Qualitative and quantitative evaluation of brain activity in emotional stress

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Abstract

Introduction: This paper proposes a new emotional stress detection system using multi-modal bio-signals. Since EEG is the reflection of brain activity and is widely used in clinical diagnosis and biomedical researches, it is used as the main signal.

Methods and Materials: We designed an efficient IAPS acquisition protocol to acquire the EEG and psychophysiological signals under picture induction environment (calm-neutral and negatively excited) for participants. Data such as skin conductance (SC), Blood Volume Pulse (BVP), respiratory rate (RR) and EEG were continuously recorded through bio-sensors placed on the participant. In order to choose the proper EEG channels we used the cognitive model of the brain under emotional stress.

Results: After pre-processing the bio-signals, linear features were employed to extract the psychophysiological signals and chaotic (or nonlinear) invariants like; fractal dimension by Higuchi's algorithm, correlation dimension and approximate entropy were used to extract the characteristics of the EEG signals. For emotional stress detection, Genetic Algorithm (GA) and Elman neural network are applied to design the emotional stress classifier are investigated. The results show that, classification accuracy with fusion link between EEG and psychophysiological signals was 82.6% using the Elman classifier in two classes from emotional stress space.

Conclusion: Chaotic analysis can be representing good of human brain and behaviour in emotional stress states. This is a good improvement in results compared to other similar published researches.

Keywords: EEG signals, Psychophysiological signals, Emotional stress, Feature extraction, Classification

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Introduction

A lot of researches have been undertaken in the assessment of stress over the last years; the main reason of which has been the fact that emotions are present in many situations where human beings are involved. Stress is often defined as the body's reaction to a perceived mental, emotional or physical distress. This definition may appear to be circular, but there are significant concepts contained in it.(1) A major problem in understanding emotion is the assessment of the definition of emotions. In fact, even psychologists have problem agreeing on what is considered an emotion and also how many types of emotions exist. The most well known theory represents emotions in 2 or 3 dimensional spaces, originating from cognitive theories, where valence-arousal space in emotions is expressed as a combination of two continuous variables: valence ranging from negative to positive (or unpleasant to pleasant) and arousal extending from calm to excited.(2) Psychologists agree that human emotions can be categorized into a small number of cases. For example, Ekman, et al.(3) found that six different facial expressions (fearful, angry, sad, disgusted, happy and surprised) were categorically recognized by humans from distinct cultures using a standardized stimulus set. In the recognition of emotions, brain activity plays a central role. Emotion plays a major role in motivation, perception, cognition, creativity, attention, learning and decision making. However, few works have used it to assess the emotional states. Recent researches on the human EEG, revealed the chaotic nature of this signal. To identify new features, we use the fact that the EEG signal reflects the interaction of millions of neurons and that the brain follows a chaotic behaviour. Thus it is logical not to use conventional methods which assume that emotion can be analysed by linear models.(4)

Previous studies have investigated the use of psychophysiological and brain signals separately but little attention has been paid so far to the links between brain and psychophysiological signals. Analyzing the results of previous works is a difficult task, because to compare the results of the works which attempt to introduce emotion recognition systems as a classification problem, it is important to consider the way that emotions are elicited and the number of participants, the latter is important especially to introduce a user independent system.

In one study Chanel(5) asked the participants to remember past emotional events, and obtained the best result of 79% using EEG and 53% using peripheral signal for 3 categories, 76% using EEG and 73% using peripheral signals for 2 categories. In another study, Hosseini(6) used EEG and psychophysiologcal signals to stimulate participants with two different emotions, resulting in 70% of correctly identified patterns. Kim(7) used the combination of music and story as stimuli and there were 50 participants, to introduce a user

independent system, the results were 78.4%, 61% for 3 and 4 categories respectively. Takahashi[8] also used film clips to stimulate participants with five different emotions, resulting in 42% of correctly identified patterns.
The goal of our research is to produce a multimodal link between EEG and psychophysiological signals for emotion detection. The system was intended to recognize emotion from offline EEG signals. We investigated the recognition of two emotional states (calm and negatively excited) using Elman and we will discuss how multi-modal bio-signals are effective for emotion recognition. In section 2, we suggest a general cognitive model for the brain state in emotional stress. The design of emotion recognition systems is shown in section 3 and the results of our emotion recognition experiments are presented in section 4.

