Emotion Recognition with Multi-Channel EEG Signals Using Auditory Stimulus

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Abstract—**Emotions play a significant role in daily life by encouraging the individual in the survival, decision making, guessing, and communication processes. Through emotions can be explained with the activation of anatomical structures in certain regions of brain with nervous system the emotions can be understood by electroencephalogram (EEG) signals. In order to recognize emotions, the signal processing techniques were applied to recorded signals using 32-channels EEG device from the subjects during listening audios. The Self-Assessment Manikin (SAM) form was filled by 23 subjects to evaluate their feelings based on three emotion states and recorded their answers by designed Graphical User Interface (GUI) monitored in front of the subjects. In signal processing stage, the EEG signals were segmented into segmented files by cutting stimulus intervals from recorded signal and decomposed to Intrinsic Mode Functions (IMFs) by Empirical Mode Decomposition (EMD) method. Then, most meaningful IMFs has been selected by analyzing Power Spectral Density (PSD) to extract statistical and entropy-based features and then, classification algorithm has been applied to obtain feature vector to categorize states of emotion consisting of valence, arousal, dominance dimensions. It is aimed to find most useful selected IMFs, most active channels related to emotion, best suitable features for each dimension of emotion. Finally, the percentage of performance accuracy has been calculated and the best accuracy of 81.74% is found in channels ranged in frontal lobe (1-12) for valence state, 72.15% in channel TP7 for arousal state, 74.57% in channels ranged in frontal lobe (1-12) for dominance state by combining different features.**

Keywords—EEG signal; Empirical Mode Decomposition; Emotion Recognition; Feature Extraction; Intrinsic Mode Function; Power Spectral Density; Support Vector Machine.

I. INTRODUCTION

Emotions are complicated psychological and physiological changes of an individual's mental state that occur as a consequence of an interactions between biochemical (internal) and environmental conditions. They play a significant role in almost every stage of human daily life by affecting human impulses in multiple ways directly or indirectly. Their effects on human life mainly encourage the individual in the survival, decision making, guessing, communication processes together with the cognitions [1].

Through emotions can be explained with the activation of anatomical structures in certain regions of brain with nervous system the researches have been focused on the emotion recognition with physiological signals. Many popular physiological signals used for that aim involve the EEG, electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), temperature (T), respiration (RSP) [2]. These physiological signals can't be controlled by individuals intentionally. The EEG-based method is cost-effective, non-invasive technique which indicates better temporal and spatial resolution when compared to other signals. Therefore, EEG has been preferred in plenty of emotion recognition researches due to ability of reflecting emotions more accurately at the greater resolution of frequency, time and spatial [3, 4].

A great number of researches each using a different feature extraction and classification methods have been existed to recognize state of emotion recently. The most popular signal processing method has been used for emotion recognition is EMD method which simplifies the processing of non-stationary EEG signals, and therefore without requiring prior knowledge.

Chakladar et al. [5] classified 4 emotions which are angry, harmony, negative and positive with using Higher Order Statistics (HOS) composed of skewness and kurtosis, minimum, maximum, median, standard deviation, mean and mode features after filtering signal with band pass filter and Linear Discriminant Analysis (LDA) was used as a classifier. They tried different reduction of dimension method that is based on correlation to select subsets and obtained 82% accuracy with decreased channels.

Chen et al. [6] investigated 4 emotion states which were happiness-sadness and calmness-fear with using EMD methods to obtain IMFs which were used to calculate Approximate Entropy (ApEn) of each IMF after using Independent Component Analysis (ICA) to remove noises. The 16 features were found for each channel at the end of the feature extraction method. Deep Belief Network (DBN) and Support Vector Machine (SVM) were integrated to classify features and gave most accuracy rate 87.32% when compared with other classification methods as SVM, k-Nearest Neighbor (k-NN). Also, this research it was proven that gamma and beta bands are more appropriate for emotion analysis.

Mert et al. [7] used Multivariate Synchrosqueezing Transform (MSST) for extraction of features with the combination of ICA for dimension reduction in their research to represent arousal and valence states of emotions in time-frequency domain. According to results of comparing non-

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negative matrix factorization (NMF) as reduction method combined with Wigner-Ville distribution (WVD) as feature extraction method, the best accuracies 82.11% for arousal, 82.03% for valence were obtained by MSST-ICA technique with the Artificial Neural Network (ANN) classifier instead of both k-NN and SVM classifiers.

