

# A Real-Time Electroencephalography Classification in Emotion Assessment Based on Synthetic Statistical-Frequency Feature Extraction and Feature Selection

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## ABSTRACT

**Purpose:** To assess three main emotions (happy, sad and calm) by various classifiers, using appropriate feature extraction and feature selection.

**Materials and Methods:** In this study a combination of Power Spectral Density and a series of statistical features are proposed as statistical-frequency features. Next, a feature selection method from pattern recognition (PR) Tools is presented to extract major features and apply to classifiers.

**Results:** The experimental results on various classifiers demonstrated the priority of proposed emotion assessment system to the previous ones where Back-Propagation Neural Network was the most accurate classifier to complete the proposed system and Linear Discriminant Analysis was the best choice regarding to the accuracy and runtime of the system.

**Conclusion:** In this paper we proposed a prominent method that led to a highly accurate system with three emotion states. In this regard, unequal numbers of experiments on different emotion states were employed. This idea indicated that in order to avoid domination of one emotion state rather than other states in self-induced emotion signals unequal number of different states should be applied.

**Keywords:** electroencephalography; classification; emotions; physiology; humans; pattern recognition; methods; evoked potentials.

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## INTRODUCTION

Brain Computer Interface (BCI) creates a direct communication channel between human brain and external device, which will make a remote sensing communication. In this respect, assessing human emotions by computer plays a key role in improving this communication. In recent years many physiological researches have been made to take advantage of this communication in promoting life of war invalids and motor disable people.<sup>(1-6)</sup>

The most practical, non-invasive and non-expensive signal acquisition device of BCI systems

is Electroencephalograms (EEGs) whereas Magneto encephalogram (MEG) and Electrocorticogram (ECoG) are applied to a few BCI systems. Various types of BCI systems are designed using two major EEG potentials: Spontaneous and Evoked Potentials (EP).<sup>(7)</sup>

In the case that BCI system is working with external stimulation of the user and acquires his or her reaction in unconscious way, the EP is received, whereas in the spontaneous case, the subject's signal is acquired based on an internal cognitive process without any stimulation.

Movement Imagination (MI), mental task and Slow Cortical Potential (SCP) methods use spontaneous signals

whereas P300 and EPs use the evoked signals to run a BCI system.<sup>(8)</sup>

In recent years, physiological researches about emotions and brain relation demonstrated a strong involvement of cognitive process in emotions.<sup>(9-11)</sup> There is a kind of signal that is practically a combination of spontaneous and EP, which is called Self-Induced Emotion (SIE). In this case, an emoticon picture is shown to the subject and he or she is asked to remember one of his or her past emotional memories related to the regarding emoticon. The advantage of such method is the activation of many areas of brain, because cognitive processes related to memory retrieval are located throughout the brain.

Domasio and colleagues demonstrated that brain regions are involved in the mapping and/or regulation of internal organism states which underscore the close relationship between emotion and homeostasis.<sup>(12)</sup> Smith and colleagues showed that both memory content and behavioral context impact large scale neuronal dynamics underlying emotional retrieval.<sup>(14)</sup> Chanel proposed a protocol for short-term SIE acquisition based on the participants' recall of past emotional episodes and a classification approach for physiological signals of three main emotions (happy, calm and sad).<sup>(15)</sup> In all of the above researches, the concept of SIE signals is referred as past memory emotions which activate many brain areas. Thus, assigning a specific part of brain regarding to SIE would be a wrong issue. Following the previous works, an approach should be concerned for achieving a higher accuracy in SIE signal classification.

