DETECTION OF DISTINGUISHING FEATURES USING SELECTION METHODS FOR ROBOT-ASSISTED REHABILITATION SYSTEM, REHABROBY

by

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ABSTRACT

DETECTION OF DISTINGUISHING FEATURES USING SELECTION METHODS FOR ROBOT-ASSISTED REHABILITATION SYSTEM, REHABROBY

Task involvement is a key factor in sustaining subjects' participation in rehabilitation programs. An appropriate challenging rehabilitation task can increase engagement of the subjects. In this way, it is desirable that task difficulty must be suitably challenging to acquire great performance from rehabilitation tasks. In order to find the appropriate challenging level for each subject, it is important to detect the subject's feelings (he/she is either getting to be noticeably exhausted or disappointed), and after that to change the rehabilitation task to better suit the subjects capacities by considering their feelings. In this thesis, three main biofeedback sensors Blood Volume Pulse (BVP), Skin Conductance (SC), and Skin Temperature (ST) are used to detect the feelings of the subjects when they use a robot-assisted rehabilitation system called RehabRoby. It is also important to know which features are distinctive to properly detect the feelings of the subjects from the physiological signals acquired by these biofeedback sensors. In this thesis, we explore the distinctive features from physiological signals using both sequential forward selection (SFS) and ANOVA feature extraction methods.

ÖZET

ROBOT YARDIMLI REHABİLİTASYON SİSTEMİ KULLANILARAK AYIRT EDİCİ ÖZNİTELİKLERİN SEÇİM YÖNTEMLERİNİN DEĞERLENDİRİLMESİ

Görev katılımı, hastaların rehabilitasyon programlarına katılımlarının sürdürülmesinde önemli bir faktördür. Uygun zorlayıcı bir rehabilitasyon görevi denekleri motive edebilir ve denekler için maksimum katılım sağlayabilir. Bu nedenle, görev zorluğunun rehabilitasyon görevlerinden iyi performans elde etmek için uygun bir zorlukta olması arzu edilmektedir. Uygun zorluk seviyesini bulmak için, kişinin duygularını tespit etmek (denek ya sıkılıyor ya da zorlanıyordur) ve daha sonra rehabilitasyon görevini, deneğin duygularını dikkate alarak yeteneklerine daha iyi uyacak şekilde modifiye etmek önemlidir. Bu tezde, kişinin duygularını tespit etmek için Kan Hacmi Darbesi (BVP), Deri İletkenliği (SC), ve Deri Sıcaklığı (ST) olmak üzere gibi üç biyogeribildirim algılayıcı kullanıldı. Kullanılan biyogeribildirim algılayıcılar yardımıyla fizyolojik sinyallerden deneklerin duygularını doğru bir şekilde tespit etmek için ayırt edici özniteliklerin hangileri olduğunu bilmekde oldukça önemlidir. Bu tezde, ardışık ileri seçim ve tek yönlü ANOVA öznitelik çıkarım yöntemleri kullanılarak fizyolojik sinyallerden ayırt edici öznitelikler tespit edildi.

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LIST OF SYMBOLS/ABBREVIATIONS

μ	Mean Value
ANOVA	Analysis of Variance
argmax	Arguments of the maxima
BVP	Blood Volume Pulse
BVP_{tp}	Blood Volume Pulse Total Power
$Deriv_{bvp}$	First Derivative of Blood Volume Pulse
$Deriv_{sc}$	First Derivative of Skin Conductance
$Deriv_{temp}$	First Derivative of Skin Temperature
HAHV	High Arousal / High Valence
HALV	High Arousal / Low Valence
HF	High Frequency
HF_{norm}	High Frequency Norm
HR	Heart Rate
HRV	Heart Rate Variability
kNN	k-Nearest Neighbors
LAHV	Low Arousal / High Valence
LALV	Low Arousal / Low Valence
LF	Low Frequency
LF_{norm}	Low Frequency Norm
$Mean_{bvp}$	Mean Blood Volume Pulse
$Mean_{IBI}$	Mean Inter beat Interval
$Mean_{sc}$	Mean Skin Conductance
$Mean_{temp}$	Mean Skin Temperature
MI	Mutual Information
MRMR	Minimal-Redundancy-Maximal-Relevance
Per_{HF}	Percentage Ratio of the High Frequency
Per_{LF}	Percentage Ratio of the Low Frequency

Per_{VLF}	Percentage Ratio of the Very Low Frequency
plomb	Lomb-Scargle Periodgram
POSM	Partially Ordered Set Master
RSFS	Random Subset Feature Selection
SAM	Self-Assessment Manikin
SC	Skin Conductance
SCP	Set Covering Problem
SCR	Skin Conductance Response
SD	Statistical Dependency
SFFS	Sequential Floating Forward Selection
SFS	Sequential Forward Selection
ST	Skin Temperature
$StdIBI$	Standard Deviation of InterBeat Interval
Var_{bvp}	Variance of blood volume pulse
Var_{sc}	Variance of skin conductance
Var_{temp}	Variance of skin temperature
VLF	Very Low Frequency

1. INTRODUCTION

Robot-assisted rehabilitation systems have first been utilized as a part of extensive scaled clinical tests in 1998, and from that point forward various robot-assisted rehabilitation systems have been developed. Robotic training has shown to improve motor impairment and strength of the subjects [1], [2]. The robotic devices have been developed to only assist shoulder movement [3] or elbow movement [4], [5] or both should and elbow movement movements [6], [7], [8], [9], [10], [11], [12], [13] and [14] or shoulder, elbow and forearm movements [15], [16], [17]. Additionally, robotics devices have been developed to assist shoulder, elbow, forearm and wrist movements together [18], [19], [20], and whole arm [21], [22], [23]. The developed robotic devices are considered into two categories in terms of mechanical structure, which are end-effector-based MIT-MANUS [24], ARM Guide [7], BFIAMT [8], MEMOS [12], NeReBot [13], GENTLE/S [15], Robot-therapist [18] and exoskeleton-based [3], Dampace [10], L-Exos [16], [11], RehabExos [17], RUPERT IV [19], Salford Arm Rehabilitation Exoskeleton (SRE) [20], ARMin III [21], ARMOR [22]. There are also few robotic devices that combine both end-effector based, and exoskeleton-based approaches which are ArmeoSpring system (courtesy of Hocoma AG), BONES [9], MIME-RiceWrist [25], [26], REHAROB [14], iPAM [27] and UMH [28]. An exoskeleton-based upper-extremity robot-assisted rehabilitation system, in Yeditepe University Robotics Research Laboratory which is called RehabRoby [29], [30], [31] have been developed.

RehabRoby is designed to assist shoulder (flexion/extension, rotation), elbow (flexion/ extension), and forearm (pronation/supination) movements and their combinations. For this thesis, only elbow(flexion-extension) movements with RehabRoby have been studied. Here, there are two force sensors used in RehabRoby to detect the applied force for flexion and extension movements. The details of RehabRoby can be found in [29], [30], [31].

Robot-assisted rehabilitation systems have appeared to be useful in neuromotor rehabilitation since it is possible to convey intelligent and repeatable sensorimotor exercise, and monitor the real performance persistently. Motivation and mental engagement of the subjects are recognized as an important factor to enhance the result of the rehabilitation procedure, and

therapy results [32], [33], [34]. Additionally, motor learning has shown to decrease in the presence of the over-challenging task [35]. The learning rate of a motor task has shown to be maximum at a task difficulty level that emphatically challenges and energizes subjects while not being excessively stressful or exhausting [36]. In this way, task difficulty should be suitably challenging to acquire great performance from rehabilitation tasks. Too much challenge may increase workload, which will then be appraised by the subject as low excitement. Similarly, not enough challenge may induce boredom and both these situations may result in less involvement, engagement and motivation. An appropriate challenging rehabilitation task can motivate, and cause most extreme mental engagement for the subjects [37], [38]. Additionally, it has previously been mentioned that if a robot understands the subject's feelings, human machine interaction may become more smooth and efficient [39]. Thus, it is important that a robot-assisted rehabilitation system supporting in rehabilitation tasks ought to be able to do first recognizing subject's feelings (he/she is either getting to be noticeably exhausted or frustrated), and afterward changing the rehabilitation task to better suit the subjects capacities by considering his/her feelings.

Face, voice and/or gestures have previously been used to understand the feelings of people [40], [41], [42]. It is possible for a person not to express his/her feelings through speech, gestures or facial expressions; however, a change in physiological signal pattern can be detected correctly. Thus, in this thesis biofeedback sensors are used to detect the feelings of subjects. Biofeedback sensors have previously been used to understand the feelings of subjects. Blood Volume Pulse (BVP), skin conductance (SC), and skin temperature (ST) have been used to classify subjects feelings such as excited, overstressed, bored during robot-assisted gait rehabilitation [43], [44]. Subjects' feelings in terms of arousal and valence have also been estimated in a rehabilitation environment through measurements of physiological responses [45]. Additionally, biofeedback sensors (pulse, SC, ST) have been used to adaptively and dynamically change the complexity of the therapy through real-time displays of a virtual reality system [46]. In the literature, the features that are extracted from the BVP sensor, such as heart rate (HR), spectral features of heart rate variability (HRV) have shown to be related with arousal (arousal represents a persons general level of mental activity such as sleepy or focused) and stress [47]. It has already been demonstrated that increased value of HR infers increased excitement and valence (the persons feelings are positive or

negative such as miserable or happy) [48]. Additionally, HR has been shown to correlate positively with valence [49]. The power in the low frequency (LF) band of the HRV range has shown to decrease when, a higher levels of cognitive load exists [50]. HRV has beforehand been translated to give information on the relative feelings of the subject [51]. SC (or skin conductance response (SCR)) has additionally appeared to be a decent indicator for excitement or arousal [49], [52], [53]. SC has been found to increase during demanding tasks contrasted with rest periods [54]. SCR has additionally been related with cognitive load particularly with excitement or arousal [55], [56], [57], and the number of SCR has been shown to be a sensitive indicator for emotional strain [58]. In this thesis, twenty-four features are extracted from BVP, SC and ST sensors to understand the subjects' feelings when they perform a rehabilitation task with RehabRoby.

When subjects perform the task, the biofeedback sensors start to collect physiological data from these subjects. First of all, we first use baseline normalization because each subject has different feeling thus different heart rate when they start to perform the task. We use filtering technique (Savitzky-Golay) to filter the raw data from the biofeedback sensors to remove the noise from the signals. When filtering is completed, then the seventeen features from BVP, four features from SC and three features from ST sensors are extracted.

Two difficulty adjustment algorithms are used to change the difficulty level of the task when subjects perform the task with RehabRoby. One of the algorithms is called partially ordered set master (POSM) [30]. POSM learns from observations, and predicts the difficulty level. POSM is selected because it does not require off-line training, it can ported to any task and it can guarantee the number of mistakes that can make before learning the suitable setting. The other algorithm is a well-known increment/decrement one level algorithm which increase/decrease the difficulty level only one level depending on the scores of the subjects during the performance of the rehabilitation task. In this context, in [59], the exercise difficulty level has also been adjusted considering the increment one level up and decrement one level down by considering the performance (score) of the subjects. Additionally, the increment/decrement one level algorithm has been used to adjust the difficulty level of the rehabilitation game for I-TRAVLE robotic system [60]. It is possible to have different distinctive features when subjects perform the task with two different difficulty level

adjustment algorithms.

Various feature selection methods such as sequential forward selection (SFS), sequential floating forward selection (SFFS), minimal-redundancy-maximal-relevance (MRMR), set covering problem of correct classifications (SCP), random subset feature selection (RSFS), statistical dependency between features and labels (SD) and mutual information (MI) have previously been used [61]. In this thesis, we use the sequential forward selection method (SFS) to extract the distinctive features in each algorithm, and in between two algorithms. We then use a commonly used method analysis of variance (ANOVA) to find the distinctive features between two algorithms.

