triangle SH*$) is greater than the difference between the $Mean_{sc}$ increase rate value, and the high threshold ($\triangle SCH*$), then the observation result becomes +1, in the opposite case, the observation result becomes -1. The observation result is 0 in case of equality.

Table 3.4. Rules to define observation value in POSM

		$Mean_{sc}$		
		Easy	**Medium**	**Hard**
Score	**Easy**	Observation: +1	If $\Delta S_H \geq \Delta SC_L$ Observation: +1 Else Observation: 0	If $\Delta S^*_H > \Delta SC^*_H$ Observation: +1 Else if $\Delta S^*_H < \Delta SC^*_H$ Observation: -1 Else Observation: 0
	Medium	If $\Delta S_H > \Delta SC_L$ Observation: 0 Else Observation: +1	Observation: 0	If $\Delta S_L > \Delta SC_H$ Observation: 0 Else Observation: -1
	Hard	If $\Delta S_L > \Delta SC_L$ Observation: -1 Else if $\Delta S_L < \Delta SC_L$ Observation: +1 Else Observation: 0	If $\Delta S_L \geq \Delta SC_H$ Observation: -1 Else Observation: 0	Observation: -1

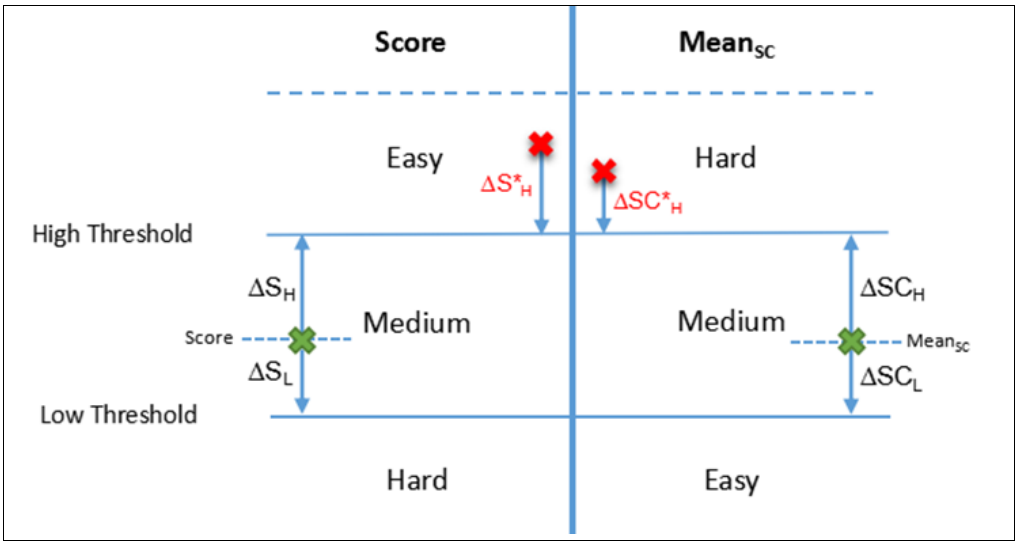


Figure 3.16. Difficulty regions for score and $Mean_{sc}$ according to the threshold levels

4. EXPERIMENTS

This section presents the subjects, experimental procedure as well as the measures used in the analysis.

4.1. SUBJECTS

Twenty subjects (9 female and 11 male) took part in the experiments. The ages of the subject were in the range of 21-27. Nineteen subjects were right-handed. One subject was left handed. The subjects who participated in the experiments are healthy. Additionally, all subjects had no background of any diseases that can affect the results of the experiments. Five of the subjects had experience with robot-assisted rehabilitation systems, and 11 subjects had computer games experience.

4.2. EXPERIMENTAL PROCEDURE

The experimental set-up is given in Figure 4.1. Subjects were asked to complete five experimental trials (Figure 4.2). Each trial was different from each other because the difficulty level was changed considering the performance (score) and the physiological signal ($Mean_{sc}$) of the subjects. Subjects did not know at which difficulty level he/she was doing the rehabilitation task in all trials.

Initially, the subjects were asked to be less tense. Then, the subjects were asked to close their eyes for 3 minutes to obtain baseline data from the biofeedback sensors. Later, subjects filled the self-assessment manikin (SAM) survey that was displayed on the screen (Figure 3.10).

After subjects completed the SAM survey, a 2 minutes break was given to the subjects. Later, subjects performed a practice trial to get familiar with RehabRoby, and the fruit picker game. Physiological signals from BVP, SC, and ST sensors (Figure 3.8) were collected during the practice trial. Then, subjects were asked to complete the SAM, and a 2 minutes break was given to the subjects. Then, subjects did the same rehabilitation task 5 times. Another trial started automatically after 2 minutes break when a trial was over and the SAM survey completed by the subjects. The duration of the rehabilitation task was 3 minutes. The order of the trials was shown in Figure 4.2.

Figure 4.1. Experimental set-up

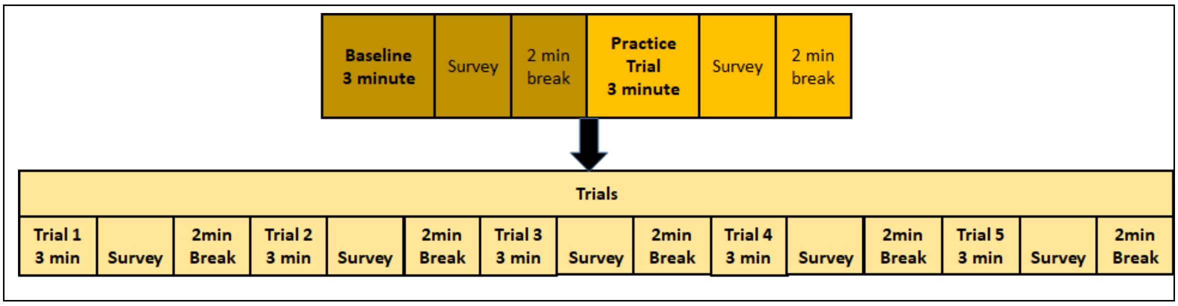


Figure 4.2. The order of the trials

There were three groups, as mentioned in Section 3.4.2. The evaluation of the proposed feedback adjustment that is PFBA, PHFBA, and PPFBA was done using a crossover study. The following list demonstrates the number of subjects in each PFBA, PHFBA, and PPFBA. Additionally, the list provided information on how the crossover study had been designed:

- 7 subjects (3 female and 4 male), 7 subjects (2 female and 5 male) and 6 subjects (4 female and 2 male) were asked to complete the experiment using PFBA, PHFBA, and PPFBA, respectively in the first week of the experiments.

- 8 subjects (4 female and 4 male), 6 subjects (4 female and 2 male) and 6 subjects (1 female and 5 male) were asked to complete the experiment using PFBA, PHFBA, and PPFBA, respectively in the second week of the experiments.

- 5 subjects (2 female and 3 male) completed the experiment using PFBA, seven subjects (3 female and 4 male) completed the experiment using PHFBA, and eight subjects (4 female and 4 male) completed the experiment using PPFBA.

As a result, the following orders had been completed in the experiment. It could be noticed all order combinations had been performed by the subjects. The subjects in each group were assigned randomly.

- 4 subjects (2 female and 2 male) completed the experiment in PFBA-PHFBA - PPFBA order.

- 3 subjects (1 female and 2 male) completed the experiment in PFBA-PPFBA - PHFBA order.

- 4 subjects (2 female and 2 male) completed the experiment in PHFBA-PFBA-PPFBA order.

- 3 subjects (3 male) completed the experiment in PHFBA-PPFBA-PFBA order.

- 4 subjects (2 female and 2 male) completed the experiment in PPFBA-PFBA-PHFBA order.

- 2 subjects (2 female) completed the experiment in PPFBA - PHFBA - PFBA order.

4.3. ETHICS STATEMENT

The approval of the Institutional Review Board of Sabancı University had been taken to conduct the experiments. Subjects were asked to sign the consent form.

5. RESULTS AND DISCUSSION

We had first analyzed the difficulty level changes when Performance Feedback Based Adjustment (PFBA), Physiological Feedback Based Adjustment (PHFBA) and Performance and Physiological Feedback Based Adjustment (PPFBA) methods were used. All subjects played the rehabilitation task for 3 minutes and the game difficulty level was updated at every 10 seconds based on PFBA or PHFBA or PPFBA concept (Figure 4.2). The mean difficulty level over all the steps performed by all subjects averaged over all five different trials was found. We found the mean and variance of the difficulty level selections at consecutive 18 steps performed by all the 20 subjects averaged over a total of 100 trials and performed by randomly selected one of the subjects (subject-4) averaged over a total of 5 trials. Figure 5.1 and 5.2 show the mean difficulty levels over each step proposed by PFBA, PHFBA and PPFBA for all subjects and subject-4 respectively. Figure 5.3 and 5.4 show the variance (or variability) of the difficulty levels at each step over 5 different trials for all subjects and subject-4 respectively.

The mean difficulty level distribution showed that PHFBA on the average suggests slightly easier difficulty levels (all subjects: 2.62±0.43, subject-4: 2.3±0.52) than PFBA (all subjects: 5.93±0.88, subject-4: 5.91±1.07) and PPFBA (all subjects: 3.99±0.38, subject-4: 4.23±0.9) (Figure 5.1 and 5.2). The difficulty variance of PPFBA (all subjects: 4.97±2.06) was higher than PFBA (all subjects: 1.48±0.49) and PHFBA (all subjects: 3.52±1.41) for all subjects which meant that PPFBA offered difficulty levels in a wider range when all subjects were examined together. (Figure 5.3). Difficulty level selections in a wider variety may provide more engagement due to the experienced surprise [107]. It was also noted that the variance of the difficulty levels was lower in PFBA (subject-4: 0.55±0.6) for both all subjects and subject-4 (Figure 5.3 and 5.4) than PHFBA(subject-4: 3.4±2.1) and PPFBA(subject-4: 2.16±1.13).

We then had analysed the the performance (score) rate and mean skin conductance ($Mean_{sc}$) increase rate for each adaptation method (PFBA, PHFBA and PPFBA). We looked at the mean values averaged over five different trials for all subjects and an arbitrary subject (subject-4).