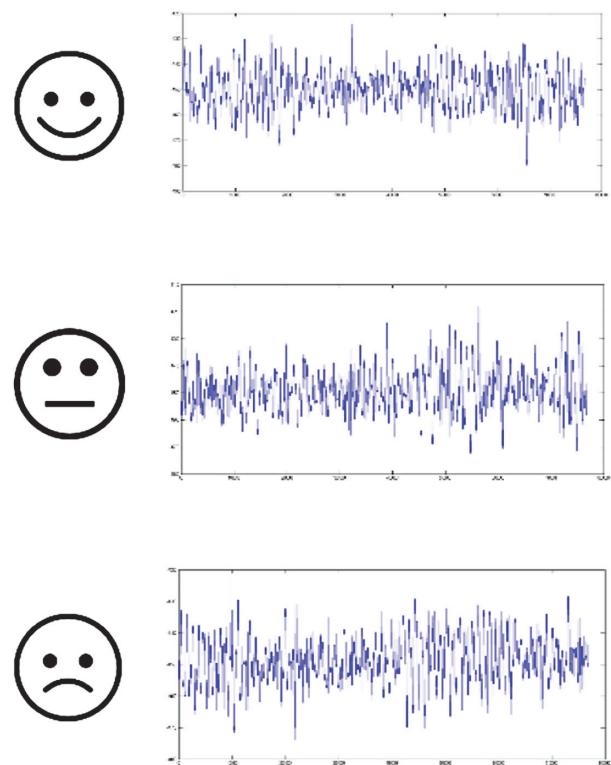
Regarding the characteristics of physiological SIE signals, in this research we propose a real-time SIE-based BCI system to be used for war casualties and motor disabled people. Imagine a disable person who cannot express his or her emotions, has physical constraints and would not be able to share his or her feelings in various situations (disability in speaking and even in pushing a button to ask for help). To promote life of such cases, there must be a BCI system that covers these deficiencies. To do so, the EEGs are recorded from the scalp during the remembrance of happy, sad and calm memories of the subject. Then, the features are extracted in two phases: Preprocessing and Main Processing. Later, by considering the results of various classifiers, we pursued the highest accuracy with real-time operation. According to our results, using the Back-Propagation Neural Network (BPNN) delivers the highest accuracy whereas the Linear Discriminant Analysis (LDA) brings a bit less accuracy in comparison to BPNN with real-time performance.

## MATERIALS AND METHODS

In this section, the material and methods of the proposed system will be discussed in details. In subsection A the experiment settlement and data acquisition is explained and subsection B explains signal analysis.

### Experimental Settlement and Data Acquisition

In this study samples have been acquired by Biosemi Active II with sampling frequency of 1024 Hz. Three hundred experiments are settled on each participant. Each experiment's duration is 8 seconds and the 64 channel EEG cap is used for data acquisition. Emotion stimulation is done by SIE as the participants are asked to have a happy memory, sad memory and calm memory in mind and remind each one whenever a related emoticon is displayed to him or her (**Figure 1**). The 300 experiments in this study are divided into 96 happy experiments (case 1), 80 calm experiments (case 2) and 124 sad experiments (case 3). These experiments were carried out in the CVML Laboratory of informatics department of Geneva University. (It should be noted that the whole research was done on 11 participants including 7 male and 4 female in the range of 26 to 40 years old, but in this study we had the permission of 300 experiments of one participant).



**Figure 1.** Acquired recalling signal samples after seeing related emoticon.

## Signal Analysis

The analysis of the acquired data of subsection A is done in two phases: Preprocessing and Main processing, which will be thoroughly discussed as follow.

### Preprocessing

In this section the primitive procedures of achieving features of the proposed emotion assessment system is studied. Since EEG signals were acquired through 64 channel cap, common potentials between adjacent electrodes are inevitable. Thus, such signals are dependent to each other and as a consequence the signals of different emotions have similarities, which make a low accurate assessment system. To avoid this overlapping and achieve independent signals, they should be mapped into an orthogonal space where the Principle Component Analysis (PCA) has been chosen in this regard. Therefore In the first step of preprocessing in each of 300 experiments, the 64 channels of EEG signals are mapped into 64 channels of an orthogonal space by PCA (by assuming that each channel could have independent signal from other channels, the signal space dimension is chosen to be equal to number of channels for each experiment) and then are sorted based on their priorities. Regarding to the procedures of experiments where subject is asked to recall a memory for each emoticon that he or she sees on display, having noise during recalling the memories is unavoidable. Therefore In the second step, the first 0.5 second of each channel in all experiments is removed for the following reasons: firstly, this time window is not expected to have information about emotions since in this period the subject is about to remember the memory related to the displayed emoticon. Secondly, this part contains P300 waves and may have emotional information related to the nature of the displayed emoticon.<sup>(10)</sup> Proposed first and second steps are effective in noise removal and assist in distinguishing different emotional signals, but they do not work strictly. To obtain more purified signals, a feature extraction method should be utilized in this regard. In the third step, according to the proposed feature extraction,<sup>(16)</sup> Power Spectral Density (PSD) based feature of data is computed:

$$(1) \text{feature} = \frac{|FFT\{R_{xx}^n\}|_{f=MF}}{N} = PSD$$

Where,  $R_{xx}^n$  is the autocorrelation of data from the second step,  $FFT\{\cdot\}$  is the Discrete Fourier Transform, MF, on contrary to Adolphs and colleagues' idea,<sup>(11)</sup> is the sampling frequency of the recording EEG signals and N is the total number of samples in frequency domain.