The thesis is organized as follows. We provide details of an exoskeleton-based upper extremity robot-assisted rehabilitation system, (RehabRoby), the measurement of physiological signals, the process of feature extraction from these physiological signals, distinctive feature selection methods, task description, and algorithms to adjust the difficulty level of task in Chapter II. We provide information about the experimental set-up in Chapter III. We demonstrate the distinctive feature selection results in Chapter IV. We give the conclusion and future work of the presented work in Chapter V.

2. MATERIALS AND METHODS

2.1. GENERAL ARCHITECTURE

The general archictecture of the system is given in Fig. 2.1. In this thesis, we use an exoskeleton-based upper-extremity robot-assisted rehabilitation system, which is called RehabRoby. We present the details of RehabRoby in [30]. We detect the features that are most distinctive when subjects perform rehabilitation task using RehabRoby. We first record the data from the biofeedback sensors during the use of RehabRoby. Then use baseline normalization and filtering method to reduce noisy signal from the biofeedback sensors raw data. We extract the features from the processed sensor data. Later, we use feature selection methods to decide the distinctive features for this application.

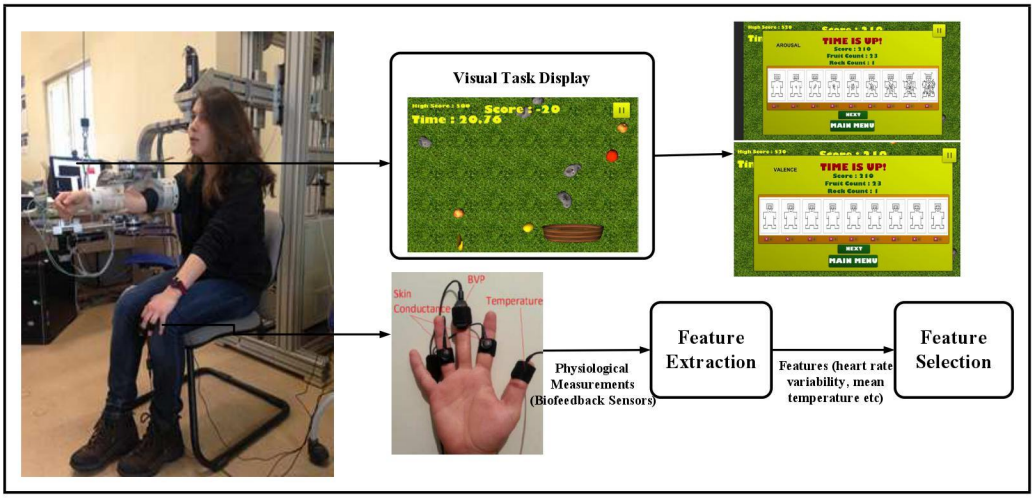

Figure 2.1. General architecture of the proposed system.

2.2. FRUIT GAME

We use a single player Fruit Picker task [62] that provides elbow flexion/extension task using various difficulty levels. The Fruit Picker game contains a basket, fruits and rocks as shown in Fig. 2.2. We can change the parameters of the 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) systematically to obtain different difficulty levels of game [63]. We also demonstrate the score to the subjects during execution of the game to increase their participation to the game.

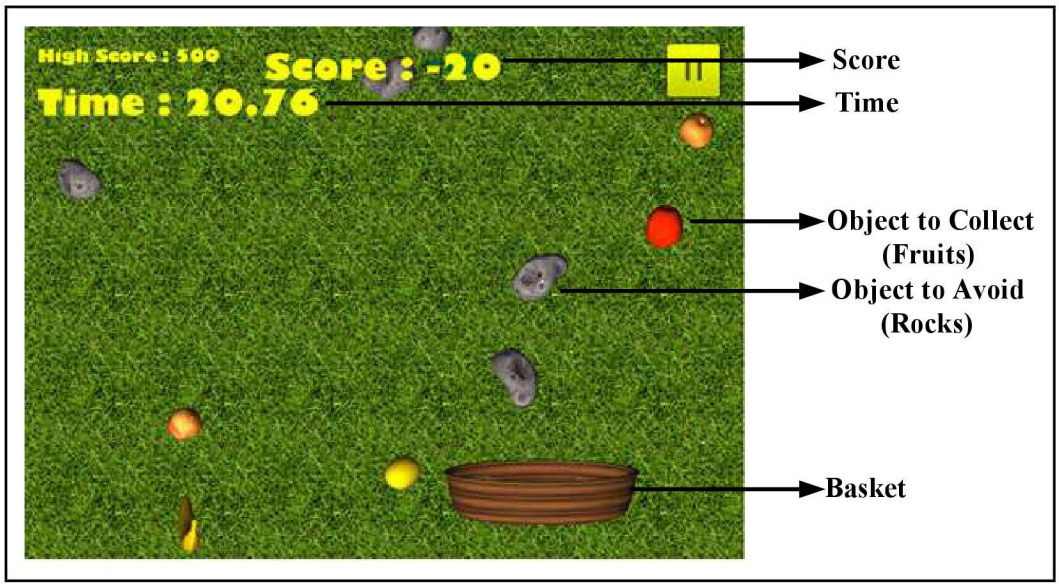

Figure 2.2. Visual display of the task.

The fruits and rocks fall continuously on the game. We instruct the subjects to collect the fruits and avoid the rocks within a given time as given in Fig. 2.2. The objective of the game is to collect the fruits, and get away from the rocks by shifting the basket. When the subject collects the fruits s/he earns 10 points, and when the subject collects the rocks s/he looses 20 points. Subjects perform elbow flexion and extension movements with RehabRoby robot to move the basket. When the subject makes elbow flexion, the basket acts towards to the left side, and when the subject makes elbow extension, the basket acts towards to the right side. At the beginning, the basket is in the right side of the monitor, so for each subject, game starts within 90 degree elbow extension position, and the game has a working range from 0 to 90 degree which is appropriate for the human anatomy.

7 difficult levels (Level 1-Level 7) are defined. Level 1 is easy (under-challenged), Level 4 is the medium (challenged), and Level 7 is the difficult (over-challenged) as shown in Fig. 2.3. Selection of adaptation game parameters depend on the objective of the rehabilitation program. The goal of the rehabilitation program with RehabRoby is to improve the interval between

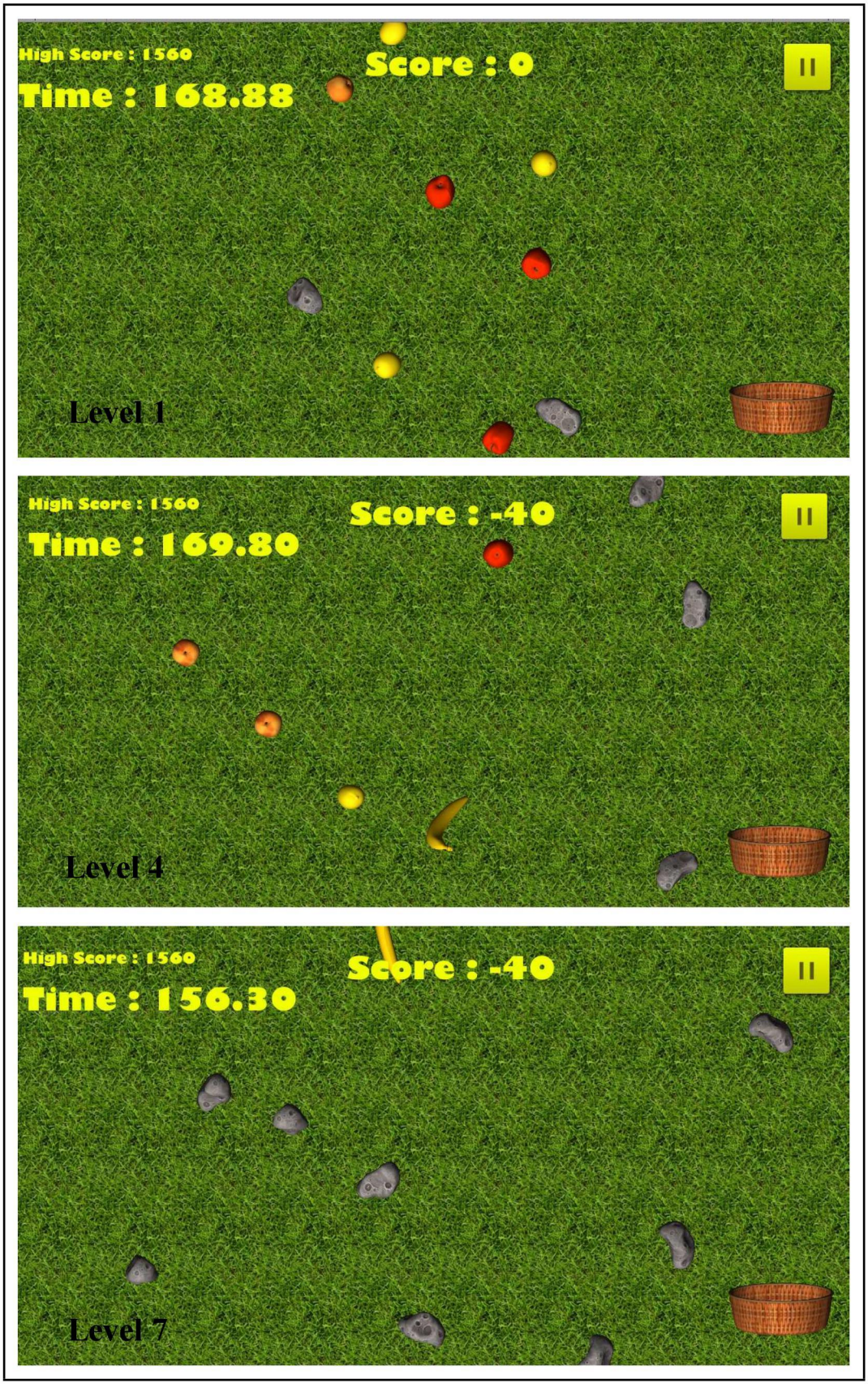

Figure 2.3. Examples of game modes.

the appearance/dispersion of targets. Thus, the falling range of fruits and rocks are increased to make the task challenging, and subjects are required to move in a wider range to collect fruits and to avoid rocks. Additionally, rock number and rock speed are raised to increase the difficulty level. Fruit number, fruit speed and basket size are kept same for all 7-difficulty level.

2.3. ALGORITHMS USED TO ADJUST THE TASK DIFFICULTY OF FRUIT GAME

We adjust the fruit game task difficulty using two difficulty level adjustment algorithms.

2.3.1. Partially Ordered Set Master Algorithm

Partially Ordered Set Master Algorithm (POSM) learns from observations made during the task, and predicts the appropriate difficulty setting [30]. The dynamic difficulty adjustment mechanism input can be subjects performance (e.g. score), time on tasks, and movement accuracy. In this thesis, POSM is used as the first algorithm to adjust the difficulty level considering the performance (score) of the subjects. POSM models a ”more difficult than” relation. The following these three stages are performed when the fruit game is played by the subjects: in the first stage, the POSM predicts a difficulty setting, and in the second stage the subject performs the task in the defined difficulty setting for a period of time, and in the last stage the POSM receives a feedback, which includes one of the following information, to understand how the defined difficulty setting fits the subject. These steps repeat until the task ends. The task is under-challenged if the predicted difficulty setting has not been hard enough for the subject. The task is challenged if the predicted difficulty setting has been appropriate for the subject and over-challenged if the predicted difficulty setting has been above the skill level of the subject. We use POSM as the first algorithm (A1) to detect the distinctive features.

2.3.2. Increment/Decrement One Level Algorithm

We also use another algorithm called increment/decrement to detect the distinctive features as the second algorithm (A2). This algorithm looks at the difference in the scores in previous 10 s period, and decides the action as given in Table 2.1. The △Score1 is the difference between the score at t + 10 and score at t, and △Score2 is the difference between the score at t+20 and score at t+10 as shown in Fig. 2.4. Low means △Score is 40 and lower points, medium means △Score is between 40 and 60 points, and high means △Score is bigger than 60 points. For example, if △Score1 is 30 points and next period △Score2 is 50 points, increment/decrement algorithm decides to stay at same level for next period. These score ranges are generally used ones and it is possible to change these ranges.

