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Real-Time Electroencephalography-Based Emotion Recognition System

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Abstract – *This paper proposes parametric, general and effectively automatic real time classification method of electroencephalography (EEG) signals based on emotions. The specific characteristics of the high-frequency signals (alpha, beta, gamma) are observed, and then Fourier Transform, Features Extraction (mean, standard deviation, power) and the K-Nearest Neighbors (KNN) are employed for signal processing, analysis and classification. The proposed method consists of two stages for a multi-class classification and it can be considered as the framework of multi-emotions based on Brain Computer Interface (BCI). The first stage, the calibration, is off-line and it computes the signal processing, determines the features and trains the classification. The second stage, the real-time, is the test on new data. The FFT is applied to avoid redundancy in the selected features; then the classification is carried out using the KNN. The results show that the average accuracy results are 82.33% (valence) and 87.32% (arousal).*

***Keywords**: BCI, Electroencephalography (EEG), HCI, Real-Time Emotion Recognition*

Nomenclature

Corr (x, y)	Correlation value between vector x and vector y
Cov (x, y)	Covariance value between vector x and vector y
σ_X	Standard deviation on each row (*x*) or per-channel
$\bar{X}$	Average EEG data in each row or per-channel
n	Length of EEG data in each row or per-channel
X_k	EEG data in each row or per-channel
e	Euler's number
i	Imaginary symbol
k	The number of each channel
X_{2n}	EEG even-data per channel
X_{2n+1}	EEG odd-data per channel
$d(p, q)$	Canberra Distance between data p and q
A	Mixing matrix
s	Original EEG data

I. Introduction

Emotions have a significant effect in decision making, human interaction, human intelligence and perception. Emotions are also an important factor of human beings which can motivate action and add meaning. In Human Computer Interaction (HCI), traditionally users should not involve any emotions in order to work efficiently and with rationality on computers [1], [2].

Nowadays, interfacing directly with human brain is possible by using sensors that can monitor several brain activities related to certain forms of thought.

This technology is used to build a Brain-Computer Interface (BCI) which can directly monitor and measure brain activities [3]. Moreover, a user can manipulate his brain activity to control a computer or the communication devices.

In this research, human emotions are analyzed based on brain physiological signals from persons. A mobile EEG is utilized to measure the human brain physiological signals. EEG uses non-invasive techniques in recording data. Thus, EEG can detect emotions directly from the human brain [4].

The main problem of emotion recognition is the difficulty to equate the emotional state of persons eventhough they are treated with the same stimuli since each person has a different emotional experience [2], [4]. A previous research has used EEG to determine emotion classification [5]. The significant preprocessing method has been chosen to determine (i) denoising method, (ii) frequency bands, (iii) subjects, (iv) channels, and (v) features using statistical analysis [6]. The results showed that using the statistical analysis gives better results with the average accuracy using SVM are 66.09% (valence) and 75.66% (arousal) while the average accuracy using KNN are 82.33% (valence) and 87.32% (arousal). In this research a real-time emotion recognition is proposed by employing EEG-based BCI interfaces. This research explores three classes of both valence and arousal.

The proposed method consists of two stages. The first stage is offline and it collects valence and arousal data, then it extracts the features. The second stage is online, it recognizes emotion according to valence and arousal from EEG data. Real-time processing of EEG data may improve the accuracy of the emotion classification since the data are continuous and complete.

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The advantages of this study can be utilized into various fields [7]-[11].

This paper is organized as follows: Section 2 describes the fundamental and related previous work of EEG emotion recognition; Section 3 describes the proposed methods; Section 4 describes several experiments conducted on different settings; and Section 5 describes the conclusions and the future works of this research.

II. Literature Review

Emotions can be classified into two taxonomy models:

1. *Discrete model* which classifies the basic emotions into happiness, sadness, fear, disgust, anger, surprise; it classifies some mixed emotions such as motivational into thirst, hangers, pain, mood; moreover it classifies self-awareness into shame, shame, guilt.
2. *Dimensional model* which is expressed into two emotion dimensions; ie. Valence (sad, happy) and Arousal (calm, excited) [4].

Several previous researches on emotion recognition were focused on: i) utilizing speech (voice tone and discourse) with an accuracy of about 60%; ii) utilizing facial expressions and body movements with an accuracy of 78-90%. However, the experiment of emotions utilizing facial expressions required an activity far from natural human emotion. Another technique for emotion recognition used audio signal achieving a classification accuracy of about 60-90% [3]; whereas other methods used non-linguistic vocalizations (ie. laughs, tears, screams) to recognize the complex emotional states such as anxiety, sexual interest, boredom. Bi-modal methods also incorporated audio input and facial expressions since human emotions can stimulate behavior and physiological responses while experiencing these emotions. Most of the recognition methods utilized the expression of emotions and in some cases they cannot be natural. Also, emotion recognition from facial expressions required to monitor subjects by using one face position. Whereas, audio-based recognition was difficult to implement whenever the subject had speaking disability [1], [12]. EEG is a non-invasive technique and effective way to measure activities in brain, which are reflected by electric potentials. There are four main tasks [3] to analyze emotion based on EEG. Those are :

1. *Signal processing:* EEG device can directly receive signals from the brain. However, there are several sources of noise known as an artifact (i.e., flashing, the effects of muscle, vascular effects). The digital signal processing techniques should be applied to represent the signal using frequency and harmonic functions [4], [13].
2. *Feature extraction:* EEG signals have many dimensions, so the computation becomes very complex. Therefore, the different features should be extracted to simplify the emotions classification. Common methods use wavelet transform [13], statistical metrics (i.e., median, standard deviation, kurtosis symmetry), spectral density [14], Hjorth parameters [14], Fast Fourier transform, and fractal dimension [14], logarithmic band power (Log BP) [15].
3. *Feature selection:* one of the techniques used for feature selection in emotion recognition is by combining the metaheuristic method known as Genetic Algorithm (GA) and Support Vector Machines (SVM). GA-SVM approach looks for the best set of features originally represented as chromosome features evolved as GA takes place, so it can then be given as input to the SVM classifier [16]. The other method is by using the statistical analysis Pearson-correlation. This method can search for the best correlation among EEG data with emotion.
4. *Emotions classification:* emotions are classified by emotion state that had been previously identified. There are several methods of classification that can be used. These methods are SVM, KNN, neural network. The example in the previous research uses KNN using FFT and Wavelet features to identify four types of emotion (i.e., joy, sad, angry, relax) with accuracy results between 54% and 67%. Other researches used statistical methods such as Quadratic Discriminant Analysis (QDA) by appliyng the statistic features, to measure the level of arousal with an average accuracy 63% [4], [13], [17], [18].