Using this equation, the informative part of acquired signals will be strengthened while the noise part will be attenuated. Since the PSD spectrum is symmetrical, in order to reduce the computations and avoid repetitive part of signals, half of effective part is extracted as the feature.

Although the resulting signals of the third step have been reinforced and their noise has been reduced, they still contain undesired parts. Considering non-ideal orthogonal methods such as PCA that can analyze the independent components of signals, utilizing them for multiple times through processing procedures would be useful. Thus, in the fourth step by using PCA, the extracted features of 64 channels in each experiment are mapped into an orthogonal space and since the orthogonal vectors of signal channels have been sorted by their priority degree in PCA, it would be efficient to remove the vectors with the slightest priority degree. As a consequence, the channels with higher priorities will be chosen for further processing.

### Main Processing

One of the attributes of SIE signals which are considered in this research is that they activate almost all brain regions such that it is not possible to determine any specific part of brain to them. This has been led to facing huge data to be processed which would cause massive computations and longtime processing. Additionally, huge data processing of SIE makes it hard for the assessment system to distinguish different emotional states' signals. For that reason and regarding to low accurate previous systems,<sup>(15)</sup> to achieve a high accurate emotional assessment system an approach should be employed that reduces the amount of computations and also extracts discriminative features on emotional states' signals. Thus, a synthetic extraction approach should be used. In this regard, in preprocessing section of this study, the primitive PSD features in Fourier domain were extracted after noise reduction steps. In this section and in the first step, the statistical features of Fourier domain will be extracted from PSD features of preprocessing phase.

$$(2) PSD_{x_{mean}} = \frac{1}{T} \sum_{f=1}^T PSD_x(f) = \mu$$

$$(3) PSD_{x_{std}} = \sqrt{\frac{1}{T} \sum_{f=1}^T (PSD_x(f) - \mu)^2} = \sigma$$

$$(4) PSD_{x_{var}} = \frac{1}{T} \sum_{f=1}^T (PSD_x(f) - \mu)^2 = \sigma^2$$

$$(5) PSD_{x_{rms}} = \sqrt{\frac{1}{T} \sum_{f=1}^T PSD_x(f)^2}$$

$$(6) PSD_{x_{iqr}} = Q_3(PSD_x(f)) - Q_1(PSD_x(f))$$

$$(7) PSD_{x_{med}} = Q_2(PSD_x(f))$$

$$(8) PSD_{x_{skn}} = \frac{E(PSD_x(f) - \mu)^3}{\sigma^3}$$

$$(9) PSD_{x_{krt}} = \frac{E(PSD_x(f) - \mu)^4}{\sigma^4}$$

$$(10) PSD_{x_{geom}} = \left[ \prod_{f=1}^T PSD_x(f) \right]^{\frac{1}{T}}$$

$$(11) PSD_{x_{harm}} = \frac{T}{\sum_{f=1}^T \frac{1}{PSD_x(f)}}$$

$$(12) PSD_{x_{trim}} = \frac{1}{R} \sum_{f=1}^R PSD_x(k + f),$$

$$k = \frac{TP}{100}, R = T - 2k$$

$$(13) PSD_{x_{max}} = \max(PSD_x(f))$$

$$(14) PSD_{x_{min}} = \min(PSD_x(f))$$

$$(15) PSD_{x_{mod}} = \text{mode}(PSD_x(f))$$

$$(16) PSD_{x_{rang}} = PSD_{x_{max}} - PSD_{x_{min}}$$

$$(17) PSD_{x_{sum}} = \sum_{f=1}^T PSD_x(f)$$

$$(18) PSD_{x_{trp}} = \frac{1}{2} (PSD_x(1) + PSD_x(T)) \\ + 2 \sum_{f=2}^{T-1} PSD_x(f)$$