Table 2.1. The Mechanism of Algorithm

Action	$\Delta Score1$	$\Delta Score2$
Decrement One Level	Low	Low
	Medium	Low
	High	Low
Stay At Same Level	Low	Medium
	Medium	Medium
	High	Medium
Increment One Level	Low	High
	Medium	High
	High	High

2.4. PHYSIOLOGICAL RECORDINGS

We use blood volume pulse (BVP), skin conductance (SC) and skin temperature (ST) sensors from Thought Technology Ltd for biofeedback sensory information. We record BVP using BVP Flex-Pro sensor, which is put on the left hand center finger as given in Fig. 2.5. We measure SC using skin conductance sensor (sc flex pro) as shown in Fig. 2.5. We put the electrodes of skin conductance (SC) on the center phalanx of forefinger and ring finger.

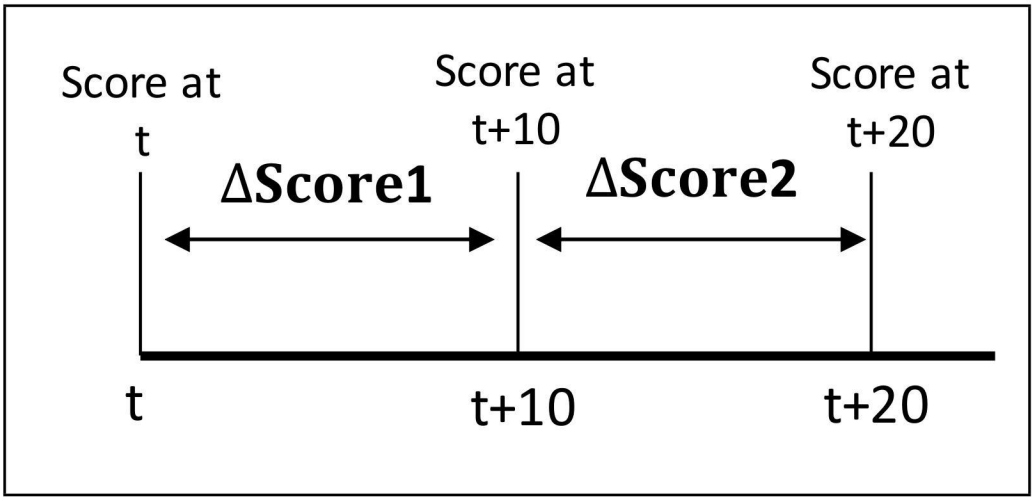

Figure 2.4. Algorithm score calculation.

We record ST utilizing a skin sensor that is put on the fingertip of the thumb. The sensors are wearable. The sensors are lightweight, non-invasive and FDA approved. We sample physiological signals at 20 Hertz using Procomp Infinite Encoder using MATLAB software [64].

2.5. NORMALIZATION

Feature extraction includes normalization, and dimension reduction. Features exhibit variability as a result of age, gender, time of the day, thus normalization is needed to reduce the effect of these variations. Various normalization methods have been proposed such as subtracting the mean value of all feature vectors and dividing the result by the standard deviation of all feature vectors. In this thesis, we evaluate six different normalization techniques. The equations of these normalization techniques are given in below.

- The first normalization technique is calculated by subtracting the mean value of all feature vectors (μ_X) and dividing the result by the standard deviation of all feature vectors (X_i)(Equation 2.1).

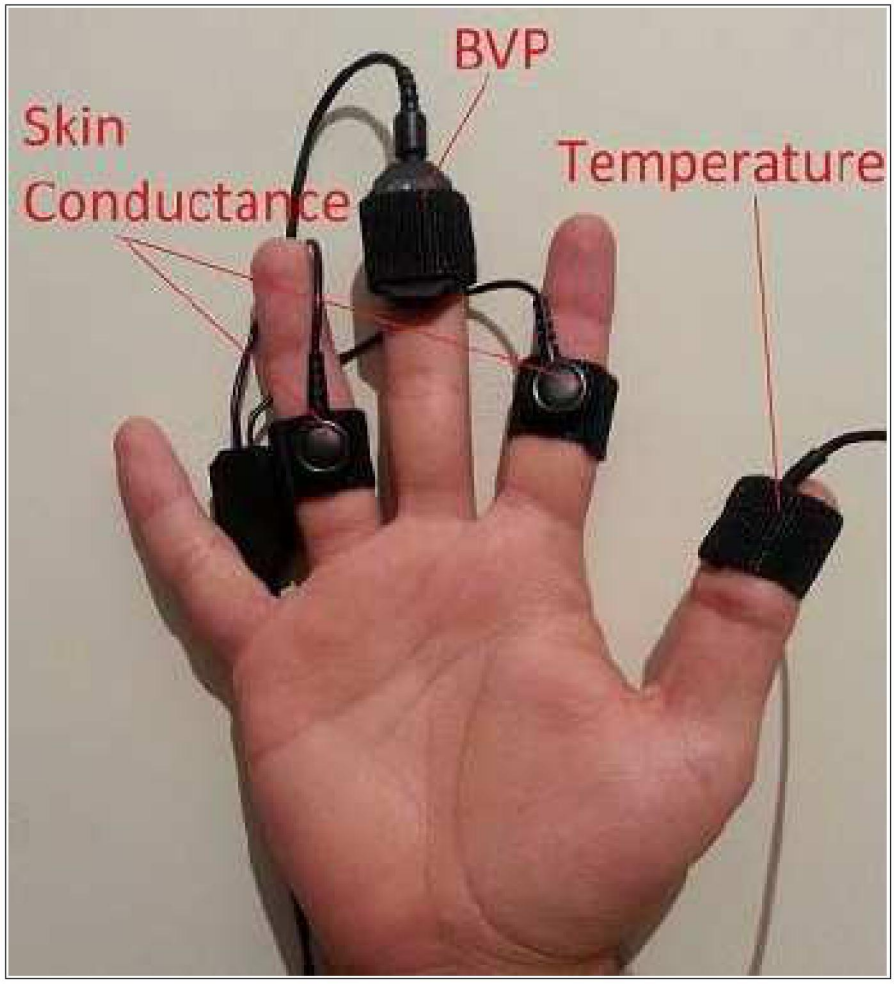

Figure 2.5. Placement of sensors on the hand.

$$X_i = \frac{X_i - \mu_X}{std(X_i)} \tag{2.1}$$

- The second normalization technique is the subtracting from mean value of baseline ($\mu_{baseline}$) and dividing the result by the maximum absolute value of all feature vectors (X_i) subtracting mean value of baseline ($\mu_{baseline}$) where the equation is given below.

$$X_i = \frac{X_i - \mu_{baseline}}{max|X_i - \mu_{baseline}|} \tag{2.2}$$

- Another normalization technique is calculated by subtracting the mean value of baseline vectors ($\mu_{baseline}$) and dividing the result by the standard deviation of all feature vectors($std(X_i)$). The equation of this technique is given in Equation 2.3.

$$X_i = \frac{X_i - \mu_{baseline}}{std(X_i)} \tag{2.3}$$

- In the fourth normalization technique the mean value of baseline vectors ($\mu_{baseline}$) is subtracted from all feature vectors (X_i) and the result is divided by the standard deviation of mean value of baseline ($std(\mu_{baseline})$).

$$X_i = \frac{X_i - \mu_{baseline}}{std(\mu_{baseline})} \tag{2.4}$$

- In another simple normalization technique the mean value of baseline vectors ($\mu_{baseline}$) is subtracted from all feature vectors (X_i) as given in below equation.

$$X_i = X_i - \mu_{baseline} \tag{2.5}$$

- The last normalization technique equalize the feature vectors to itself,

$$X_i = X_i \tag{2.6}$$

It can be noticed that the third normalization technique (Equation 2.3) and fourth one

(Equation 2.4) are derived from first normalization technique (Equation 2.1). We selected the fifth normalization technique (Equation 2.5) because the raw signal from biofeedback sensors were best discriminated using Equation 2.5. When the normalization process completed then we extracted the features.

2.6. FEATURE EXTRACTION FROM BIOFEEDBACK SENSOR SIGNALS

Extraction of features from skin temperature (ST) generally involves the raw data mean, raw data variance and mean absolute derivative over a certain time period. Since the raw data from the biofeedback sensors are noisy there is a need to use a filter. We use a Savitzky-Golay filter to filter the raw data from ST and SC. On the other hand, extraction of heart rate variability (HRV) from BVP sensor involves careful filtering, peak detection, interpolation and power spectral density calculation. Some signals have signal specific features such as heart rate (HR), which is generally characterized by a number of time-domain, and frequency-domain features of HRV [37]. SC is often characterized by the amplitude and frequency of SCR [37]. There is an extensive list of features in [65], and computational methods to find the features in [66], [67].

We initially find the heart rate (HR) in thumps every moment (BPM) from the BVP sensor. We also obtain mean and standard deviation of inter-beat intervals (IBI) from pulse intervals and labeled as $mean_{IBI}$ and std_{IBI} , respectively. We find Heart Rate Variability (HRV) signal [68] by counting the inter-beat interval between subsequent pulse peak intervals. We take Lomb-Scargle periodogram (plomb) spectrum of the HRV signal, and divide HRV spectrum into three intervals which are a very low frequency, a low frequency and a high frequency [69], [70]. If interval is between 0 - 0.04 Hertz interval, it means that it is the very low frequency (VLF) interval (Equation 2.7). The code is given in Appendix A.

$$VLF = \sum_{0Hz}^{0.04Hz} plomb(findpeaks(databvp)) \tag{2.7}$$

If interval is between 0.04 - 0.15 Hertz interval, it means that it is the low frequency (LF) interval (Equation 2.8). The code is given in Appendix A.

$$LF = \sum_{0.04Hz}^{0.15Hz} plomb(findpeaks(databvp)) \tag{2.8}$$

If interval is between 0.15 - 0.4 Hertz interval, it means that it is the high frequency (HF) interval. The code is given in Appendix A.

$$HF = \sum_{0.15Hz}^{0.4Hz} plomb(findpeaks(databvp)) \tag{2.9}$$

$$BVP_{tp} = \sum_{0Hz}^{0.4Hz} plomb(findpeaks(databvp)) \tag{2.10}$$

We calculate LF/HF ratio feature, that indicates the overall balance between sympathetic and parasympathetic systems [71]. We also find the ratio between the total sum of VLF and LF to HF as using $(VLF + LF)/HF$ [69]. We obtain the percentage ratio of the very low frequency (per_{VLF}) when BVP total power (BVP_{tp}) is divided by very low frequency total power using the following equation. The code is given in Appendix A.

$$per_{VLF} = \frac{VLF}{BVP_{tp}} \times 100 \tag{2.11}$$

We find the percentage ratio of the low frequency (per_{LF}) by dividing the low frequency total power with BVP total power (BVP_{tp}). The code is given in Appendix A.

$$per_{LF} = \frac{LF}{BVP_{tp}} \times 100 \tag{2.12}$$

We extract the percentage ratio of the high frequency (per_{HF}) when BVP total power (BVP_{tp}) is divided by high frequency total power. The code is given in Appendix A.

$$per_{HF} = \frac{HF}{BVP_{tp}} \times 100 \tag{2.13}$$

Ratio of low frequency of total power and low-high frequency total power gives low frequency norm (LF_{norm}) (Equation 2.14), and ratio of high frequency of total power and low-high frequency total power gives high frequency norm (HF_{norm})(Equation 2.15). The code of these feature calculations are given in Appendix A.

$$LF_{norm} = \frac{LF}{LF + HF} \times 100 \tag{2.14}$$

$$HF_{norm} = \frac{HF}{LF + HF} \times 100 \tag{2.15}$$

Moreover, we obtain mean value and variance of BVP sensor ($Mean_{bvp}$), (Var_{bvp}), and the

first derivative of the blood volume pulse ($Deriv_{bvp}$) from the BVP sensor. The codes of these feature calculations are given in Appendix A.

