Emotion Recognition with Multi-Channel EEG Signals Using Visual Stimulus

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***Abstract*—Emotions are complex and may vary from person to person in a situation. The purpose of this study is to perform emotion analysis by using specific signal processing algorithms, to find the features and channels that are effective in the emotion recognition by using 60 visual stimuli with obtained EEG signals from the 32-channel EEG device that is branded Brain Products from 25 volunteers. The graphical user interface (GUI) has been designed to display visual stimuli at certain time intervals. Empirical mode decomposition (EMD) method has been applied to EEG signals and Intrinsic Mode Functions (IMFs) have been obtained. The most meaningful IMF has been investigated by using signal analysis methods such as Power Spectrum Density (PSD) using Periodogram and Welch's method. Feature extractions have been performed for filtered signal, IMF1, IMF2, IMF3 and average of first three IMFs. The classification has been done by the support vector machine (SVM). Different channels and features have been classified. It has been found that IMF1 and IMF2 are the most meaningful IMFs, Hjorth parameters have highest success rate as features and F4, T7, T8 EEG channels were the most effective channels with a success rate of 81.80%, 77.13%, 76% in emotions recognition.**

Keywords*—*EEG Signal; Emotion Recognition; Empirical Mode Decomposition; Feature Extraction; Graphical User Interface; Intrinsic Mode Functions; Support Vector Machine.

I. INTRODUCTION

Emotions consist of situational and individual processes. There is no clear definition for emotions. Moreover, there are no specific standards for an emotional response [1]. Experiences, physiological and behavioral events are related to shaping emotions but the inner emotion is different and reflects real emotions [2]. For understanding the inner feeling, EEG emotion recognition method [2, 3] is used. Different stimuli are used to stimulate individuals to reveal different emotions. It is possible to use music, text, video and images, and thus emotion signals can be recorded. Emotion signals can be used to diagnose specific emotions using various stimuli, and data can be used for disease diagnosis [4].

Emotion recognition is a field of Brain Computer Interface (BCI) [5, 6]. Because of development of the BCI, a lot of research is done on emotion recognition to understand the real feelings of people. Emotion estimates are made for computers and robots to interact better with people [7]. Through emotion recognition based on EEG signals and classifying emotions, computers are more likely to understand people's emotions. The EEG signal is commonly used to detect different emotions [8]. EEG is one of the methods used in investigation of functions of living human brain. The EEG uses the International 10/20 system [9]. Neurological problems can be detected with signals from the EEG device [3, 10] and data about psychiatric diseases can be obtained. EEG is used in neurology, neurosurgery, pediatrics, anesthesia and psychiatry [11]. It is also used to diagnose epilepsy [12], to diagnose tumor, to investigate behavioral disorders, to analyze mood disorders and to help diagnose and treat such diseases. Genetic factors and socio-cultural mechanisms and unique personal experiences are very important determinants of the personality functioning and human relations of individuals [13].

For emotion models discrete models consist of basic emotions such as joy, anger, sadness, fear, disgust and surprise. The dimensional model is affected by 3 different factors. These are Valence, Arousal and Dominance [14]. In general, valence refers to the state of being happy or unhappy. Arousal refers to the state of calmness or excitement. Dominance means control of emotion. These form the VAD model.

The aim of this study is classification of various emotions which reveal during focusing on images and during listening sounds as stimulus using recorded EEG signals concerning each images and each sounds with EMD methods applied by MATLAB for emotion recognition by using EEG signals. The study is based on the classification of different EEG-based features with classification algorithm.

II. MATERIAL AND METHOD

A. Data Acquisition

In this study, EEG recordings of 25 healthy participants were used, including 13 female and 12 male volunteers. The EEG signals were taken from a Brain Products branded 32-channelled Brain Vision BrainAmp EEG device by using 60 visual and 60 auditory stimulus that could stimulate various emotions. From International Affective Picture System (IAPS) database [15], the 48 images are used to evoke emotions. Then from International Affective Digitized Sounds (IADS) database [16], the 48 sounds are used as the auditory stimuli. Visual and auditory stimuli were selected from IAPS and IADS according to certain criteria and other stimuli that are 12 images and 12 sounds were selected in the same criterion by ours. These 12 images and 12 sounds have been added for comparison with stimuli from IAPS and IADS.