III. Proposed Methods

EEG signal classification provides a fast and automatic computation without any previous knowledge of particular induced emotions. The EEG signals correspond to unknown emotions to different channels and different frequency bands. The data are transformed to enhance the useful information content by using Fast Fourier Transform (FFT) which preserves useful signal content and filters out the noise. Features are selected by the mean, standard deviation, and power.

Then, the selected features are classified using the K-Nearest Neighbor (KNN) to classify the signals. Fig. 1 shows the block diagram of the overall procedure. The next subsections explain briefly the used fundamental techniques proponing the used methods in this research.

III.1. Emotion Classes

Self-Assessment Manikin (SAM) is a questionnaire expressed in manikin forms [19]. Each score indicates the different emotion expressions. The score of valence or arousal is among 1 to 9.

The emotions were categorized into 9 classes, which were the combination of three categories of valence scores and three categories of arousal scores. Details of each class are shown in Table I.

III.2. EEG Signals Acquisition

In this study, EEG data were taken from participants.

TABLE I
DETAIL OF CLASSES WHICH WERE THE COMBINATION OF THREE VALENCE AND THREE AROUSAL CATEGORIES

	#	Arousal: Low [1-3]	Arousal: Medium [4-6]	Arousal: High [7-9]
Valence	Low [1-3]	**Unpleasant Deactivated** • Tired • Bored • Depressed	**Unpleasant** • Miserable • Sad • Unhappy	**Unpleasant Activated** • Tense • Nervous • Stressed
Valence	Medium [4-6]	**Deactivated** • Quiet • Still • Sleepy	**Neutral**	**Activated** • Aroused • Hyper-activated
Valence	High [7-9]	**Pleasant Deactivated** • Calm • Relaxed	**Pleasant** • Happy • Pleased	**Pleasant Activated** • Excited • Elated

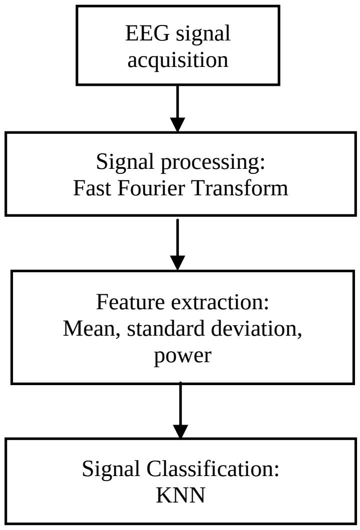

Fig. 1. Block diagram of the used classification procedure

The obtained result is better if the number of participants is greater. For the study, the participants were selected from ITS student. Total participating students were 34, among them 20 were men and 14 were women (with an average age of 20.5). The majority of EEG data recording performed during a day with total time for each participant was 25 minutes.

Emotiv EPOC is a device used to obtain EEG data from the participants. As seen in Fig. 2, there are 14 channels used in Emotiv EPOC+, named respectively AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1 and O2. Sampling rate used in the device is 128 Hz.

In this study, the proposed procedure was applied to EEG emotion recognition using pictures, music, and videos stimuli.

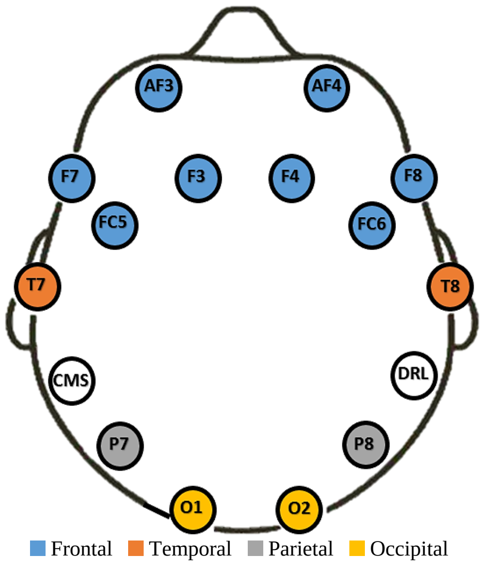

Fig. 2. Emotiv EPOC channels and its scalp location

The EEG data were taken by 20 males and 14 females participants of age among 18 and 22.

In order to record EEG data, each participant sat in a comfortable armchair in a quiet and lit room. The stimuli screen used a 42 Inch Toshiba LED Smart TV.

The participants were previously informed that they had to look at the pictures without blinking. If the stimuli is music, the participants had to listen it with closed eyes.

If the stimuli is video, the participants had to reduce their eyes blinking when watching it. After each stimulus had shown, the participants were asked to tell their valence and arousal.

III.3. EEG Signals Processing

Independent Component Analysis can eliminate noise in EEG data, among them (i) muscle movement, (ii) heart rate, (iii) eyeball movement, and (iv) eyes blinking [5].

ICA works by separating data between noise and original EEG data. In this study, ICA was performed on each trial of all the subjects. As seen in (1), ICA transforms the data in a linear form:

$$x = As \qquad (1)$$

where x is a mixture of EEG data (resulted from mixed EEG data and their noise), A is mixing matrix, and s is the original EEG data containing independent component (IC):

$$s = Wx \qquad (2)$$

The purpose of ICA is to search for the s by estimating matrix W which is the inverse of matrix A. Thus the form of equation becomes as shown in (2).

