Clustering of Emotional States under Different Task Difficulty Levels for the Robot-assisted Rehabilitation system-RehabRoby

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Abstract: In this paper, we study an unsupervised learning problem where the aim is to cluster the emotional state (excitedness, boredom, or stress) using the biofeedback sensor data while subjects perform tasks under different difficulty levels on the robot assisted rehabilitation system-RehabRoby. The dimension of the training vectors has been reduced by using the Principal Component Analysis (PCA) algorithm after collecting the biofeedback sensor measurements from different subjects under different task difficulty levels to better visualize the sensor data. The reduced dimension vectors are fed into a K-means clustering algorithm. Numerical results have been given to demonstrate that for each training vector, the emotional state decided by the clustering algorithm is consistent with the subjects declaration of his/her emotional state obtained via surveys after performing the task.

1 INTRODUCTION

Robot-assisted rehabilitation systems were first used in large scaled clinical tests in 1998 and since then several robot-aided rehabilitation systems have been developed. There are two kinds of robot-assisted rehabilitation systems for the upper extremities in terms of mechanical design, which are end-effector-based, and exoskeleton type rehabilitation robots. MIT-MANUS (Krebs et al., 2004), MIME (Lum et al., 2006), GENTLE/S (Loureiro et al., 2003) and NeReBot are end-effector-based, and ARMin (Nef et al., 2009), CADEN-7 (Perry et al., 2007), RUPERT IV (Balasubramanian et al., 2008), WREX (Rahman et al., 2006), SRE (Caldwell et al., 2007), RehabExos (Vertechy et al., 2009), ExoRob (Rahman et al., 2009), SUEFUL-7 (Kiguchi et al., 2008), IntelliArm (Ren et al., 2009) are exoskeleton type robot-assisted rehabilitation systems. Exoskeleton type robots resemble the anatomy of the human arm and each of the robot's joints can be controlled separately, which reduces the control complexity. Recently, we have developed an exoskeleton type upper-extremity robot-assisted rehabilitation system, which is called RehabRoby (Ozkul et al., 2012), (Ozkul and Barkana, 2013). Robot-assisted rehabilitation systems have shown to be helpful in neuromotor rehabilitation because it is possible to deliver interactive and repeatable sensorimotor exercise, and monitor the actual performance continuously. However, to obtain optimal performance from such exercises, the task difficulty needs to be appropriately challenging. Note that a rehabilitation task that is too easy or under challenging can be perceived as boring, while a task that is too challenging can be frustrating. An optimally challenging rehabilitation task can motivate and cause maximum mental engagement for the patients (Novak et al., 2012). Mental engagement of patients have shown to be a key factor to improve the outcome of the rehabilitation (Maclean and Pound, 2000). Motor learning theory states that learning rate increases when the rehabilitation task challenges and excites the subjects (Guadagnoli and Lee, 2004). Thus, it is important that a robot- assisted rehabilitation system aiding in rehabilitation tasks should be capable of detecting that patient is either becoming bored or frustrated, and then modifying the rehabilitation task to better suit the patient's abilities.

A recent survey paper presents the current state of the art and the new challenges in automatic, dimensional and continuous analysis and synthesis of human emotional behavior (Gunes et al., 2011).