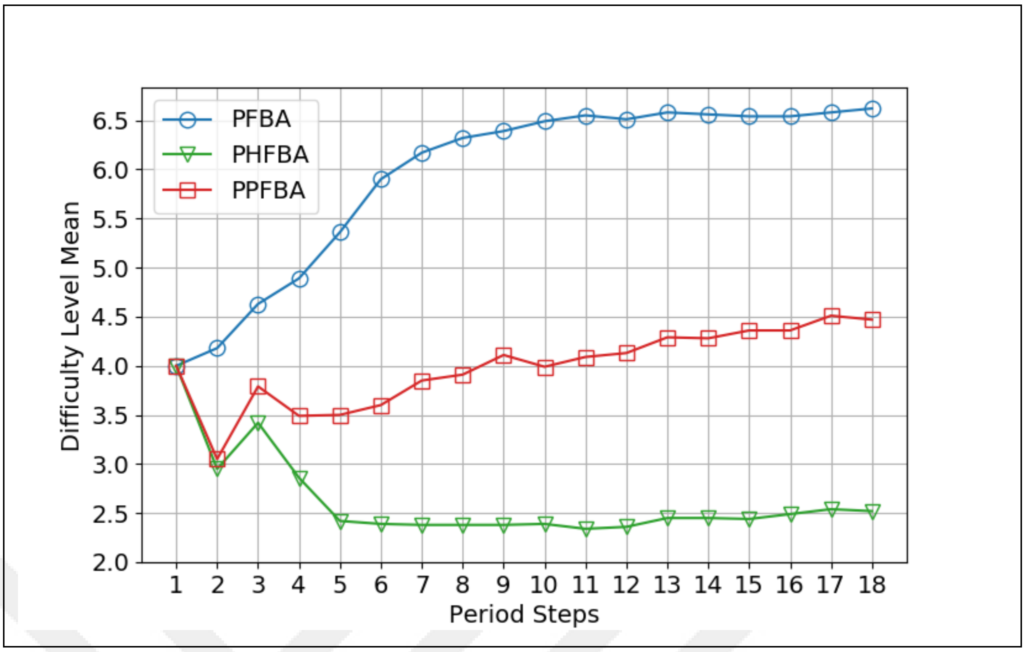


Figure 5.1. The mean of the selected difficulty levels at each step of rehabilitation task play averaged over the 100 trials of 20 subjects

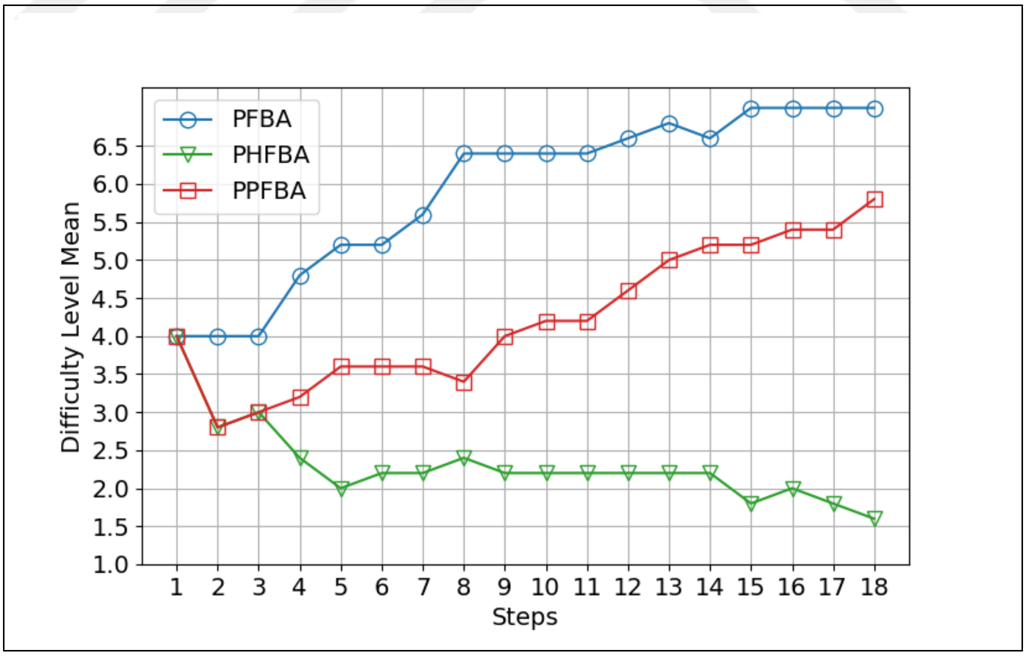


Figure 5.2. The mean of the selected difficulty levels at each step of rehabilitation task play averaged over the 5 trials of subject-4

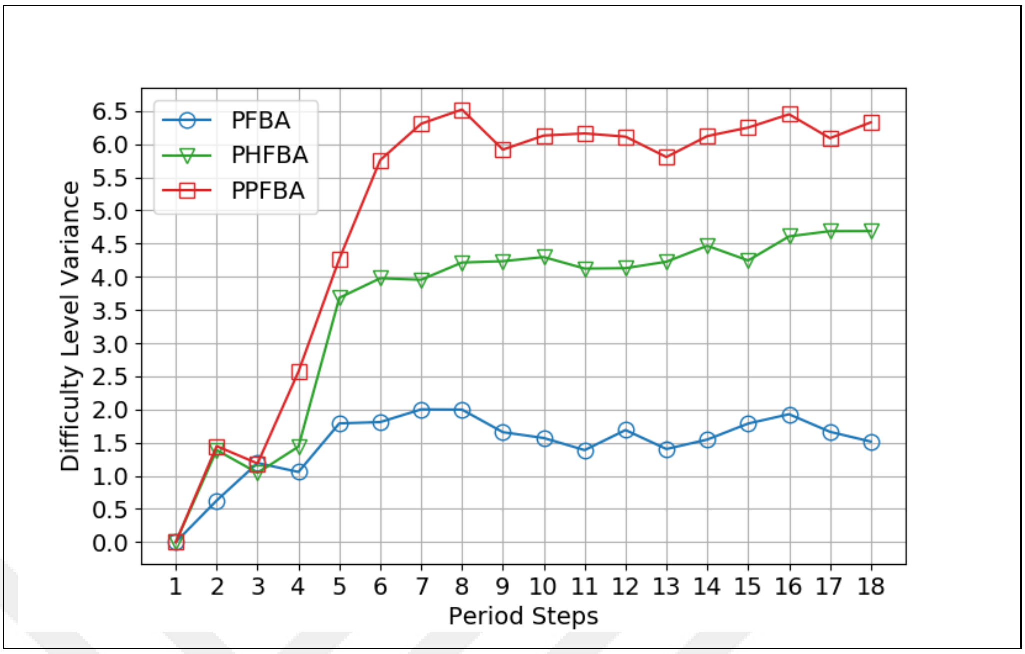


Figure 5.3. The variance of the selected difficulty levels at each step of rehabilitation task play for all the subjects

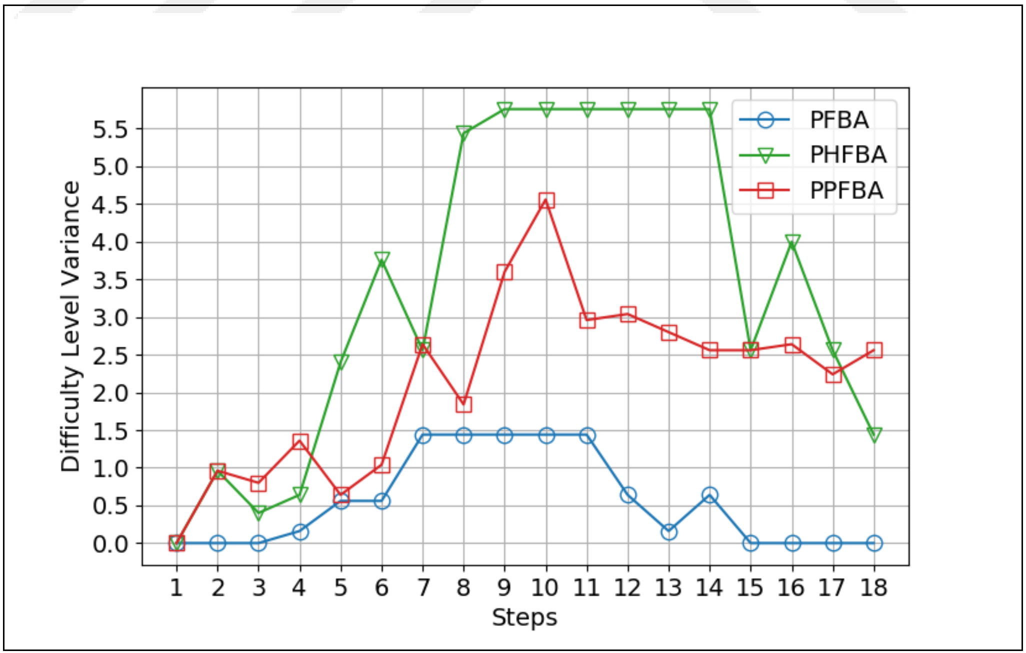


Figure 5.4. The variance of the selected difficulty levels at each step of rehabilitation task play for subject-4

The score rate was calculated as ((score in period)/Max_{score})*100. The maximum score (Max_{score}) a subject could have in a task period was 200. The mean performance (score) rate performed by all the 20 subjects averaged over a total of 100 trials for each adaptation method is given in Figure 5.5. In Figure 5.6 the mean score rate of subject-4 averaged over 5 trials for each adaptation method is given. As seen from the Figure 5.5 and 5.6 the mean score rate in PFBA (all subjects: 65.45±12.75, subject-4: 69.62±17.85) was higher than PHFBA (all subjects: 42.04±6.39, subject-4: 50.06±9.17) and PPFBA (all subjects: 44.06±5.45, subject-4: 32.21±6.86) for both all subjects and subject-4. It was also noted that the mean score rate in PPFBA was slightly higher than PHFBA when all subject were examined together. When we looked at the mean score rate of subject-4, the values in PHFBA were slightly higher than PPFBA.

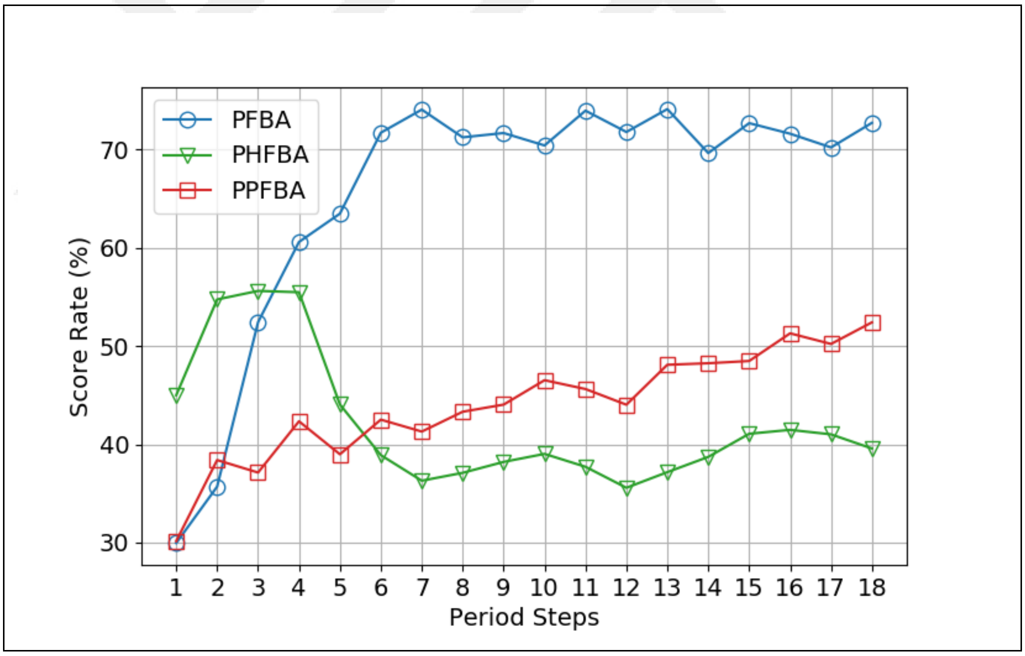


Figure 5.5. The mean of the score rate values at each step of rehabilitation task play averaged over the 100 trials of 20 subjects in PFBA, PHFBA and PPFBA

The mean skin conductance ($Mean_{sc}$) increase rate was calculated as the increase rate according to the baseline using (($Mean_{sc}$ in period)-(mean(baseline)))/mean(baseline)*100. Figure 5.7 shows the mean of $Mean_{sc}$ increase rate at consecutive 18 steps performed by all the 20 subjects averaged over a total of 100 trials for each adaptation method. The mean of

$Mean_{sc}$ increase rate for 5 trials of subject-4 is shown in Figure 5.8. As seen from Figure 5.7, the mean of $Mean_{sc}$ increase rate in PHFBA (all subjects: 93.57±9.8) was lower than PFBA (all subjects: 105.77±6.25) and PPFBA (all subjects: 107.78±4.86) for all subjects. The mean of $Mean_{sc}$ increase rate in PPFBA (95.07±11.34) was slightly higher than PFBA (69.72±5.92) and PHFBA (79.83±11.69) for subject-4 (Figure 5.8).