In this study, EMD method was used as signal processing technique to decompose raw signal into IMFs and then first 3 IMFs together with the raw signal were selected using PSD analysis to extract statistical and entropy based features and then, classification algorithm (SVM) were applied to EEG signals which are obtained from 23 subjects (12 females, 11 males) with listening the stimulus as sounds using auditory stimulus data-set to increase accuracy of emotion recognition. According to emotion model valence, dominance and arousal dimensions were classified for each channel combined with different feature groups.

II. Material and Method

A. Experimental Setup

In this experiment, The International Affective Digitized Sounds (IADS-2) were used as audial stimuli. The 48 sounds were chosen based on the mean of assessed arousal, valence and dominance dimension values for all participants by considering the 8 emotion states. These 8 states are Positive/ Low arousal /Low dominance (PLL), Positive/ Low arousal /High dominance (PLH), Positive/ High arousal/ Low dominance (PHL), Positive/ High arousal/ High dominance (PHH), Negative/ Low arousal /Low dominance (NLL), Negative/ Low arousal /High dominance (NLH), Negative/ High arousal /Low dominance (NHL), and Negative/ High arousal /High dominance (NHH) [8]. 6 sounds for each case were selected by considering the extreme values of dimensions to assure to exposure of each emotion. In addition to IADS sounds, 12 audial stimuli taken by a piece of music were selected as stimuli. Totally 60 sounds were considered to use as audial stimuli.

Self-assessment is necessary to identify real emotions because emotions towards the same sounds, pictures or videos are subjective and vary from person to person. SAM shown in Fig. 1. is a pictorial self-assessment form that is scaled from 1 to 9, which directly measures the parameters of pleasure, arousal, dominance associated with a person's emotional responses to various stimuli [9]. The markings higher than 5 are assumed high valence, high arousal and high dominance while the markings lower than 5 are assumed low valence, low arousal and low dominance for the classification step.

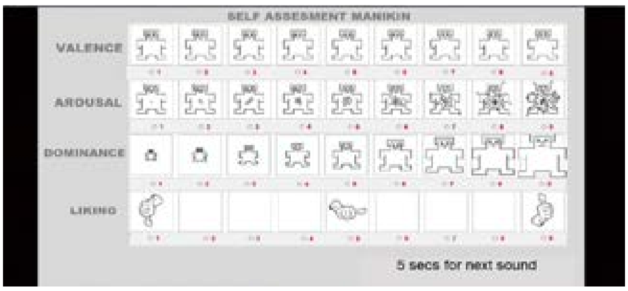

Fig. 1. SAM Form monitored in GUI during experiment.

The MATLAB GUI was used to design program that can display stimuli one by one without the need for user selection, automatically. The answers of SAM Forms belong to subjects were recorded thanks to designed GUI. Each trial of audio loop consists of 60 seconds preparation process for the relaxation, 6 seconds listening stimuli, 14 seconds displaying SAM digital form, 5-seconds countdown before passing on to next stimulus and one second black screen before passing next stimulus as seen in Fig. 2.

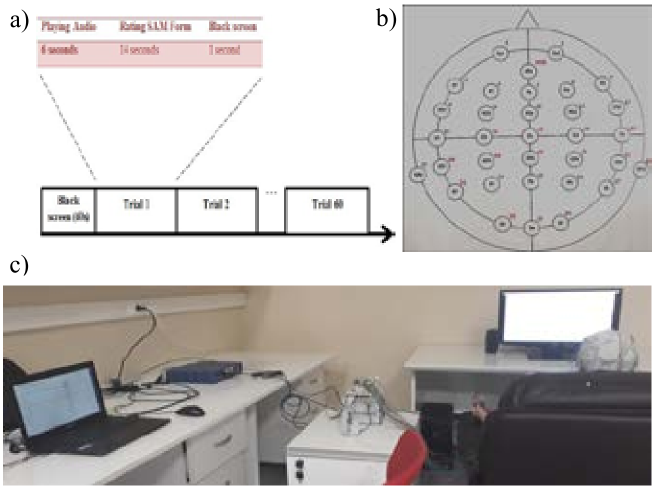

Fig. 2. a) A protocol of experiment. b) EEG channel representation of 32-Channel Brain Vision EEG device. c) A subject during experiment.