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The most commonly employed strategy in automatic dimensional emotional state detection is the 2D valence-arousal (V-A) emotion model (Russell, 1989). Various difficulty levels of a rehabilitation task has previously been defined according to the circumplex model of affect (Koenig et al., 2011b), (Koenig et al., 2011a). Emotional state may become apparent by subjective experiences (how the person feels), internal/inward expressions (psychophysiological measurements) and external/outward expressions (audio/ visual signals) (Gunes et al., 2011). The great challenge of psychophysiological measurements is the abundance of available data, and the hundreds of features that can be extracted by considering all the physiological responses. Psychophysiological measurements such as heart and muscle activity, brain activity, blood pressure, skin temperature, respiration, are multichannel recordings from both the central nervous system (CNS), and the autonomic nervous systems (ANS). These measurements are all rich sources of information concerning the physiological responses of the human body. The transition from one emotional state to another, for instance, from state of boredom to state of anxiety is accompanied by dynamic shifts in indicators of ANS activity. Furthermore, it has previously been mentioned that the signals from the autonomic nervous system (ANS) can indicate mental engagement (Filipovic and Andreassi, 2001). Changes in psychophysiological measurements can be used to assess mood and engagement, and to understand emotions of people in a variety of applications (Mandryk and Atkins, 2007), (Rani et al., 2003b), (Rani et al., 2003a). Psychophysiological measurements can also be used to understand emotions of patients during the execution of a rehabilitation task using a robotic system. Heart rate, skin conductance responses, and skin temperature have previously been used to estimate and classify a patient's psychological state during robot-assisted gait rehabilitation (Koenig et al., 2011b), (Koenig et al., 2011a).The biofeedback sensors can be used to measure the emotions. In this study, we use skin conductance, electrocardiography (ECG), temperature, blood volume pulse (BVP) and respiratory rate biofeedback sensors to detect if the subject has been bored, overstressed or excited (emotional states) during the execution of a rehabilitation task.

Since the raw data from the biofeedback sensors are inadequate, several features from the raw sensor data have previously been defined to classify the emotion states (Koenig et al., 2011b), (Koenig et al., 2011a). Note that proper feature selection from the sensory data determines the accuracy of the emotional state classification. The Pulse Transit Time (PTT) and Heart Rate Variability (HRV) have previously been used as feature for Electrocardiography (ECG), and delta(1-3Hz), theta(4-7Hz), alpha1(8-9Hz), alpha2(10-12Hz), beta1(13-17Hz), beta2(18-30Hz), gamma1(31-40Hz), gamma2(41-50Hz) have been used as features for Electroencephalography (EEG) sensor (Kandemir, 2013). High frequency components, standard deviation, standard deviation of coefficients of Daubechie transform (3th and 4th) and mean of the peak values of ECG signal have previously been used as features to detect the excitement, anxiety, boredom, frustration and anger (Rani et al., 2007). Mean values derived for phasic and tonic components of raw skin conductance data, amplitude of hurbis, mean and median frequency of hurbis, and standard deviation of raw EMG and mean, power spectrum density and slope of skin temperature have also been used as features to detect the emotions (Rani et al., 2007). In this study, we use the features heart rate(HR), HR mean(beat/min), interbeat interval(IBI), pulse transit time(with BVP) (PTT(ms)), very low frequency(VLF) power(%), low frequency(LF) power(%), high frequency(HF) power(%), total VLF power, total LF power, total HF power, and HR standard deviation (from ECG); time between two successive beats of the heart (IBI) (from BVP); skin conductance value(%), mean of skin conductance value(uS), and percentage of mean of the skin conductance level (from skin conductance); mean of the temperature (deg), percentage of the mean of the temperature, and percentage value of temperature (from temperature sensor), and respiration rate(br/min) (from the respiratory rate) to detect the emotional states (boredom, stress and excitement).