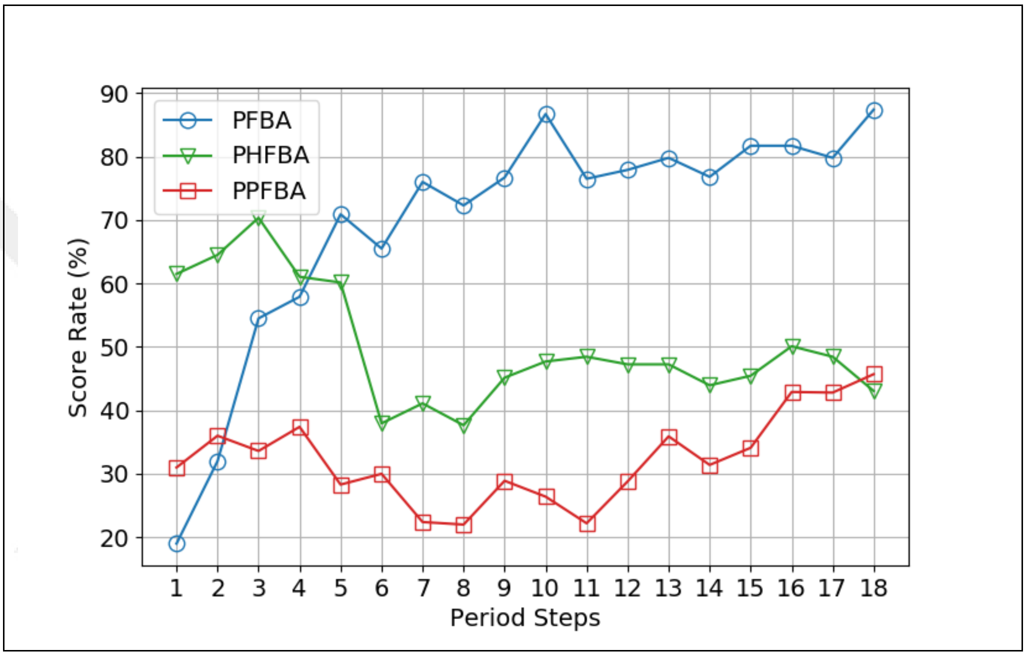


Figure 5.6. The mean of the score rate values at each step of rehabilitation task play averaged over the 5 trials of subject-4 in PFBA, PHFBA and PPFBA

We had looked at the distinctive features from skin conductance (SC), blood volume pulse (BVP) and skin temperature (ST) that had significant differences when the difficult levels had been changed using PFBA, PHFBA, and PPFBA. We had evaluated the skin conductance response (SCR), heart rate (HR), and mean temperature ($Mean_{temp}$). These values were evaluated to understand how the internal state of the subjects change and how subjects feel when these three different feedbacks were used.

We had noticed a low SCR response in PHFBA (9.35±8.9, mean±std) compared to PFBA (14.23±11.5, mean±std) and PPFBA (13.19±10.53, mean±std) (Figure 5.9). Additionally, the SCR values were distributed in a wider range in PFBA and PPFBA compared to PHFBA (Figure 5.10). The values of SCR in PHFBA were distributed in lower values, which might

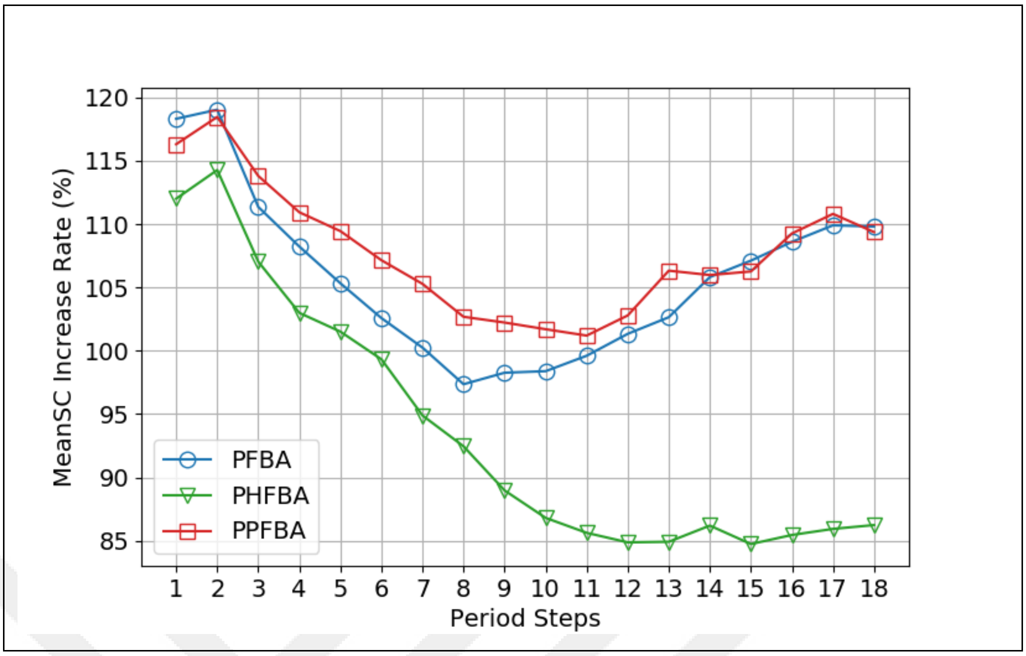


Figure 5.7. The mean of the $Mean_{sc}$ increase rate values at each step of rehabilitation task play averaged over the 100 trials of 20 subjects in PFBA, PHFBA and PPFBA

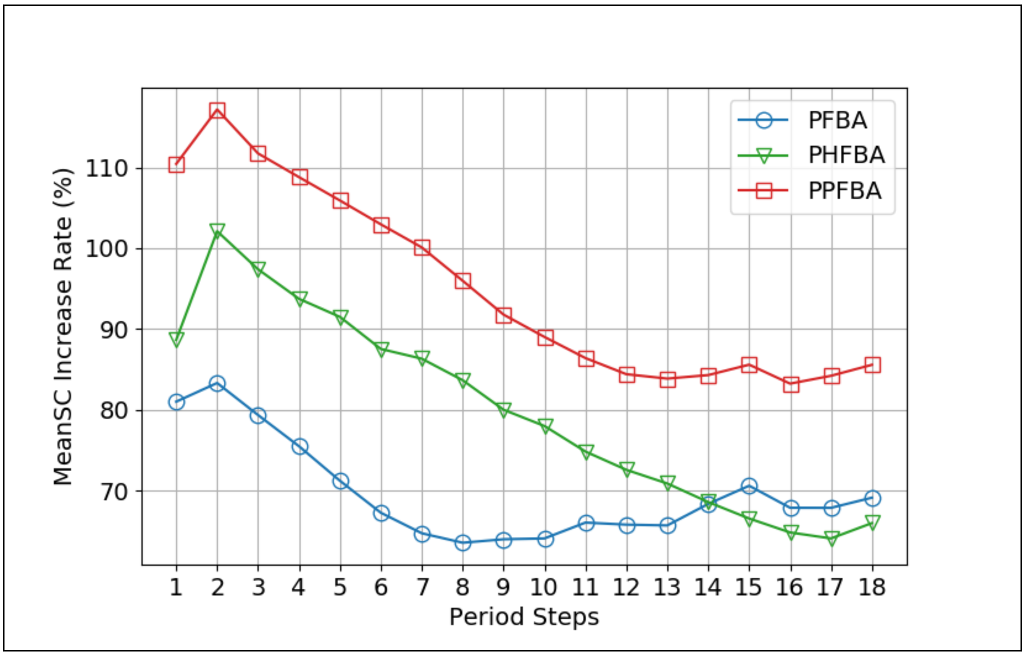


Figure 5.8. The mean of the $Mean_{sc}$ increase rate values at each step of rehabilitation task play averaged over the 5 trials of subject-4 in PFBA, PHFBA and PPFBA

be because of subjects played less challenging difficulty level rehabilitation tasks (Figure 5.1), and they were not happy and amused. It had previously shown that SCR values were increased when the subjects were happy and amused [110], [111], [112]. SCR had shown to exhibits a decrease during relaxation and a sharp increase in response to novel stimuli [113]. Thus, subjects were calm and had positive emotions in PPFBA compared to PFBA and PHFBA because the difficulty level was appropriately challenging.

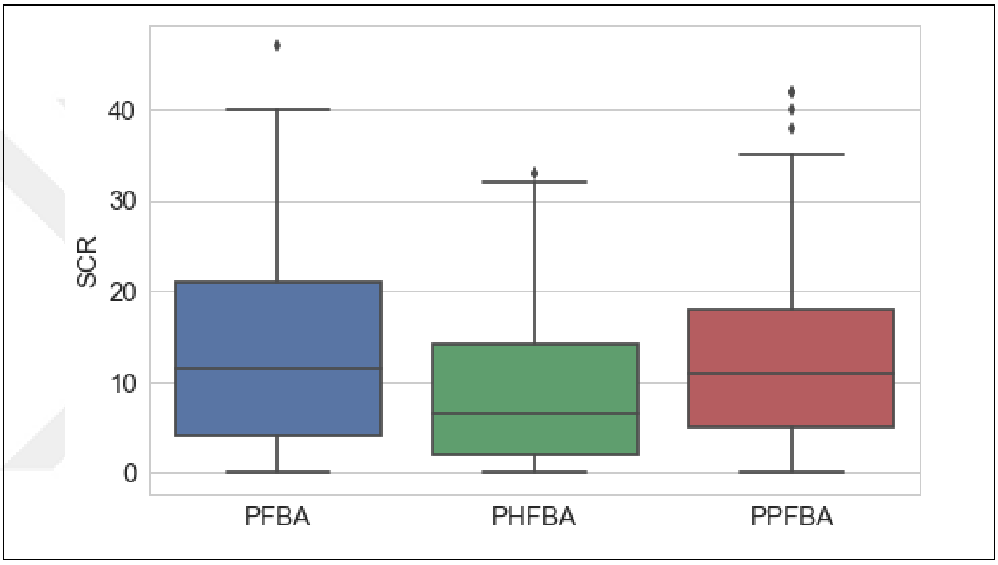


Figure 5.9. Boxplots with median values of SCR for all trials in PFBA, PHFBA, and PPFBA

We had noticed a low HR response in PHFBA (89.27±9.35, mean±std) compared to PFBA (91.86±8.73, mean±std) and PPFBA (94.44±8.18, mean±std) (Figure 5.11). Additionally, the HR values distribution were given in Figure 5.12. The values of HR in PPFBA were distributed in a wider range, which might be because of a wider difficulty challenging level rehabilitation tasks in PPFBA (Figure 5.3). It had previously shown that HR values were increased when the subjects were happy and amused [112], [114]. Additionally, the subjects had shown to prepare action when HR increased, and they were more relaxed when HR decreased [115]. HR had also been found to increase for a number of negative emotions such as anger, anxiety, as well as for some positive emotions such as joy, happiness [76]. The subject had been happier when they performed the rehabilitation task using PFBA and PPFBA.