Because matrix W and matrix A are unknown, the value of matrix W needs to be estimated. ICA can estimate the value of W by maximizing the non-Gaussian. Higher is the value of non-Gaussian from W and x, more independent will be the value of the s.

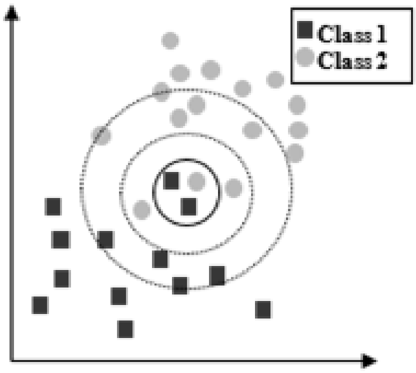

Fig. 3. Classification process using KNN

III.4. Feature Extraction And Selection

Fast Fourier Transform (FFT) is a signal processing method which works by converting the EEG signal from the time domain to the frequency domain.

Results of FFT are 5 frequency bands of EEG data, which are (i) delta (0.5-4 Hz), (ii) theta (4-8 Hz), (iii) alpha (8-13 Hz), (v) beta (13-30 Hz), and (v) gamma (30-50 Hz). In this study FFT is carried out on each channel of the entire trials and subjects. The implementation of the FFT is formulated in (3), where X is EEG data, N is the length of EEG data, k is an index iteration from 1 to N, and i is the imaginary unit:

$$X_k = \frac{1}{\frac{N}{2}} \sum_{k=1}^{\frac{N}{2}} X_{2n} e^{\frac{(2\pi i)2nk}{\frac{N}{2}}} + \\ + \frac{1}{N/2} \sum_{k=1}^{N/2} X_{2n+1} e^{(2\pi i)2nk/(\frac{N}{2})} \quad (3)$$

$$corr(x,y) = \frac{cov(x,y)}{\sigma_x \sigma_y} \quad (4)$$

$$cov(x,y) = \sum_{i=1}^{N} \frac{(x_i - \bar{x})(y_i - \bar{y})}{N} \quad (5)$$

$$d\,(p,q) = \sum_{i=1}^{n} \frac{|p_i - q_i|}{|p_i| + |q_i|} \quad (6)$$

Some features are taken from FFT results. There are several features which are used in this study, among them mean, standard deviation, and power. To determine the most significant features between EEG and emotion, the statistical analysis: Pearson-correlation was used.

Pearson-Correlation can measure the linear relationship between two random variables [21].

There are 2 steps for calculating Pearson-correlation which are the calculation of covariance value from two variables, and the ratio calculation of covariance result divided by the multiplication of their standard deviations.

The formula to calculate the Pearson-correlation is presented in (4), where x and y indicate each data between the two variables. The formula to calculate the covariance is presented in (5), where x_i and y_i are the data on the column number i.

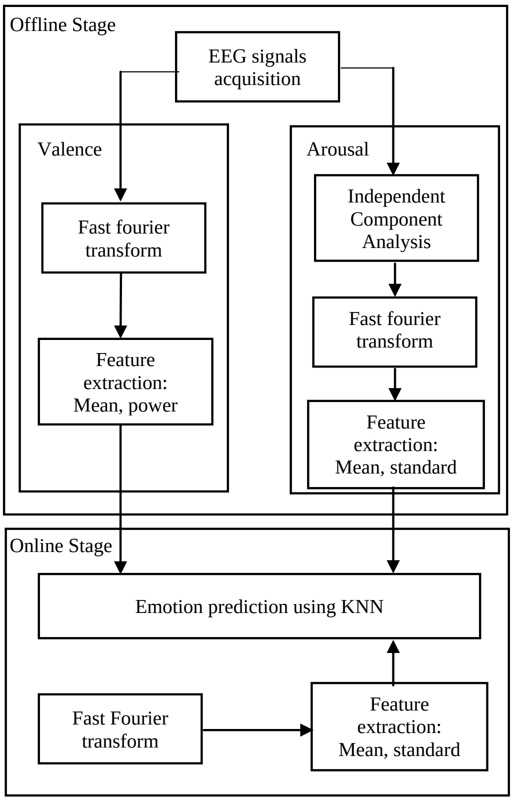

Fig. 4. Flowchart proposed method

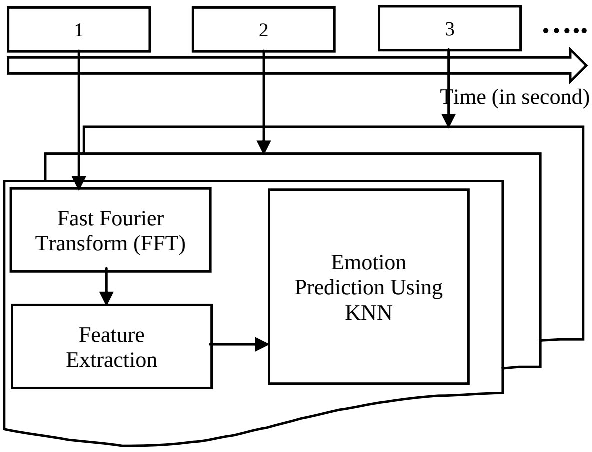

Fig. 5. Online method

III.5. Signal Classification

K-Nearest Neighbors (KNN) is utilized in this study as classification method. KNN is a method that calculates distance between prediction data and training data.

The chosen label is taken from the nearest distances with majority label as shown in Fig. 3.

The distance method used in this study is Canberra Distance (CD). The equation of Canberra Distance is shown in (6). The classification in this study is divided into two parts: a classification with valence (high valence and low valence) and a classification with arousal (high arousal and low arousal). To measure the accuracy of the classification, it is necessary to train and test the data.