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B. MATLAB – Graphical User Interface

GUI was designed to display visual stimuli at certain time intervals. Specific visuals, commands and warnings are used to make it easier for users to understand and complete the experiment more easily. The 3 different parts are designed in GUI as visual, auditory and video. However, only the visual and auditory parts were used. Fig. 1. (a) shows the presented window of GUI to users. After each stimulus, Self Assessment Manikin (SAM) questionnaire has been performed in order to enable users to evaluate their feelings according to valence, arousal, dominance and liking on the GUI. Fig. 1. (b) shows the SAM questionnaire for users.

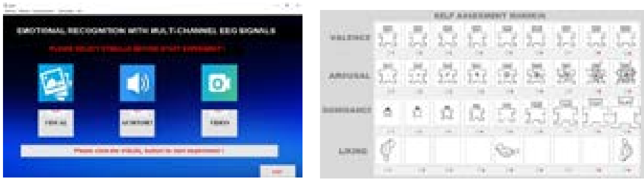

Fig. 1. a) Presented window of GUI to users b) SAM in designed GUI.

In this SAM form, there are 4 scales rated from 1 to 9 and each stimulus is evaluated according to the degree of the emotions evoked by stimuli. Briefly the valance scale refers to unhappiness and happiness. Arousal scale refers to the state of calmness and excitement. Dominance refers to domination and control of emotions. Liking scale refers to like or dislike.

The Brain Vision BrainAmp EEG device is used to record EEG signals. Electrodes on the Brain Cap have been placed on the entire scalp according to the International 10-20 system and 32 channels of EEG device.

C. Experiment Protocol

The visual experiment lasts 22 minutes. Fig. 2. (a) shows the used images from IAPS. The photo taken during the experiment is available in Fig. 2. (b). Fig. 3. shows the demonstration plan for the visual stimulus experiment.

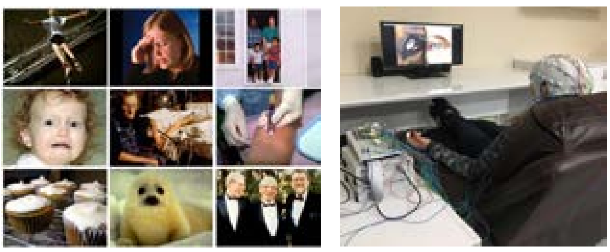

Fig. 2. a) Examples from used IAPS images b) a photo taken from the participant.

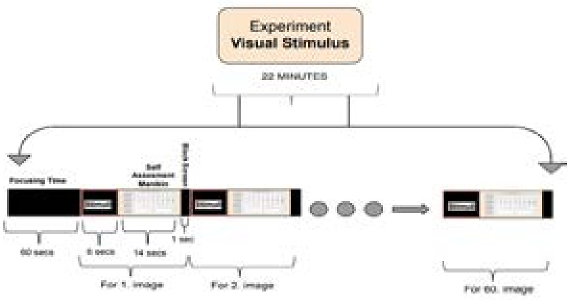

Fig. 3. Demonstration plan for the visual stimulus.

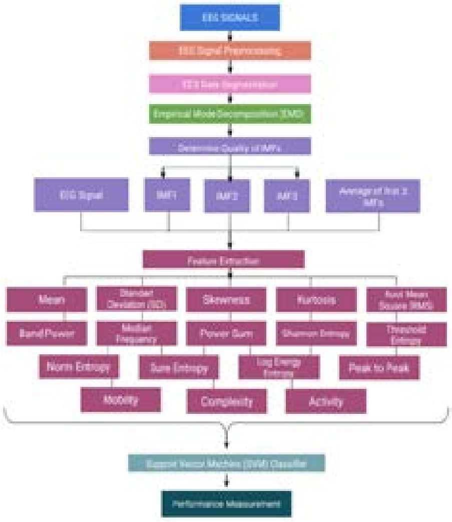

Fig. 4. Block diagram of the proposed method.

Fig. 4. shows the block diagram of proposed method. Firstly, obtained EEG signals have been preprocessed. As a filter in the recording program of the EEG signals, we have applied the 0.7 Hz low pass filter, 250 Hz high pass filter and 50 Hz notch filter. Then segmentation has been performed according to the time intervals of the stimuli. We wanted to examine the emotions of people in the time intervals of stimuli. Firstly, the focusing part which was 60 seconds from all filtered signal was removed. Then segmentation was performed. The remaining signals were segmented for 6 seconds, and the 14 seconds survey sections and 1 second black screen portion were removed. EMD implementation has been done to the segmented EEG signals. The IMFs [17] are obtained from decomposition of multicomponent signal with the helping of EMD algorithm. More than one IMF has been obtained after EMD implementation.

