TIPTEKNO'18
TIP TEKNOLOJİLERİ KONGRESİ
8-10 Kasım 2018 / Gazi Magosa / KKTC

Emotion Recognition from EEG Signals by Using Empirical Mode Decomposition

Murside DEGIRMENCI and Mehmet Akif OZDEMIR
Department of Biomedical Engineering
Izmir Katip Celebi University
Izmir, Turkey
mrsddgrmnc.09@gmail.com, makif.ozdemir@ikc.edu.tr

Reza SADIGHZADEH[1] and Aydin AKAN[2]
[1]Business Administration, [2]Biomedical Engineering
Izmir Katip Celebi University
Izmir, Turkey
riza@taimaksan.com, aydin.akan@ikc.edu.tr

***Abstract*— This study investigates improved properties of empirical mode decomposition (EMD) for emotion recognition by using electroencephalogram (EEG) signals. The emotion recognition from EEG signals is a difficult study by the reason of nonstationary behavior of the signals. These signals are affected from complicated neural activity of brain. To analyze EEG signals, advanced signal processing techniques are required. In our study, data are collected from one channeled BIOPAC lab system. EEG signals were obtained from visual evoked potentials of 13 female and 13 male volunteers for 12 pleasant and 12 unpleasant pictures. To analyze nonlinear and nonstationary characteristics of EEG signals, an EMD-based method is proposed for emotion recognition. Various time and frequency domain techniques such as power spectral density (PSD), and higher order statistics (HOS) are used to analyze the IMFs extracted by EMD. Support vector machine (SVM), Linear discriminant analysis (LDA), and Naive Bayes classifiers are utilized for the classification of features extracted from the IMFs, and their performances are compared.**

Keywords*— Emotion recognition; Electroencephalogram; Empirical mode decomposition; Intrinsic mode functions; Power spectral density; Higher order statistics; Support vector machine; Naive Bayes; Linear discriminant analysis

I. Introduction

Emotion is personally conscious, characterized by mental states or unconscious experience that are characterized with physiological expressions, biological reactions, and mental states. In recent years, the machine interaction, communication between people and machines has begun to take an important place. To create an interactive interface, machines must be equipped with units for describing developing brain computer interfaces and the emergence of human and perceiving human emotions [1].

Brain-computer interface (BCI) has been one of the most important research field [2]. It can be thought of as technology that control external devices by modulating brain waves of humans. Applications of BCI known as noninvasive brain signal processing, a lot of successful EEG-based BCI applications are available. It can be used for understanding mental states of the person. Algorithms fill the gap between human and machine interactions [1].

In recent years, different types of EEG based emotion recognition algorithms were introduced [2-5]. The electrical potentials of neurons in the brain are recorded and they are known as EEG signals. The electrodes on the scalp provide EEG signal. The noninvasive measurement of EEG signal is provided with the helping of the 10-20 electrode positioning system [2].

To analyze the signals of EEG studies, some decomposition methods are used. In nonlinear and nonstationary time series, EMD is most using recurrent method [6]. IMFs that are known as oscillations into a signal are obtained by decomposing EEG signal. The various time and frequency techniques are used to analyze IMFs extracted by EMD.

A study that is conducted by [2] examine emotion recognition with using multivariate empirical mode decomposition (MEMD)-based feature extraction method. Emotion recognition showed as high/low arousal and high/low valence states [7]. DEAP emotional EEG data set are used to analyze as test data [8, 9]. They compared their study with previous studies that used MEMD algorithm for feature extraction. Band power ratios, power spectral density, Hjorth parameters [10], entropy, spectral power asymmetry, correlation, and coherence are used to analyze IMFs of the EEG signals. The k-nearest neighbor (k-NN) and artificial neural network (ANN) were used to classify the IMFs. The accuracy rate of k-NN is 51.01, and the accuracy rate of ANN is 75 for arousal and valence states. Therefore, this study showed that ANN gives higher accuracy to emotion recognition of EEG signals.