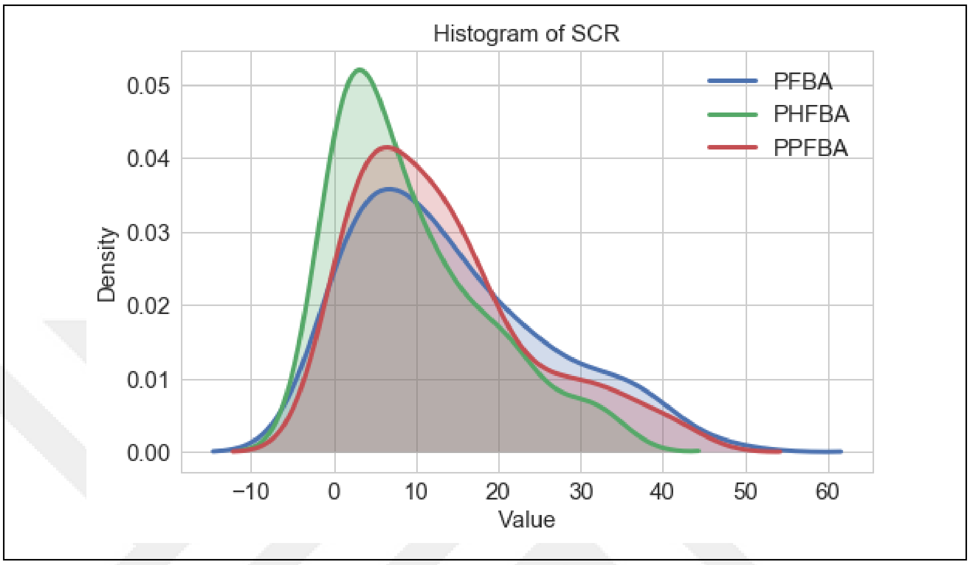


Figure 5.10. Histogram of SCR for all trials in PFBA, PHFBA, and PPFBA

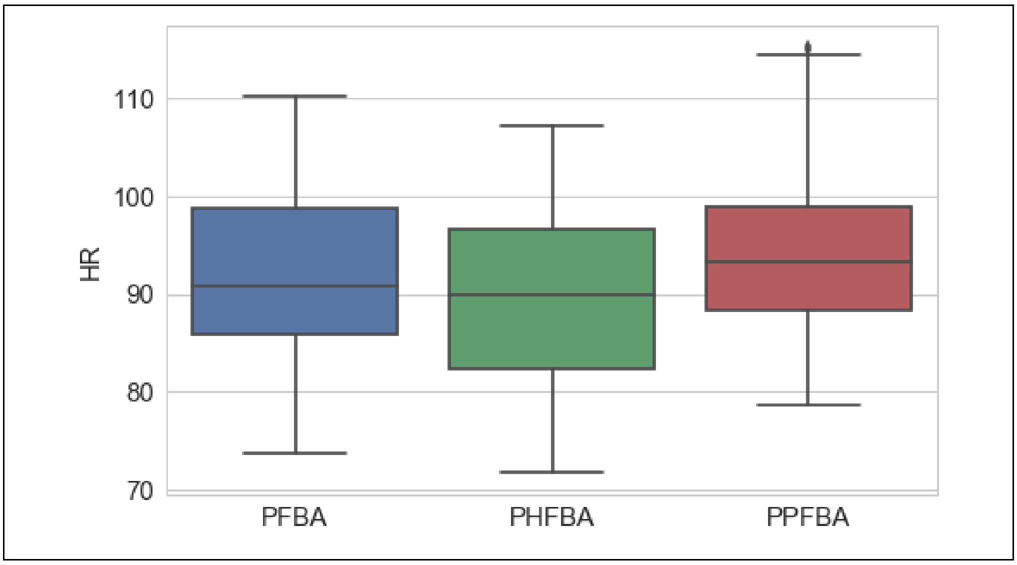


Figure 5.11. Boxplots with median values of HR for all trials in PFBA, PHFBA, and PPFBA

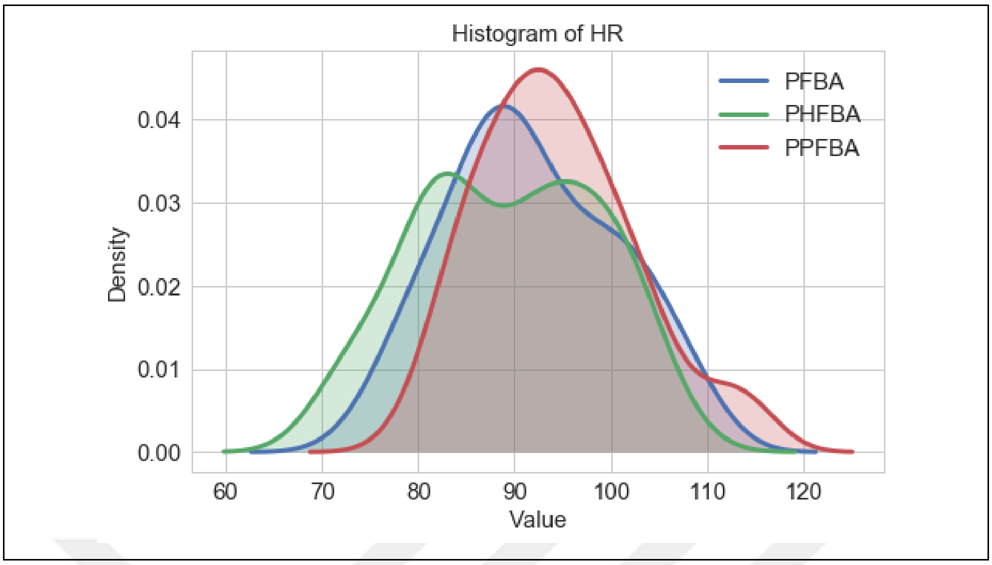


Figure 5.12. Histogram of HR for all trials in PFBA, PHFBA, and PPFBA

We had noticed low $Mean_{temp}$ in PPFBA (1.33±1.47, mean±std) compared to PFBA (2.39±1.78, mean±std) and PHFBA (2.03±1.58, mean±std) (Figure 5.13). Additionally, the values of $Mean_{temp}$ in PPFBA were distributed in lower values compared to PFBA and PHFBA (Figure 5.14). It had previously shown that $Mean_{temp}$ values were decreased when subjects were more engaged in the game [116], [117] and during appropriate challenging rehabilitation tasks [107], [118], then we could say the selection of the difficulty levels in PPFBA was appropriately challenging for the subjects than the ones in PFBA and PHFBA. The $Mean_{temp}$ in PFBA was the highest compared to PPFBA and PHFBA, which might be because subjects were asked to perform the rehabilitation game task with over-challenging difficulty levels (Figure 5.1).

Finally, we had quantified the task engagement and the feeling of the subjects via SAM survey on arousal, valence, and dominance ratings. We calculated the normalized arousal and valence values by taking the mean value divided by the standard deviation for all five trials for each algorithm (PFBA, PHFBA, and PPFBA). Figure 5.15 showed the normalized valence–arousal ratings on the plane [119]. The execution of the rehabilitation game task using PFBA, PHFBA, and PPFBA appeared to be associated with an increase in arousal and valence when compared to the subjects' baseline. We found no significant difference between PFBA, PHFBA, and PPFBA in all subjective ratings. This might be because it was not easy for the subjects to rate their real feelings. However, we noticed a higher arousal and valence values in PFBA and PPFBA compared to PHFBA, which might be because of the subjects performed the task with less challenging difficulty levels in PHFBA (Figure 5.1). Note also that the psychological literature indicates that positive valence signals engaged subjects to complete the task [120], [121]. Thus we could say the subjects in all PFBA, PHFBA, and PPFBA were engaged to complete the task; however with different ratings.

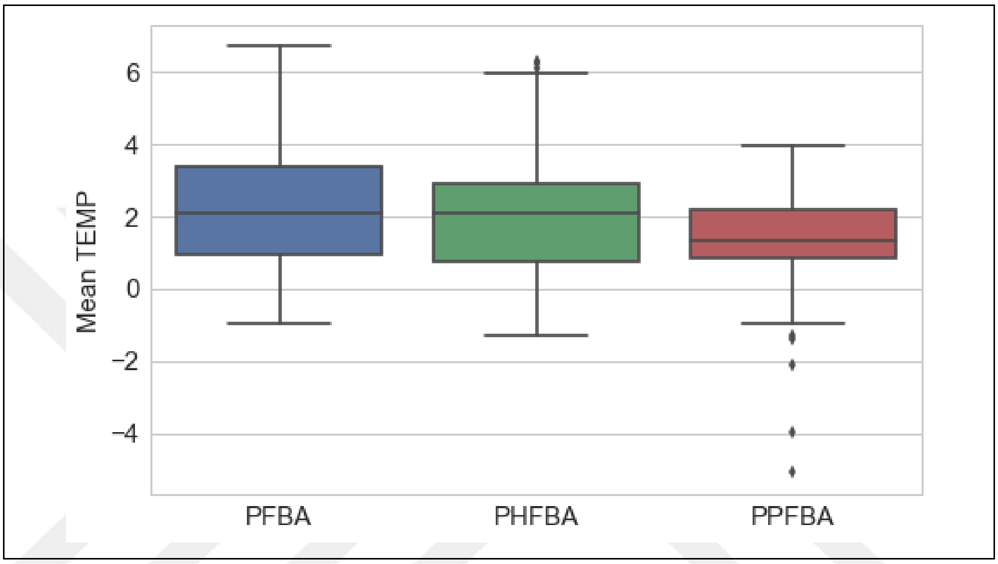


Figure 5.13. Boxplots with median values of $Mean_{temp}$ for all trials in PFBA, PHFBA, and PPFBA