In this paper, an unsupervised learning problem has been considered. The biofeedback signals from different subjects under different difficulty levels have been collected. The aim is to distinguish the emotional state of the subjects while performing a rehabilitation task with a robot-assisted rehabilitation system-RehabRoby. The emotional states that we want to classify are excitedness, boredom, and overstress. Correct classification of the emotional state is an important step for the later steps of the rehabilitation task. As an example, if it is determined that the subject is bored, the difficulty level of the task can be very easy for the subject, and the difficulty level may need to be increased. If, on the other hand, it is determined that the subject is excited, we can deduce that the task difficulty level is optimal for the subject. Finally, if the subject is found to be stressed, the difficulty level of the task can be very challenging for the subject and the difficulty level may need to be decreased (Koenig et al., 2011b).The emotional states can be classified solely based on the survey results after performing the task but the subjects may not be sure about their feelings, may not want to reveal their feelings or may declare a misleading answer (Novak et al., 2012). Therefore, emotional state classification based on biofeedback sensor data may depend on the surveys. On the other hand, survey results can still be used to determine the accuracy of the classification algorithm (Koenig et al., 2011b). The output of the classification algorithm can be further used in the later steps of the rehabilitation task. In this paper, after collecting biofeedback signals from subjects, we develop a clustering problem by using principal component analysis (PCA) and K-means clustering algorithms (Bishop, 2006) to obtain the clusters related with each emotional state. The training vectors related to each emotional state is then compared with the survey results to test the accuracy of the clustering algorithm.

The rest of this paper is organized as follows, in Section II, we present our materials, experiments and unsupervised learning methods. In Section III, we present our numerical results. In Section IV, we conclude our work and address future research directions.

2 MATERIALS AND METHODS

In this section, we present the details of the hardware properties of the robot-assisted rehabilitation system, RehabRoby, the task, and the unsupervised learning method used for classification of the emotional states.

2.1 Hardware

In this study, an exoskeleton type upper-extremity robot-assisted rehabilitation system, which is called RehabRoby, has been used (Fig. 1). RehabRoby has been designed in such a way that i) it can implement passive mode therapy, active-assisted mode therapy and resistive mode therapy, ii) it can be easily adjusted for people of different heights and with different arm lengths, and iii) it can be used for both right and left arm rehabilitation. RehabRoby is designed to provide extension, flexion, abduction, adduction, rotation, pronation and supination upper-extremity movements and the combinations of these movements that are necessary for the tasks and activities of daily living. An arm splint, which has humeral and forearm thermoplastic supports with Velcro straps and a single axis free elbow joint, has been designed and attached to RehabRoby (Figure 1). The thermoplastic arm splint designed for the RehabRoby has humeral and forearm supports with Velcro straps, and a thermoplastic inner layer that is covered by a soft material (Plastazote). Two force sensors (Kistler - 9313AA1; Kistler France, Les Ulis, France) are placed in the inner surface of the plate attached dorsally to the forearm splint (Figure 1). One of the force sensors measures the force applied during the elbow flexion movement and the other measures the force applied during the shoulder flexion movement. Ensuring the safety of the subject is a critical issue for a robot-assisted rehabilitation system. Thus, in the event of an emergency situation, the therapist can press an emergency button to stop the RehabRoby (Figure 1), and the motor drivers of RehabRoby are disabled separately or together by pressing the driver enable/disable buttons without turning off RehabRoby. The system is powered by an uninterruptible power supply, thus, there can be no power loss and RehabRoby will not collapse at any time.

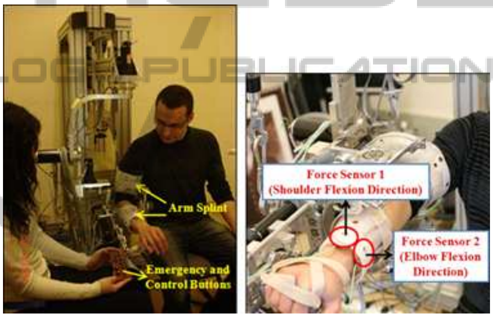

Figure 1: Robot-Assisted Rehabilitation System-RehabRoby.