In this work, EMD-based features were used for classification of emotions from EEG signal to define emotional state as pleasant (happy) or unpleasant (unhappy). Visual evoked potentials (VEPs) obtained from 26 (13 females, 13 males) volunteers. EEG signals are decomposed by EMD, and extracted IMFs are analyzed using various signal processing methods namely PSD, and first, second, third, fourth moment for feature extraction. To increase accuracy rate of the emotion recognition, oscillations in the EEG signal are extracted on most of the IMFs. To classify extracted features, SVM, Naive

Bayes, LDA classifiers were used and compared their performance in classification.

II. MATERIAL AND METHOD

A. Data Collection

The experiment is emotion recognition by showing 12 images that can fell happy (pleasant images) and 12 images that can feel bad or angry (unpleasant images).

Firstly, 24 pictures were chosen, 12 of them had to be pictures that are reminiscent of pleasant things or that feel good, and the other 12 had to be pictures that are reminiscent of unpleasant things. This experiment was performed with the help of 13 female and 13 male volunteers. In the experimental phase, two computer systems (one used for slide show and the other used for EEG recording), BIOPAC Electrode Lead Test (SS2L), three BIOPAC disposable electrodes for each subject, BIOPAC student lab systems were used. The 10-20 EEG electrode position system is the most favorite placement scheme that is defined by the International Federation of EEG Societies [2, 8]. This system is defined the boundary of the electrode positions is the root of the nose, nasion, and the inion ossification on the occipital lobe.

During the EEG recording, the red lead known as signal lead is places 10% above from inion point and between O1 and O2 in the experiment because the occipital lobe is said to be here according to 10-20 EEG electrode position system as shown in Fig. 1. (a). The black lead known as ground lead is attached to electrode that is placed on the right ear as shown in Fig. 1(b). The white lead known as reference lead is attached to electrode that is placed on the left ear as shown in Fig. 1(c).

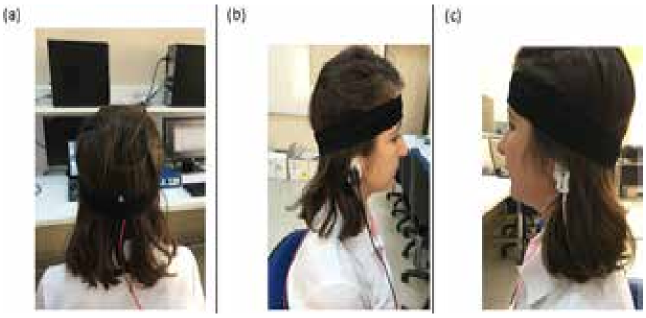

Fig 1. (a) Placement of signal lead on occipital lobe; (b) Placement of ground lead on right ear; (c) Placement of reference lead on left ear.

The signal processing of EEG signals that were received from subjects, was conducted with the helping of MATLAB®. The unwanted signals are mixed in the signals that were received. To get rid of their effects some signal filtering techniques were used. In this study, firstly a Butterworth 10th order low pass filter that has cutoff frequency of 40 was applied. Then a Butterworth 3th order high pass filter that has passband frequency of 0.2. By applying low pass and high pass, band pass filter effect was created. The flow chart of the operations to be performed after the filtration is available in Fig. 2.

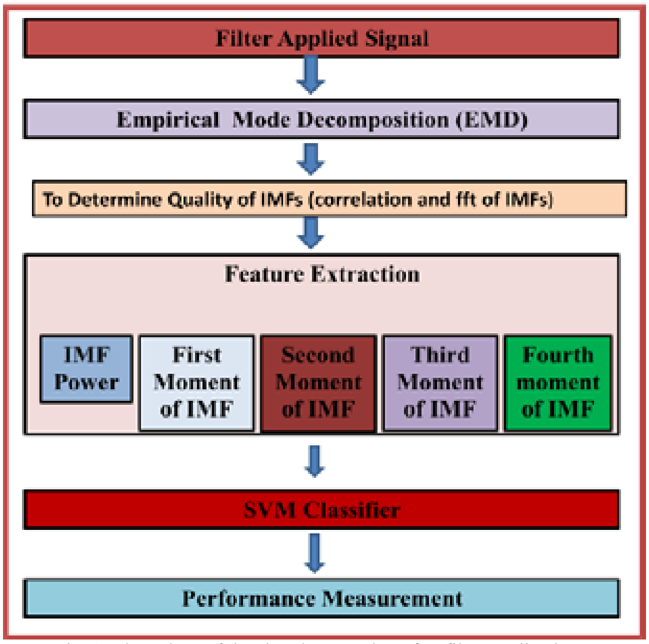

Fig. 2. Flow chart of the signal processing after filter applications.