We record average skin conductance ($Mean_{sc}$) value, and the variance of skin conductance value (Var_{sc}) for a given period of 180 seconds from the SC sensor. We get skin conductance response (SCR) as the total number of brief increments in the skin conductivity signal [72]. The code of SCR calculation is given in Appendix A. In this thesis, peaks and valleys of the skin conductivity signal are found out. After that, we look at from one valley to its subsequent peak is higher than 0.05, at that point we choose the peak as a substantial SC response number. Then the total number of such responses forms the SCR value. The algorithm of the SCR calculation is given in Algorithm 2.1.

We take the data from the SC sensor to evaluate the mean first derivative of skin conductance ($Deriv_{sc}$)(The code is given in Appendix A). Finally, we use ST to find mean temperature ($Mean_{temp}$), variance of temperature (Var_{temp}), and the first derivative of the temperature ($Deriv_{temp}$). The codes of these features calculated from the ST are given in Appendix A. We give a list of biofeedback sensors, and their related features used in this thesis in Table 2.2.

2.7. DISTINCTIVE FEATURE SELECTION METHODS

2.7.1. Sequential Forward Selection (SFS)

We select sequential forward selection (SFS) method [75] to find the distinctive features because it is straightforward algorithm to regularly perform aggressively to sequential floating forward selection [76]. However, it has been previously mentioned that search technique of SFFS makes it all the more viably overfit the features to the feature determination informational data and may have driven scientists to overestimate its execution if extra approval information have not been utilized. Notwithstanding these contemplations, the computational cost of SFFS was observed to be too high for the extensive beginning feature pool utilized as a part of the thesis. By and large, SFFS neither neglected to join to a steady list of feature of a particular size nor it was ready to come to the predefined most extreme list

Algorithm 2.1. Skin Conductance Response Calculation

Start with the P = [] T = [] a = 1 b = 1 i = 0 d = 0 E = 0.05
xL = length(datasc)
while $i \neq xL$ **do**
  i = i + 1
  if $d = 0$ **then**
    if $datasc(a) \geqslant (datasc(i) + E)$ **then**
      d = 2
    else
      d = 1
    end if
    if $datasc(a) \leqslant (datasc(i))$ **then**
      a = i
    else
      b = i
    end if
  else if $d = 1$ **then**
    if $datasc(a) \leqslant (datasc(i))$ **then**
      a = i
    else
      P = [P a]
      b = i
      d = 2
    end if
  else if $d = 2$ **then**
    if $datasc(i) \leqslant (datasc(b))$ **then**
      b = i
    else
      T = [T b]
      a = i
      d = 1
    end if
  end if
end while
scr = length(P)

Algorithm 2.2. Sequential Forward Selection

1. Start with the empty set $Y_o = \oslash$
2. Select the next best feature $x^+ = argmax[J(Y_k) + x)]$
3. Update $Y_{k+1} = Y_k + x^+; k = k + 1$
4. Go to 2

of feature size of 200 features in a sensible calculation time. In a few past reviews that have assessed SFFS, the algorithm has not been keep running until feature of such size prompting expansive search spaces, not even in late paralinguistic examination thinks about it. In the few situations where SFFS managed to achieve include set sizes stipulated for the algorithms in this thesis, it was found to perform more worse than SFS. The computational cost of SFS, then again, was practical, albeit still observably high in contrast with all the new feature selection algorithms assessed. In the SFS technique, features are chosen progressively by including the locally best feature point, the feature point that gives the most noteworthy incremental biased data, to the current feature set. Consequently, SFS is a conspicuous decision for the feature selection in the thesis.

SFS algorithm begin from null dataset, sequentially attach the features x^+ that outcomes in the highest objective function $J(Y_k) + x^+)$ when joined with the features Y_k that have just been chosen. The arguments of the maxima (argmax) are the points of the domain of function at which the function values are maximized. Note that, SFS performs best when the optimal subset has a small number of features. The algorithm of SFS is given in Algorithm 2.2. with the objective function evaluated by means of K nearest neighbours (kNN) classification [61]. The SFS is used to find distinctive features between two difficulty adjustment algorithms (A1 and A2) and in each algorithm by itself.

K nearest neighbours (kNN) is connected as the order run in this thesis [73], the estimated class labelled for each test occurrence is resolved as the one that is seen most much of the time among the k labelled preparing examples that are nearest to the sample as far as the Euclidean distance. In spite of being thoughtfully straightforward and simple to execute (notwithstanding computational productivity issues), it is in any case a capable example

order technique that, sufficiently given preparing information, can show complex non linear decision boundaries in the feature space [74]. In any case, kNN is known to be defenseless to the impacts of the scourge of dimensionality [73], [74]. From another perspective, kNN in its fundamental frame does not have any inward feature to manage include pertinence. This is as opposed to classifiers, for example, support vector machines and random forests, which are better ready to deal with high dimensionalities and unessential features. These things legitimize the decision of kNN with the end goal of this thesis: being an able, non linear pattern classification method whose execution, be that as it may, is moderately very subject to the nature of the list of feature set, it is especially appropriate for looking at the execution and heartiness of various feature determination approaches.

We standardized each feature in both the preparation and assessment dataset to have zero mean and unit difference inside the comparing data collection before kNN classification. When settling on a choice on an input vector in light of its k nearest neighbours as indicated by the Euclidean distance, the tallies of various classes inside the k-neighbourhood are scaled by dividing them by the frequencies of event of similar classes in the training data so as to make up for possibly one-sided class appropriations.

The quantity of neighbours k is picked in this thesis by first choosing the best-performing esteem k_0, from a given scope of qualities, in the grouping of an improvement set utilizing training data. In grouping the test data, the improvement set is fused into the training material. So as to keep up the measure of the k_0-neighbourhood as far as the Euclidean distance in spite of the expanded sample thickness of the augmented training set.

2.7.2. Analysis of Variance (ANOVA)

In this thesis, we also use a well-known method called analysis of variance (ANOVA) to select the distinctive features in between algorithms A1 and A2. We use one-way repeated-measure ANOVA, and post hoc pairwise multiple comparisons with Bonferroni correction when necessary.

Each group of n sample and k get one of our group. Variance analysis, that k is equal to

average of the group whether one allows the testing of statistical. $x_{i,j}$, i. group j. element ($j\epsilon\{1,2,,n\}$ & $i\epsilon\{1,2,,k\}$). Group mean (μ_i) is calculated. Then the sum of the squares within groups (SSW) is calculated. The average of all samples μ_0 is calculated. The total sum of squares (TSS) is calculated. Calculated $\mu_0, \mu_1, , \mu_K$ the sum of squares between groups with values (SSB) is calculated.Let consider the following equation:

$$TSS = SSB + SSW \tag{2.16}$$

SSB and SSW using calculations F-score defined as follows:

$$F_{score} = ((SSB/(k-1)))/((SSW/(k(n-1)))) \tag{2.17}$$

Calculated above F_{score} also compared with F-test. F-test gives the F-point value satisfies a predetermined probability p. If value of p is small, hypothesis can refused. For specifying a p-value, required minimum F-score, can be calculated by using F-table $(k-1, k(n-1))$. In summary, hypothesis test is performed as follows:

$$F_{score} > F(k-1, k(n-1))F_{score} < F(k-1, k(n-1)) \tag{2.18}$$

Here results of analysis of variance test gives p-value and looking from p values to selecting features.

Table 2.2. Features of Physiological Signals

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. EXPERIMENTAL SET-UP

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

3.1. SUBJECTS

20 subjects (10 female and 10 male), whose ages were in the range of 20-37, participated in our study. They did not receive money, course credit,or any other incentive. We prepare a questionnaire to collect information on the subject's previous experience with the robot-assisted rehabilitation systems and computer games. The questionnaire also consisted of demographic questions designed to solicit knowledge about gender and age. All the subjects were using his right hand. All subjects were healthy and no information was available about any disease that could affect the study. Only one of the subjects had experience with robot-assisted rehabilitation systems, and only eight subjects have computer games experience. We received the Institutional Review Board of Sabanci University approval to conduct all the experiments. In the Institutional Review Board application, we reported all details of the experiments, and we emphasized that the health and safety of the subjects was by no means endangered by participating in these experiments. We drafted a detailed consent form that acquainted the subjects with the experimental procedure and their role in it. We allowed subjects to participate in the experiment only after their consent had been obtained through a signed consent form.

3.2. EXPERIMENTAL PROCEDURE

Each subject received one practice trial and five experimental trials, and all five were slightly different from each other because we modified the difficulty level according to the score that subjects obtained as shown in Fig. 3.1. Thus, the subjects did not know at which difficulty level he/she was doing the task in all trials. After admission into the laboratory, we asked to

fill the subjects a consent form and we informed them about the purpose of the experiments. After we explained the instructions were verbally, then we asked the subjects to relax and to close their eyes for 3-minutes to obtain baseline data from BVP, SC and ST sensors that were recorded with the BioGraph Infiniti. Then, we asked subjects to complete a self-assessment manikin (SAM) survey that was displayed on the screen as given in Fig. 3.2. We wanted them to respond to a 9-point scale by choosing a number that best represents their current psychological state. The lowest arousal represented inactive and the highest arousal represented excited. The lowest valence represented unpleasant and the highest valence represented very happy. The lowest dominance represented helpless and the highest dominance represented in control everything.

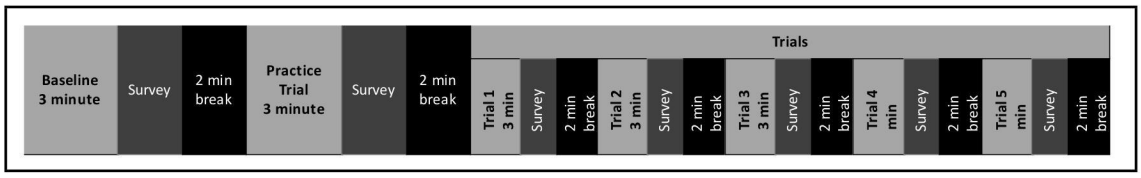

Figure 3.1. The order of the trials.

After completion of the SAM survey, we gave a 2-minute break to the subjects, and practice trial started as shown in Fig. 3.1. We presented a practice trial to each subject to familiarize him/her with the system and the task. We record physiological signals from BVP, SC and ST sensors. Once the subjects finished the practice trial, we asked subjects to complete the SAM, and we gave a 2-minute break to the subjects. Then, we asked subjects to do the same task 5 times as given in Fig. 3.1. Each task took 3 minutes. When a trial was over, another trial was started automatically after 2-minute break, and completion of the SAM survey.