$$(19) PSD_{x_{mad}} = Q_2[|PSD_x(f) - Q_2[PSD_x(f)]|]$$

$$(20) PSD_{x_{cf}} = \frac{PSD_{x_{max}}}{PSD_{x_{rms}}}$$

$$(21) PSD_{x_{sf}} = \frac{PSD_{x_{rms}}}{\mu}$$

$$(22) PSD_{x_{if}} = \frac{PSD_{x_{max}}}{\mu}$$

Where, in the above features  $f$  and  $T$  are the sampling number and the total number of samples, respectively,  $Q_1(\cdot)$ ,  $Q_2(\cdot)$  and  $Q_3(\cdot)$  compute the first, second and the third quartile of the given signal, respectively,  $\mu$  is the mean of  $PSD_x(f)$ ,  $\sigma$  is the standard deviation of  $PSD_x(f)$  and  $E(\cdot)$  represents the expected value of the quantity  $t$ . In feature (12)  $P$  is the trimmed  $P$  percent samples from both ends of signal  $PSD_x(f)$  and  $k$  is the number of trimmed samples trimmed in each end of the signal  $PSD_x(f)$ .  $\max(\cdot)$  and  $\min(\cdot)$  compute the largest and smallest sample in signal  $PSD_x(f)$ , respectively.  $\text{mod}(\cdot)$  computes the most frequent value in signal  $PSD_x(f)$ . These statistical features are actually extracting statistical attributes of Fourier curves of the signals, which will reduce the size of processing data and make it easier for the system to assess different emotional states.

Based on characteristics of each statistical feature, these features have different range of variation. Since they are about to be presented as an input to system's classifier, features should be aligned and compatible for each experiment. Then, in the second step of Main Processing phase the corresponding features of all channels in each experiment will be normalized in relation to each other. Gathering the features of all channels in each experiment, the inputs of each experiment to classifiers is provided in the third step. Despite the processing that has been done in order to reduce the size of features and making them more discriminative in the different emotional states, the achieved synthetic Statistical-Frequency features still have large size to be used as an input for each experiment. Thus, based on a ranking algorithm proposed in pattern recognition (PR) Tools<sup>(17)</sup> 8 major features of each experiment will be determined as final inputs in the fourth step. The remarked algorithm on PR Tools is served to rank the features on individual performance for classification purpose. By applying this operator on the train dataset (including features of each experiment as an input of the train dataset and corresponding emotion state of that experiment as an output of the train dataset, where part of experiments are used in this regard), the output



includes the input features, which return in decreasing performance sort.

Although preprocessing steps has reduced noise of EEG signals, the presence of noise in EEG signals is inevitable, which will cause the final features of classifier to be noisy yet. As a result, the classifier will face scarce situations among train and test data. Moreover, as the experiments in this study are limited, repetitive data would cause a complicated space for classifier's algorithm which is called over fitting. To avoid such occurrence, K-fold Cross Validation is used, which makes K sets of data from the main data. In each K set of data 1/K data is included as the test data and the rest is the train data. What makes the difference between these K sets is the fact that the test data is shifted through the main data from one set to another. Therefore, in the fifth step the K-fold Cross Validation is applied to dataset and in the sixth (final) step the K-folded Cross Validation dataset will be classified.

To evaluate the performance of the proposed system, the equation (23) is applied to determine the accuracy of each classifier:

$$(23) \text{ Accuracy} = \frac{TC_1 + TC_2 + TC_3}{TC_1 + FC_1 + TC_2 + FC_2 + TC_3 + FC_3}$$

Where  $TC_i$ ,  $i = 1, 2, 3$  is the number of experiments of  $i^{\text{th}}$  class which have been truly assessed, while  $FC_i$ ,  $i = 1, 2, 3$  is the number of false assessed experiments in  $i^{\text{th}}$  class.

## RESULTS

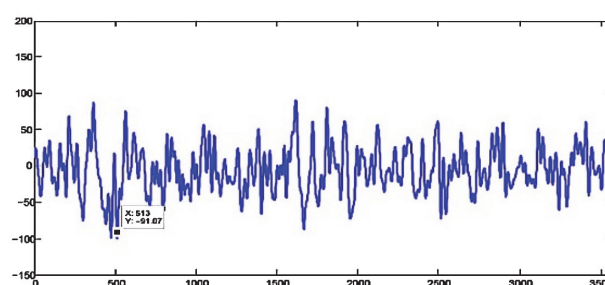
In this section, the experimental results of the proposed system are presented.

### Preprocessing Results

In the first step of preprocessing, the effect of PCA on acquired 64 channels of SIE signals is performed where it maps the signals into a 64 orthogonal space and sorts the resulted orthogonal vectors based on their priority degree.