B. Empirical Mode Decomposition

Huang et al in 1998 [11], suggested EMD that is an adaptive and data driven signal processing technique. The intrinsic mode functions are obtained from decomposition of multicomponent signal with the helping of EMD. If the amplitude and frequency modulated IMFs are collected, total will obtain original signal. EMD is an alternative method, which can be used in the analysis of non-linear and non-stationary signals. By using the EMD, multiple components are opened in the form of zero mean IMFs that occur part of the signals. Thus, which IMF is meaningful for the purpose of the work being done, it can be used and the analysis of the signal is easier. The IMF number of signal and statistical properties of IMFs are different for signal of each picture. The shifting process is the main part of the algorithm. EMD algorithm steps are available in Fig. 3.

The Algorithm Steps

(i) The local maxima as Mj, j=1, 2, . . ., and minima as mp, p=1, 2, ... , are determined.

(ii) The lower and upper envelopes are found by the interpolating signals m(n)= *f*m (mp, n), and M(n)= *f*m (Mj, n) with cubic spline.

(iii) The mean of envelopes are computed. H(n)= [m(n) + M(n)]/2

(iv) If IMF requirements is supplied by H(n), take it as an IMF Q(n)=H(n), and subtraction of H(n) from original signal is made; Y(n)= Y(n)-H(n).

(v) The residue of Y(n) signal take as R(n)=H(n), for stopping criteration of Y(n) signal

Fig. 3. EMD algorithm steps.

These operations continue until the following stopping criteria supplied.

$$SD=\sum_{J=0}^{N-1}\left[\left[\frac{|H(p-1)(n)-H(p)(n)|^2}{H^2(p-1)(n)}\right]\right] \quad (1)$$

where p and n represent iteration number of the shifting processes and sample total number. The original signal can be showed by the IMFs as following (2).

$$Y(n)=\sum_{j=1}^{L} Qj(n)+R(n) \quad (2)$$

In Fig. 3, step (v) gives idea about the stopping criterion, it provides standard deviation method (SD)-based method search out the retained signal changes available or not. The IMFs obtained from original signal have to two important criteria at least. These are, it must have equal number of the extreme and the number of zero crossing or must differ only one of them and the local maxima and minima of the IMF must be used to determine the envelopes [2-6]. So IMFs have limited instantaneous frequency and bandwidth [12]. The example of the IMFs are obtained from decomposition of multicomponent signal with the helping of EMD in Fig. 4.

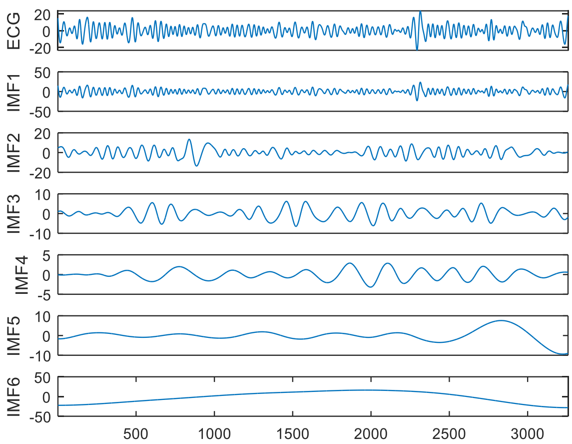

Fig. 4. IMFs were obtained from EMD that decomposes a happy image.

C. Selection of the IMFs

After EMD application, more than one IMF is obtained. But the identified feature extraction techniques were applied to some of the IMFs. That's way, determination of the most meaningful IMF is necessary to apply feature extraction for classification. IMF1 and IMF2 were the most meaningful IMFs based on their spread in frequency bands and their bandwidth for choosing the most meaningful IMF. Also, IMF1 and IMF2 gave the highest correlation value.