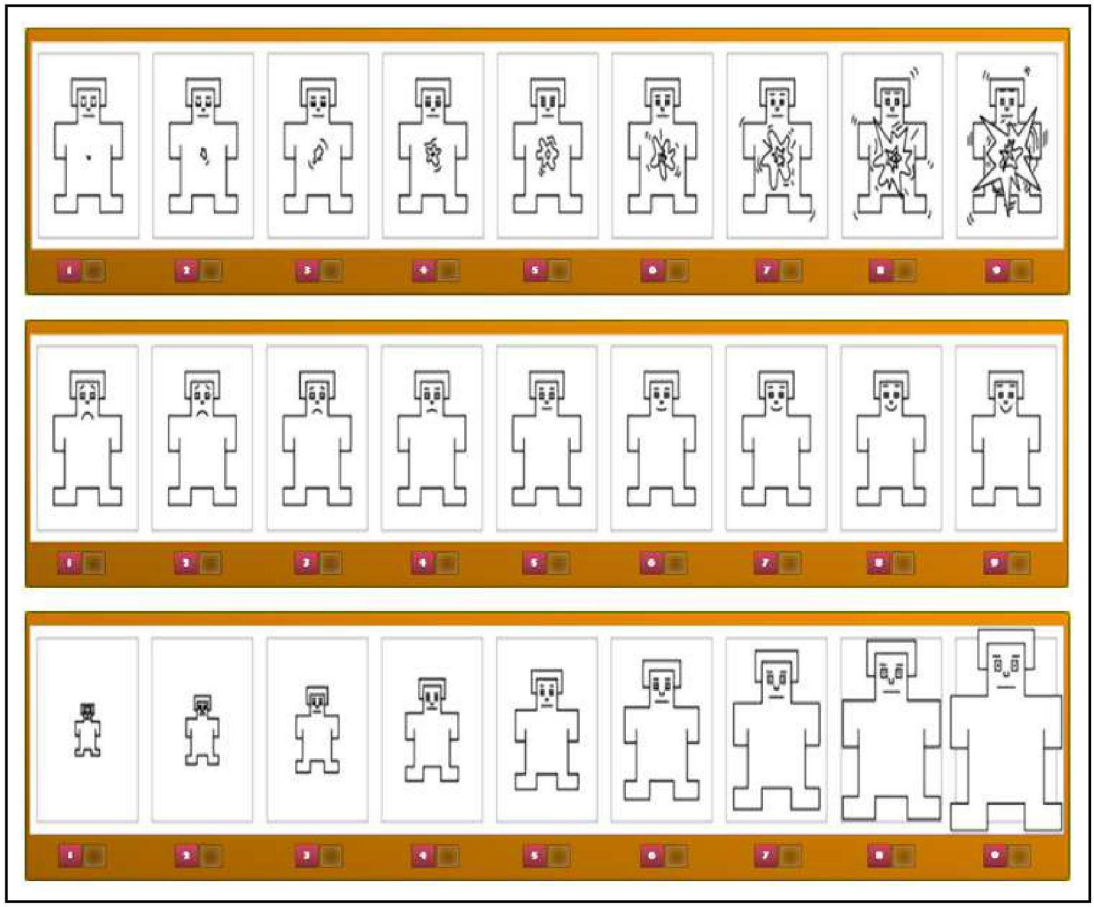

Figure 3.2. SAM arousal (top), valence (middle), and dominance (bottom).

4. RESULTS

4.1. SELECTION OF DISTINCTIVE FEATURES

4.1.1. Sequential Forward Selection Analysis

Accuracy was found 78.95%, 78.95%, 89.47%, 84.21%, 68.42% and 78.95% for arousal, valence, dominance, arousal-valence, arousal-dominance and valence-dominance, respectively when partially ordered set master algorithm (POSM)(A1) was used for difficulty level adjustment for RehabRoby. We found 4 distinctive features per_{LF}, $Deriv_{temp}$, $Mean_{bvp}$, $Deriv_{bvp}$ when the label set was arousal. When label set was valence, only 2 distinctive features per_{LF} and Var_{temp} were found. We found 2 distinctive features Var_{temp} and $Mean_{bvp}$ when label set was dominance. When label set was arousal-valence, the following 5 features Var_{temp}, per_{LF}, $Deriv_{temp}$, Var_{sc}, $Deriv_{bvp}$ were found as distinctive. On the other hand, when label set was selected as arousal-dominance, we found 5 distinctive features $Deriv_{bvp}$, $Mean_{bvp}$, per_{VLF}, Var_{temp}, VLF. When label set was choosed as valence-dominance, we found 2 distinctive features per_{LF} and Var_{temp}. We give the label set which is arousal, valence, dominance, arousal-valence, arousal-dominance and valence-dominance respectively for kNN, and accuracy was found 78.95%, 84.21%, 78.95%, 63.16%, 68.42% and 68.42%, respectively when increment/decrement algorithm (A2) was used for difficulty level adjustment of RehabRoby. When the label set was selected as arousal, we found 4 distinctive features $Mean_{sc}$, SCR, $Mean_{bvp}$, LF/HF. We found 1 distinctive features $Deriv_{bvp}$ when the label set was selected as valence. On the other hand, we found 3 distinctive features $Deriv_{sc}$, $Mean_{sc}$ and $Mean_{bvp}$ when the label set was dominance. When label set was as arousal-valence, then we found 5 distinctive features per_{HF}, SCR, per_{VLF}, $Deriv_{sc}$, HF_{norm}. We found 4 distinctive features Var_{bvp}, HR, $Deriv_{bvp}$, $Deriv_{sc}$ when the label set was arousal-dominance. When the label set was selected as valence-dominance, we found 2 distinctive features $Deriv_{sc}$ and $Mean_{sc}$. All distinctive features, which were extracted from raw data, are shown in Table 4.2 and the accuracy of these distinctive features was given on Table 4.1.

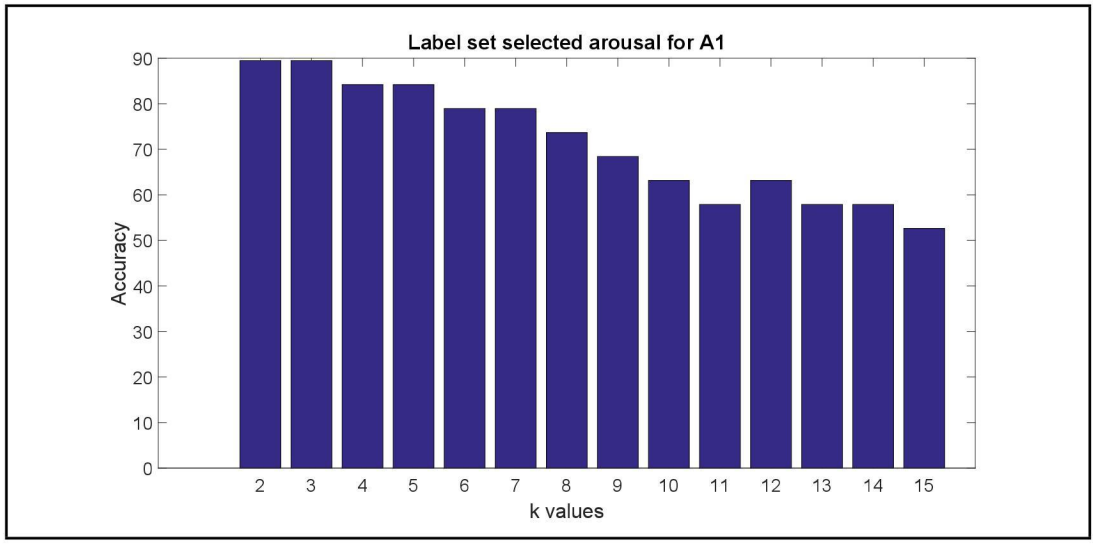

Figure 4.1. Selecting optimum k value.

Table 4.1. Accuracy with Optimum k Value

Algorithm	**Label Set**	**k**	**Accuracy (%)**
A1	Arousal	7	78.95
	Valence	9	78.95
	Dominance	7	89.47
	Arousal-Valence	5	84.21
	Arousal-Dominance	5	68.42
	Valence-Dominance	7	78.95
A2	Arousal	5	78.95
	Valence	9	84.21
	Dominance	7	78.95
	Arousal-Valence	5	63.16
	Arousal-Dominance	5	68.42
	Valence-Dominance	5	68.42

We classified the extracted features as Partially ordered set master algorithm (A1) and increment/decrement one level algorithm (A2) using kNN classifier. The accuracy was calculated by changing the value of k from 2 to 15. The best k value was chosen by looking at the best performance of the kNN algorithm. K value provides an accuracy by looking at the nearest neighbors. When we started with k equal to 2, it might give best accuracy percentage. Thus, it just looked at 2 nearest neighbors. However, the algorithm might not classify as desired when k is selected as 2. Thus, the best k value was not always 2. For example, when we selected label set as arousal for A1 algorithm, optimum k value was selected 7 as shown in Fig. 4.1. We gave label set as arousal, valence, dominance, arousal-valence, arousal-dominance and valence-dominance respectively for kNN. The accuracy with optimum k value for each label in each algorithm A1 and A2 had been given in Table 4.1. The distinctive features at these optimum k values were presented in Table 4.2. It could be noticed that different features had been found as distinctive ones. Furthermore, the distinctive features between A1 and A2 algorithms had been found as Std_{IBI}, and Per_{VLF} as shown in Fig. 4.2 and Fig. 4.3.

Table 4.2. Sequential Forward Selection Results

Algorithm	**Label Set**	**Distinctive Feature**
A1	Arousal	Per_{LF}, $Deriv_{temp}$, $Mean_{bvp}$, $Deriv_{bvp}$
	Valence	Per_{LF}, Var_{temp}
	Dominance	Var_{temp}, $Mean_{bvp}$
	Arousal-Valence	Var_{temp}, Per_{LF}, $Deriv_{temp}$, Var_{sc}, $Deriv_{bvp}$
	Arousal-Dominance	$Deriv_{bvp}$, $Mean_{bvp}$, Per_{VLF}, Var_{temp}, VLF
	Valence-Dominance	Per_{LF}, Var_{temp}
A2	Arousal	$Mean_{sc}$, SCR, $Mean_{bvp}$, LF/HF
	Valence	$Deriv_{bvp}$
	Dominance	$Deriv_{sc}$, $Mean_{sc}$, $Mean_{bvp}$
	Arousal-Valence	Per_{HF}, SCR, Per_{VLF}, $Deriv_{sc}$, HF_{norm}
	Arousal-Dominance	Var_{bvp}, HR, $Deriv_{bvp}$, $Deriv_{sc}$
	Valence-Dominance	$Deriv_{sc}$, $Mean_{sc}$

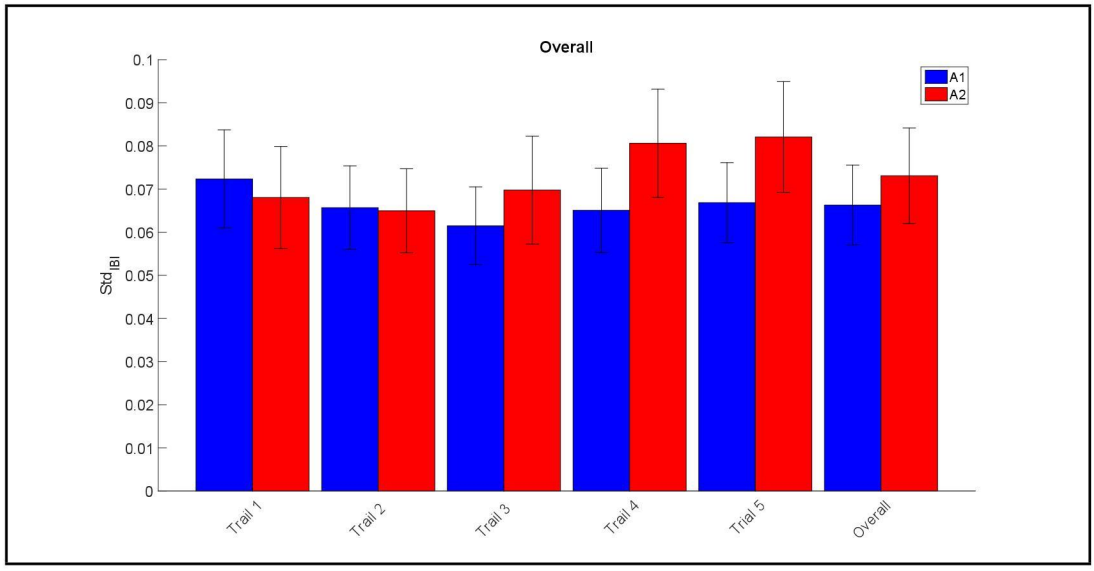

Figure 4.2. Distinctive feature Std_{IBI}.

4.1.2. One-way Anova Analysis

We used one way repeated measures ANOVA and post hoc pairwise multiple comparisons with Bonferroni correction when necessary. We classified the extracted features as A1 and A2 (p value was selected as 0.05). We found a distinctive feature $Mean_{temp}$. We observed a significant difference in $Mean_{temp}$ between A1 and A2 (p=0.0245). We also conducted the analysis by summing across all trials however for purposes of depiction. Fig. 4.4 illustrated the $Mean_{temp}$ in each trial for each A1 and A2 algorithms. We observed that temperature was lower than the baseline (temperature before the trials began) when subjects performed the task using A1 algorithm as shown in Fig. 4.4. Based on the relevant literature, such as [77]), this could be interpreted as the subjects' excitement level increased during A1 trials when compared to A2 trials.