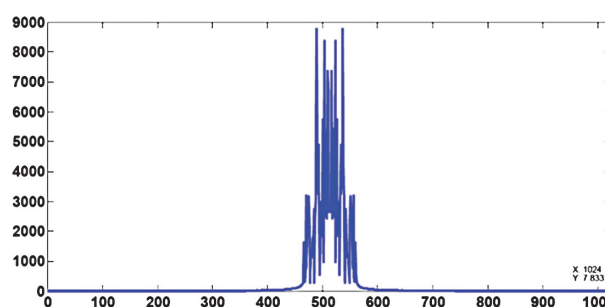
Based on the second step of Preprocessing, in order to avoid the initial noise in signal acquisition, the first 0.5 second of the 8 seconds in all channels and every 300 experiments is removed. Since the sampling frequency of EEG device recorder is 1024 Hz, each channel of all experiments has 8192 recorded samples. Thus the first 0.5 second contains the first 512 samples of the whole and the remaining samples are in the range of (513-8192), as it can be seen on (Figure 2).

In order to fulfill the third step of Preprocessing

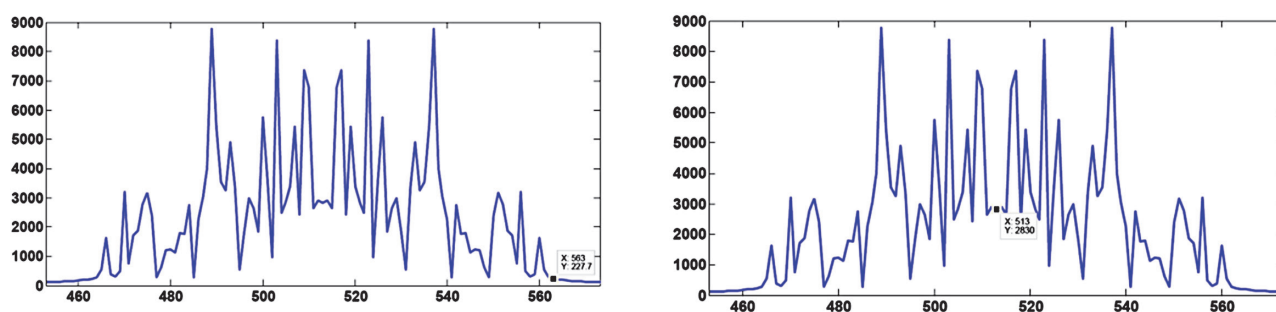


**Figure 2.** The plot of the first channel in the first experiment after the first step of Preprocessing(it can be seen that the peaks in the time domain are in the range of -50 to 50  $\mu\text{V}$ ).

phase, PSD features of each channel of the SIE signals are extracted in the following manner: first, for each channel of any experiment resulted from the previous step, the autocorrelation is calculated. Then, the Fast Fourier Transform (FFT) is applied on the auto correlated channels of each experiment, and after that the results are shifted to rearrange the outputs by moving the zero-frequency component to the center of the array, as it can be seen in (Figure 3). As it can be seen, the amplitude of the plot in (Figure 3) is totally strengthened from its corresponding plot of Time domain in (Figure 2), where the amplitude has been squared and running it through the Fourier Transform has decomposed this unit over frequency which has resulted to  $(\mu\text{V})^2/\text{Hz}$ . The most remarkable values of this step are mainly around the range (400-600) Hz. Hence, (Figure 4) has accurately magnified the main range of valuable part of the plot in (Figure 3). Additionally, since the sampling frequency of EEG recording device is 1024 Hz, it can be observed that the spectrum is symmetric around the frequency of 513 Hz. Therefore, in order to avoid repetitive signals and reduce computations, half of the effective samples of the regarding plot in range of 513-563 Hz is extracted for the next steps. It should be mentioned that since the statistical features are going to be extracted in Main Processing phase from the PSD feature of channels,



**Figure 3.** The PSD spectrum of the EEG signal of one channel in one experiment (3<sup>rd</sup> step of the Preprocessing phase) with the output range of 0 to 9000  $(\mu\text{V})^2/\text{Hz}$ .