Band pass filter was formed using 0.7 Hz low-pass and 250 Hz high-pass filter before starting of EEG recording on the recorder software of EEG device.

B. Processing of Data

The proposed method after collecting all filtered EEG data is given in Fig. 3.

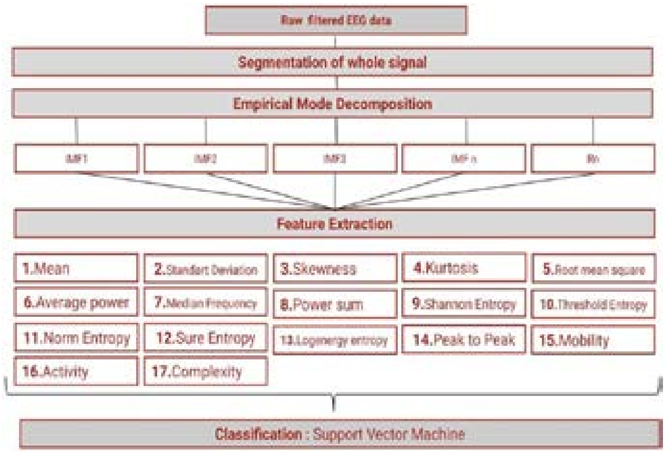

Fig. 3. Block diagram of targeted model.

Whole EEG recording was segmented in time domain to extract meaningful segments as during stimuli with extracting recording before starting of stimuli loop, a record of 15 seconds marking SAM form of each stimulus and 60 seconds baseline signal recording.

EMD is a time-frequency based signal processing technique that can decompose a data set or signal into a finite number of components near the station. The principal algorithm of EMD method as shifting in Fig. 4. was applied until IMFs satisfy these conditions; the number of end points must be equal to number of zero crossings or equal to 1 at difference and mean of the upper and lower envelopes must be zero. An example of IMFs formed as a result of EMD is shown in Fig. 5.

The EMD Shifting Process

- Local minimum and maximum points of $x(t) = \sum_{n=1}^{N}(IMF_n + R)$ are found.
- The upper $e_{max(t)}$ and lower $e_{min(t)}$ envelopes are obtained by integrating extremity points with cubic interpolation. Mean values at every point of envelopes are obtained $m(t) = \frac{e_{max(t)}+e_{min(t)}}{2}$
- If $h(t)$ meets IMF criteria, $IMF_n = h(t)$ and go to next step. Otherwise, suppose $x(t) = h(t)$ and cycle it again to occur $h_2(t)$. $h(t) = x(t) - m(t)$
- If $h_2(t)$ is not able to satisfy the two conditions, the stop criterion as standard deviation (SD) is calculated to terminate the elimination process. If $x(t)$satisfies the stop criteria, it is stopped and saved as residue $R(t) = h(t)$. $R(t) = R(t) - IMF_n$

Fig. 4. The steps of EMD algorithm's shifting process.

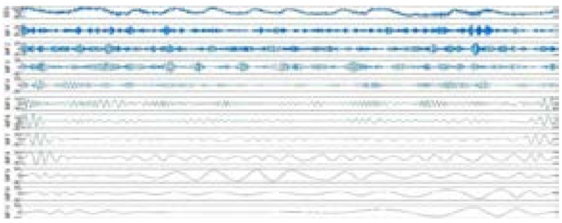

Fig. 5. IMFs of 1^{st} channel of signal of PHH sound (IADS no: 311).

C. IMF Selection Method

The Welch method estimates the power spectral density by means of averaged periodograms [10]. PSD of each IMF were calculated with periodogram using square of absolute FFT (Fast- Fourier Transform) of IMFs and also P-Welch method. The first three IMFs and average of these 3 IMFs were chosen due to meaningful results were obtained due to wide distribution of power over the frequency as shown in Fig. 6.

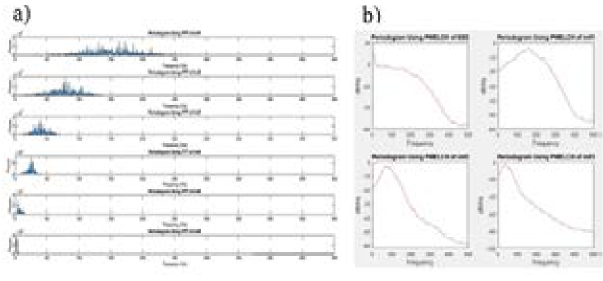

Fig. 6. a) Distribution of power per frequency periods of 6 IMFs (happy sound/IADS no: 352). b) PSD using P-Welch method of 4 IMFs.