4.2. SUBJECTIVE EVALUATION

The mean values of arousal, valence and dominance rating had been shown in Fig. 4.5. It could be noticed that when subjects performed the rehabilitation task using A1 algorithm they had a higher valence (positive feeling), and a feeling of empowerment because of higher

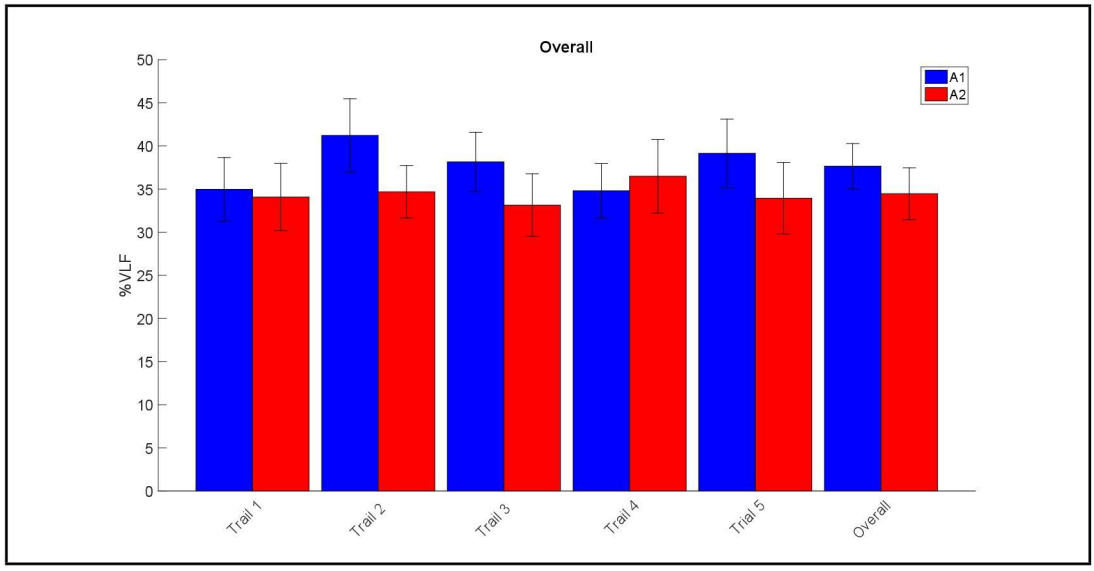

Figure 4.3. Distinctive feature Per_{VLF}.

values in dominance ratings. The mental literature puts that positive full of feeling valence signals that an subject receives an accessible goal in a given task [78]. That is, subjects occupied with a given task are occupied with fruitful inhibitory control [79] which brought about higher inspiration.

We used SAM survey results to draw Russells valence-arousal scale [80]. The valence-arousal space are divided into 4 quadrants, which are low arousal/low valence (LALV) for first quadrants, low arousal/high valence (LAHV) for second quadrants, high arousal/low valence (HALV) for third quadrants and high arousal/high valence (HAHV) for fourth quadrants. We calculated normalized arousal and valence values by taking arousal and valence values minus by the baseline mean value for all 5 trials for each algorithm (A1 and A2). Fig. 4.6 demonstrated the normalized arousal-valence ratings on the plane. Partially ordered set master algorithm (A1) is shown with red dot and it is in the fourth quadrants. It means that when subjects were playing task during A1 algorithm, they were excited. Increment/decrement one level algorithm (A2) is shown with black circle and it is in the second quadrants. It means that when subjects were playing task during A2 algorithm, they were relaxed. Partially ordered set master algorithm (A1) for baseline is shown with blue square and it is in the first quadrants. It means that when subjects were resting before they start the practice task during A1 algorithm, they were bored. Increment/decrement one level algorithm (A2) for baseline is shown with

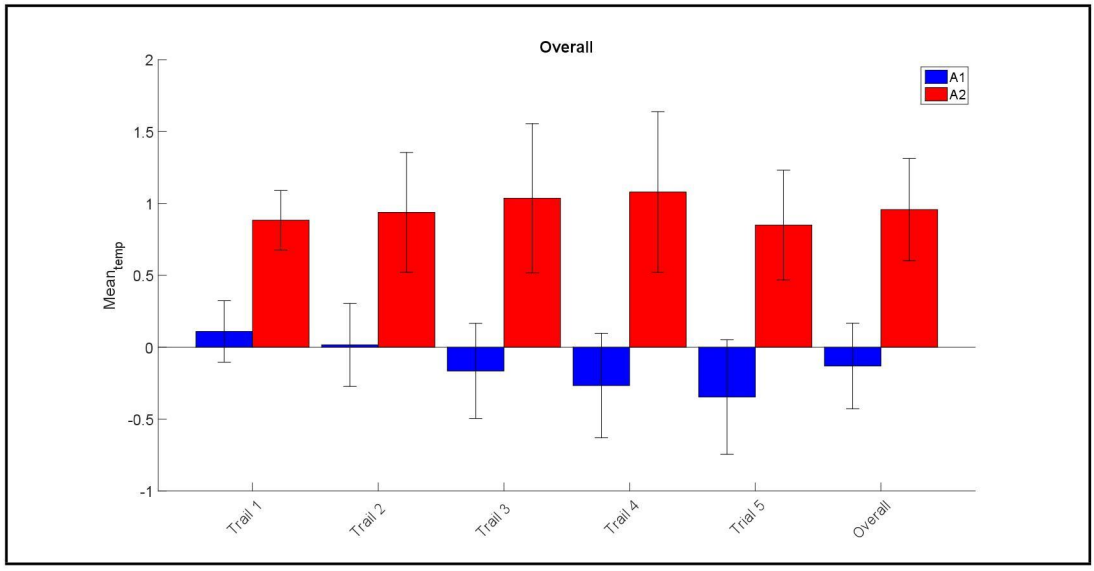

Figure 4.4. Distinctive feature $Mean_{temp}$.

green diamond and it is in the first quadrants. It means that when subjects were resting before they start the practice task during A2 algorithm, they were bored. When compared to subjects' baseline, the execution of the rehabilitation task using A1 algorithm could be associated with a large increase in arousal and only a moderate increase in valence. We had also noticed that ratings of the subjects in A1 are in HAHV quadrant which meant they are excited and pleasured (which had also been shown in Section 4.1 with $Mean_{temp}$).

We had also investigated the correlation of the different ratings with each other as given in Table 4.3. Significant correlation ($p < 0.05$) according to Spearman correlation method were indicated by stars. When we looked survey data which were taken during the partially ordered set master algorithm, we observed high positive correlations between arousal and valence, and between dominance and valence. Seemingly, subjects had positive feeling when they were excited and were able to control the game. Additionally, high positive correlation was observed between valence and dominance in A1, which meant subjects were happy when they could control the game.

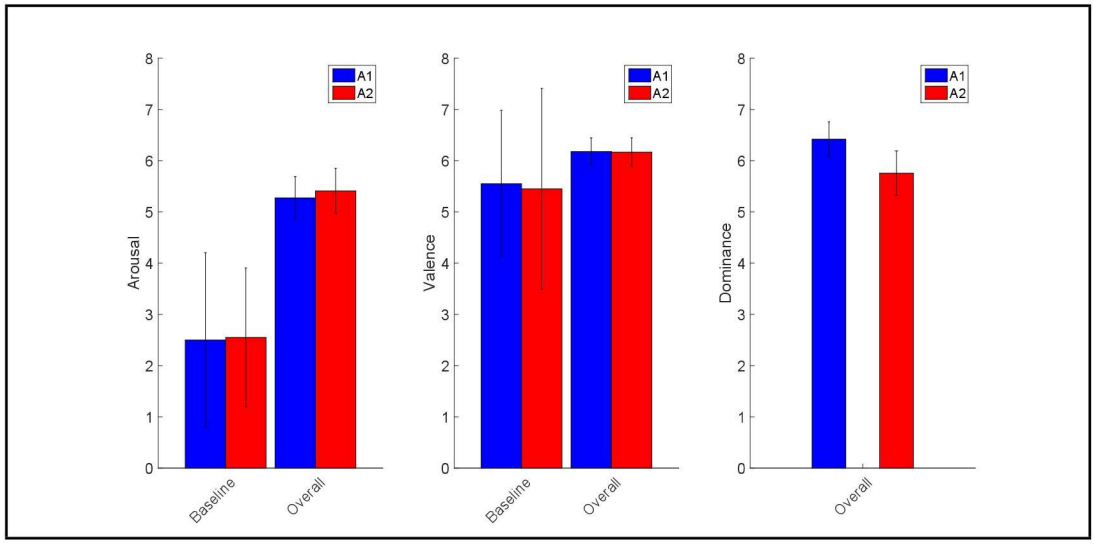

Figure 4.5. Arousal, Valence and Dominance Ratings.

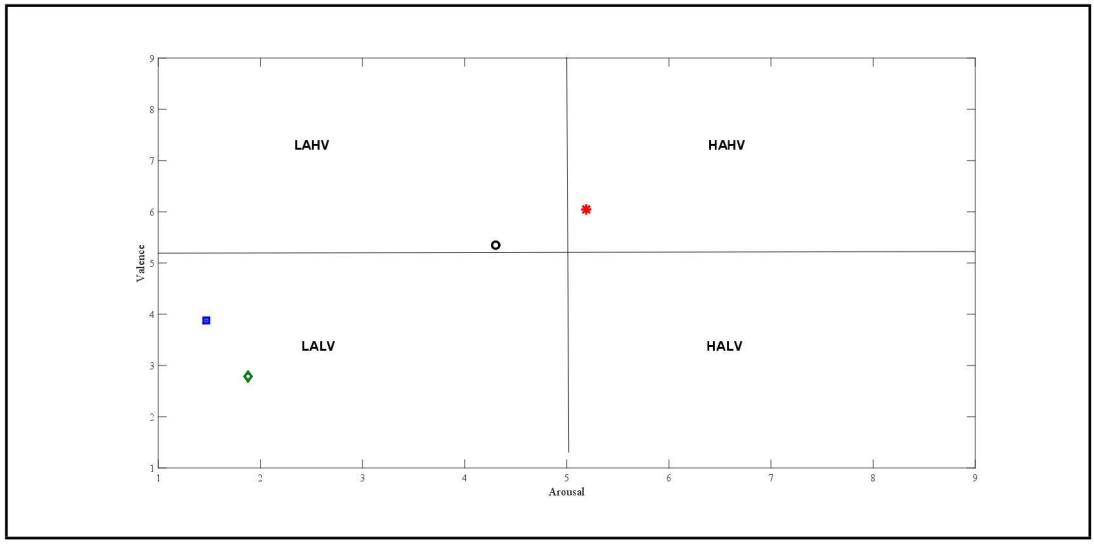

Figure 4.6. Normalized Arousal-Valence Ratings.

Table 4.3. Correlations Between the Scales of Valence, Arousal, Dominance

Algorithm	**Scale**	**Arousal**	**Valence**	**Dominance**
A1	Arousal	1	0.81*	0.41
	Valence	1	0.71*	
	Dominance	1		
A2	Arousal	1	0.53	0.39
	Valence	1	0.53*	
	Dominance	1		

5. CONCLUSION

We assessed distinctive features using two adaptation algorithms by looking at the physiological signals and subjective reports of emotional state as indexed by SAM survey results. We overviewed and interpreted the main findings below.

We asked subjects to perform rehabilitation tasks with RehabRoby where the difficulty level of the task was modified with two algorithms called partially ordered set master (POSM) and increment/decrement. BVP, SC and ST were recorded during execution of the tasks. The features from these sensory data were extracted. Two different methods SFS and ANOVA were used to find distinctive features. First, distinctive features were found in the two algorithms in each by using SFS method, and between two algorithms. Then, distinctive features were also found between A1 and A2 algorithm using ANOVA.