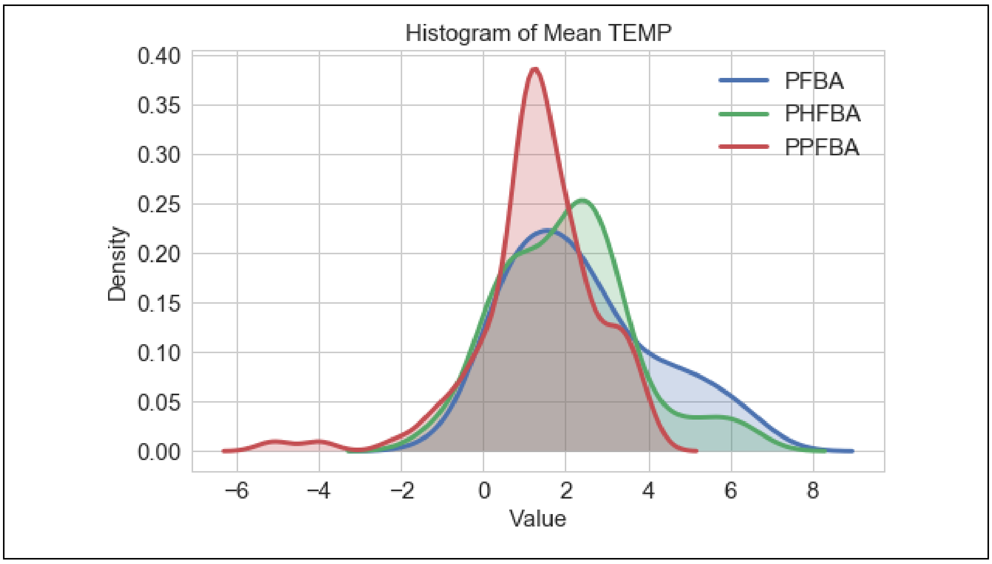


Figure 5.14. Histogram of $Mean_{temp}$ for all trials in PFBA, PHFBA, and PPFBA

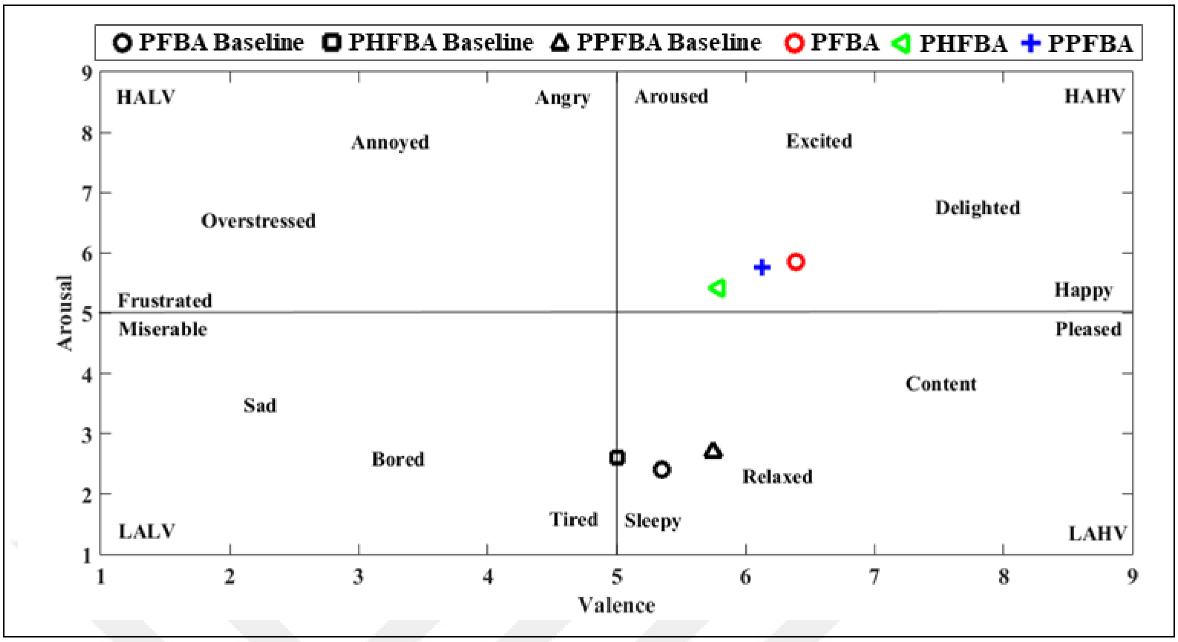


Figure 5.15. Valence and arousal reports for each session are overlaid on Russell's circumplex model (normalized arousal- valence rating)

We had also looked at the arousal, valence, and dominance ratings in each PFBA, PHFBA, and PPFBA separately. The arousal ratings were (6.05±1.66, mean±std), (5.45±1.6, mean±std), and (5.85±2.17, mean±std) in PFBA, PHFBA, and PPFBA, respectively (Figure 5.16). It could be noticed that subjects were more aroused in PFBA and PPFBA compared to PHFBA, which might be because subjects performed the task with less challenging difficulty levels in PHFBA.

The valence ratings were (6.95±0.86, mean±std), (5.70±0.95, mean±std), and (6.20±0.93, mean±std) in PFBA, PHFBA, and PPFBA, respectively (Figure 5.17). It could be noticed that subjects had higher valence values in PFBA and PPFBA compared to PHFBA, which might be because subjects performed the task with less challenging difficulty levels in PHFBA.

We had also looked at the dominance ratings that evaluated the feelings of the subjects about how much they were able to control the rehabilitation task with various difficulty levels. The dominance ratings were (7.00±1, mean±std), (5.9±1.5, mean±std), and (6.10±1.3, mean±std) in PFBA, PHFBA, and PPFBA, respectively (Figure 5.18). Subjects felt more control over the game in PFBA when the game was more challenging (Figure 5.1).

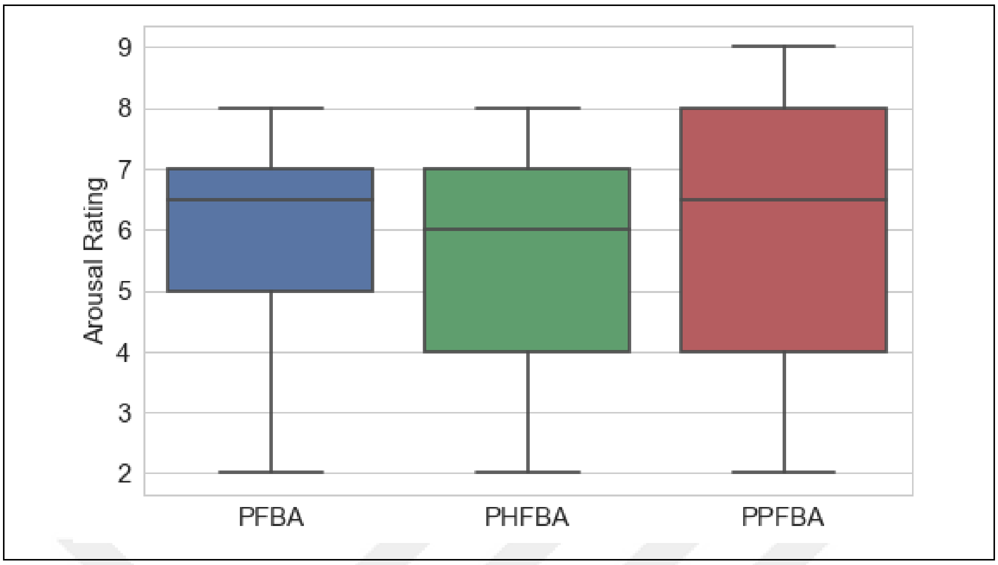


Figure 5.16. Boxplots with median values of arousal ratings for all trials in PFBA, PHFBA, and PPFBA

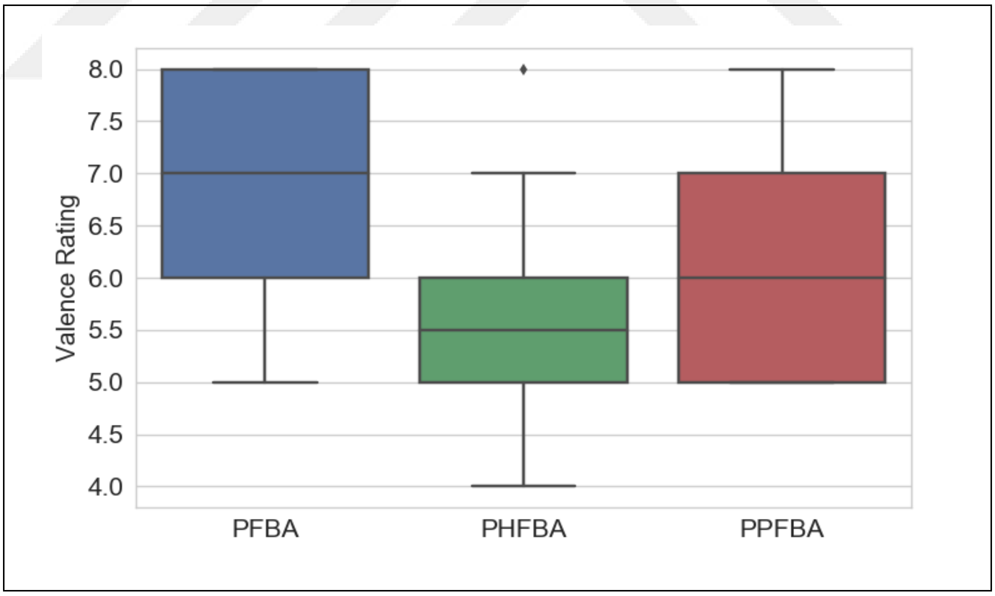


Figure 5.17. Boxplots with median values of valence ratings for all trials in PFBA, PHFBA, and PPFBA

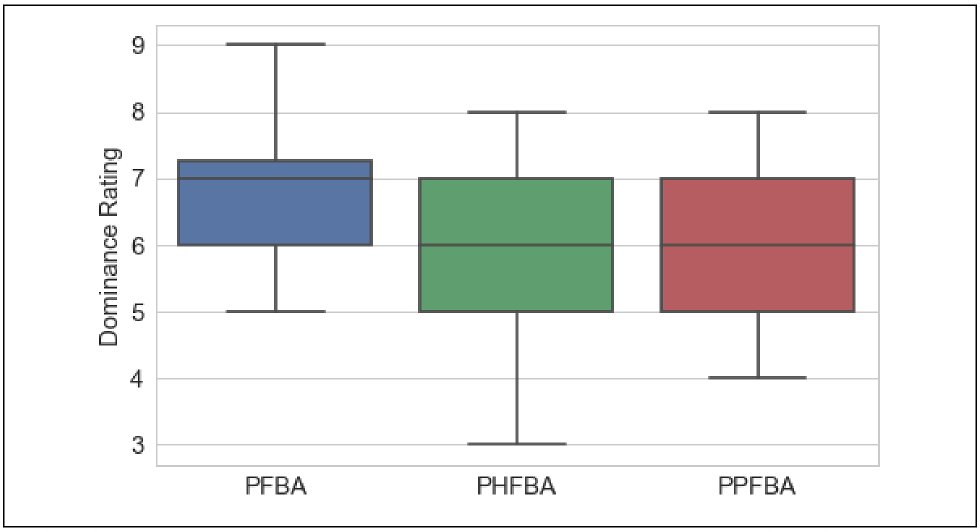


Figure 5.18. Boxplots with median values of dominance ratings for all trials in PFBA, PHFBA, and PPFBA

6. CONCLUSIONS

The dynamic difficulty adjustment to enhance the engagement of the subjects during rehabilitation therapy has become the focus of many studies. The aim of this study was to compare the engagement of subjects when the difficulty adjustment mechanism uses three feedbacks, which are score (PFBA), physiological signal (PHFBA), and score and physiological signal together (PPFBA) for difficulty level, in robot-assisted rehabilitation. Both objective measures, such as physiological signals, and performance (score) and subjective measures, such as survey reports were used for the comparison.

A particular strength of the present findings is that they come from a within-subjects design; that is, it is the same participants who played the game with PFBA, PHFBA, and PPFBA, and are not influenced by factors occur in between-subjects designs, such as age, gender, skill level, etc. Another novel aspect of the present study is that it takes not only objective measures into account but also the subjective states of the subjects. Since the ultimate aim is to use a robot-assisted rehabilitation system that adjusts itself to the changing needs of the individuals, it is important that the subjects do not perceive the tasks as difficult (over-challenging) or under-challenging.