**Figure 4.** The magnified PSD spectrum of the EEG signal of one channel in one experiment with the limited range of 400 to 600 Hz on X-axis; the left plot represents the symmetrical characteristic around central frequency 513 Hz and the right plot corresponds to the last effective frequency of the spectrum 563 Hz, respectively.

values of PSD features are not normalized.

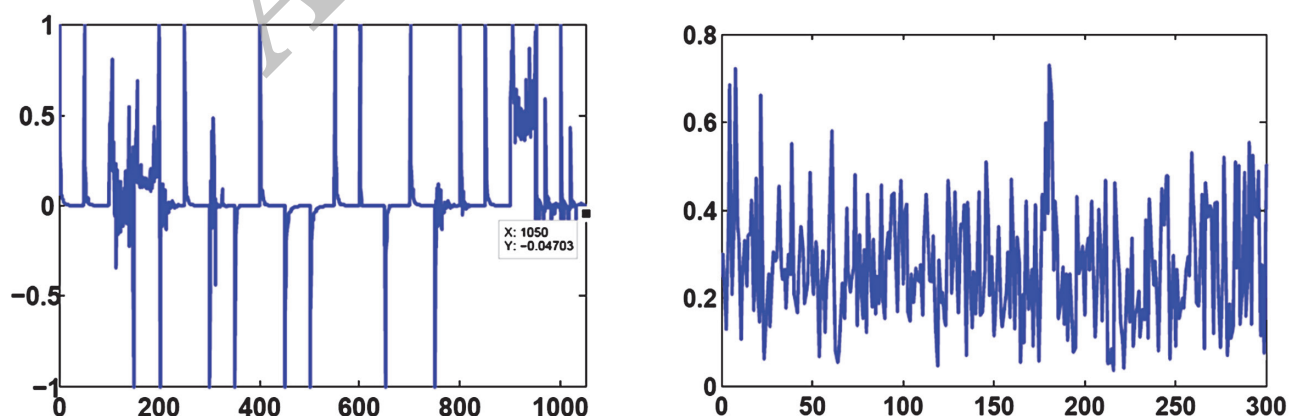
In the fourth step of Preprocessing, in order to reduce noise and discriminate major components of EEG signals, the 64 channels of each experiment is mapped through an orthogonal space with equal dimension to number of channels for each experiment by PCA and sorted by their priority degree. Since the last vectors with lowest priority have slightest information about SIE states, they are removed from the further processing. In this study, 50 vectors correspond to the most remarkable 50 channels of SIE signals extracted for next steps.

### Main Processing Results

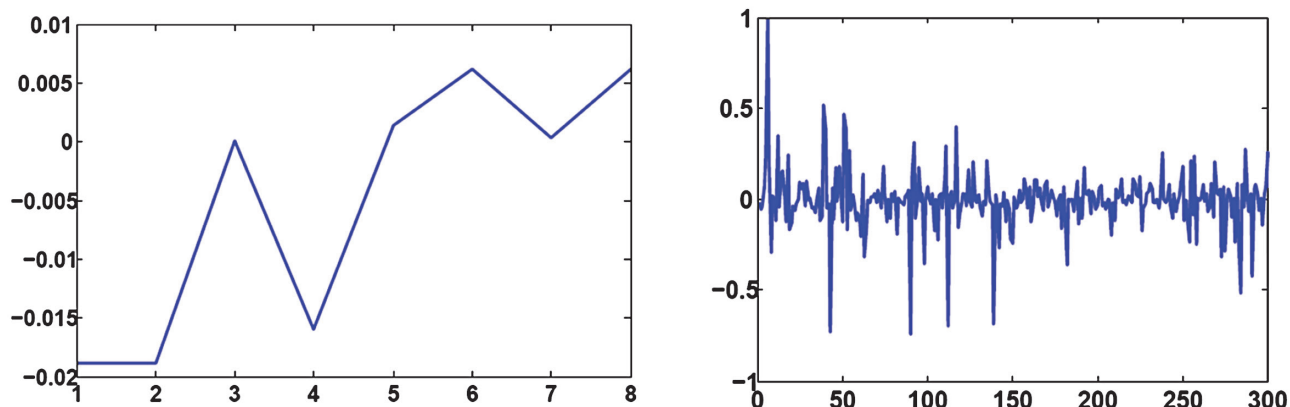
In the first step of the Main Processing, in order to reduce the size of processing data and facilitate emotion assessment, the statistical features based on equations 2-22 are applied to primitive PSD features. Since for each channel the PSD features include 51 samples and considering the 50 final mapped channels that have been chosen in the 4<sup>th</sup> step of the preprocessing phase for each experiment, there are 2550 samples as a total features for each experiment before applying Main Processing phase.