Various distinctive features were found in each algorithm when SFS was used. However, the $Mean_{bvp}$, $Deriv_{bvp}$ and Var_{temp} features were mostly the common ones. Additionally, Std_{IBI} and Per_{VLF} were found as distinctive ones between A1 and A2 algorithms. When ANOVA method was used, only $Mean_{temp}$ had been found as distinctive feature between A1 and A2 algorithms.

With regards to the physiological signals found while subjects were performing the game, the only a distinctive feature between the two algorithms was observed in the $Mean_{temp}$. Specifically, our results show that the A2 $Mean_{temp}$ was lower than that of A1 across all trials. A key finding from the research literature on physiological outcomes of the affective states suggested that a lower body temperature means that arousal/excitement level was high [77]. A certain level of excitement is welcome in most rehabilitation tasks. However if the excitement level (i.e., low temperature) across the trials is due to the increasing difficulty provided by the game, the subjects then may feel over-challenged and eventually drop out of the rehabilitation exercises. The higher body temperature across the tasks in A1 seemed to demonstrate a more controlled level of excitement, and therefore providing an adaptive level of challenge for the individual.

The above interpretation was also confirmed by the subjective ratings provided by the subjects. Even though there were no significant differences in the reported subjective ratings (valence, and arousal levels) when subjects were performing under A1 and A2, an interesting difference emerged in the dominance ratings. The findings yielded that under A1, subjects felt their dominance level was higher when compared to when they were performing with A2. This leaded to the conclusion that with changing levels of difficulty the subjects had the subjective sense of being in control during the game in A1 when compared to A2 (recall that in A2, the difficulty levels are present; i.e. increasing with each trial). Clearly, the subjects did not feel they can control the tasks in this situation.

A couple of limitations of the present thesis are listed: It had only been conducted with healthy subjects. In the future studies, new feature selection methods can be tried and compared against previous results. All in all, research on robot-assisted systems that are capable of not only detecting the subject's performance but also detecting subject's feelings and then dynamically adjusting the difficulty level of the rehabilitation task to better suit the patients feelings and abilities have gained momentum in the recent years. It has previously been shown that it is possible to develop more efficient and effective robot-assisted treatments when the subject's feelings are in the control loop [81]. The long-term goal of this thesis is to perform closed loop control of difficulty level of the task during robot-assisted rehabilitation automatically to stimulate a desired level of engagement during rehabilitation by using not only performance but also physiological signals.

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APPENDIX A: FEATURE EXTRACTION FOR EACH SUBJECT

```
function Table = extractfeatures(userId, condId) if nargin == 0
userId = 1;
condId = 1;
end
if condId == 1
condText = 'g1';
else
condText = 'g2';
end
load(sprintf('../matfiles/u%02d%s', userId, condText));
condTitles = {'Game1', 'Game2', 'Game3', 'Game4', 'Game5'};
% Normalization
for j=1:3
for i=1:length(game1)
normalizeddatagame1(i,j) = (game1(i,j)-mean(baseline(:,j)));
end
end
for j=1:3
for i=1:length(game2)
normalizeddatagame2(i,j) = (game2(i,j)-mean(baseline(:,j)));
end
end
for j=1:3
for i=1:length(game3)
normalizeddatagame3(i,j) = (game3(i,j)-mean(baseline(:,j)));
end
end
for j=1:3
for i=1:length(game4)
```

```
normalizeddatagame4(i,j) = (game4(i,j)-mean(baseline(:,j)));
end
end
for j=1:3
for i=1:length(game5)
normalizeddatagame5(i,j) = (game5(i,j)-mean(baseline(:,j)));
end
end
bvp = [normalizeddatagame1(:,1);normalizeddatagame2(:,1);normalizeddatagame3(:,1);...
normalizeddatagame4(:,1);normalizeddatagame5(:,1)];
sc = [normalizeddatagame1(:,2);normalizeddatagame2(:,2);normalizeddatagame3(:,2);...
normalizeddatagame4(:,2);normalizeddatagame5(:,2)];
temp = [normalizeddatagame1(:,3);normalizeddatagame2(:,3);normalizeddatagame3(:,3);...
normalizeddatagame4(:,3);normalizeddatagame5(:,3)];
% Savitzky-Golay filtering
filtbvp=sgolayfilt(bvp,1,21);
filtsc=sgolayfilt(sc,1,21);
filttemp=sgolayfilt(temp,1,21);

% LPF to remove false peaks, cutting frequency fc = 2 Hz
fs=100;
[b, a] = butter(5,2*2/fs);
lpfbvp = filter(b,a,bvp);
lpfsc = filter(b,a,sc);
lpftemp = filter(b,a,temp);
% Game1
datacell{1}=[lpfbvp(1:length(normalizeddatagame1)) ...
filtsc(1:length(normalizeddatagame1))...
filttemp(1:length(normalizeddatagame1))];
% Game2
datacell{2}=[lpfbvp(length(normalizeddatagame1)+...
```

```
1:length(normalizeddatagame1+length(normalizeddatagame2))...
filtsc(length(normalizeddatagame1)+1:length(normalizeddatagame1)...
+length(normalizeddatagame2)) filttemp(length(normalizeddatagame1)...
+1:length(normalizeddatagame1)+length(normalizeddatagame2))];
% Game3
datacell{3}=[lpfbvp(length(normalizeddatagame1)...
+length(normalizeddatagame2)+1:length(normalizeddatagame1)...
+length(normalizeddatagame2)+length(normalizeddatagame3))...
filtsc(length(normalizeddatagame1)+length(normalizeddatagame2)+...
1:length(normalizeddatagame1)+length(normalizeddatagame2)...
+length(normalizeddatagame3)) filttemp(length(normalizeddatagame1)...
+length(normalizeddatagame2)+1:length(normalizeddatagame1)...
+length(normalizeddatagame2)+length(normalizeddatagame3))];
% Game4
datacell{4}=[lpfbvp(length(normalizeddatagame1)+
length(normalizeddatagame2)+length(normalizeddatagame3)+
1:length(normalizeddatagame1)+length(normalizeddatagame2)+
length(normalizeddatagame3)+length(normalizeddatagame4))
filtsc(length(normalizeddatagame1)+
length(normalizeddatagame2)+length(normalizeddatagame3)+
1:length(normalizeddatagame1)+length(normalizeddatagame2)+
length(normalizeddatagame3)+length(normalizeddatagame4))
filttemp(length(normalizeddatagame1)+
length(normalizeddatagame2)+length(normalizeddatagame3)+
1:length(normalizeddatagame1)+length(normalizeddatagame2)+
length(normalizeddatagame3)+length(normalizeddatagame4))];
% Game5
datacell{5}=[lpfbvp(length(normalizeddatagame1)+length(normalizeddatagame2)+...
length(normalizeddatagame3)+length(normalizeddatagame4)+...
1:length(normalizeddatagame1)+length(normalizeddatagame2)+...
length(normalizeddatagame3)+length(normalizeddatagame4)+...
```

```
length(normalizeddatagame5)) filtsc(length(normalizeddatagame1)...
+length(normalizeddatagame2)+length(normalizeddatagame3)+...
length(normalizeddatagame4)+1:length(normalizeddatagame1)+...
length(normalizeddatagame2)+length(normalizeddatagame3)+...
length(normalizeddatagame4)+length(normalizeddatagame5))...
filttemp(length(normalizeddatagame1)+length(normalizeddatagame2)+...
length(normalizeddatagame3)+length(normalizeddatagame4)+...
1:length(normalizeddatagame1)+length(normalizeddatagame2)+...
length(normalizeddatagame3)+length(normalizeddatagame4)+...
length(normalizeddatagame5))];


for r=0:4 % r=0 means Game1 / r=1 means Game2 / r=2 means Game3 / r=3 means Game4 /
r=4 means Game5
fs=100;
data=datacell{1, r + 1};
databvp = data(:,1);
datasc = data(:,2);
datatemp = data(:,3);


meanbvp=mean(databvp); % mean bvp
meansc=mean(datasc); % mean sc
meantemp=mean(datatemp); % mean temp
vbvp=var(databvp); % variance bvp
vsc=var(datasc); % variance sc
vtemp=var(datatemp); % variance temp


fdmbvp=mean(diff(databvp)/(1/fs)); %first difference mean for smoothed data bvp
fdmsc=mean(diff(datasc)/(1/fs)); %first difference mean for smoothed data sc
fdmtemp=mean(diff(datatemp)/(1/fs)); %first difference mean for smoothed data temp
```

```
% bvp calculation %
m = length(databvp);
time = (0:m-1)/fs;
[pks, locs]=findpeaks(databvp); % This is an important step, false peaks may %deceive the
features.
tpeaks = time(locs);
figure(1)
subplot(5,1,r+1);
plot(time,databvp)
hold on
plot(tpeaks,pks,'r*')
title(sprintf('BVP-%s', condTitles{r+1}));
% This is an important step, false peaks may deceive the features.
tvar = diff(tpeaks);
tvec = tpeaks(2:end);
xvec = tvar;
[power, f] = plomb(xvec,tvec);

figure(3)
subplot(5,1,r+1);
plot(f,power)
xlim([0 0.5])
xlabel('Frequency')
ylabel('Power')
hold on
plot(0.04*ones(1,10),linspace(0,max(power),10),'r-','LineWidth',2)
plot(0.15*ones(1,10),linspace(0,max(power),10),'g-','LineWidth',2)
plot(0.4*ones(1,10),linspace(0,max(power),10),'k-','LineWidth',2)
title(sprintf('Spectrum of HRV - %s', condTitles{r+1}));
grid on
[u, v]=find(f>0 & f<=0.4);
```

```
bvptp = sum(power(u));
[u, v]=find(f>0 & f⩽0.04);
bvpvlf = sum(power(u));
[u, v]=find(0.04<f & f⩽0.15);
bvplf = sum(power(u));
[u, v]=find(0.15<f & f⩽0.4);
bvphf = sum(power(u));
bvplfhf = bvplf/bvphf;
percenthf=(bvphf/(bvphf+bvplf+bvpvlf))*100;
percentlf=(bvplf/(bvphf+bvplf+bvpvlf))*100;
percentvlf=(bvpvlf/(bvphf+bvplf+bvpvlf))*100;
lfnorm = (bvplf/(bvplf + bvphf))*100;
hfnorm = (bvphf/(bvplf + bvphf))*100;
ratio = (bvpvlf+bvplf)/bvphf;
stdIBI = std(tvar);
meanIBI = mean(tvar);
BPM = 60/meanIBI;
BVPFeatureVec(:,r+1) = [BPM; meanIBI; stdIBI; bvptp;
bvpvlf;bvplf;bvphf;bvplfhf;percentvlf;percentlf;percenthf; lfnorm;hfnorm;ratio];
% SCR calculation %
P = [] ; T = []; a = 1; b = 1; i = 0; d = 0;
E = 0.05;
xL = length(datasc);
while (i = xL)
i = i + 1 ;
if (d == 0)
if (datasc(a) >= (datasc(i) + E)) % E threshold value
d = 2;
elseif (datasc(i) >= (datasc(b) + E ) )
d = 1;
end;
```

```
if (datasc(a) <= datasc(i) )
a = i;
elseif (datasc(i) <= datasc(b) )
b = i;
end;
elseif (d == 1)
if (datasc(a) <= datasc(i) )
a = i;
elseif (datasc(a) >= (datasc(i) + E))
P = [Pa]; b = i; d = 2; % peaks
end;
elseif (d==2)
if (datasc(i) ¡= datasc(b) )
b = i;
elseif (datasc(i) >= (datasc(b) + E ) )
T = [Tb]; a = i; d = 1; %troughs
end;
end;
end;
scr= length(P);
m = length(datasc);
time = (0:m-1)/fs;
figure(11);
subplot(5,1,r+1);
plot(time,datasc)
hold on
plot(time(P),datasc(P),'r*')
title(sprintf('SC - %s', condTitles{r+1}));
SCFeatureVec(:,r+1) = [scr;meansc;vsc;fdmsc];
TempFeatureVec(:,r+1) = [meantemp;vtemp;fdmtemp];
BVPFeatureVec1(:,r+1) = [meanbvp;vbvp;fdmbvp];
```

```
end
ALLFEATURE=[SCFeatureVec;BVPFeatureVec;BVPFeatureVec1;TempFeatureVec];
Features = {'SCR';'MeanSC';'VarianceSC';...
'FirstDerivativeMeanSC';'HR';'MeanIBI';'StdIBI';...
'BvpTotalPower';'VeryLowFrequency';'LowFrequency';...
'HighFrequency';'LowFreq/HighFreq';...
'%VeryLowFrequency';'%LowFrequency';'%HighFrequency';...
'LowFrequencyNorm';'HighFrequencyNorm';...
'Ratio of Frequencies';'MeanBVP';'VarianceBVP';...
'FirstDerivativeMeanBVP';'MeanTEMP';...
'VarianceTEMP';'FirstDerivativeMeanTEMP'};
MeanGame = mean(ALLFEATURE')';
StdGame = std(ALLFEATURE')';
Table = table(ALLFEATURE,MeanGame,StdGame,'RowNames',Features);
save(sprintf('../tables/u%02d%s', userId, condText),'Table')
```