D. Feature Extraction

In order to distinguish of success of variety of statistical and entropy-based features different kinds of features were used with different combination to extract feature vector as given in Table I.

E. Classification

SVM was designed with the aim of binary classifications and it is possible to obtain certain classification results using small number of sample of data [11]. SVM was used to classify 2 classes (True Positive, True Negative) for each emotion state which are valence, arousal, and dominance.

TABLE I. COMBINATIONS OF FEATURES EXTRACTED FOR CLASSIFICATION.

Group 1	Mean, Standard Deviation, Skewness, Kurtosis, Root Mean Square, Average Power, Median Frequency
Group 2	Power Sum, Shannon Entropy, Threshold Entropy, Norm Entropy, Sure Entropy, Log Energy Entropy
Group 3	Mean, Standard Deviation, Skewness, Kurtosis, Root Mean Square, Average Power, Median Frequency, Peak to Peak, Activity, Mobility, Complexity
Group 4	Root Mean Square, Average Power, Median Frequency, Peak to Peak, Activity, Mobility, Complexity
Group 5	Hjorth parameters (activity, mobility, complexity)
Group 6	Kurtosis, Root Mean Square, Average Power, Median Frequency, Peak to Peak, Activity, Mobility, Complexity

III. RESULTS AND DISCUSSION

In this study, it is aimed to classify the emotions based on dimensions of valence, arousal, and dominance and results were investigated to find most useful IMFs obtained by decomposing raw signal using EMD method, most active channels related to emotion, best suitable feature groups for each dimension of emotion.

Table II shows that the most successful IMF is IMF 1; IMF 2, IMF 3 and average of three IMFs indicated success at the same number in valence state. When we compare the performance of feature groups, it is seen that the best accuracy 81.74% belongs to group 4 and group 6 in channels ranged 1-12. Features of group 1 shows highest accuracy 75.01% in channels ranged 13-22 while features of group 4 indicates most accuracy 73.04% in channels ranged 23-32. Table III shows that the most successful IMF is IMF 1 and IMF 2 follows this success, IMF 3 and average of three IMFs indicated slightly success in arousal state. When we compare the performance of feature groups, it is seen that the best accuracy 59.35% belongs to group 1 in channels ranged 1-12. Features of group 4 shows highest accuracy 61.38% in channels ranged 13-22 while features of group 6 indicates most accuracy 59.42% in channels ranged 23-32. In Table IV, it is seen that the best accuracy 74.57% belongs to group 3 in channels ranged 1-12. Features of group 6 and 3 show highest accuracy 59.42% in channels ranged 13-22 while features of group 4 indicates most accuracy 59.93% in channels 23-32.

The accuracy rates for each 32 channels also calculated and some channels showed higher success for each emotion state. The channels 22 (TP8), 31 (TP9) and 32 (TP10) have better accuracy rates noticeably which are 67.15%, 65.77%, 63.52% respectively in valence state. In arousal state, one-channel accuracies indicate broad distributions over channels when we compare it with valence state, so most of channels reach accuracies over 65% which are 18 (TP7), 32 (TP10), 2 (Fp2), 30 (O2), 27 (P8), 25 (Pz), 26 (P4), 5 (Fz), 10 (FCz), 1 (Fp1), 22 (TP8), 13 (T7), 28 (O1), 29 (Oz), 24 (P3), 19 (CP3) , 4 (F3), 6 (F4), 11 (FC4), 23 (P7) correspond to accuracies 72.15%, 71.94%, 70.85%, 70.41%, 70.7%, 69.04%, 68.82%, 68.67%, 68.46%, 68.31%, 68.09%, 67.59%, 67.15%, 67.15%, 67.08%, 66.42%, 66.13%, 65.99%, 65.77%, 65.05%, respectively. In dominance state, the accuracies of channel 23 (P7) and 32 (TP10) are slightly higher than accuracy of other EEG channels with the accuracy rates of 61.35%, 60.91% respectively.