Cognitive model of emotional stress

Cognitive models (also termed cognitive or agent architectures) aim to emulate cognitive processing such as attention, learning, perception, and decision-making, and are used by cognitive scientists to advance understanding of the mechanisms and structures mediating cognition.[9] In the case of fear conditioning leading to emotional stress, several hypotheses have been proposed to explain how neural changes occur in the different components in a circuit leading to the observed behavioural responses. In mammalians, a part of the brain, called the limbic system, is mainly responsible for emotional processes.[10,11] We are going to describe developing a cognitive model of the limbic system based on these concepts. The main components of the limbic system involved in emotional processes are amygdala, orbitofrontal cortex, thalamus, sensory cortex, hypothalamus, hippocampus and some other areas.[11] In this section, we are trying to briefly describe these components and their tasks. The amygdala, a small structure in the temporal lobes, plays a central role in emotional stress. It is generally accepted that the amygdala is crucial for the acquisition and expression of conditioned fear responses (for a review, see.[12] The amygdala, specifically its lateral nucleus, receives inputs from all the main sensory systems, as well as from higher-order association areas of the cortex and the hippocampus. Sensory information reaches the amygdala from the thalamus by the way of two parallel pathways: the direct pathways reach the amygdala quickly, but they are limited in their information content, as the thalamic cells of origin of the pathway are not very precise stimulus discriminators. The cortical pathway, on the other hand, is slower but capable of providing the amygdala with a much richer representation of the stimulus.[13]
The sensory cortex is the component next to the Thalamus and receives its input through this component. The Amygdala and orbitofrontal cortex receive highly analyzed input from the sensory cortex. The orbitofrontal cortex

is another component which interacts with the amygdala reciprocally. The term prefrontal cortex refers to the very front of the brain, behind the forehead and above the eyes. It appears to play a critical role in the regulation of emotion and behaviour by anticipating the consequences of our actions. The prefrontal cortex may play an important role in delayed gratification by maintaining emotions over time and organizing behaviour toward specific goals.[10] The locus ceruleus (LC) contains a large proportion of the noradrenalin cell bodies found in the brain and it is a key brain stem region involved in arousal.[14] The bed nucleus of the stria terminalis (BNST) is considered to be a part of the extended amygdala. It appears to be a centre for the integration of information originating from the amygdala and the hippocampus, and is clearly involved in the modulation of the neuroendocrine stress response.[14] The hypothalamus (paraventricular nucleus (PVN) and lateral hypothalamus (LH)) lies below the Thalamus and it is believed to have various functions that regulate the endocrine system, the autonomous nervous system and primary behavioural surviving states.[14,15] The hypothalamic-pituitary-adrenal (HPA) axis ultimately regulates the secretion of glucocorticoids which are adrenocortical steroids that act on target tissues throughout the body in order to preserve homeostasis during stress.[16,17] The hypothalamus also releases corticotrophin-releasing hormone (CRH) which travels to the anterior pituitary gland, where it triggers the release of adrenocorticotropic hormone (ACTH) which, along with β-endorphin, is released into the bloodstream in response to stress.[18] ACTH travels in the blood to the adrenal glands, where it stimulates the production and release of glucocorticoids such as cortisol.[19] Cortisol feedback at the hypothalamus reduces CRF release. At the pituitary, it inhibits ACTH release, and at the adrenal gland it inhibits further cortisol release. cortisol feedback at the hippocampus inhibits CRF secretion from the hypothalamus. The release of all these chemicals causes important changes in the body's ability to respond to threats such as increased energy, heart rate and blood sugar resulting in increased arousal and pain relief.[19]

Methods and Materials

3.1 Protocol and data acquisition

Several methods exist for subject stimulation. For example, participants could be looking at pictures, looking at movies, listening to sounds, stroop test or playing games. However, most experiments (e.g.[2,3,20,21,22,23]) that measure emotion from EEG signals use pictures from the subset of the International Affective Picture System (IAPS). The IAPS contains 956 emotionally evocative images evaluated by several American participants on two dimensions of nine points each (1-9).[3,22,24] In our study the stimuli to elicit the target emotions (calm and negatively excited) were some of the pictures in IAPS databases. The use of IAPS allows better control of emotional stimuli and simplifies the experimental design. The images in these classes were picked according to the rules in equation,(1) where the arousal and valence scales were from 1 to 9. Particular images (for example erotic images) were removed from the selection.