By extracting the statistical features of the first step in the Main Processing, there are 21 features for each channel and 50 mapped channels for each experiment. Thus, the total number of features after this step is 1050 samples. On surveying the 1050 features of 300 experiments, it is perceived that statistical feature (21) and (22) of the following samples have infinite values on: channel 16 of experiment 14, channel 27 of experiment 15 and channel 13 of experiment 169. Having infinite values in the input of classifier makes trouble in the true assessment. Thus, these values should be replaced with real values. More studying on the mentioned data proves that the remarked infinite values are caused by relevant statistical feature (6) of the same channel in corresponding experiment which has zero value. To solve this problem, the mentioned zero-valued statistical feature (6) is replaced with minimum value among statistical feature (6) of all channels in each corresponding experiment.

In the second step of Main processing and after replacing infinite and zero samples with real values, the features of all channels in each experiment are normalized by finding the maximum value among the same feature



**Figure 5.** The typical plot of the statistical features in the second step of the Main Processing; the left and the right plot correspond to one of the typical statistical features in all experiments, respectively.



**Figure 6.** The plot of 8 major features of one experiment; the left and the right plot correspond to one of the major features in all experiments, respectively.

of all channels in each experiment, to which they are all divided. (Figure 5) displays a typical extracted statistical feature in Fourier Domain after the second step in Main Processing phase of one experiment and one of the extracted statistical features in all experiments, respectively. As it can be seen, the resulting features are mapped in the range of 0-1.

The result of fourth step of Main Processing is indicated in (Figure 6). In this figure, the plot of 8 major features of one experiment and the plot of one of the major features in all experiments is displayed, respectively. According to the proposed algorithm of PRTools toolbox, it maximizes the difference between various emotional states, by choosing the most discriminative features with higher priorities.

In the fifth step of the Main Processing, 5-Fold Cross Validation is applied to all dataset of 300 experiments. In this regard, there are 5 sets in which we have 20% (60 experiments) in each to test and 80% (240 experiments) for training. The 20% test data is shifted from one set to another.

Finally, in the sixth step of the Main Processing, the final features are applied to various classifiers in order to assign the best one for proposed emotional assessment system. (Table 1) shows the confusion matrices of classifying 3 emotional classes by the following classifiers: K-Nearest Neighbor (KNN), Nearest Mean Classifier (NMC), Fisher's Least Square Linear Classifier (FLSLC), Linear Discriminant Analysis (LDA), Radial Basis Neural Network (RBNN), Levenberg-Marquardt Rule Neural Network (LMNN), Back-Propagation Neural Network (BPNN) and Radial Basis SVM (RBSVM). In each confusion matrix, the  $i^{\text{th}}$  row, ( $i = 1,2,3$ ) demonstrates the number of  $C_i$ , ( $i = 1,2,3$ ) experiments that have been assessed truly into their own class  $a_{ii}$ , ( $i = 1,2,3$ ) and in

other classes  $a_{ij}$ , ( $i \neq j$ ,  $i,j = 1,2,3$ ) where the diagonal elements  $a_{ii}$  are equivalent to  $TC_i$  of equation (23) and sum these diagonal elements is the total number of truly assessed experiments.

(Table 2) represents the accuracy of the mentioned classifiers with their Runtime. As it can be seen in (Table 2), the best result in accuracy concept of classification is achieved by BPNN with 86.33%, whereas the LDA is considered as the best classifier in both aspects of accuracy with 84.33% and Runtime with 0.98 seconds. It should be noted that all the processes in this research is done by a DELL-VOSTRO 1520 laptop with 2.67 GHz, core 2Duo CPU and 4 GB RAM.

## DISCUSSION

In this research, the performance of a Real-Time assessment system is investigated. To do so, the EEG signals were recorded from the subjects who were asked to recall their happy, sad and calm memories. Analyzing these signals was performed in two phases: Preprocessing and Main Processing. The final synthetic features were applied to various classifiers in order to achieve the best result.

In the Preprocessing phase, based on the previous researches,<sup>(15)</sup> the first 0.5 second of all channels in every experiment were removed. Then, the PSD spectrum and the half effective part of them were extracted. Finally by using the PCA method, the PSD spectrums of 50 major channels out of 64 channels in the orthogonal space were chosen.