D. Feature Extraction

In feature extraction step, the total power of the IMF1s and IMF2s, and the higher order frequency moments $<\omega^n>$, n= 1,2,3,4 of IMF1s and IMF2s are used for each data. The feature of IMFs was calculated and the difference between the groups was examined by using a periodogram. The power spectral analysis is based on estimation the power distribution over the frequency band of a stationary random system with signal that has final length. The power distribution of the signal over the frequencies is obtained by the Power Spectral Density (PSD). The PSDs of the signals in our study are estimated by the Periodogram which is calculated by the magnitude square of the discrete Fourier transform *X[k]* of the signal,

$$S(k)=\frac{1}{L}|X[k]|^2 \quad k=1, \ldots., L, \quad (3)$$

$$Ptotal=\sum_{k=1}^{L} S[k]. \quad (4)$$

In equations (3) and (4), the calculation of the periodogram estimate of the PSD, and the total power applied to IMF1s are given. The length of IMFs is referred as L in (3) and (4). In addition, higher order frequency moments are calculated as,

$$m_n=\sum_{m=1}^{L}\left(\frac{2\pi m}{L}\right)^n S(m) \quad n=1,2,3,4. \quad (5)$$

where m_n shows the n^{th} order frequency moment of the signal and n changes from 1 to 4. First, second, third, and fourth order moments of IMF1s and IMF2s are calculated as features to be used in classification.

E. Classification

Classification is done after the appropriate features are extracted and the feature vector is created. Classifiers are initially trained and then determine the class of an unknown feature vector. To determine the performance of the classifiers, the training and test data sets are determined by using LOO Cross Validation scheme [13, 14]. Therefore, some of the data are used as test data, the rest another data are used as training data. In this study, a training data of 624 x 15 matrix of IMF1 and IMF2 that include PSD, moment1, moment2, moment3, moment4 of original (signal that did not apply EMD), PSD, moment1, moment2, moment3, moment4 of IMF1 and IMF2. SVM, LDA, Naive Bayes classifiers were used for classification of feature extracted IMFs.

F. Performance Measurement

Performance evaluations (accuracy, sensitivity, specificity) that are used for performance measurement are given in (6), (7), (8).

$$ACC=\frac{Tp+Tn}{Tp+Fp+Fn+Tn} \quad (6)$$

$$SEN=\frac{Tp}{Tp+Fn} \quad (7)$$

$$SPE=\frac{Tn}{Tn+Fp} \quad (8)$$

Here, Tp shows that it actually belongs to a class the number of data assigned to the same class by the classifier, Fn indicates the number of data that is assigned incorrectly to a different class. TN actually belongs to a different class, the number of data assigned to a different class by the classifier, FP incorrectly indicates the number of data that is assigned to the same classifier [15].

III. RESULTS AND DISCUSSION

Pleasant and unpleasant state of participants are recognized by using EMD based features with SVM, LDA, Naive Bayes classifiers, and their performances are compared.

TABLE I. The evaluations of the SVM classifier.

SVM CLASSIFIER	TP	TN	FP	FN	ACC	SEN	SPE
Class1 (Happy)	58	263	30	71	0.76	0.44	0.89
Class2(Unhappy)	82	222	105	33	0.72	0.41	0.67
Class3 (Happy)	16	330	8	68	0.82	0.19	0.97
Class4(Unhappy)	79	288	42	13	0.87	0.86	0.87

TABLE II. The evaluations of the LDA classifier.

LDA CLASSIFIER	TP	TN	FP	FN	ACC	SEN	SPE
Class1 (Happy)	20	447	21	136	0.74	0.12	0.95
Class2(Unhappy)	21	429	39	135	0.70	0.07	0.91
Class3 (Happy)	44	357	111	112	0.64	0.28	0.76
Class4(Unhappy)	114	204	264	42	0.50	0.73	0.53

TABLE III. The evaluations of the Naive Bayes classifier.