$$\begin{aligned} &Calm: arousal < 4 \\ &\quad 4 < valence < 6 \\ &Negative exiting: arousal > 5 \\ &\quad valence < 3 \end{aligned} \tag{1}$$

The participant sits in front of a computer displaying the images to inform him about the specific emotional event he has to think of. Each experiment consists of 8 trials. Each stimulus consists of a block of 4 pictures, which ensures stability of the emotion over time. And each picture is displayed for 3 seconds leading to a total 12 seconds per block. Prior to displaying images, a dark screen with an asterisk in the middle is shown for 10 seconds to separate each trial and to attract the participant's attention. The detail of each trial is shown in figure 1.

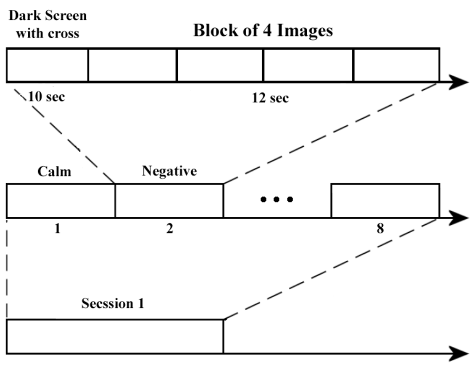

Figure 1: The protocol of data acquisition

Nine healthy volunteer subjects were right-handed males between the age of 21 and 28 years. Most subjects were students from biomedical engineering department of Islamic Azad University in Mashhad Branch. Each participant was examined by a dichotic listening test to identify the dominant hemisphere. This was done to eliminate any differences in subjects. Then each participant was given a particulars questionnaire. All subjects had normal or corrected vision; none of them had neurological disorders. All participants gave written informed consent. Data such as skin conductance (SC), photoplethysmograph (PPG), respiratory rate (RR) and EEG were continuously recorded through bio-sensors placed on the participant

(Figure2,3). In this study, we recorded SC by positioning two dedicated electrodes on the top of left index and middle fingers. RR was recorded by a respiration belt, counting the chest cavity expansions over time. Finally, a photoplethysmograph was placed on the thumb of the participant to record his blood volume pressure. EEG was recorded using electrodes placed at 6 positions. The scalp EEG was obtained at location FP1, FP2, T3, T4, O1 and O2, as defined by the international 10-20 system. The sample rate of the EEG acquisition device was 256Hz. We used a Flexcom Infiniti electroencephalograph which uses the right ear as the earth and the left ear as the reference.

At the end of the experiment, each participant was asked to fill in a questionnaire about the experiment and give their opinions.

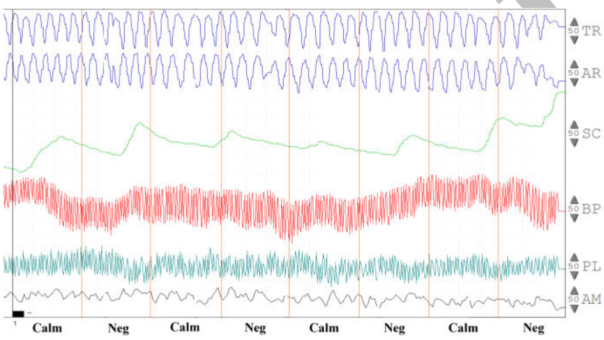

Figure 2: Typical waveforms of the psychophysiological signals (Recorded with CPS polygraphy)

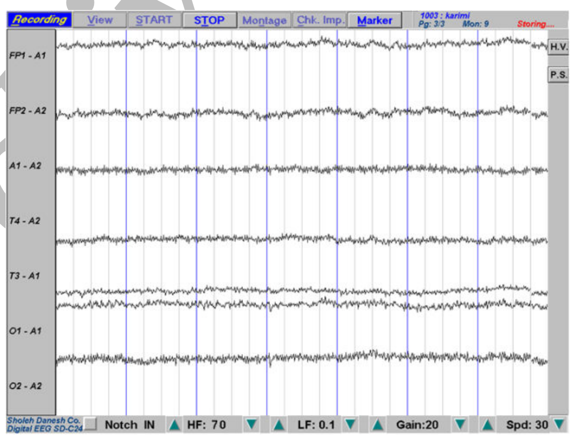

Figure 3: Typical waveforms of the EEG signals (Recorded with sholeh danesh "SD-C24")