K fold cross-validation with the value $K = 10$ is used for separating training data and testing data.

III.6. Real-time Method

There are two stages algorithm. The first consists of offline stages utilized for getting the training data of valence and arousal. The second consists of online stages used for predicting emotion according to valence and arousal from EEG data as shown in Fig. 4. An off-line stage allowed the identification of the most predominant features referring to the different conditions to be classified by considering that the stage of a given signal was unknown in advance. The on-line stage was the classification of a signal of which the allowance to each task was unknown in advance and had to be discovered by classification as real time. The problem at hand may be faced in the framework of machine learning problems.

Fig. 5 shows an explanation of online method. The EEG signal in each second is processed to get emotion prediction. Multithreading is used to create parallel programming between data acquisition and processing.

IV. Results

EEG analysis of 31 subjects while receiving stimuli was obtained. The device used to record the EEG was Emotiv EPOC [22]. It has 16 channels (two channels are used as reference), 16 bit resolution per channel, 128 Hz sampling rate, and band-pass filtering between 0.16 and 43 Hz. The main characteristics of the measured signals based on picture, music, and video that used as stimuli to get person emotion. Each subject received stimuli continuously from 5 pictures, 25 music, and 20 videos; and every trial with period 5 seconds the subject answered the valence and arousal scores.

TABLE II
PEARSON-CORRELATION ANALYSIS RESULT WITH VALENCE

Electrode name	Frequency bands				
	δ	θ	α	β	γ
AF3	-0.136	0.042	-0.060	0.079	0.035
F7	-0.051	0.149	0.087	0.114	0.148
F3	-0.081	-0.004	-0.002	0.098	0.203
FC5	-0.072	0.084	-0.033	0.026	0.181
T7	0.032	0.061	0.211	0.463	0.578
P7	0.072	0.039	-0.010	0.096	0.314
O1	0.014	0.016	-0.052	0.054	0.216
O2	-0.078	-0.200	-0.142	-0.130	0.063
P8	0.044	0.099	-0.033	0.165	0.237
T8	-0.061	-0.023	-0.034	0.384	0.484
FC6	-0.165	-0.062	-0.081	-0.107	0.005
F4	-0.117	0.087	-0.053	0.050	0.170
F8	-0.202	-0.224	-0.083	-0.019	0.125
AF4	-0.255	-0.056	-0.156	0.139	0.302

TABLE III
PEARSON-CORRELATION ANALYSIS RESULT WITH AROUSAL

Electrode name	Frequency bands				
	δ	θ	A	β	γ
AF3	0.309	0.392	0.191	0.390	0.545
F7	0.373	0.499	0.355	0.325	0.524
F3	0.315	0.352	0.118	0.002	0.140
FC5	0.331	0.396	0.302	0.415	0.578
T7	0.276	0.293	0.315	0.438	0.518
P7	0.345	0.324	0.059	0.078	0.271
O1	0.305	0.305	-0.104	0.105	0.186
O2	0.235	0.084	-0.080	0.025	0.167
P8	0.374	0.336	0.003	0.205	0.216
T8	0.362	0.326	0.116	0.464	0.549
FC6	0.196	0.269	0.233	0.182	0.259
F4	0.335	0.329	0.164	0.309	0.411
F8	0.162	0.292	0.151	0.176	0.334
AF4	0.270	0.391	0.119	0.425	0.529

TABLE IV
EEG DATA SEGMENT DIVIDED INTO 2 VALENCE CATEGORIES

SAM score	Number of EEG data (N=50)	
	Low Valence	High Valence
[1] [2-9]	3	47
[1-2] [3-9]	6	44
[1-3] [4-9]	15	35
[1-4] [5-9]	21	29
[1-5] [6-9]	30	20
[1-6] [7-9]	34	16
[1-7] [8-9]	43	7
[1-8] [9]	48	2

TABLE V
EEG DATA SEGMENT DIVIDED INTO 2 AROUSAL CATEGORIES

SAM score	Number of EEG data (N=50)	
	Low Arousal	High Arousal
[1] [2-9]	3	47
[1-2] [3-9]	8	42
[1-3] [4-9]	14	36
[1-4] [5-9]	20	30
[1-5] [6-9]	29	21
[1-6] [7-9]	36	14
[1-7] [8-9]	43	7
[1-8] [9]	48	2

Every second of analog EEG signals is digitized into 128 data. Every subject has 640 data for each trial; therefore, for 250 seconds each subject has 32000 data.

Band power analysis performed as standard parameters in the analysis of EEG. It is observed an absolute power in five frequency bands (delta, theta, alpha, beta and gamma) in the overall electrode sites.

EEG data observed in this study showed a certain tendency between EEG properties and SAM. Based on the results in Fig. 4, it was found that the EEG signal has similar characteristic to SAM regarding the emotional state of the person. To investigate whether the EEG signal has a common characteristic compared to the emotion condition provided by SAM, a correlation analysis should be done between EEG signal and SAM in each channel and frequency band.

Pearson-correlation coefficient result of absolute band power and each electrode with corresponding to SAM score. According to the Table II, it was found that the absolute powers in T7 and T8 electrode have the highest correlation between EEG signal and valence SAM score in high frequency bands.