The three feedback based dynamic difficulty adjustment during rehabilitation task with RehabRoby is evaluated in 20 healthy subjects. The mean difficulty level distribution showed that PHFBA on the average suggests slightly easier difficulty levels (2.62±0.43, mean±std) to the subjects than PFBA (5.93±0.88, mean±std) and PPFBA (3.99±0.38, mean±std). Easier difficulty level adjustment resulted in less engaged subjects and correspondingly lower subjects's skin conductance response (SCR) (9.35±8.9, mean±std) and heart rate (HR) (89.27±9.35, mean±std) values in PHFBA compared to PFBA and PPFBA. Additionally, easier difficulty level adjustment resulted in lower valence value (5.7±0.95, mean±std), arousal (5.45±1.6, mean±std) and dominance (5.9±1.5, mean±std) subjective ratings in PHFBA compared to PFBA and PPFBA. Subjects experienced a better range of difficulty levels in PFBA and PPFBA that may help them to become more engaged, and therefore, they were amused and happy. It was also noted that the difficulty variance of PPFBA (4.97±2.06, mean±std) was higher than PFBA (1.48±0.49, mean±std) and PHFBA (3.52±1.41, mean±std) which meant that PPFBA offered wider levels to each subject. A wider variety of difficulty level suggestions might increase the amazement experienced by the subject, and the subject might become more engaged in the rehabilitation task, and consequently, $Mean_{temp}$ value in PPFBA (1.33±1.5, mean±std) was lower than the PFBA (2.39±1.78, mean±std) and PHFBA (2.03±1.58, mean±std).

7. LIMITATIONS AND FUTURE WORK

The results from the presented study, while encouraging, should be treated with caution because of the inherent limitations.

One of the limitations is that the experiments are conducted only with healthy subjects. This study is the first step to evaluate the proposed three feedback based difficulty level adjustment, safety, and usability. We are aware that manual dexterity, physiological signal response to affect changes, and the appropriateness and level of games are all potentially different for target clinical populations, i.e., people with upper limb sensorimotor impairment (for example, caused by stroke or cerebral palsy (CP)). Stroke patients may have different physiological responses than healthy subjects [122], [123] and thus the intensity of the chosen physiological features and perhaps the physiological features themselves may need to be reassessed when these difficulty adjustment algorithms are implemented for the patient population. Thus it is advised to use caution in interpreting the generalizability of the results obtained for the healthy subjects. We believe that this study provides a basis for further exploring the role of dynamical difficulty adjustment algorithms in robot-assisted rehabilitation of stroke patients.

Another limitation is there is a need to design experiments to observe motor learning because confounding factors such as general sensory acuity decrease (e.g., the vision of older persons), and communication and cognitive impairment are the issues that need to be considered when evaluating the proposed system with patients. Note also that this is a preliminary study to explore how the difficulty adjustment in a rehabilitation task can increase engagement when three different feedbacks from the subjects are used. Once demonstrated that such an approach works, future tasks will embed force field, distortion, etc. to align the training with therapeutic goals. In this dissertation, the goal was not to improve mobility or strength, rather explore whether engagement could be improved.

The mean of the skin conductance signal ($Mean_{sc}$) was used as real-time physiological feedback in this study. Different features obtained from the physiological signals such as heart rate (HR) and skin conductance ratio (SCR) can be used together in the adaptation mechanism by designing proper experimental setup to achieve a more accurate emotion state.

The rehabilitation task designed for this study includes only elbow flexion/extension movement. Rehabilitation tasks that enable combined joint movements such as elbow flexion/extension together with shoulder abduction/adduction may be designed in further studies to provide more complex movements in the therapy.

Biomechanical measurements (e.g., EMG) may be integrated into the designed difficulty level adaptation mechanism, and the relationship between the physiological signals and the biomechanical measurements may be examined in further studies.

REFERENCES

1. Woldag H, Hummelsheim H. Evidence-based physiotherapeutic concepts for improving arm and hand function in stroke patients: A review. *Journal of Neurology*. 2002;249(5):518-528.

2. Lotze M, Braun C, Birbaumer N, Anders S, Cohen LG. Motor learning elicited by voluntary drive. *Brain*. 2003;126(4):866-872.

3. Le V, Takahashi CD, Motiwala RR, Der-Yeghiaian L, Cramer SC. Robot-based hand motor therapy after stroke. *Brain*. 2007;131(2):425-437.

4. Choi Y, Gordon J, Park H, Schweighofer N. Feasibility of the adaptive and automatic presentation of tasks (ADAPT) system for rehabilitation of upper extremity function post-stroke. *Journal of NeuroEngineering and Rehabilitation*. 2011;8:42.

5. Gordon J. *Assumptions underlying physical therapy intervention: Theoretical and historical perspectives*. Gaithersburg: Aspen Publishers; 2000.

6. Colombo R, Sterpi I, Mazzone A, Delconte C, Pisano F. Taking a lesson from patients' recovery strategies to optimize training during robot-aided rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering.* 2012;20(3):276-285.

7. Marchal-Crespo L, Reinkensmeyer DJ. Review of control strategies for robotic movement training after neurologic injury. *Journal of NeuroEngineering and Rehabilitation*. 2009;6:20.

8. Kan P, Huq R, Hoey J, Goetschalckx R, Mihailidis A. The development of an adaptive upper-limb stroke rehabilitation robotic system. *Journal of NeuroEngineering and Rehabilitation.* 2011;8:33.

9. Zimmerli L, Krewer C, Gassert R, Müller F, Riener R, Lünenburger L. Validation of a mechanism to balance exercise difficulty in robot-assisted upper-extremity rehabilitation after stroke. *Journal of NeuroEngineering and Rehabilitation*. 2012;9:6.

10. Xu G, Gao X, Pan L, Chen S, Wang Q, Zhu B, Li J. Anxiety detection and training task adjustment in robot-assisted active stroke rehabilitation. *International Journal of Advanced Robotic Systems*. 2018;15(6).

11. Kong KH, Yap SGM, Loh YJ, *Rehabilitation technology, Handbook of Rehabilitation Medicine*. Singapore: World Scientific; 2016.

12. Maclean N, Pound P. A critical review of the concept of patient motivation in the literature on physical rehabilitation. *Social Science and Medicine*. 2000;50(4):495-506.

13. Kaelin-Lang A, Sawaki L, Cohen LG. Role of voluntary drive in encoding an elementary motor memory. *Journal of Neurophysiology*. 2004;93(2):1099-1103.

14. Soleymani M, Asghari-Esfeden S, Fu Y, Pantic M. Analysis of EEG signals and facial expressions for continuous emotion detection. *IEEE Transactions on Affective Computing*. 2016;7(1):17-28.

15. El Ayadi M, Kamel MS, Karray F. Survey on speech emotion recognition: Features, classification schemes, and databases. *Pattern Recognition*. 2011;44(3):572-587.

16. Kleinsmith A, Bianchi-Berthouze N. Affective body expression perception and recognition: A survey. *IEEE Transactions on Affective Computing*. 2013;4(1):15-33.

17. Koelstra S, Mühl C, Soleymani M, Lee JS, Yazdani A, Ebrahimi T. DEAP: A database for emotion analysis; Using physiological signals. *IEEE Transactions on Affective Computing*. 2012;3(1):18-31.

18. Kwakkel G, Kollen BJ, Krebs HI. Effects of robot-assisted therapy on upper limb recovery after stroke: A systematic review. *Neurorehabilitation and Neural Repair*. 2008;22(2):111-121.

19. Mehrholz J, Platz T, Kugler J, Pohl M. Electromechanical and robot-assisted arm training for improving arm function and activities of daily living after stroke. *Cochrane Database of Systematic Reviews*. 2008;8(4):CD006876

20. Kiguchi K, Iwami K, Yasuda M, Watanabe K, Fukuda T. An exoskeletal robot for human shoulder joint motion assist. *IEEE/ASME Transactions on Mechatronics*. 2003;8(1):125-135.

21. Rosen J, Brand M, Fuchs MB, Arcan M. A myosignal-based powered exoskeleton system. *IEEE Transactions on Systems, Man, and Cybernetics*. 2001;31(3):210-222.

22. Song R, Tong K, Hu X, Li L. Assistive control system using continuous myoelectric signal in robot-aided arm training for patients after stroke. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2008;16(4):371-379.

23. Reinkensmeyer D, Burgar C, Rymer WZ, Mahoney R, Lum P. Robotic devices for movement therapy after stroke: Current status and challenges to clinical acceptance. *Topics in Stroke Rehabilitation*. 2005;8(4):40-53.

24. Reinkensmeyer DJ, Kahn LE, Averbuch M, McKenna-Cole A, Schmit BD, Zev Rymer W. Understanding and treating arm movement impairment after chronic brain injury: Progress with the ARM guide. *Journal of Rehabilitation Research & Development*. 2000;37(6):653-662.

25. Chang JJ, Tung WL, Wu WL, Huang MH, Su FC. Effects of robot-aided bilateral force-induced isokinetic arm training combined with conventional rehabilitation on arm motor function in patients with chronic stroke. *Archives of Physical Medicine and Rehabilitation*. 2007;88(10):1332-1338.

26. Spencer S, Bobrow JE, Reinkensmeyer DJ, Allington J, Klein J. Optimization of a parallel shoulder mechanism to achieve a high-force, low-mass, robotic-arm exoskeleton. *IEEE Transactions on Robotics*. 2010;26(4):710-715.

27. Jannink MJA, van der Kooij H, Aalsma AMM, Hekman EEG, Stienen AHA, Prange GB, et al. Dampace: Design of an exoskeleton for force-coordination training in upper-extremity rehabilitation. *Journal of Medical Devices*. 2009;3(3):031003

28. Kiguchi K, Rahman MH, Sasaki M, Teramoto K. Development of a 3DOF mobile exoskeleton robot for human upper-limb motion assist. *Robotics and Autonomous Systems*. 2008;56(8):678-691.

29. Guglielmelli E, Minuco G, Pisano F, Micera S, Dario P, Cappiello G. A simple robotic system for neurorehabilitation. *Autonomous Robots*. 2006;19(3):271-284.

30. Rosati G, Gallina P, Masiero S. Design, implementation and clinical tests of a wire-based robot for neurorehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2007;15(4):560-569.

31. Toth A, Fazekas G, Arz G, Jurak M, Horvath M. Passive robotic movement therapy of the spastic hemiparetic arm with REHAROB: Report of the first clinical test and the follow-up system improvement. *In: Proceedings of the 2005 IEEE 9th International Conference on Rehabilitation Robotics*; 2005: IEEE.

32. Amirabdollahian F, Loureiro RCV, Gradwell E, Collin C, Harwin WS, Johnson G. Multivariate analysis of the Fugl-Meyer outcome measures assessing the effectiveness of GENTLE/S robot-mediated stroke therapy. *Journal of NeuroEngineering and Rehabilitation*. 2007;4:4.

33. Frisoli A, Borelli L, Montagner A, Marcheschi S, Procopio C, Salsedo F, et al. Arm rehabilitation with a robotic exoskeleton in Virtual Reality. *10th International Conference on Rehabilitation Robotics, ICORR'07*. 2007: IEEE.

34. Vertechy R, Frisoli A, Dettori A, Solazzi M, Bergamasco M. Development of a new exoskeleton for upper limb rehabilitation. *IEEE International Conference on Rehabilitation Robotics; ICORR*. 2009: IEEE.

35. Furusho J, Kikuchi T, Oda K, Ohyama Y, Morita T, Shichi N. A 6-DOF rehabilitation support system for upper limbs including wrists "robotherapist" with physical therapy. *10th International Conference on Rehabilitation Robotics, ICORR'07*; 2007: IEEE.

36. Balasubramanian S, Wei HR, Perez M, Shepard B, Koeneman E, Koeneman J. Rupert: An exoskeleton robot for assisting rehabilitation of arm functions. *Virtual Rehabilitation, IWVR;* 2008: IEEE.

37. Tsagarakis NG, Caldwell DG. Development and control of a "soft-actuated" exoskeleton for use in physiotherapy and training. *Autonomous Robots*. 2003;15(1):21-33.