3.2 Analysis of psychophysiological signals

In order to analyze the psychophysiological signals quantitatively, we need to pre-process them, to remove environmental noises by applying filters. We used a common set of feature values for the signals. The respiration features are from both frequency and time domains, the skin conductance features and the photoplethysmograph features are from time domain. (Table 1)

Table 1: Features Extracted from psychophysiological signals

SIGNAL	EXTRACTED FEATURES
Respiration	Mean, variance, Standard deviation, Kurtosis, Skewness, Maximum minus Minimum value, Mean of derivative and calculating the power 5 frequency band of 0.25 to 2.75Hz.
Skin Conductance	Mean, variance, Standard deviation, Kurtosis, Skewness, Maximum response, Mean of derivative, energy response and proportion of negative samples in the derivative vs. all samples.
Photo plethysmograph	Mean, variance, Standard deviation, Kurtosis, Skewness, Mean of trough variability, Variance of trough variability, Mean of peak variability, Variance of peak variability, Mean of amplitude variability, Variance of amplitude variability, Mean value variability, Variance of mean value variability, Mean of baseline variability, Variance of baseline variability

3.3 Analysis of EEG signals

3.3.1 Pre-processing

The brain produces electrical activity in the order of microvolt. Because these signals are very weak, it usually contains a lot of noise. We need to pre-process EEG signals, remove environment noises and drifts by applying a 0.5-35Hz band pass filter. This band is selected because the frequency intervals of interest in EEG are the θ (4-8Hz), α (8-12Hz) and β (12-30Hz) bands. This filter will remove all high frequency noise, and also removes most of the artefacts. Before analysis, we first remove the data segment which contains obvious eye blinking through electrooculogram (EOG).

3.3.2 Normalization

In order to normalize the features in the limits of [0, 1], we used equation.(2)

$$Y_{norm} = \frac{-2Y_s^{'} + Y_{s\max}^{'} + Y_{s\min}^{'}}{Y_{s\min}^{'} - Y_{s\max}^{'}} \qquad (2)$$

In this equation Y_{norm} is the relative amplitude.

3.3.3 Feature extraction

Feature extraction is the process of extracting useful information from the signal. Features are characteristics of a signal that are able to distinguish between different emotions. We use a common set of feature values for nonlinear features of brain signals.

Nonlinear measures have received the most attention in comparison with the measures mentioned before, for example time domain, frequency domain and other linear features. The nonlinear set of features used include fractal dimension, correlation dimension, and entropy signals. These 3 features are extracted for each electrode of EEG signals.

a) Fractal dimension by Higuchi's Algorithm

The term "fractal dimension" refers to a noninteger or fractional dimension of a geometric object. Fractal dimension (FD) analysis is frequently used in biomedical signal processing, including EEG analysis [25]. Higuchi's algorithm unlike many other methods requires only short time intervals to calculate fractal dimension. This is very advantageous because EEG signal remains stationary during short intervals and because in EEG analysis it is often necessary to consider short, transient events (for a review in equation, see.[25])

b) Correlation dimension

Correlation dimension (D_2) is one of the most widely used measures of a chaotic process. We used the Grassberger and Procaccia algorithm (GPA)[26] for estimating D_2 in our work (for a review in equation, see.[26]) The choice of an appropriate time delay r and embedding dimension d is important for the success of reconstructing the attractor with finite data. We calculated D_2 with d_E values varying from 2 to 10 for all the subjects. It can be seen that D_2 saturates after the embedding dimension of 7. Therefore we have chosen d_E=8 for constructing the embedding space and estimation of the invariants. The determination is based on calculating the relative number of pairs of points in the phase-space set that is separated by a distance less than r. For a self-similar attractor, the local scaling exponent is constant, and this region is called a scaling region. This scaling exponent can be used as an estimate of the correlation dimension. If the d_E=8 plots C(N, r) vs. r on a log-log scale, the correlation dimension is given by the slope of the log C(r) vs. log r curve over a selected range of r, and the slope of this curve in the scaling region is estimated by the least slope fitting.