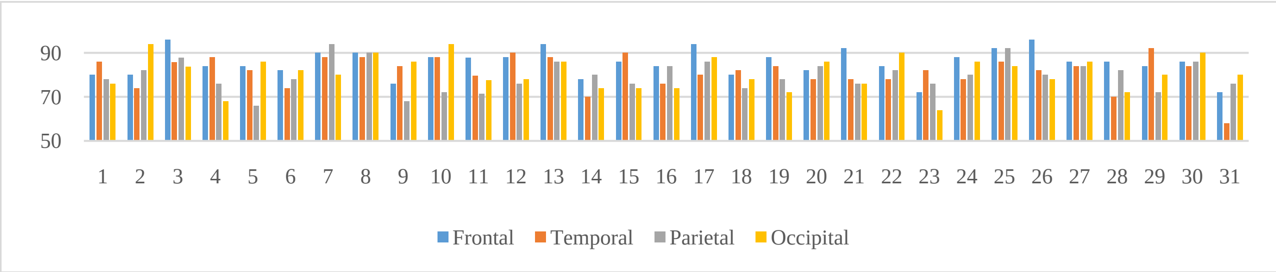

Fig. 6. Classification accuracy of the different scalp location for each subject in two valence categories

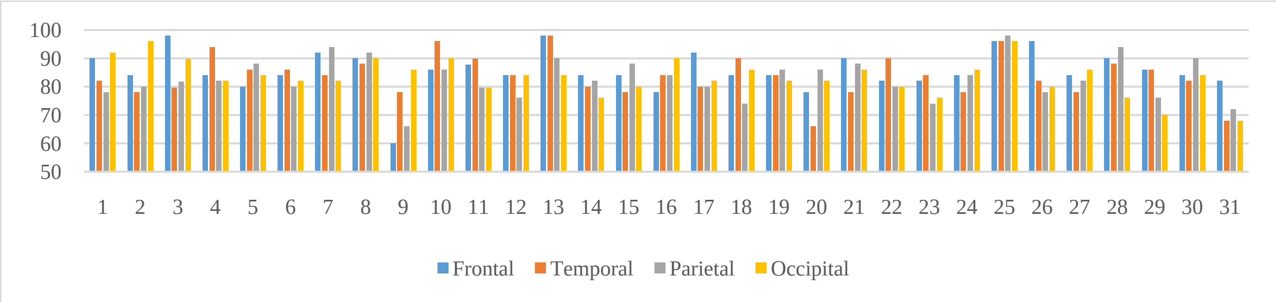

Fig. 7. Classification accuracy of the different scalp location for each subject in two arousal categories

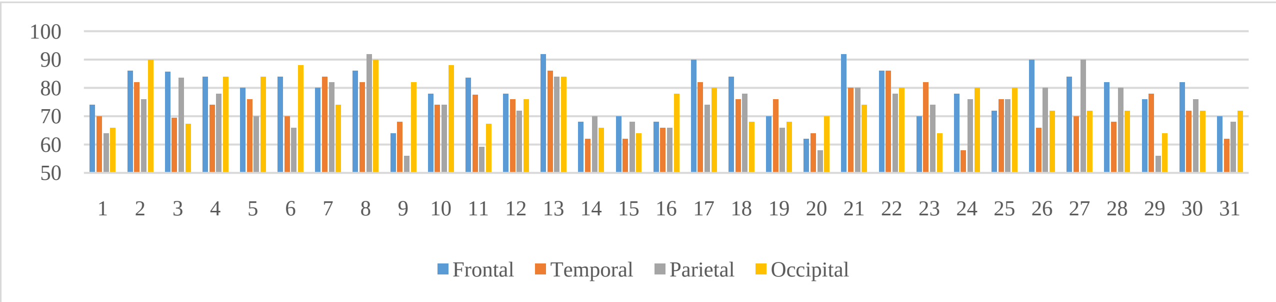

Fig. 8. Classification accuracy of the different scalp location for each subject in three valence categories

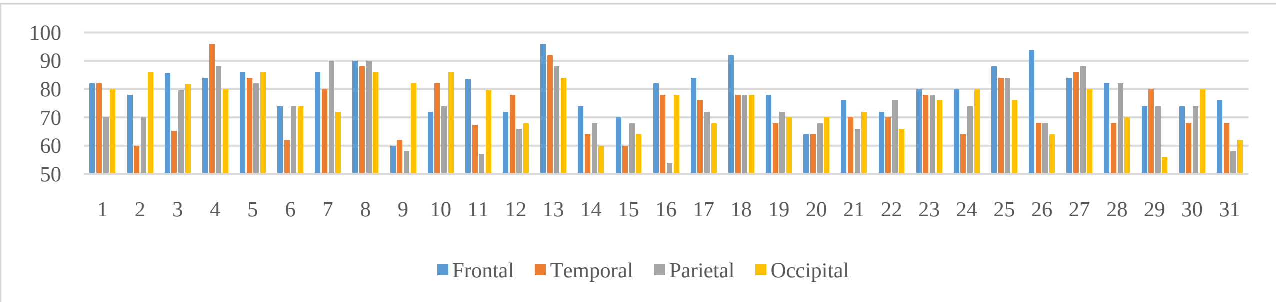

Fig. 9. Classification accuracy of the different scalp location for each subject in three arousal categories

Table III shows that the absolute powers in AF3, F7, FC5, T7, T8, and AF4 electrode have the highest correlation between EEG signal and arousal SAM score in high frequency bands. Generally, when both valence and arousal are compared to all the channels, T7 and T8 show the highest correlation parameters with the emotional state in high frequency bands.

Once observed a Pearson correlation analysis, it is possible to evaluate SAM scores based on the amount of EEG data. The investigation results for EEG data portion are shown in Table IV and Table V.

In this study, 50 power band EEG data are obtained (by 5 seconds of EEG recording). The goal is finding the balance portion of EEG data to SAM score regarding low and high emotional condition.

In other words, the average EEG data when divided into two categories should be of about 25 data in each category.

Based on these results, a good portion of EEG data is 21 and 29 for both valence and arousal, when the EEG data is divided into valence SAM < 5 & valence SAM ≥ 5 and arousal SAM < 6 & arousal SAM ≥ 6.

The classification accuracy for number of classes two (low and high) and three (low, medium, and high) is calculated for both valence and arousal in each subject.

The purpose is to measure the performance of the system. Moreover, the accuracy is calculated by various ways, among them different frequencies, scalp location, and stimuli for each subject.