APPENDIX B: PLOTTING THE FEATURES

```
%% overall features table
clear all
close all
clc
condText1 = 'g1';
condText2 = 'g2';
table = zeros(24,7);
%% G1
for i = 1:20
load(sprintf('u%02d%s', i, condText1),'Table')
Table = table2array(Table);
table = Table(:,:)+table(:,:);
end
overallg1table = table/20; % mean
%% G2
clear table;
table = zeros(24,7);
for i = 1:20
load(sprintf('u%02d%s', i, condText2),'Table')
Table = table2array(Table);
table = Table(:,:)+table(:,:);
end
overallg2table = table/20; % mean
% ploting data using bar command
Features = {'SCR';'Mean{sc}';...
'Var{sc}';'Deriv{sc}';...
'HR';'Mean{IBI}';'Std{IBI}';...
'BVP{tp}';'VLF';'LF';'HF';'LFtoHF';...
'%VLF';'%LF';'%HF';'LF{norm}';...
```

```
'HF{norm}';'(VLF+LF)toHF';...
'Mean{bvp}';'Var{bvp}';...
'Deriv{bvp}';'Mean{temp}';...
'Var{temp}';'Deriv{temp}'};
xlabel= {'Trail 1','Trail 2 ','Trail 3 ',...
'Trail 4','Trial 5','Overall'};
overalltable = [overallg1table(:,1) overallg2table(:,1) ...
overallg1table(:,2) overallg2table(:,2) overallg1table(:,3) ...
overallg2table(:,3) overallg1table(:,4) overallg2table(:,4) ...
overallg1table(:,5) overallg2table(:,5) ...
overallg1table(:,6) overallg2table(:,6)];
%%
table = zeros(24,6);
for y = 1:24
for i = 1:20
load(sprintf('u%02d%s', i, condText1),'Table')
Table = table2array(Table);
table(i,:) = Table(y,1:6);
end
table = [table(1:20,:)];
overallg1std(y,:)=std(table)./sqrt(length(table));
end
%%
table = zeros(20,6);
for y = 1:24
for i = 1:20
load(sprintf('u%02d%s', i, condText2),'Table')
Table = table2array(Table);
table(i,:) = Table(y,1:6);
end
table = [table(1:20,:)];
```

```
overallg2std(y,:)=std(table)./sqrt(length(table));
end
%%
overallstd = [overallg1std(:,1) overallg2std(:,1) ...
overallg1std(:,2) overallg2std(:,2) ...
overallg1std(:,3) overallg2std(:,3) ...
overallg1std(:,4) overallg2std(:,4) ...
overallg1std(:,5) overallg2std(:,5) ...
overallg1std(:,6) overallg2std(:,6)];
for i = 1:24
figure(i);
m = [overalltable(i,1:2);overalltable(i,3:4);...
overalltable(i,5:6);overalltable(i,7:8);...
overalltable(i,9:10);overalltable(i,11:12)];
s = [overallstd(i,1:2);overallstd(i,3:4);...
overallstd(i,5:6);overallstd(i,7:8);...
overallstd(i,9:10);overallstd(i,11:12)];
errorbargroups(m',s');
hold on;
set(gca,'XTickLabel',xlabel,'XTick',[1.5 3.5 5.5 7.5 9.5 11.5],...
'XTickLabelRotation',45,'Fontsize',20)
ylabel(Features(i,1));
legend('A1','A2')
title('Overall')
end
```

APPENDIX C: ANOVA CALCULATIONS

```
clear all
close all
clc
condText1 = 'g1';
condText2 = 'g2';
t = 1;
%% G1
for y = 1:24
for i = 1:20
load(sprintf('u%02d%s', i, condText1),'Table')
Table = table2array(Table);
tableg1(t,:) = Table(y,6);
t = t+1;
end
end
%% G2
t = 1;
for y = 1:24
for i = 1:20
load(sprintf('u%02d%s', i, condText2),'Table')
Table = table2array(Table);
tableg2(t,:) = Table(y,6);
t = t+1;
end
end
%% overall
SCR = [tableg1(1:20,:) tableg2(1:20,:)];
MeanSC = [tableg1(21:40,:) tableg2(21:40,:)];
VarianceSC = [tableg1(41:60,:) tableg2(41:60,:)];
```

```
FirstDerivativeMeanSC = [tableg1(61:80,:) tableg2(61:80,:)];
HR = [tableg1(81:100,:) tableg2(81:100,:)];
MeanIBI = [tableg1(101:120,:) tableg2(101:120,:)];
StdIBI = [tableg1(121:140,:) tableg2(121:140,:)];
BvpTotalPower = [tableg1(141:160,:) tableg2(141:160,:)];
VeryLowFrequency = [tableg1(161:180,:) tableg2(161:180,:)];
LowFrequency = [tableg1(181:200,:) tableg2(181:200,:)];
HighFrequency = [tableg1(201:220,:) tableg2(201:220,:)];
RatioofLowFreqtoHighFreq = [tableg1(221:240,:) tableg2(221:240,:)];
PerVeryLowFrequency = [tableg1(241:260,:) tableg2(241:260,:)];
PerLowFrequency = [tableg1(261:280,:) tableg2(261:280,:)];
PerHighFrequency = [tableg1(281:300,:) tableg2(281:300,:)];
LowFrequencyNorm = [tableg1(301:320,:) tableg2(301:320,:)];
HighFrequencyNorm = [tableg1(321:340,:) tableg2(321:340,:)];
RatioofFrequencies = [tableg1(341:360,:) tableg2(341:360,:)];
MeanBVP = [tableg1(361:380,:) tableg2(361:380,:)];
VarianceBVP = [tableg1(381:400,:) tableg2(381:400,:)];
FirstDerivativeMeanBVP = [tableg1(401:420,:) tableg2(401:420,:)];
MeanTEMP = [tableg1(421:440,:) tableg2(421:440,:)];
VarianceTEMP = [tableg1(441:460,:) tableg2(441:460,:)];
FirstDerivativeMeanTEMP = [tableg1(461:480,:) tableg2(461:480,:)];
%% 1-Way Anova
[p, tbl] = anova1(SCR);
saveas(gcf, sprintf('../anova/SCR(%s).png','anova'));
[p, tbl] = anova1(MeanSC);
saveas(gcf, sprintf('../anova/MeanSC(%s).png','anova'));
[p, tbl] = anova1(VarianceSC);
saveas(gcf, sprintf('../anova/VarianceSC(%s).png','anova'));
[p, tbl] = anova1(FirstDerivativeMeanSC);
saveas(gcf, sprintf('../anova/FirstDerivativeMeanSC(%s).png','anova'));
[p, tbl] = anova1(HR);
```

```
saveas(gcf, sprintf('../anova/HR(%s).png','anova'));
[p, tbl] = anova1(MeanIBI);
saveas(gcf, sprintf('../anova/MeanIBI(%s).png','anova'));
[p, tbl] = anova1(StdIBI);
saveas(gcf, sprintf('../anova/StdIBI(%s).png','anova'));
[p, tbl] = anova1(BvpTotalPower);
saveas(gcf, sprintf('../anova/BvpTotalPower(%s).png','anova'));
[p, tbl] = anova1(VeryLowFrequency);
saveas(gcf, sprintf('../anova/VeryLowFrequency(%s).png','anova'));
[p, tbl] = anova1(LowFrequency);
saveas(gcf, sprintf('../anova/LowFrequency(%s).png','anova'));
[p, tbl] = anova1(HighFrequency);
saveas(gcf, sprintf('../anova/HighFrequency(%s).png','anova'));
[p, tbl] = anova1(RatioofLowFreqtoHighFreq);
saveas(gcf, sprintf('../anova/RatioofLowFreqtoHighFreq(%s).png','anova'));
[p, tbl] = anova1(PerVeryLowFrequency);
saveas(gcf, sprintf('../anova/PerVeryLowFrequency(%s).png','anova'));
[p, tbl] = anova1(PerLowFrequency);
saveas(gcf, sprintf('../anova/PerLowFrequency(%s).png','anova'));
[p, tbl] = anova1(PerHighFrequency);
saveas(gcf, sprintf('../anova/PerHighFrequency(%s).png','anova'));
[p, tbl] = anova1(LowFrequencyNorm);
saveas(gcf, sprintf('../anova/LowFrequencyNorm(%s).png','anova'));
[p, tbl] = anova1(HighFrequencyNorm);
saveas(gcf, sprintf('../anova/HighFrequencyNorm(%s).png','anova'));
[p, tbl] = anova1(RatioofFrequencies);
saveas(gcf, sprintf('../anova/RatioofFrequencies(%s).png','anova'));
[p, tbl] = anova1(MeanBVP);
saveas(gcf, sprintf('../anova/MeanBVP(%s).png','anova'));
[p, tbl] = anova1(VarianceBVP);
saveas(gcf, sprintf('../anova/VarianceBVP(%s).png','anova'));
```

$[p, tbl]$ = anova1(FirstDerivativeMeanBVP);

saveas(gcf, sprintf('../anova/FirstDerivativeMeanBVP(%s).png','anova'));

$[p, tbl]$ = anova1(MeanTEMP);

saveas(gcf, sprintf('../anova/MeanTEMP(%s).png','anova'));

$[p, tbl]$ = anova1(VarianceTEMP);

saveas(gcf, sprintf('../anova/VarianceTEMP(%s).png','anova'));

$[p, tbl]$ = anova1(FirstDerivativeMeanTEMP);

saveas(gcf, sprintf('../anova/FirstDerivativeMeanTEMP(%s).png','anova'));

APPENDIX D: SURVEY AROUSAL-VALENCE SCALE

```
clear all
close all
clc
load survey.mat
overallg1 = (game1g1+game2g1+game3g1+game4g1+game5g1)./5;
overallg2 = (game1g2+game2g2+game3g2+game4g2+game5g2)./5;
overg1=overallg1([1:2,4,6:8,10:end],:);
overg2=overallg2([1:3,5:9,11:18,20],:);
c = mean(overg1)./std(overg1);
d = mean(overg2)./std(overg2);
baselineg1=mean(bg1)./std(bg1)
baselineg2=mean(bg2)./std(bg2)
figure(2)
plot(c(1,2),c(1,1),'r*')
hold on
plot(d(1,2),d(1,1),'ko')
xlabel('Valence')
ylabel('Arousal')
plot(baselineg1(1,2),baselineg1(1,1),'b*')
plot(baselineg2(1,2),baselineg2(1,1),'bo')
legend('G1','G2','BaselineG1','BaselineG2')
axis([1 9 1 9])
```