c) Approximate entropy

Entropy is a thermodynamic quantity describing the amount of irregularity in the system. From an information theory perspective, the above concept of entropy is realized as the amount of information stored in a more general probability distribution. The theory was supported by Shannon in. Approximate Entropy (ApEn) is a family of parameters and statistics recently introduced to quantify regularity in data without any prior knowledge of the system generating them.[27] The first idea of ApEn was introduced by Steven M. Pincus in 1991 and it is a useful and complex measure for biological time series data (for a review in equation, see.[28,29])

3.4 Feature selection

The problem of the vast number of features is solved by using Genetic Algorithm (GA) as a feature selection method.[30] The emphasis on using the genetic algorithm for feature selection is to reduce the computational load on the training system while still allowing near optimal results to be found relatively quickly. The GA uses populations of 100 size, starting with randomly generated genomes. The probability of mutation was set to 0.01 and the probability of crossover was set to 0.4. The classification performance of the trained network using the whole dataset was returned to the GA as the value of the fitness function. We attempted to detect the feature sets related to negative/calm emotion response from EEG and psychophysiological signals.

3.5 Classification

After extracting the desired features, we still have to find the emotion. This process will be done by a classifier. A classifier is a system that divides some data into different classes, and is able to learn the relationship between the features and the emotional state. One very useful classifier is an Elman network[31,32] which is a two-layer back-propagation neural network, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman network to learn to recognize and generate temporal patterns, as well as spatial patterns. The Elman network has tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer. This combination is special in that the two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The Levenberg-Marquardt back-propagation algorithm is used for training. The Levenberg-Marquardt algorithm will have the fastest convergence compared with other training functions.[32] The error ratio for stop training was considered 0.001.

Results

The simulations were implemented in MATLAB (Ver. 7.6) as the mathematical software. We used a 2-second rectangular window without overlap for data segmentation. The gathered data was used to teach our system the details about recognizing emotion from the EEG and psychophysiological signals. We used around 30% of the data for the training, and 60% of the data for testing whether the learned relationship between the EEG signals and emotion is correct and the last 10% was used for validating the data. Our best results were the accuracy of 80.1% and 81.5% for the two categories (calm vs negative exited), using the EEG and psychophysiological signals respectively (Table 2). The system was tested using the 5-fold cross-validation method. This method divides the training data into five parts. One of the parts is used for testing the classifier, and the four others are used for training. The process was repeated five times, every time with another part of the data. This method reduces the possibility of deviations in the results due to some special distribution of training and test data, and ensures that the system is tested with different samples from those it has seen for training. Using a 5-fold cross validation method for training and testing, we reached an accuracy of 79.2% for the two categories of emotional stress using the EEG signals.

Table2: classifier accuracy using EEG and psychophysiological signals with Elman

	EEG	PSYCHOPHSIOLOGICAL	FUSION
Elman (accuracy)	80.1	81.5	82.6

Figure 4 shows a comparison between the results of brain signal analysis in the right and left channels.

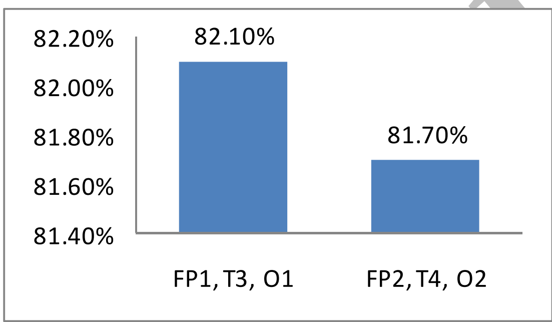

Figure 4: Comparison of the results of brain signal analysis in the right and left channels.

Discussion and Conclusion

Classically, the electroencephalogram has been the most utilized signal to assess brain function owing to its excellent time resolution. In this paper we propose an approach to classify emotions in the two main areas of the valance-arousal space by using physiological signals. During the last decade a variety of these analysis techniques has repeatedly been applied to EEG recordings during physiological and pathological conditions and was shown to offer new information about complex brain dynamics.[26,28,29] The nonlinear measures include: fractal dimension, correlation dimension and approximate entropy. For most measures a dimension should be defined to visualize the attractor in phase space, but the problem associated with all of them is that defined dimension for the phase space is not constant for all channels of recorded EEG signals or for different subjects, and depending on the conditions, the chosen dimension can be different.