D. Empirical Mode Decomposition

EMD is an algorithm that simplifies the analysis of non-stationary EEG signals. It is a tool for analysis of nonlinear, nonstationary time series [18], and therefore EMD applications are appropriate and highly efficient for analysis of EEG signals. The most important part of the EMD algorithm is the sifting algorithm. EMD is an algorithm that we recommend in this study. After the EMD algorithm has been applied to segmented EEG signals, we obtain IMFs. More than one IMF has been obtained after EMD implementation. Fig. 5. shows EEG signal and occurred IMFs at the end of the EMD implementation.

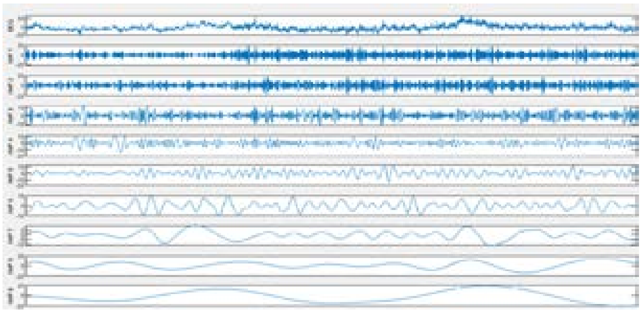

Fig. 5. EEG signals and the corresponding first nine IMFs.

E. Selection of the Intrinsic Mode Functions

We have investigated the role of each IMFs in emotion classification. PSD [19] using Periodogram and Welch's methods [20] were used for the selection of IMFs. Fig. 6. (a) and (b) show the Periodogram and Welch's method for first six IMFs.

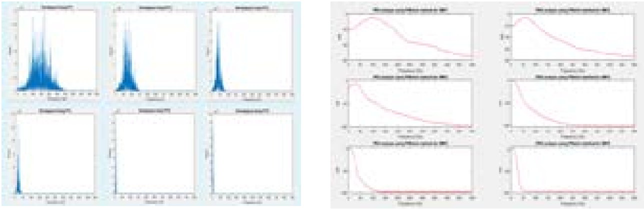

Fig. 6. a) Periodogram method b) Welch's method.

When we examine the power density by periodogram method, we observed that frequencies are spread to a wider spectrum in IMF1, IMF2 and IMF3. The frequency spectrum of IMFs is gradually decreasing. In emotion recognition studies it is known that emotion gives better results according to the high-frequency component [19]. When we examine Welch's method, we observed that frequencies are spread to a wider spectrum in the first IMFs, increasingly meaningless and does not yield meaningful results. Therefore, the features extracted from IMF1, IMF2 and IMF3 provide the highest accuracy.

F. Feature Extraction

Feature selection is the main point during the selection of the most important features that have the ability to define and maximize the differences between the different signals. Feature extraction directly affects the outcome of the classification. In our study, many features were used and applied to the filtered EEG signal, IMF1, IMF2, IMF3 and the average of first 3 IMFs. As the features, mean, standard deviation, skewness, kurtosis, root mean square, band power, median frequency, power sum, peak to peak, entropies (Shannon, threshold, norm, sure, log energy), Hjorth parameters (mobility, complexity, activity) have been applied.

G. Classification

The classification has been done after the feature vector is created by the SVM. SVM gives more successful results than many other techniques. Different channels and features have been classified. The best channel activity and the most successful feature were investigated based on the classified the certain features. To be able to make IMFs evaluation, classification process has been applied to filtered signal, IMF1, IMF2, IMF3 and average of first three IMFs. Channel groups for arousal, valence, dominance have been classified according to obtained IMFs. To measure the activity of the channel, using different features groups and IMF1, IMF2 of signals, the channel classification has been made.

H. Performance Management

Performance evaluations are made for performance measurement of classifier according to accuracy, sensitivity, and specificity. As a result of the classification, confusion matrices were obtained and success rates were obtained from these matrices. Fig. 7. (a) shows the confusion matrix calculation and (b) shows an obtained confusion matrix.