In this study, skin conductance, electrocardiography (ECG), temperature, blood volume pulse (BVP) and respiratory rate from Thought Technology Ltd have been used for biofeedback sensory information to detect three emotion states boredom, overstressed and excited. Physiological signals have been sampled at 256Hz using Procomp Infinite Encoder. Skin conductance has been measured using skin conductance sensor (sc-flex pro) (Figure 2-left). The electrodes have been placed on the middle phalanx of index finger and ring finger. There are three ECG electrodes used for the measurement. Two of them are placed where the Deltoid anterior heads and Pectoralis major muscles intersect, several centimeters below the clavical. The third ECG electrode is placed near the xiphoid. Temperature has been recorded using a skin type sensor that is placed on the finger tip of the thumb (Figure 2-left). Blood volume pulse (BVP) has been recorded using BVP-Pro flex sensor that is placed on the finger tip of the middle finger (Figure 2-left). Respiration sensors (resp-flex pro), which have been placed around abdomen and the chest, have been used to record the respiratory rate (Figure 2-right). Skin conductance, temperature and respiratory rate signals have been sampled at 256Hz and ECG and BVP have been sampled at 2048Hz. The features derived from the signals of these sensors have been downsampled to 32Hz for learning algorithm because of the hardware limitations of the computer.

BioGraph Infinity is the interface software provided by Thought Technology Ltd to get both raw sensor data and the features from the raw data. 19 features from the skin conductance, electrocardiography (ECG), temperature, blood volume pulse (BVP) and respiratory rate sensory data have been selected for this study. The physiological signals we examined were: various features of ECG, including heart rate(HR), HR mean(beat/min), interbeat interval(IBI), pulse transit time(with BVP) (PTT(ms)), very low frequency(VLF) power(%), low frequency(LF) power(%), high frequency(HF) power(%), total VLF power, total LF power, total HF power, and HR standard deviation; time between two successive beats of the heart (IBI) (from BVP); skin conductance value(%), mean of skin conductance value(uS), and percentage of mean of the skin conductance level (from skin conductance); mean of the temperature (deg), percentage of the mean of the temperature, and percentage value of temperature (from temperature sensor), and respiration rate(br/min) (from the respiratory rate). These signals were selected because they i) were shown to capture important information about the underlying targeted emotion states, (ii) could be measured non-invasively; and iii) were relatively resistant to movement artifacts.

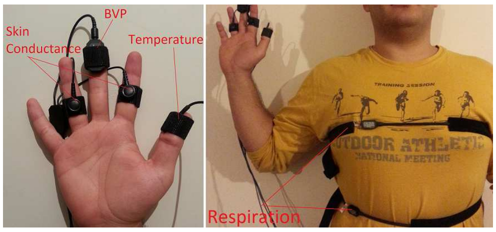

Figure 2: Sensor Placement on Subjects.

2.2 Task

A well-known rehabilitation tasks has been selected in consultation with therapists at Yeditepe University's Physiotherapy and Rehabilitation Department. The task is the elbow flexion and extension movement (i.e., reaching up to the chest button up). Each task takes one minute. Subjects are seated in the chair, and their arms are placed in the splint and tightly secured with Velcro straps (Figure 1). The height of the RehabRoby can be adjusted for each subject so that they would start the task in the same arm configuration. Initially, the subject's shoulder is positioned at an extension of 90°, the elbow is it the neutral position, the lower arm is at a pronation of 90°, and the hand and the wrist are free at the neutral position. A computer monitor has been placed in front of the subject to provide visual feedback about his/her motion trajectory during the execution of the task.

The subject is asked to catch a ball that is displayed on the computer monitor (Figure 3). Black ball demonstrates the reference trajectory and red ball demonstrates the subject's movement. Subjects are expected to perform the same task with five different difficulty levels following resting period. The different difficulty level is defined by changing the number of repeated flexion and extension movement in a certain amount of time. For example, the subject is asked to flex and extend his/her arm 5 times in 4 minutes for the first difficulty level and 25 times for the fifth difficulty level. Thus, the angular speeds of these five different levels are 2.5°/s,5°/s,7.5°/s,10°/s and 12.5°/s considering the repetition numbers. The reference trajectories for each difficulty level are computed using minimum-jerk trajectory.