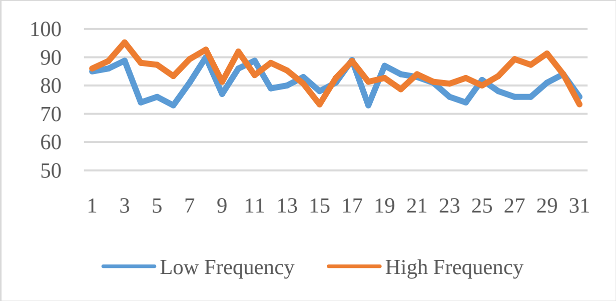

Fig. 10. Classification accuracy of the different frequency for each subject in two valence categories

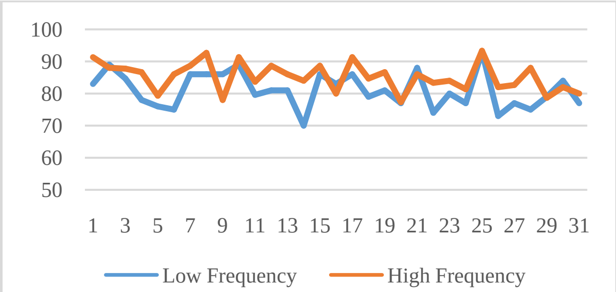

Fig. 11. Classification accuracy of the different frequency for each subject in two arousal categories

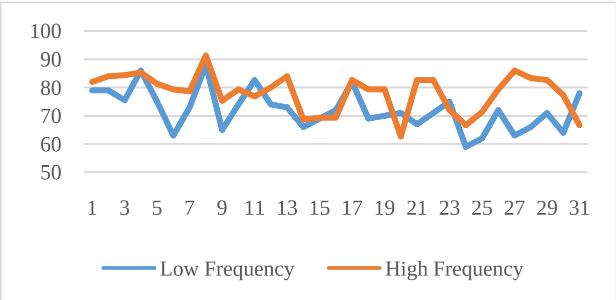

Fig. 12. Classification accuracy of the different frequency for each subject in three valence categories

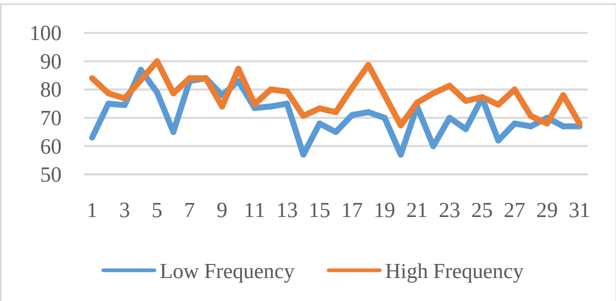

Fig. 13. Classification accuracy of the different frequency for each subject in three arousal categories

IV.1. Varying Scalp Location

The classification accuracy among each scalp location (i.e., frontal, temporal, parietal, and occipital) is compared with different categories: two valence categories, two arousal categories, three valence categories, and three arousal categories. The details of channels in each scalp location can be seen in Fig. 2. Fig. 6, shows the average accuracy in two valence categories at 85.47% given by frontal scalp. Fig. 7 shows the average accuracy in two arousal categories at 85.73% given by frontal scalp. Fig. 8 shows the average accuracy in three valence categories at 79.01% given by frontal scalp. Fig. 9 shows the average accuracy at 79.78% given by frontal scalp. As a result, it can be concluded that the frontal lobe is more effective for classifying emotions for both valence and arousal.

IV.2. Varying Frequencies

The classification accuracy among each frequency (i.e., low frequency and high frequency) is compared with different categories: two valence categories, two arousal categories, three valence categories, and three arousal categories. Low frequency contains delta and theta, while high frequency contains alpha, beta, and gamma. Fig. 10 shows the average accuracy in two valence categories at 84.72% given by high frequency.

Fig. 11 shows the average accuracy in two arousal categories at 85.22% given by high frequency. Fig. 12 shows the average accuracy in three valence categories at 78.19% given by high frequency. Fig. 13 shows the average accuracy at 77.86% given by high frequency.

As a result, it can be concluded that high frequency is more effective for classifying emotions for both valence and arousal.

IV.3. Varying Stimuli

The classification accuracy among each stimuli (i.e., low frequency and high frequency) is computed using selected channel and frequency. Fig. 14 shows the average accuracy in picture stimuli at 67.64% given by man. Fig. 15 shows the average accuracy in music stimuli at 87.85% given by woman in almost all categories (except in two arousal categories).

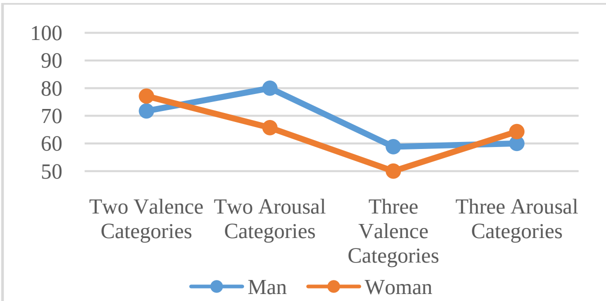

Fig. 14. Classification accuracy of the picture stimuli for each categories between man and woman

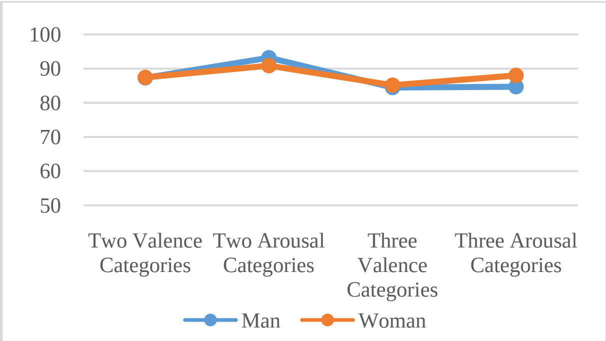

Fig. 15. Classification accuracy of the music stimuli for each categories between man and woman

Fig. 16 shows the average accuracy in video stimuli at 93.81% given by man in all categories. As a result, it can be concluded that the man leads higher accuracy in picture and video stimuli. Also it can be concluded that video is more effective for classifying emotions for both valence and arousal.