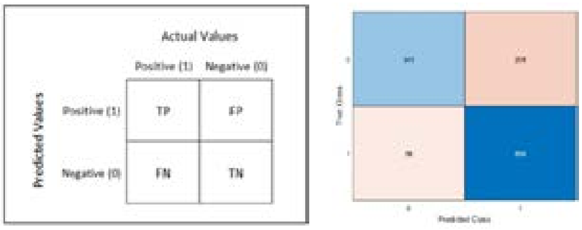

Fig. 7. a) Confusion Matrix b) Obtained confusion matrix.

III. RESULTS AND DISCUSSION

Different channels and features have been classified. The best channel activity was investigated and the comparison was made based on the classified the certain features. The best results were obtained by trying different combinations.

Firstly, 32 channels have been examined as 3 sections. Channel groups were chosen as frontal, parietal-temporal and occipital. From 1 to 12 the first section, from 13 to 21 second sections and from 22 to 32 third sections were defined. Fig. 8. shows the selected channels. We have been grouped the channel groups according to the filtered signal, IMF1, IMF2, IMF3 and the average of first three IMFs using only the Hjorth parameters for arousal, valence, dominance. The significance of IMF, and the effects of channel groups on emotion recognition were examined.

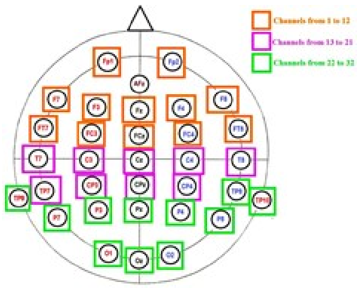

Fig 8. Selected channel groups.

TABLE I. EVALUATIONS OF IMFS AND CHANNEL GROUPS

With Hjorth Parameters		VALENCE			AROUSAL			DOMINANCE		
CHANNELS	SIGNALS	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8	Filtered Signal	0.5914	0.3905	0.6311	0.6314	0.8609	0.2244	0.5594	0.3542	0.7486
	IMF1	0.8293	0.0988	0.9800	0.6374	0.9500	0.0831	0.6623	0.4396	0.8676
	IMF2	0.8302	0.0990	0.9940	0.6414	0.9859	0.0305	0.6434	0.4188	0.8503
	IMF3	0.7542	0.1000	0.8870	0.6184	0.8469	0.2133	0.5445	0.3563	0.7179
	IMF average	0.8312	0.0988	0.9800	0.6394	0.9969	0.0055	0.4815	0.998	0.0296
T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4	Filtered Signal	0.6124	0.3114	0.6695	0.5235	0.5438	0.4875	0.5165	0.5250	0.5086
	IMF1	0.8322	0.0651	0.9880	0.6334	0.9875	0.0055	0.6094	0.7125	0.5144
	IMF2	0.8342	0.0296	0.9976	0.6364	0.9953	0.0988	0.5165	0.0188	0.9750
	IMF3	0.4825	0.5089	0.4772	0.4975	0.5234	0.4515	0.5994	0.5292	0.6641
	IMF average	0.8343	0.0533	0.9928	0.6394	0.990	0.0296	0.5574	0.2729	0.8196
TP7, P7, P3, Pz, P4, P8, O1, Oz, O2, TP9, TP10	Filtered Signal	0.7752	0.1479	0.9026	0.5824	0.6969	0.3795	0.4825	0.8938	0.1036
	IMF1	0.8312	0.0178	0.9964	0.6474	0.9922	0.0360	0.6174	0.7146	0.5278
	IMF2	0.8302	0.0998	0.9988	0.6444	0.9938	0.0249	0.6414	0.7813	0.5125
	IMF3	0.7033	0.2130	0.8029	0.6034	0.8234	0.2149	0.4815	0.9708	0.0307
	IMF average	0.8311	0.0980	0.9990	0.6503	0.9984	0.0332	0.5634	0.8021	0.3436

In Table I, generally the highest accuracy rate has been provided by IMF1, IMF2 and the average of first three IMFs. Valence has accuracy rates 83.02%, arousal has 64.44%, dominance has 64.14% with SVM. The highest success rates were obtained on the valence axis.

When we investigated the channel groups, the highest success rates for the first group; 83.1% in valence, for the second group; 83.4% in valence, for the third group; 83.1% in valence were obtained. When we look at the results of channel groups, overall success rates are close to each other.

To measure the activity of the channel, using different features groups and IMF1, IMF2 of signals, the channel classification has been made. In this section, the features are divided into four groups; statistical based, entropy based, peak to peak feature and Hjorth parameters. By using IMF1 and IMF2, 32 channels were classified separately.