TABLE II. ACCURACY (ACC), SENSITIVITY (SEN), SPECIFICITY (SPE) OF EACH IMF CORRESPONDING FEATURE GROUPS IN VALENCE.

FEATURE GROUP	VALENCE STATE	Channels Between 1-12					Channels between 13-22					Channels between 23-32				
		IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signal	IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signal	IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signal
	SEN (V>5)	0.7381	0.1031	0.4484	0.0458	0.8204	0.7284	0.2320	0.9627	0.7788	0.4129	0.6052	0.9781	0.5287	0.4891	0.0533
	SPE (V<5)	0.8698	0.9544	0.8659	0.9948	0.1434	0.7702	0.9161	0.0223	0.5855	0.5836	0.8112	0.0260	0.8867	0.8607	0.9349
1	ACC	0.8115	0.5772	0.6809	0.5743	0.4523	0.7511	0.6315	0.4135	0.6737	0.5057	0.7107	0.4907	0.7120	0.6793	0.5047
	SEN (V>5)	0.8702	0.4052	0.9444	0.9918	0	0.7941	0.2026	0.1422	0.3382	0	0.5654	0.3791	0.9167	0.0049	0
	SPE (V<5)	0.0417	0.9792	0.0482	0.0299	1	0.0326	0.9193	0.8698	0.8216	1	0.4622	0.7201	0.1589	0.9740	1
2	ACC	0.4460	0.7246	0.4457	0.4565	0.5565	0.3703	0.6014	0.5471	0.6072	0.5565	0.5080	0.5688	0.4949	0.5442	0.5565
	SEN (V>5)	0.7386	0.0408	0.8644	0.1111	0.0196	0.5670	0.1291	0.4510	0.2729	0	0.9641	0.2778	0.4134	0.4232	0.9722
	SPE (V<5)	0.8763	0.9792	0.0911	0.9714	0.9531	0.8555	0.9648	0.8307	0.9297	0.9740	0.0313	0.9609	0.9427	0.9232	0.0156
3	ACC	0.8152	0.5630	0.4341	0.5899	0.5391	0.7275	0.5942	0.6623	0.6384	0.5420	0.4449	0.6580	0.7080	0.7014	0.4399
	SEN (V>5)	0.7516	0.0441	0.9788	0.0327	0.0310	0.6863	0.2892	0.9461	0.1242	0.9395	0.6095	0.9902	0.4232	0.4003	0.0098
	SPE (V<5)	0.8698	0.9714	0.0313	0.9727	0.9479	0.0964	0.7891	0.0378	0.9583	0.0130	0.8268	0.0260	0.9284	0.8997	0.9349
4	ACC	0.8174	0.5601	0.4514	0.5558	0.5413	0.3580	0.5674	0.4406	0.5884	0.4239	0.7304	0.4536	0.7043	0.6783	0.5246
	SEN (V>5)	0.1765	0.0392	0.9608	0	0	0.2026	0.0261	0.2337	0	0.5458	0.2451	0.0016	0.0458	0	0
	SPE (V<5)	0.9844	0.9779	0.0156	0.9987	0.9688	0.9818	0.9870	0.8984	0.9987	0.6992	0.9844	0.9961	0.9740	1	0.9622
5	ACC	0.6261	0.5616	0.4348	0.5558	0.5391	0.6362	0.5609	0.6036	0.5558	0.6312	0.6565	0.5551	0.5623	0.5565	0.5355
	SEN (V>5)	0.7418	0.1373	0.9461	0.9363	0.2353	0.5784	0.1340	0.4608	0.3578	0	0.5997	0.9902	0.3987	0.4150	0
	SPE (V<5)	0.8776	0.9102	0.0365	0.1706	0.9036	0.8503	0.9531	0.8255	0.8854	0.9740	0.8203	0.0260	0.9349	0.9167	0.9727
6	ACC	0.8174	0.5674	0.4399	0.5101	0.6072	0.7297	0.5899	0.6638	0.6514	0.5420	0.7225	0.4536	0.6971	0.6942	0.5413

TABLE III. ACCURACY (ACC), SENSITIVITY (SEN), SPECIFICITY (SPE) OF EACH IMF CORRESPONDING FEATURE GROUPS IN AROUSAL.