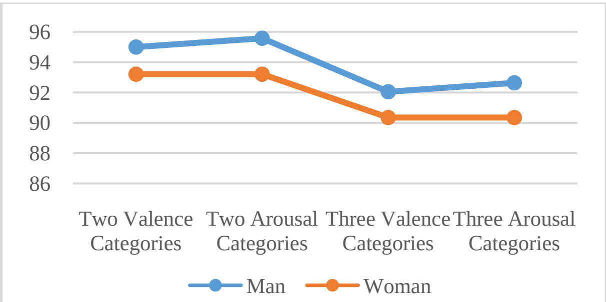

Fig. 16. Classification accuracy of the video stimuli for each categories between man and woman

IV.4. Overall Evaluation

The classification accuracy is computed using selected channel and frequency. Fig. 17 and Fig. 18 show the classification accuracy for each subject in both two and three valence/arousal categories. Table VI, Table VII, Table VIII, and Table IX show the detail of the classification accuracy for both two and three valence/arousal categories.

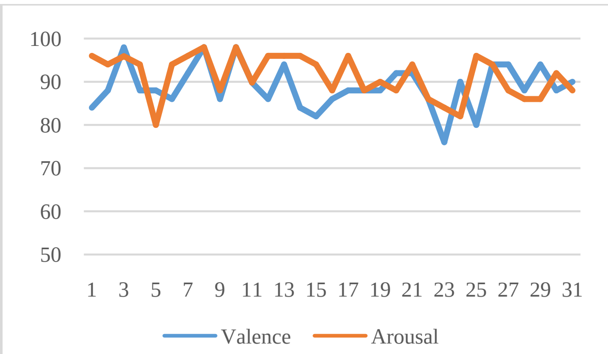

Fig. 17. Classification accuracy of the proposed model for each subject in two categories of valence and arousal

TABLE VI
DETAIL OF TWO VALENCE CATEGORIES ACCURACY TEST RESULT FOR EACH SUBJECT IN PERCENT

Subject No.	TP	TN	FP	FN	Accuracy
1	54.00	30.00	10.00	6.00	84.00
2	26.00	62.00	4.00	8.00	88.00
3	79.59	18.37	2.04	0.00	97.96
4	52.00	36.00	10.00	2.00	88.00
5	52.00	36.00	8.00	4.00	88.00
6	60.00	26.00	8.00	6.00	86.00
7	38.00	54.00	2.00	6.00	92.00
8	56.00	42.00	2.00	0.00	98.00
9	60.00	26.00	12.00	2.00	86.00
10	24.00	74.00	0.00	2.00	98.00
11	63.27	26.53	6.12	4.08	89.80
12	42.00	44.00	8.00	6.00	86.00
13	42.00	52.00	2.00	4.00	94.00
14	42.00	42.00	4.00	12.00	84.00
15	38.00	44.00	2.00	16.00	82.00
16	50.00	36.00	8.00	6.00	86.00
17	86.00	2.00	12.00	0.00	88.00
18	40.00	48.00	6.00	6.00	88.00
19	66.00	22.00	12.00	0.00	88.00
20	64.00	28.00	6.00	2.00	92.00
21	64.00	28.00	2.00	6.00	92.00
22	60.00	26.00	8.00	6.00	86.00
23	46.00	30.00	14.00	10.00	76.00
24	52.00	38.00	6.00	4.00	90.00
25	68.00	12.00	14.00	6.00	80.00
26	62.00	32.00	2.00	4.00	94.00
27	52.00	42.00	4.00	2.00	94.00
28	46.00	42.00	4.00	8.00	88.00
29	54.00	40.00	4.00	2.00	94.00
30	74.00	14.00	8.00	4.00	88.00
31	42.00	48.00	6.00	4.00	90.00
Average	51.32	34.47	8.79	5.42	85.79

TABLE VII
DETAIL OF TWO AROUSAL CATEGORIES ACCURACY TEST RESULT FOR EACH SUBJECT IN PERCENT

Subject No.	TP	TN	FP	FN	Accuracy
1	20.00	76.00	0.00	4.00	96.00
2	20.00	74.00	2.00	4.00	94.00
3	26.53	69.39	0.00	4.08	95.92
4	18.00	76.00	0.00	6.00	94.00
5	58.00	22.00	12.00	8.00	80.00
6	38.00	56.00	6.00	0.00	94.00
7	66.00	30.00	2.00	2.00	96.00
8	42.00	56.00	2.00	0.00	98.00
9	42.00	46.00	8.00	4.00	88.00
10	40.00	58.00	0.00	2.00	98.00
11	40.82	48.98	6.12	4.08	89.80
12	66.00	30.00	4.00	0.00	96.00
13	44.00	52.00	4.00	0.00	96.00
14	66.00	30.00	0.00	4.00	96.00
15	20.00	74.00	2.00	4.00	94.00
16	32.00	56.00	8.00	4.00	88.00
17	24.00	72.00	0.00	4.00	96.00
18	56.00	32.00	4.00	8.00	88.00
19	28.00	62.00	4.00	6.00	90.00
20	52.00	36.00	6.00	6.00	88.00
21	8.00	86.00	0.00	6.00	94.00
22	38.00	48.00	6.00	8.00	86.00
23	26.00	58.00	8.00	8.00	84.00
24	46.00	36.00	12.00	6.00	82.00
25	4.00	92.00	2.00	2.00	96.00
26	54.00	40.00	4.00	2.00	94.00
27	40.00	48.00	6.00	6.00	88.00
28	30.00	56.00	8.00	6.00	86.00
29	62.00	24.00	10.00	4.00	86.00
30	32.00	60.00	6.00	2.00	92.00
31	26.00	62.00	4.00	8.00	88.00
Average	34.92	52.63	5.92	6.53	87.55