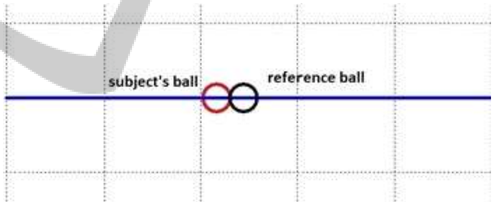

Figure 3: The Reference Trajectory and the Subject's Movement.

2.3 Experiment Procedure

Initially, the biofeedback sensors were placed on the subject as shown in (Figure 2). Then subject was asked to track the black ball as shown in (Figure 3) for all 5 different angular velocities (2.5°/s,5°/s,7.5°/s,10°/s and 12.5°/s). Subjects were asked to complete The Self-Assessment Manikin (SAM) survey, which has previously been used to measure emotional responses (Bradley and Lang, 1994). We also used SAM to verify the difficulty levels of the task really resulted in feelings of boredom, stress and excitement.

2.4 Classification Method

In unsupervised learning, we have m training vectors $\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^m$ to be clustered where a training vector i ($i \in \{1, 2, \ldots, m\}$), $\mathbf{x}^i$ has n features. Then,

$\mathbf{x}^i \triangleq [x_1^i, x_2^i, \ldots, x_n^i]^T$ where T is the transpose operator.

The elements of each training vector is obtained from,

- x_1^i, IBI from BVP: Used to compute the time between beats (period) from a BVP signal (Average of every 15 samples).
- x_2^i, Heart Rate(HR) from IBI: Number of heart beats during a one minute period(from bvp sensor) (Average of every 15 samples).
- x_3^i, ECG VLF power(%): Percentage of very low frequency power (Average of every 285 samples).
- x_4^i, ECG LF power(%):Percentage of low frequency power (Average of every 285 samples).
- x_5^i, ECG HF power(%):Percentage of high frequency power (Average of every 285 samples).
- x_6^i, ECG VLF power(total): Very low frequency components of total power (Average of every 285 samples).
- x_7^i, ECG LF power(total): Low frequency components of total power (Average of every 285 samples).
- x_8^i, ECG HF power(total): High frequency components of total power (Average of every 285 samples).
- x_9^i, Skin Conductance value(%): Percentage value of skin conductance (Average of every 400 samples).
- x_{10}^i, Temperature value(%): Percentage value of temperature (Average of every 400 samples).
- x_{11}^i, ECG Heart Rate(HR) Mean:Mean of number of heart beats during a one minute period(from ecg sensor) (Average of every 380 samples).
- x_{12}^i, ECG HR standart deviation: Standard deviation of heart rate (Average of every 380 samples).
- x_{13}^i, Skin Conductance mean:Mean of skin conductance value(uS) (Average of every 400 samples).
- x_{14}^i, Skin Conductance mean(%): Percentage of mean of the skin conductance level (Average of every 400 samples).
- x_{15}^i, Temperature mean: Mean of the temperature (Deg) (Average of every 400 samples)
- x_{16}^i, Temperature mean(%):Percentage of the mean of the temperature (Average of every 400 samples).
- x_{17}^i, Respiration Rate: Number of the breaths during a one minute period (Average of every 380 samples).
- x_{18}^i, ECG IBI NN Intervals: Inter-beat interval between nearest neighbor beats (Average of every 380 samples).
- x_{19}^i, Pulse Transit Time (PTT): Time it takes fort he blood pumped by heart to reach arteries in the arms (Average of every 15 samples).

In our experiments, we have $m = 798$ training vector which are obtained under 5 difficulty levels and one resting period as explained in Section 2.2. Then each training vector reflects the emotional state for 1.8 seconds. We ask the subject to express his/her the emotional feelings after each 4 minute task executions. Then SAM surveys are used to validate the classification results.