38. Nef T, Quinter G, Müller R, Riener R. Effects of arm training with the robotic device ARMin I in chronic stroke: Three single cases. *Neurodegenerative Diseases*. 2009;6(5–6):240-251.

39. Mayr A, Kofler M, Saltuari L. ARMOR: an electromechanical robot for upper limb training following stroke. A prospective randomised controlled pilot study. *Handchir Mikrochir Plast Chir.* 2008;40:66-73.

40. Crema A, Micera S, Gföhler M, d'Amico E, Miseikis J, Rossini M. MUNDUS project: Multimodal neuroprosthesis for daily upper limb support. *Journal of NeuroEngineering and Rehabilitation*. 2013;10:66.

41. Maciejasz P, Eschweiler J, Gerlach-Hahn K, Jansen-Troy A, Leonhardt S. A survey on robotic devices for upper limb rehabilitation. *Journal of NeuroEngineering and Rehabilitation*. 2014;11:3.

42. Krebs HI, Hogan N, Aisen ML, Volpe BT. Robot-aided neurorehabilitation. *IEEE Transactions on Rehabilitation Engineering*. 1998;6(1):75-87.

43. Schoone M, Van Os P, Campagne A. Robot-mediated active rehabilitation (ACRE) A user trial. *10th International Conference on Rehabilitation Robotics, ICORR'07;* 2007: IEEE.

44. Spencer SJ, Klein J, Minakata K, Le V, Bobrow JE, Reinkensmeyer DJ. A low cost parallel robot and trajectory optimization method for wrist and forearm rehabilitation using the Wii. *Proceedings of the 2nd Biennial IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, BioRob 2008*; 2008: IEEE.

45. Beer RF, Naujokas C, Bachrach B, Mayhew D. Development and evaluation of a gravity compensated training environment for robotic rehabilitation of post-stroke reaching. *Proceedings of the 2nd Biennial IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, BioRob 2008*; 2008: IEEE.

46. Kikuchi T, Hu X, Fukushima K, Oda K, Furusho J, Irioue A. Quasi-3-DOF rehabilitation system for upper limbs: Its force-feedback mechanism and software for

rehabilitation. *10th International Conference on Rehabilitation Robotics, ICORR'07*; 2007: IEEE.

47. Ren Y, Park HS, Zhang LQ. Developing a whole-arm exoskeleton robot with hand opening and closing mechanism for upper limb stroke rehabilitation. *IEEE International Conference on Rehabilitation Robotics, ICORR 2009*; 2009: IEEE.

48. Just F, Gunz D, Duarte J, Simonetti D, Riener R, Rauter G. Improving usability of rehabilitation robots: Hand module evaluation of the ARMin exoskeleton. *Proceedings of the 4th International Symposium on Wearable Robotics, WeRob2018;* 2018: Springer

49. Gupta A, O'Malley MK, Patoglu V, Burgar C. Design, control and performance of RiceWrist: A force feedback wrist exoskeleton for rehabilitation and training. *International Journal of Robotics Research*. 2008: IEEE.

50. Burgar CG, Lum PS, Shor PC, Machiel HF, Machiel Van der Loos HF. Development of robots for rehabilitation therapy: the Palo Alto VA/Stanford experience. *Journal of Rehabilitation Research & Development*. 2000;37(6):663-673.

51. Loureiro RCV, Harwin WS. Reach & grasp therapy: Design and control of a 9-DOF robotic neuro-rehabilitation system. *IEEE 10th International Conference on Rehabilitation Robotics, ICORR'07*; 2007: IEEE.

52. Mihelj M, Podobnik J, Munih M. HEnRiE - Haptic environment for reaching and grasping exercise. *Proceedings of the 2nd Biennial IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, BioRob 2008*; 2008: IEEE.

53. Culmer PR, Jackson AE, Makower S, Richardson R, Cozens JA, Levesley MC. A control strategy for upper limb robotic rehabilitation with a dual robot system. *IEEE/ASME Transactions on Mechatronics*. 2010;15(4):575-585.

54. Morales R, Badesa FJ, García-Aracil N, Sabater JM, Pérez-Vidal C. Pneumatic robotic systems for upper limb rehabilitation. *Medical and Biological Engineering and Computing*. 2011;49(10):1145-1156.

55. Özkul F, Barkana DE, Demirbas SB, İnal S. Evaluation of elbow joint proprioception with RehabRoby: a pilot study. *Acta Orthop Traumatol Turc*. 2012;46(5):332-338.

56. Barkana DE, Özkul F. A robot-assisted rehabilitation system - RehabRoby. *Interdisciplinary Mechatronics: Engineering Science and Research Development*. 2013:145-162.

57. Wiemeyer J, Schneider P. Applying serious games to motor learning in sport. *International Journal of Game-Based Learning*. 2014;2(4):61-73.

58. Burke JW, McNeill MDJ, Charles DK, Morrow PJ, Crosbie JH, McDonough SM. Optimising engagement for stroke rehabilitation using serious games. *Visual Computer*. 2009;25(12):1085-1099.

59. Brown C, Radtka S, Dowling GA, Mastick J, Hone R, Melnick ME. Feasibility of computer-based videogame therapy for children with cerebral palsy. *Games for Health Journal*. 2013;2(4):222-228.

60. Li C, Rusák Z, Horváth I, Ji L. Influence of complementing a robotic upper limb rehabilitation system with video games on the engagement of the participants: A study focusing on muscle activities. *International Journal of Rehabilitation Research*. 2014;37(4):334-342.

61. Van der Loos HFM, Lohse K, Hodges N, Shirzad N, Verster A. Video games and rehabilitation: using design principles to enhance engagement in physical therapy. *Journal of Neurologic Physical Therapy*. 2013;37(4):166-175.

62. Taylor JA, Thoroughman KA. Motor adaptation scaled by the difficulty of a secondary cognitive task. *Public Library of Science (PLOS) One*. 2008;3(6):e2485.

63. Guadagnoll MA, Lee TD. Challenge Point: A framework for conceptualizing the effects of various practice conditions in motor learning. *Journal of Motor Behavior*. 2004;36(2):212-224.

64. Csikszentmihalyi M. *Flow: The psychology of optimal experience*. New York: Harper & Row; 1990.

65. Halton J, Boulanger P, Annett M, Ranson Q, Anderson F, Bischof WF. Using a multi-touch tabletop for upper extremity motor rehabilitation. *Proceedings of the 21st Australasian Computer-Human Interaction Conference*; 2009: DBLP.

66. Andrade KDO, Fernandes G, Caurin GAP, Siqueira AAG, Romero RAF, Pereira RDL. Dynamic player modelling in serious games applied to rehabilitation robotics. *Proceedings - 2nd SBR Brazilian Robotics Symposium, 11th LARS Latin American Robotics Symposium and 6th Robocontrol Workshop on Applied Robotics and Automation, SBR LARS Robocontrol 2014 - Part of the Joint Conference on Robotics and Intelligent Systems*; 2015: IEEE.

67. Andrade KDO, Pasqual TB, Caurin GAP, Crocomo MK. Dynamic difficulty adjustment with evolutionary algorithm in games for rehabilitation robotics. *IEEE International Conference on Serious Games and Applications for Health, SeGAH 2016*; 2016: IEEE.

68. Hocine N, Gouaïch A, Cerri SA, Mottet D, Froger J, Laffont I. Adjustment in serious games for upper-limb rehabilitation: an approach to improve training outcomes. *User Modeling and User-Adapted Interaction*. 2015;25(1):65-98.

69. Pirovano M, Mainetti R, Baud-Bovy G, Lanzi PL, Borghese NA. Self-adaptive games for rehabilitation at home. *IEEE Conference on Computational Intelligence and Games, CIG 2012*; 2012: IEEE.

70. Octavia JR, Coninx K. Adaptive personalized training games for individual and collaborative rehabilitation of people with multiple sclerosis. *Journal of Biomedicine and Biotechnology*. 2014(3):345728.

71. Choi Y, Qi F, Gordon J, Schweighofer N. Performance-based adaptive schedules enhance motor learning. *Journal of Motor Behavior*. 2008;40(4):273-280.

72. Chaouachi M, Chalfoun P, Jraidi I, Frasson C. Affect and mental engagement: Towards adaptability for intelligent systems. *Proceedings Twenty-Third International Florida Artificial Intelligence Research Society Conference;* 2010: DBLP.

73. Poh MZ, Swenson NC, Picard RW. A wearable sensor for unobtrusive, long-term assessment of electrodermal activity. *IEEE Transactions on Biomedical Engineering*. 2010;57(5):1243-1252.

74. Ax AF. The physiological differentiation between fear and anger in humans. *Psychosomatic Medicine*. 1953;15(5):433-442.

75. Lang PJ. The emotion probe: Studies of motivation and attention. *American Psychologist*. 1995;50(5):372-385.

76. Boucsein W. *Electrodermal activity*: New York: Springer Science & Business Media; 2012.

77. Brown R, Macefield VG. Skin sympathetic nerve activity in humans during exposure to emotionally-charged images: Sex differences. *Frontiers in Physiology*. 2014;5:111.

78. Mackersie CL, Cones H. Subjective and psychophysiological indexes of listening effort in a competing-talker task. *Journal of the American Academy of Audiology*. 2011;22(2):113-122.

79. Swangnetr M, Kaber DB. Emotional state classification in patient-robot interaction using wavelet analysis and statistics-based feature selection. *IEEE Transactions on Human-Machine Systems*. 2013;43(1):63-75.

80. Gunther A, Witte OW, Hoyer D. Autonomic dysfunction and risk stratification assessed from heart rate pattern. *Open Neurology Journal*. 2010;4(2):39-49.

81. Osumi M, Saijo A, Kataoka H, Yasuda M, Kano H, Yoshida H. Development of a skin temperature measuring system for non-contact stress evaluation. *Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Vol.20 Biomedical Engineering Towards the Year 2000 and Beyond (Cat. No.98CH36286)*; 1998: IEEE.

82. Rimm-Kaufman SE, Kagan J. The psychological significance of changes in skin temperature. *Motivation and Emotion.* 1996;20(1):63-78.

83. Novak D, Mihelj M, Munih M. A survey of methods for data fusion and system adjustment using autonomic nervous system responses in physiological computing. *Interacting with Computers*. 2012;24(3):154-172.

84. Kreibig SD. Autonomic nervous system activity in emotion: A review. *Biological Psychology*. 2010;84(3):394-421.

85. Özkul F, Barkana DE. Upper-extremity rehabilitation robot RehabRoby: Methodology, design, usability and validation. *International Journal of Advanced Robotic Systems*. 2013;10(401):1-13.

86. Özkul F, Barkana DE, Maşazade E. Admittance filter parameter adjustment of a robot-assisted rehabilitation system (RehabRoby). *Mechatronics and Robotics Engineering for Advanced and Intelligent Manufacturing*. 2017: 87-96.

87. Özkul F, Barkana DE. Design of an admittance control with inner robust position control for a robot-assisted rehabilitation system RehabRoby. *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM;* 2011: IEEE.

88. Özkul F, Barkana DE. Design and control of an upper limb exoskeleton robot RehabRoby. *In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).* 2011:125-136.

89. Özkul F, Barkana DE. Robot-destekli rehabilitasyon sistemi RehabRoby'nin pozisyon kontrolü. *Otomatik Kontrol Ulusal Toplantısı TOK*. 2010.

90. Fasoli SE, Krebs HI, Hogan N. Robotic technology and stroke rehabilitation: translating research into practice. *Topics in Stroke Rehabilitation*. 2005;11(4):11-9.