The results of our study show that the D_2 of negative emotional activity is less as compared to that of calm activity. It can also be observed that Higuchi's algorithm indicates similar trend of reduction in FD value for negative emotional EEG compared to normal EEG. The reduction in FD values and D_2 characterizes the reduction in brain system complexity[26] for participants with negative emotional state. Hence the application of nonlinear time series analysis to EEG signals offers insight into the dynamic nature and the variability of the brain signals. The chaotic measures distinctly characterize the normal and negative emotional EEG signals. The results show that fusion between EEG and psychophysiological--- is more robust compared to the signals separately. Our results show the importance of EEG signals for emotion assessment by classification as they have better time response than psychophysiological signals. We used 2 second time intervals to analyze the brain signals which resulted in a time resolution of 2 seconds in emotional stress recognition. If we had used shorter time intervals with overlap, we could have achieved a greater but virtual time resolution, which, for example, can be useful in biofeedback applications. The classification accuracy in two emotional states was 81.5% using EEG signals. Due to the differences in the conditions of the experiment, we cannot compare our results with the results of the works which have attempted to introduce emotion recognition systems as a classification problem. But in comparison to similar works, we achieved an improvement of about 11% in our results. As can be seen in figure 4, in short emotional stress states, there is no particular brain asymmetry.

Future work to acquire data from more participants is underway to validate the current results. We are pursuing this track as it should lead to a better identification of emotions.

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ارزیابی کیفی و کمّی فعالیّت الکتریکی مغز در حالت استرس هیجانی

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چکیده

سابقه و هدف: هدف از این مقاله آشکارسازی استرس هیجانی به‌کمک سیگنال‌های حیاتی به روشی چند وجهی می‌باشد. سیگنال EEG حاصل فعالیّت الکتریکی مغز بوده و در کاربردهای تشخیصی، درمانی و تحقیقات حوزۀ مهندسی پزشکی استفادۀ گسترده‌ای دارد.

روش بررسی: به این منظور آزمون IAPS، برای ثبت سیگنال‌های مغزی و سایکوفیزیولوژی طراحی شد. در مدت زمان اجرای این آزمون، تصاویری متناسب با دو حالت آرامش و هیجان منفی به شرکت کننده‌ها نمایش داده می شود و همزمان با آن، سیگنال‌های هدایت الکتریکی پوست، فتوپلتیسموگراف، تنفس و مغزی به‌صورت پیوسته ثبت گرفته شده است. در این تحقیق برای انتخاب کانال‌های مؤثرتر سیگنالِ مغزی از یک نقشۀ شناختی کمک گرفته شده است.

یافته‌ها: پس از پیش‌پردازش سیگنال‌ها، ویژگی‌های خطی از سیگنال‌های سایکوفیزیولوژی و ویژگی‌های غیرخطی و آشوب‌گونه‌ای نظیر بُعد فرکتال به شیوۀ هایوچی، بُعد همبستگی و آنتروپی تقریبی از سیگنال‌های مغزی استخراج شد. برای آشکارسازی استرس هیجانی از ترکیب الگوریتم ژنتیک و شبکۀ عصبی اِلمن بهره گرفته شده است. نتایج نشان می‌دهد، سیگنال‌های مغزی با درصد صحت تفکیک ۸۰/۱٪ و ترکیب سیگنال‌های مغزی و سایکوفیزیولوژی به درصد صحت تفکیک ۸۲/۶٪ منجر شده است.

نتیجه‌گیری: تحلیل آشوب‌گونۀ می‌تواند بازنمایی خوبی از رفتار مغز در حالت استرس هیجانی داشته باشد. نتایج حاصله از این تحقیق، بهبود خوبی را نسبت به نتایج تحقیقات گذشته نشان می‌دهد.

واژگان کلیدی: سیگنال‌های مغزی، سیگنال‌های سایکوفیزیولوژی، استرس هیجانی، استخراج ویژگی، طبقه‌بندی