FEATURE GROUP	AROUSALS TATE	Channels Between 1-12					Channels between 13-22					Channels between 23-32				
		IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signa	IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signal	IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signa
	SEN (A>5)	0.9805	0.9948	0.9922	0.9948	0.0599	0.9714	0.8763	0.9661	0.8815	0.1576	0.9987	0.9922	0.9935	0.9987	0.4017
	SPE (A<5)	0.1078	0.0163	0.0212	0.0408	0.9183	0.1111	0.2582	0.0621	0.2647	0.8775	0	0.0556	0.0131	0.0163	0.6287
1	ACC	0.5935	0.5609	0.5616	0.5717	0.4406	0.5899	0.6022	0.5652	0.6080	0.4768	0.5558	0.5768	0.5587	0.5630	0.5242
	SEN (A>5)	0.6667	0.5521	0.3220	0.4831	1	0.9570	0.2253	0.4727	0.8034	1	0.9727	0.0260	0.1693	0.0508	0.7826
	SPE (A<5)	0.4216	0.4232	0.7288	0.4232	0	0.1029	0.9052	0.4559	0.1389	0	0.0899	0.9657	0.8186	0.9820	0.2778
2	ACC	0.5580	0.4949	0.5080	0.4565	0.5565	0.5783	0.5268	0.4652	0.5087	0.5565	0.5812	0.4428	0.4572	0.4683	0.5587
	SEN (A>5)	0.9648	0.9909	0.9076	0.9987	0.0872	0.9635	0.9635	0.9792	0.9870	0.0130	0.9935	0.9297	0.9961	0.9948	0.0156
	SPE (A<5)	0.1013	0.0392	0.1748	0.0539	0.8922	0.1732	0.1258	0.0408	0.0539	0.9837	0.0033	0.1634	0.0212	0.0278	0.9673
3	ACC	0.5819	0.5688	0.5826	0.5797	0.4442	0.6130	0.5920	0.5630	0.5732	0.4435	0.5543	0.5899	0.5638	0.5659	0.4377
	SEN (A>5)	0.9714	0.9857	0.1055	0.9974	0.0273	0.8971	0.8542	0.9961	0.9727	0.0143	1	0.9323	0.9974	0.9961	0.0599
	SPE (A<5)	0.0801	0.0376	0.9281	0.0670	0.9461	0.2582	0.2353	0.0114	0.0719	0.9673	0.0016	0.1650	0.0278	0.0163	0.9346
4	ACC	0.5761	0.5652	0.4703	0.5848	0.4348	0.6138	0.5797	0.5594	0.5732	0.4370	0.5572	0.5920	0.5674	0.5616	0.4478
	SEN (A>5)	0.9844	0.9935	0.9948	1	0.9401	0.8893	0.9870	0.9935	0.0326	0.0130	0	0.9818	0.9974	0.9987	0.9857
	SPE (A<5)	0.0245	0.0065	0.0082	0	0.0507	0.1503	0.0147	0.0049	0.9951	0.9869	1	0.0735	0.0065	0.0163	0.0147
5	ACC	0.5587	0.5558	0.5572	0.5565	0.5457	0.5616	0.5558	0.5551	0.4594	0.4449	0.5565	0.5790	0.5580	0.5630	0.5551
	SEN (A>5)	0.9596	0.9948	0.0846	0.9922	0.0247	0.9466	0.9779	0.9727	0.9779	0.0130	0.9987	0.9427	0.9987	0.9987	0.0130
	SPE (A<5)	0.1160	0.0310	0.9526	0.0556	0.9493	0.1732	0.0458	0.0605	0.0441	0.9673	0	0.1569	0.0229	0.0212	0.9788
6	ACC	0.5855	0.5674	0.4696	0.5768	0.4348	0.6036	0.5645	0.5681	0.5638	0.4362	0.5558	0.5942	0.5659	0.5652	0.4413

TABLE IV. ACCURACY (ACC), SENSITIVITY (SEN), SPECIFICITY (SPE) OF EACH IMF CORRESPONDING FEATURE GROUPS IN DOMINANCE.