In the Main Processing phase, 21 statistical features were extracted from the PSD spectrum of the Preprocessing phase. After normalizing the features, a feature ranking algorithm of PRTools<sup>(17)</sup> was applied and the 8 major features were chosen as an input of each

**Table 1.** The confusion matrices of classifiers on SIE EEG signals; (A) KNN, (B) NMC, (C) FLSLC, (D) LDA, (E) RBNN, (F) LMNN, (G) BPNN and (H) RBSVM

<b>(A) K-Nearest Neighbor (KNN)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	63	5	28	96
2	34	8	38	80
3	14	6	104	124
Totals	111	19	170	300

<b>(B) Nearest Mean Classifier (NMC)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	51	24	21	96
2	30	15	35	80
3	22	35	67	124
Totals	103	74	123	300

<b>(C) Fisher's Least Square Linear Classifier (FLSCL)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	60	5	31	96
2	8	64	8	80
3	2	1	121	124
Totals	70	70	160	300

<b>(D) Linear Discriminant Analysis (LDA)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	69	3	24	96
2	8	65	7	80
3	4	1	119	124
Totals	81	69	150	300

<b>(E) Radial Basis Neural Network (RBNN)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	79	19	5	96
2	49	30	1	80
3	34	13	77	124
Totals	155	62	83	300

<b>(F) Levenberg-Marquardt Rule Neural Network (LMNN)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	50	15	31	96
2	7	68	5	80
3	27	5	92	124
Totals	84	88	128	300

<b>(G) Back-Propagation Neural Network (BPNN)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	80	7	9	96
2	7	70	3	80
3	11	3	110	124
Totals	98	80	122	300

<b>(H) Radial Basis SVM (RBSVM)</b>				
True Labels	Estimated Labels			Totals
	1	2	3	
1	43	11	42	96
2	17	32	31	80
3	4	0	120	124
Totals	64	43	193	300

**Table 2.** Accuracy and runtime of classifiers.

Classifier Name	Accuracy (%)	Runtime (second)
KNN	58.33	0.96
NMC	44.33	0.89
FLSLC	81.67	1.18
LDA	84.33	0.98
RBNN	59.67	2.50
LMNN	70	88.02
BPNN	86.67	80.66
RBSVM	65	692.46

experiment.

Finally the prepared features were applied to various classifiers and their accuracies were evaluated. Based on the results, the classifier from the accuracy aspect for the proposed system is BPNN, whereas in considering both accuracy and Runtime the LDA is the best choice. It should be noted that in this research the aim was to apply less complex classifiers in order to get higher processing speed, whereas the synthetic classifiers may lead to higher accuracy rate.

In most of recent researches on emotion assessment, the analyses were performed on paired emotions separately. Also in the case of assessing among more than two emotional states, the results indicate low accurate systems,<sup>(14,15,18,19)</sup> where the most accurate system was not more than 71%. Thus, the proposed emotional assessment is superior in this regard.

The key point in achieving good results in this study is believed to be the employment of unequal number of different experiments. In this study 96 experiments of happy memories, 80 experiments of calm memories and 124 experiments of sad memories were used. In other words, different emotions were chosen with a sort of high, middle and low numbers of experiments with the point that low number of experiments should not be far from the high one because of avoiding a nearly two pair assess systems. Moreover, the empirical results has led us to the belief that in the case of equal number of experiments, the feature values of one emotion state could dominate the other emotion states. Thus, the equal or close to equal number of experiments for different emotion states of SIE signals are not recommended.

It is recommended, for future researches, to assign an approach that can distinguish unreliable experiments and remove them from further processing. By applying such an approach, it is expected to have more accurate system. On the other side, the influence of the amplitude of different emotional states on system accuracy could be investigated from final features in order to find out if increasing or decreasing the number of experiments



of an emotional state with higher amplitude could affect the accuracy.

## CONCLUSIONS

Achieving an accurate emotional system is one of the challenges to help war invalids and motor disable people at present time. Regarding to similar works to classify the emotions; it has been shown that the accuracy was dramatically diminished when facing more than two emotion states. In this paper, we proposed a prominent method that improved the accuracy of three-emotional system, which relies on unequal number of emotional states, synthetic statistical-frequency feature extraction and feature selection methods.

## CONFLICT OF INTEREST

None declared.

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