TABLE II. EVALUATIONS OF CHANNEL ACTIVITY ACCORDING TO DIFFERENT FEATURES IN VALENCE

Features / Channels	Statistical Based		Entropy Based		Peak to Peak		Hjorth Parameters	
	IMF1	IMF2	IMF1	IMF2	IMF1	IMF2	IMF1	IMF2
Fp1	43.16	41.69	51.23	51.23	53.37	51.70	55.10	51.90
Fp2	69.73	52.25	66.67	75.13	74.00	74.67	74.53	74.60
F7	46.70	35.73	64.67	65.53	65.53	66.73	67.53	67.27
F3	53.20	62.80	53.33	54.13	51.40	51.40	67.80	46.53
Fz	46.00	41.87	51.20	53.20	54.67	52.80	56.80	46.67
F4	63.60	63.60	54.33	63.60	62.00	76.80	81.80	81.20
F8	62.00	50.73	63.40	60.33	74.93	74.80	74.73	74.40
FT7	64.80	45.93	45.80	40.73	52.87	54.40	82.20	76.40
FC3	53.40	45.47	46.93	46.87	53.00	53.67	53.40	53.07
FCz	49.20	56.27	48.53	55.93	50.60	51.40	69.13	76.13
FC4	73.60	73.80	68.80	70.93	72.47	73.00	73.73	75.40
FT8	32.33	41.93	38.20	41.07	69.73	70.07	71.10	70.53
T7	46.40	46.40	56.87	54.67	52.53	51.73	77.13	76.70
C3	46.67	47.93	55.60	48.07	49.60	52.40	53.64	52.84
Cz	53.07	56.20	60.20	73.60	57.60	58.53	73.07	70.07
C4	73.00	74.67	68.60	60.33	74.67	74.73	74.93	74.67
T8	56.47	57.93	58.33	59.20	55.60	58.00	71.40	76.00
TP7	47.73	46.53	58.00	54.40	53.27	52.20	53.53	46.13
CP3	52.73	54.87	51.20	51.73	51.60	55.13	67.80	55.67
CPz	65.87	63.73	58.13	57.33	68.27	69.93	70.13	70.60
CP4	78.13	52.32	74.07	73.80	72.93	73.67	72.67	73.67
TP7	44.33	53.80	49.60	46.67	52.47	52.27	45.73	54.33
P7	45.00	47.40	45.93	47.00	55.60	56.60	53.80	56.20
P3	44.13	50.20	44.13	57.13	55.73	55.93	56.53	57.43
Pz	74.67	60.00	46.80	49.33	75.00	75.20	75.60	75.27
P4	42.27	39.67	51.87	40.73	59.80	61.40	60.53	60.60
P8	49.40	53.40	53.33	53.33	54.13	55.93	53.67	54.27
O1	51.75	47.42	52.78	44.67	54.85	53.26	52.78	52.99
Oz	56.76	33.53	67.96	67.96	67.18	67.96	68.41	68.80
O2	45.00	49.60	74.67	74.67	74.07	74.60	74.27	73.80
TP9	48.87	50.67	50.13	50.60	51.13	52.93	51.13	53.27
TP10	37.33	56.67	53.33	53.87	57.87	55.67	53.87	54.87

When we examine Table II, we have obtained the highest success as the feature in the Hjorth parameters, the peak to peak feature, the entropy-based features, and the statistical-based features, respectively. The best channel success rates in the Hjorth parameters were obtained on the Fp2, F4, F8, FC4, FT8, T7, Cz, C4, T8, CPz, CP4, Pz and O2 channels as 74.60%, 81.90%, 74.73%, 82.20%, 76.13%, 75.40%, 71.10%, 77.13%, 73.07%, 74.93%, 76%, 70.60%, 73.67%, 75.60% and 74.27%.

When we look at the emotion recognition studies in the literature, it was observed in our study that the channels with high success rate were compatible with the effective channels determined in the literature [21].

IV. CONCLUSION

In this study, emotion recognition has been performed using visual stimulus-based EEG signals. We have evaluated the EEG signals for the classification of channels and features. We have found that IMF1 and IMF2 show the most significant results in valence, arousal, dominance states. Hjorth parameters are very effective as features.

The channels were examined separately to find the best channel activity. As a result, more successful results were obtained in occipital lobe, best channel activity has been obtained from Fp2, F4, F8, FC4, FT8, T7, Cz, C4, T8, CPz, CP4, Pz, O2 EEG channels for emotion recognition.

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