FEATURE GROUP	DOMINANC E STATE	Channels Between 1-12					Channels between 13-22					Channels between 23-32				
		IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signa	IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signal	IMF 1	IMF 2	IMF 3	IMF AVG	Raw Signal
	SEN (D>5)	0.0339	0.9701	0.0221	0.8971	0.0911	0.9974	0.9896	0.9922	1	0.9792	1	0.9948	0.9948	0.9987	0.0599
	SPE (D<5)	0.9036	0.0670	0.9804	0.5441	0.9232	0.0098	0.0114	0.00098	0	0.0163	0	0.0131	0.0098	0.0016	0.9167
1	ACC	0.4196	0.5696	0.4471	0.7406	0.4601	0.5594	0.5558	0.5565	0.5565	0.5522	0.5565	0.5594	0.5580	0.5565	0.4399
	SEN (D>5)	0.9818	0.5820	0.2109	0.7695	1	0.4167	0.9440	0.4427	0.9935	1	0.2760	0.9688	0.4948	0.9779	0.5625
	SPE (D<5)	0.0997	0.0490	0.9592	0.1699	0	0.5261	0.0261	0.4281	0.0016	0	0.6522	0.0163	0.7042	0.0163	0.3382
2	ACC	0.5906	0.3457	0.5428	0.5036	0.5565	0.4652	0.5370	0.4362	0.5536	0.5565	0.4442	0.5464	0.5877	0.5541	0.4630
	SEN (D>5)	0.0417	0.882	0.8893	0.9076	0.2331	0.9206	0.0247	0.9857	0.9440	0.0859	0.9349	0.9779	0.9909	0.9805	0.0859
	SPE (D<5)	0.8938	0.5735	0.5359	0.5310	0.6650	0.1520	0.9837	0.0065	0.1552	0.9248	0.1503	0.1046	0.0114	0.0507	0.9314
3	ACC	0.4196	0.7457	0.7326	0.7406	0.4246	0.5797	0.4500	0.5514	0.5942	0.4580	0.5870	0.5906	0.5565	0.5681	0.4609
	SEN (D>5)	0.8411	0.8958	0.9063	0.9219	0.1159	0.9909	0.9844	0.9922	0.9805	0.1732	0.5990	0.9870	0.9883	0.9844	0.0977
	SPE (D<5)	0.6046	0.5458	0.4820	0.4739	0.9412	0.0131	0.0131	0.0147	0.0261	0.8186	0.5997	0.0114	0.0131	0.0163	0.9706
4	ACC	0.7362	0.7406	0.7181	0.7232	0.4819	0.5572	0.5536	0.5587	0.5572	0.4594	0.5993	0.5543	0.5558	0.5551	0.4848
	SEN (D>5)	0.9792	0.9857	0.9844	0.9909	0.2695	0.9935	0.9961	0.9961	0.9870	0.0794	1	1	0.9935	1	0.0352
	SPE (D<5)	0.1258	0.0082	0.0098	0.0065	0.7190	0.0016	0.0114	0	0.0163	0.8840	0	0.0131	0.0049	0.0163	0.9820
5	ACC	0.6007	0.5522	0.5522	0.5543	0.4688	0.5536	0.5594	0.5543	0.5565	0.4362	0.5565	0.5623	0.5551	0.5638	0.4551
	SEN (D>5)	0.8398	0.8893	0.8737	0.9206	0.1107	0.9427	0.9870	0.9870	0.9492	0.1497	0.9284	0.9720	0.9870	0.9701	0.0716
	SPE (D<5)	0.6144	0.5588	0.5801	0.4951	0.9493	0.1258	0.0180	0.0049	0.1487	0.8693	0.1487	0.1160	0.0114	0.0588	0.9575
6	ACC	0.7399	0.7428	0.7435	0.7319	0.4826	0.5804	0.5572	0.5514	0.5942	0.4688	0.5826	0.5928	0.5543	0.5659	0.4645

IV. CONCLUSION

In conclusion, it can state that prediction of emotion using EEG signals can give more accurate results if true technique is selected especially for EMD method, if most useful IMFs are used, if most suitable features are used before classification, and if appropriate channels are selected that is more related to emotion area in brain.

In this study different kind of features and combinations of channels were used to increase success and the best accuracy 81.74% is found in channels ranged in frontal lobe (1-12) for valence state, 72.15% in channel TP7 for arousal state, 74.57% in channels ranged in frontal lobe (1-12) for dominance state by using EMD algorithm. The temporal lobe indicated higher accuracy with the audios used in the experiment due to the sounds are interpreted with the existence of auditory cortex in that lobe.

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