2.4.1 Principal Component Analysis (PCA)

Dimensionality reduction is a useful step for visualizing and processing high-dimensional data as in this problem. In order to visualize the biofeedback sensor data under different emotional state, the 19 dimensional training vector needs to be converted in 2-dimensional or 3-dimensional vectors. Principal Component Analysis (PCA) (Bishop, 2006) is a very useful dimensionality reduction method to convert high dimensional data into lower dimensions while still keeping as much as the variations of the original data. In this paper, using the PCA method, the $n = 19$ dimensional biofeedback sensor data is mapped into $k = 2$ dimensional data as follows (Ng, 2014):

- Initialize the training vectors $\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^m$
- Feature scaling/mean normalization $\mu_j = \frac{1}{m}\sum_{i=1}^m x_j^i$ and $s_j = \sqrt{\frac{1}{m}\sum_{i=1}^m (x_j^i - \mu_j)^2}$
- Replace x_j^i with $\frac{x_j^i - \mu_j}{s_j}$.
- Compute the covariance matrix
$$\Sigma = \frac{1}{m}\sum_{i=1}^m \mathbf{x}^i(\mathbf{x}^i)^T$$
.
- Compute the eigenvectors of Σ using singular value decomposition.
- Pick the first k eigenvectors of Σ to create the matrix $\mathbf{U}$ of size $k \times n$.
- Multiply each training vector $\mathbf{x}^i$ with $\mathbf{U}$. So the reduced dimension training vector is obtained as $\mathbf{z}^i = \mathbf{U}\mathbf{x}^i$ which has dimension $k \times 1$.

2.4.2 *K*-means Clustering Algorithm

The K-means clustering algorithm partition m observations into K clusters where each observation belongs to the cluster with the nearest mean (Bishop, 2006). According to (Ng, 2014), the K-means clustering algorithm can be summarized as follows,

- Set the number of clusters K (In this problem $K = 3$) and get the reduced dimension training vectors as $\mathbf{x}^1 = \mathbf{z}^1, \ldots, \mathbf{x}^m = \mathbf{z}^m$.
- Randomly initialize K cluster centroids, $\mu_1, \ldots, \mu_K$.
- Cluster assignment step: Assign each training vector $\mathbf{x}^i$ to the cluster c^i according to

$$c^i = \arg \min_{k \in \{1,2,3\}} ||\mathbf{x}^i - \mu_k||^2$$

- Centroid update step: Update the cluster centroid based on the mean of the training vectors belong to c^i.
- Repeat Cluster assignment and Centroid update steps until the cluster centroids converge.

3 EXPERIMENTS

In this section, we demonstrate the effectiveness of the clustering algorithm with numerical results.

3.1 Ethical Approval

This study has been approved by the Institutional Review Board of Yeditepe University Hospital (IRB no.32). The subjects were informed of the experiment protocol and an orientation has been given to each subject.

3.2 Subjects

7 subjects (3 female and 4 male), whose ages are in the range of 22-26, have participated in this study. The biofeedback signal data of these 7 subjects have been used for training the clustering algorithm. All the subjects are healthy and have no background of any diseases that might have affected the study. Total task duration is about 30 min for each subject.

3.3 Results

Three different emotional states, which are classified by plotting the first two principal components, are shown in Fig.4. We further highlight the data of one particular subject who has reported her emotional state in 6 different tasks for each run in 4 minute intervals. The numerical results show that the emotional states of a subject during the rehabilitation task is separable. We first determined the emotional state by the clustering algorithm and compared this emotional state with the emotional state reported by the subject for each training sample (Table 1). The accuracy per subject is then defined as the number of training examples where the emotional states proposed by the clustering algorithm match with the subjects' own report. Numerical results show that the clustering results and the subjects' reports are consistent to each other where the overall accuracy is around 80%. In the survey case, we have assumed all training vectors reflect the same emotional state as declared by the subject during a 4 minute task. On the other hand, subjects emotional state may change during the task and in reality the subject may feel multiple emotional states while performing the task and may declare only one of them.