91. Güleç E. Anthropometric dimensions of human in Anatolia. TC Ankara University Scientific Research Project Report. 2007.

92. Jung S, Hsia TC. Neural network impedance force control of robot manipulator. *IEEE Transactions on Industrial Electronics*. 1998;45(3):451-461.

93. Okunev V, Nierhoff T, Hirche S. Human-preference-based control design: Adaptive robot admittance control for physical human-robot interaction. *Proceedings - IEEE*

International Workshop on Robot and Human Interactive Communication; 2012: IEEE.

94. Dimeas F, Aspragathos N. Fuzzy learning variable admittance control for human-robot cooperation. *IEEE International Conference on Intelligent Robots and Systems;* 2014: IEEE.

95. Thought Technology Ltd.; [cited 2019 Mar 23]. Available from: http://thoughttechnology.com/index.php/

96. Kim KH, Bang SW, Kim SR. Emotion recognition system using short-term monitoring of physiological signals. *Medical & Biological Engineering & Computing*. 2004;42(3):419-427.

97. Rani P, Sarkar N, Smith CA, Kirby LD. Anxiety detecting robotic system - Towards implicit human-robot collaboration. *Robotica.* 2004;22(1):85-95.

98. Jo J, Lee Y, Shin HS. Real-time analysis of heart rate variability for a mobile human emotion recognition system. *Recent Advances in Electrical and Computer Engineering*; 2013.

99. Heart rate variability analysis system, Medicore; [cited 2019 Mar 23]. Available from: http://medi-core.com/download/HRV_clinical_manual_ver3.0.pdf

100. Yijing Z, Xiaoping D, Fang L, Xiaolu J, Bin W. The effects of guided imagery on heart rate variability in simulated spaceflight emergency tasks performers. *BioMed Research International*. 2015;2015(2):1-8.

101. Freeman JV, Dewey FE, Hadley DM, Myers J, Froelicher VF. Autonomic nervous system interaction with the cardiovascular system during exercise. *Progress in Cardiovascular Diseases*. 2006;48(5):342-362.

102. Palaska Y. *Detection of distinguishing features using selection methods for robot-assisted rehabilitation system, Rehabroby*. Istanbul: Yeditepe University; 2018.

103. Fung MT, Stouthamer-Loeber M, Lynam DR, Steinhauer SR, Venables PH, Raine A. Reduced electrodermal activity in psychopathy-prone adolescents. *Journal of Abnormal Psychology*. 2005;114(2):187-196.

104. Unity, Game engine, tools and multiplatform; [cited 2019 Mar 23]. Available from: https://unity3d.com

105. Palaska Y, Masazade E, Ekenel HK, Barkana DE, Erdogan H. Vision-based game design and assessment for physical exercise in a robot-assisted rehabilitation system. *IET Computer Vision*. 2017;12(1):59-68.

106. Missura O, Gärtner T. Predicting dynamic difficulty. *Advances in Neural Information Processing Systems;* 2011.

107. Özkul F, Palaska Y, Masazade E, Barkana DE. Exploring dynamic difficulty adjustment mechanism for rehabilitation tasks using physiological measures and subjective ratings. *IET Signal Processing*. 2019;13(3):378-386.

108. Adamovich SV, Fluet GG, Merians AS, Mathai A, Qiu Q. Incorporating haptic effects into three-dimensional virtual environments to train the hemiparetic upper extremity. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2009;17(5):512-520.

109. Cameirão MS, Badia SBI, Oller ED, Verschure PFMJ. Neurorehabilitation using the virtual reality based rehabilitation gaming system: Methodology, design, psychometrics, usability and validation. *Journal of NeuroEngineering and Rehabilitation*. 2010;7:48.

110. Ekman P, Levenson RW, Friesen WV. Autonomic nervous system activity distinguishes among emotions. *Science*. 1983;221(4616):1208-1210.

111. Benarroch EE. The central autonomic network: Functional organization, dysfunction, and perspective. *Mayo Clinic Proceedings*. 1993;68(10):988-1001.

112. Xu X, Liao D, Li Z, Li Z, Yang X, Shu L. A review of emotion recognition using physiological signals. *Sensors*. 2018;18(7):2074.

113. Dawson ME, Schell AM, Filion DL. *Handbook of psychophysiology*. New York: Cambridge University Press; 2007.

114. Bandler R, Shipley MT. Columnar organization in the midbrain periaqueductal gray: modules for emotional expression? *Trends in Neurosciences*. 1994;17(9):379-389.

115. Jang EH, Park BJ, Park MS, Kim SH, Sohn JH. Analysis of physiological signals for recognition of boredom, pain, and surprise emotions. *Journal of Physiological Anthropology*. 2015;34:25.

116. Koster R. *A theory of fun for game design*. Sebastopol: O'Reilly Media; 2013.

117. Malone TW. What makes things fun to learn? heuristics for designing instructional computer games. *SIGSMALL '80 Proceedings of the 3rd ACM SIGSMALL symposium and the first SIGPC symposium on Small systems*; 1980.

118. Olenšek A, Milavec M, Mihelj M, Podobnik J, Ziherl J, Novak D. Psychophysiological responses to robotic rehabilitation tasks in stroke. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2010;18(4):351-361.

119. Russell JA. A circumplex model of affect. *Journal of Personality and Social Psychology*. 1980;39(6):1161-1178.

120. Fishbach A, Labroo AA. Be better or be merry: How mood affects self-control. *Journal of Personality and Social Psychology*. 2007;93(2):158-173.

121. Harlé KM, Shenoy P, Paulus MP. The influence of emotions on cognitive control: feelings and beliefs - where do they meet? *Frontiers in Human Neuroscience*. 2013;7:508

122. Korpelainen JT, Sotaniemi KA, Myllylä V V. Autonomic nervous system disorders in stroke. *Clinical Autonomic Research*. 1999;9(6):325-333.

123. Goljar N, Javh M, Poje J, Ocepek J, Novak D, Ziherl J. Olenšek A, Mihelj M, Munih M. Psychophysiological responses to robot training in different recovery phases after stroke. *IEEE International Conference on Rehabilitation Robotics*; 2011: IEEE.

APPENDIX A: PROCOMP INFINITI ENCODER

About the ProComp Infiniti Encoder

The ProComp Infiniti (SA7500) comes with the following components.

- One eight-channel ProComp Infiniti encoder unit.
- One TT-USB interface unit.
- A supply of fiber optic cable (1' and 10' cables).
- Four alkaline AA batteries.

General description

The ProComp Infiniti is a eight (8) channel, multi-modality device for real-time computerized psychophysiology, biofeedback and data acquisition. It has 8 protected pin sensor inputs; 2 channels that read data at 2048 samples/second, and 6 channels that read it at 256 samples/second.

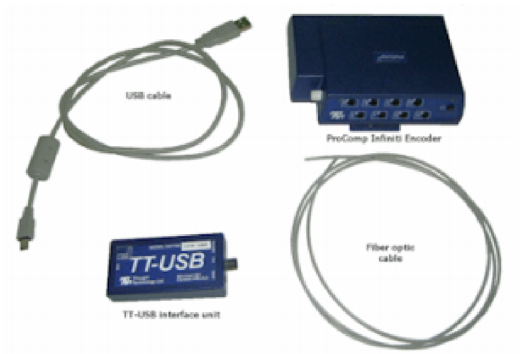
The microprocessor-powered ProComp Infiniti encoder is able to render a wide and comprehensive range of objective physiological signs used in clinical observation and biofeedback and can act as an adjunct to client evaluation, assessment, prognosis, and rehabilitation.

Sensors, connected to the ProComp Infiniti encoder by protected pin cables, measure biofeedback responses and send the raw signals to the encoder. Depending on the software being used, these may include sensors specialized for electromyography (EMG), electroencephalography (EEG), electrocardiography (EKG), skin temperature, skin conduction, respiration, or blood volume pulse (BVP). The document ***Sensors and Accessories SA7511*** contains a complete list of Thought Technology sensors that can be used with the ProComp Infiniti.

The ProComp Infiniti encoder samples the incoming signals, digitizes, encodes, and transmits the sampled data to the TT-USB interface unit. A fiber optic cable is used for transmission to the TT-USB, providing maximum freedom of movement, signal fidelity, and electrical isolation.

The TT-USB interface unit is connected to one of the host computer's USB ports. It receives the data arriving from the ProComp Infiniti in optical form and converts it into the USB format to communicate with the software.

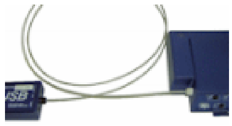
> ***Note:*** *Some hardware features may not be supported by all software programs. Consult the software manual for a full list of features supported.*
>
> *Some software programs will not function with a TT-USB, but require use of a PRO-SB in its place.*



Unconnected hardware components

Connecting the hardware

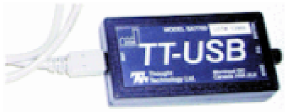
Connecting the TT-USB interface unit



Insert one end of the fiber optic cable carefully into the fiber optic port on the encoder. Tighten the nut gently so that the cable won't slip out.

Do the same with the other end of the fiber optic cable and the fiber optic port of the TT-USB interface unit.

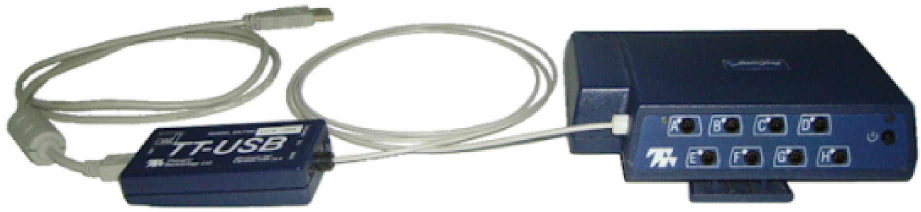
Note: *The fiber optic connectors may break if they are hit directly, for instance, if the encoder falls onto the floor. To prevent damage, it is recommended to use the encoder belt clip to fasten it to the client or to a chair.*



Insert the small connector of the USB cable into the USB port on the TT-USB interface device.

Insert the large connector of the USB cable into the USB port of your PC.

USB ports on a PC are generally located at the back of the base unit. You may also find a USB port at the front of your base unit; you can connect the other end of the USB cable to it. On a laptop, USB ports are usually located at the side or the back of the laptop.

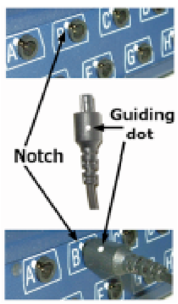


Connected hardware components

The TT-USB interface device has two additional optional connection options.

- The **Switch** is a 3.5mm jack for connecting external devices such as a muscle stimulation device. This can be used, for example, with the Switch control feedback option in the BioGraph Infiniti software.
- The **Sync** connector permits the use of a sync cable to connect an additional TT-USB interface device in order to synchronize data between units. The Sync connector can also be used for an event input.

Connecting sensor cables



Numerous regulatory bodies (such as the FDA in the USA) have adopted safety specifications requiring that all medical products for physiological monitoring be manufactured with electrode leads that have no exposed metal plugs.

For this reason, the ProComp Infiniti encoder and Thought Technology sensors use specially designed connectors that have all metallic surfaces recessed within the plastic casing. These connectors, with protected pins, require care when you are plugging and unplugging sensor cables to the encoder or an extender cable to the sensor head.

When connecting a sensor cable to the ProComp Infiniti, make sure to properly line up the guiding dot on the top of the plug with the notch in the encoder input socket, as shown in the illustration. Forcing the plug into the jack in any other position may damage your equipment.