Naive Bayes CLASSIFIER	TP	TN	FP	FN	ACC	SEN	SPE
Class1 (Happy)	18	455	13	138	0.75	0.11	0.97
Class2(Unhappy)	6	460	8	150	0.74	0.03	0.98
Class3 (Happy)	7	449	19	149	0.73	0.04	0.95
Class4(Unhappy)	155	70	398	1	0.36	0.99	0.14

If the classification algorithms are compared, the SVM classifier could distinguish both pleasant and unpleasant state with very high accuracy rate. It is understood that the SVM is a convenient and highly accurate algorithm for emotion recognition.

IV. CONCLUSION

In this paper, we present an EMD-based feature extraction method for emotion recognition as pleasant and unpleasant states. We used EEG signals obtained from visual evoked potentials of 13 female and 13 male volunteers as response to 12 happy and unhappy images. EMD that is an appropriate method to analyze nonlinear and nonstationary time series is utilized. It decomposed the signal into IMFs. Some frequency domain features such as PSD, and higher order frequency moments are used for the classification of emotional states.

Finally, pleasant and unpleasant states of the participants are recognized by using SVM, linear discriminant analysis (LDA), and Naive Bayes classifier. The evaluation tables of these classifiers reveal their performances which are compared by using their accuracy rate, sensitivity and specificity.

In summary, SVM provides better solution to emotion recognition from EEG signals by using EMD method and signal processing techniques proposed in this study.

REFERENCES

[1] P. Özel, A. Akan, and B. Yilmaz. Emotion elicitation analysis in multi-channel EEG signals using multivariate Empirical Mode Decomposition and Discrete Wavelet Transform. in Medical Technologies National Congress (TIPTEKNO), 2017. 2017. IEEE.

[2] A. Mert, and A. Akan, Emotion recognition from EEG signals by using multivariate empirical mode decomposition. Pattern Analysis and Applications, 2018. 21(1): p. 81-89.

[3] Grewal, S., Gotman, J., “An automatic warning system for epileptic seizures recorded on intracerebral EEGs”, Clinical Neurophysiology 116 (2005) 2460–2472, 2005.

[4] P.C. Petrantonakis, and L.J. Hadjileontiadis, Adaptive emotional information retrieval from EEG signals in the time-frequency domain. IEEE Transactions on Signal Processing, 2012. 60(5): p. 2604-2616.

[5] Y. Liu, O. Sourina, and M.K. Nguyen, Real-time EEG-based emotion recognition and its applications, in Transactions on computational science XII. 2011, Springer. p. 256-277.

[6] N.E. Huang, et al., On instantaneous frequency. Advances in adaptive data analysis, 2009. 1(02): p. 177-229.

[7] J.A. Russell (1980) A circumplex model of affect. J Personal Soc Psychol 39:1161–1178.

[8] S. Koelstra, et al. (2012) DEAP: a database for emotion analysis; using physiological signals. IEEE Trans Affect Comput 3:18–31.

[9] S. Jirayucharoensak, S. Pan-Ngum, P. Israsena (2014) EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation. Sci World J.

[10] B. Hjorth (1970) EEG analysis based on time domain properties. Electroencephalogr Clin Neurophysiol 29(3):306–310

[11] N.E. Huang, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. in Proceedings of the Royal Society of London A: mathematical, physical and engineering sciences. 1998. The Royal Society.

[12] G. Rilling, and P. Flandrin, One or two frequencies? The empirical mode decomposition answers. IEEE transactions on signal processing, 2008. 56(1): p. 85-95.

[13] A. Hyvarinen, E. Oja (2000) Independent component analysis: algorithms and applications. Neural Netw 13:411–430.

[14] A. Mert, K. Niyazi, E. Bilgili, A. Akan (2014) Breast cancer detection with reduced feature set. Comput Math Methods Med. Article ID 265138:11 pages

[15] E. Sayilgan, Ö.K. Cura, and Y. İşler. Use of clustering algorithms and extreme learning machine in determining arrhythmia types. in Signal Processing and Communications Applications Conference (SIU), 2017 25th. 2017. IEEE.