Table 1: The number of training vectors where the emotional states decided by the clustering algorithm match with the subjects survey results

	Accuracy
Subject 1 (Female)	82 %
Subject 2 (Male)	71 %
Subject 3 (Female)	83 %
Subject 4 (Female)	77 %
Subject 5 (Male)	84 %
Subject 6 (Male)	68 %
Subject 7 (Male)	81 %
Overall	78 %

Table 2: Percentage of training vectors under different emotional states.

	Stress	Excitedness	Boredom
Survey	12 %	33 %	52 %
Clustering	18.54 %	35.08 %	46.36 %

Finally, we compare the percentage of training vectors under different emotional states obtained with the clustering algorithm and the survey results. Table 2 shows that the ratio of solutions obtained with the clustering algorithm for stress, excitement and boredom are consistent with the survey results.

4 CONCLUSIONS

In this paper, we consider an unsupervised learning problem where the task is to classify the emotional states of a subject while in performing different difficulty levels of a robot assisted rehabilitation task. We have first used dimensionality reduction using PCA to reduce the dimension of each training example with 19 features to 2 dimensions to better visualize the data. Then, we have used the K-means clustering algorithm and decided the clusters associated with each

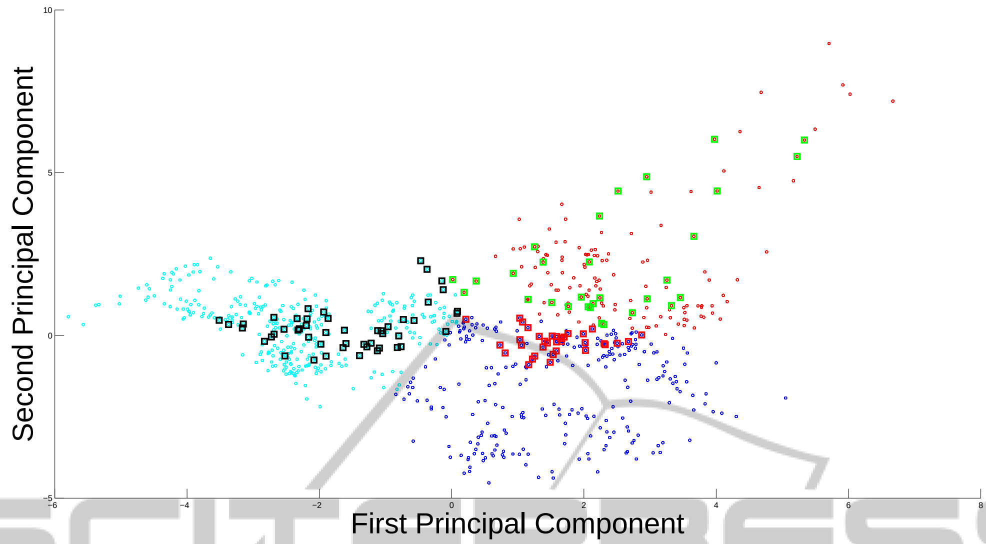

Figure 4: Visualization of the biofeedback sensor data after dimensionality reduction and K-means clustering. Cyan dots represent the boredom cluster, blue dots represent the excitedness cluster, and purple dots represent the stress cluster. One particular subject (Subject 1) declared her emotional state as bored for the vectors represented with red squares, excited for the vectors represented with blue squares and stressed for the vectors represented with black squares.

emotional state. Numerical results show that the clusters offered by the clustering algorithm are consistent with the survey results where subjects report their own emotional state.

The proposed clustering algorithm provides a basis for the supervised learning problems for the robot-assisted rehabilitation task. As a future work, we need to determine the decision boundaries among clusters reflecting different emotional states. Therefore, while subjects perform the task, the learning algorithm will be able to predict the emotional state of the subject, and accordingly adjust the difficulty level of the task in real-time. Furthermore, more comparative results can be included when different learning algorithms are used for classification of emotional states. Additionally, it is also desirable to evaluate the accuracy of the classification algorithms for the disabled people.

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