TABLE VIII
DETAIL OF THREE VALENCE CATEGORIES ACCURACY TEST RESULT FOR EACH SUBJECT IN PERCENT

Subject No.	TP	TN	FP	FN	Accuracy
1	34.00	50.00	4.00	12.00	84.00
2	20.00	70.00	2.00	8.00	90.00
3	51.02	38.78	6.12	4.08	89.80
4	6.00	82.00	6.00	6.00	88.00
5	12.00	68.00	0.00	20.00	80.00
6	22.00	58.00	8.00	12.00	80.00
7	20.00	66.00	2.00	12.00	86.00
8	0.00	96.00	2.00	2.00	96.00
9	50.00	34.00	8.00	8.00	84.00
10	18.00	68.00	0.00	14.00	86.00
11	28.57	51.02	4.08	16.33	79.59
12	28.00	54.00	12.00	6.00	82.00
13	40.00	52.00	4.00	4.00	92.00
14	18.00	58.00	2.00	22.00	76.00
15	16.00	60.00	4.00	20.00	76.00
16	32.00	50.00	4.00	14.00	82.00
17	30.00	54.00	12.00	4.00	84.00
18	8.00	78.00	2.00	12.00	86.00
19	46.00	40.00	12.00	2.00	86.00
20	36.00	50.00	4.00	10.00	86.00
21	10.00	80.00	2.00	8.00	90.00
22	22.00	74.00	2.00	2.00	96.00
23	0.00	70.00	2.00	28.00	70.00
24	40.00	38.00	8.00	14.00	78.00
25	20.00	48.00	16.00	16.00	68.00
26	28.00	60.00	2.00	10.00	88.00
27	32.00	60.00	2.00	6.00	92.00
28	24.00	64.00	4.00	8.00	88.00
29	34.00	50.00	6.00	10.00	84.00
30	48.00	36.00	6.00	10.00	84.00
31	8.00	80.00	0.00	12.00	88.00
Average	23.15	57.29	6.04	13.52	80.44

TABLE IX
DETAIL OF THREE AROUSAL CATEGORIES ACCURACY TEST RESULT FOR EACH SUBJECT IN PERCENT

Subject No.	TP	TN	FP	FN	Accuracy
1	20.00	70.00	0.00	10.00	90.00
2	10.00	76.00	0.00	14.00	86.00
3	0.00	83.67	0.00	16.33	83.67
4	2.00	90.00	0.00	8.00	92.00
5	30.00	62.00	4.00	4.00	92.00
6	18.00	70.00	6.00	6.00	88.00
7	66.00	26.00	2.00	6.00	92.00
8	20.00	74.00	0.00	6.00	94.00
9	42.00	44.00	6.00	8.00	86.00
10	30.00	60.00	0.00	10.00	90.00
11	18.37	67.35	2.04	12.24	85.71
12	30.00	62.00	2.00	6.00	92.00
13	34.00	60.00	4.00	2.00	94.00
14	50.00	40.00	4.00	6.00	90.00
15	20.00	58.00	2.00	20.00	78.00
16	10.00	70.00	2.00	18.00	80.00
17	24.00	70.00	0.00	6.00	94.00
18	16.00	74.00	4.00	6.00	90.00
19	20.00	66.00	0.00	14.00	86.00
20	28.00	52.00	0.00	20.00	80.00
21	8.00	82.00	0.00	10.00	90.00
22	26.00	58.00	4.00	12.00	84.00
23	8.00	74.00	2.00	16.00	82.00
24	24.00	56.00	4.00	16.00	80.00
25	0.00	74.00	2.00	24.00	74.00
26	52.00	38.00	6.00	4.00	90.00
27	30.00	62.00	2.00	6.00	92.00
28	20.00	58.00	4.00	18.00	78.00
29	34.00	44.00	8.00	14.00	78.00
30	18.00	64.00	4.00	14.00	82.00
31	26.00	48.00	4.00	22.00	74.00
Average	21.96	59.63	3.48	14.93	81.59

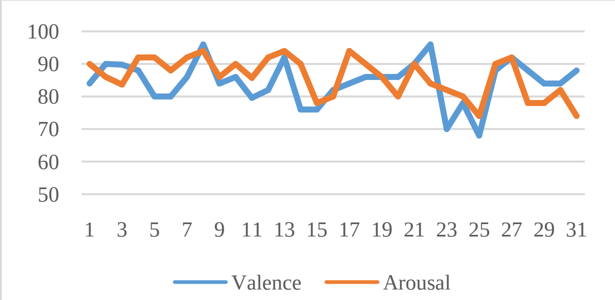

Fig. 18. Classification accuracy of the proposed model for each subject in three categories of valence and arousal

V. Conclusion

In this paper, a real-time EEG-based emotion recognition system was proposed. The emotions were categorized into 9 classes, which were the combination of three categories of valence and three categories of arousal. The method for emotion recognition consists of Fourier transform, feature extraction (minimum, maximum, average, standard deviation, power, and energy), and classification using KNN.

Each subject (person) had 250 trials, which were employed 90% for training and 10% for testing and k-fold cross validation method was utilized for random selection. The accuracy of emotion recognition was computed in various trial. The results showed that the emotion recognition with frontal scalp achieved higher accuracy than temporal, parietal, and occipital scalp in all categories. Emotion recognition with high frequency achieved higher accuracy than low frequency in all categories. Emotion recognition with man subject achieved higher accuracy than women subject in almost all stimuli, except music stimuli.

Emotion recognition with video stimuli achieved higher accuracy than picture and music stimuli. Overall evaluation results showed that two categories of valence and arousal achieved accuracy of 85.79% and 87.55%; whereas emotion recognition with three categories of valence and arousal achieved accuracy of 80.44% and 81.59%.

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