Emotional State Analysis from EEG signals via Noise-Assisted Multivariate Empirical Mode Decomposition Method

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Abstract

Emotional state analysis is an interdisciplinary arena because of the many parameters that encompass the complex neural structure and electrical signals of the brain and in terms of emotional state differences. In recent years, emotional state data have been examined by using data-driven methods such as Empirical Mode Decomposition as well as classical time-frequency methods. Although Empirical Mode Decomposition has many advantages, it has disadvantages such as being designed for univariate data, prone to mode mixing, and providing signal via a sufficient number of the local extrema. To overcome these disadvantages, in this study, the Noise-Assisted Multivariate Empirical Mode Decomposition has been shown to classify the emotional state using electroencephalographic signals.

1. Introduction

Electroencephalography (EEG), presented by Hans Berger in 1924, is a noninvasive technique that is characterized by electrical potential at various points in the brainpan and its activity is small enough to be measured as a microvolt level (mV). The brain-computer interface (BCI), a technology based on computer-assisted controls using brain activity, is based on EEG data and has found a variety of applications ranging from bioengineering to neuroprosthetics. These new developments in human-computer interaction applications also focus on the transportation of emotional states in terms of data exchange between the brain and the computer, and therefore there are many studies in the literature on emotional state analysis and modeling [1] [2] [3], however the most commonly used is a circumplex model that shows emotion as continuous state in two-dimensional (2D) or three-dimensional (3D) space. Emotions in 2D space are modeled by the arousal-valence map, and emotions in 3D space are shown by arousal-valence-dominance map. In these models of emotion, emotional states are unique with their physiologic - neural aspects separated from each other and mostly are represented by a combination of these fundamental dimensions as emotional activation- intensity of emotion (arousal), emotional valence - level of satisfaction or dissatisfaction (valence), ability to control emotion internally (dominance) [4]. The developments in recent years have brought forward methods of time-frequency analysis known as data-driven, in addition to conventional time-frequency representation algorithms. As a data-driven method, Empirical Mode Decomposition (EMD) transforms the signal into an arrangement of band-limited segments leaving well-localized representations at the instant frequency level. There are no previous assumptions for the basic signal properties that are made available for nonlinear and nonstationary data analysis in the EMD method compared to conventional time-frequency algorithms. In other words, it decomposes the given time series x(k) a set of narrowband oscillation modes, called intrinsic mode functions (IMF), that naturally occur from self-existing oscillations in the signal x(k), as opposed to constant fundamental functions in Fourier and Wavelet transforms, and provides great advantages in processing real-world signals because it is data-adaptive, comprehensive, and much more flexible than Fourier and Wavelet-based functions. The non-linearity inherent in the EMD algorithm also gives a compact representation possibility. However, the application of EMD to nonlinear signals has undercut certain issues, such as specific “mode mixing” and “aliasing” [5]. Up to now, EMD-based emotion recognition methods have been developed using standard single and multiple channels of EEG signals [6] [7] [8] [9] [10], and moreover, multivariate analysis of Multivariate Empirical Mode Decomposition (MEMD) is used in emotional state studies in the literature [11] [12] [13] [14] [15]. Despite the advantages of EMD method for linear and non-stationary [5] data, it has the disadvantage of not being practically arithmetic at the algorithmic level. The sensitivity of the EMD algorithm to local signal changes can often lead to decompositions. However, EMD method tends to be "mod mixing" which is often caused by the overlaid IMF spectra and "aliasing" which is caused by the sub-Nyquist extreme sampling. Although MEMD has certain advantages in handling multivariable non-stationary signals, it has structurally a degree of modal mixing capability, which motivated the development of Noise-Assisted Multivariate Empirical Mode Decomposition Method (NA-MEMD) [5]

In this study, NA-MEMD is evaluated as a potential idea by comparing MEMD results in the emotional state classification for the processing of EEG signals. In terms of biomedical signal processing, as well as the algorithm of MEMD which causes the question of its use for multivariate time series, an analysis of the usefulness of NA-MEMD is presented in emotion classification. As the content of our study, Section II describes Noise-Assisted Multivariate Empirical Mode Decomposition Method, the progress of our proposed model, and how we implement the classification step. Section III contains the results and evaluation of our investigations.

2. METHOD

2.1. Noise-Assisted Multivariate Empirical Mode Decomposition Method

NA-MEMD first operates by creating a multivariate signal containing one or more incoming data channels and adjacent independent events of white Gaussian noise (WGN) in separate channels. The multivariate signal, which consists of data and noise channels, is processed using the MEMD method. The corresponding IMFs are reconstructed to obtain the desired decomposition [16]. In this way, being physically separate for input and noise subspaces in the NA-MEMD prevent direct noise artifacts during the operation of the algorithm. When applied by adding WGN to a multidimensional signal, the MEMD algorithm performs as dyadic filter bank on each channel, showing a greatly improved order in the IMFs corresponding to the different channels over the same frequency range when compared to the GKA. Using this feature of MEMD, Rehman and Mandic [16] proposed a noise-assisted MEMD [5] method to further improve the mode-mixing problem. This is achieved by including a subspace with multivariate independent WGN and increasing the size of available data matrix, and the resulting composite signal is processed using the MEMD.

Algorithm 1: Multivariate EMD

1. An appropriate point for sampling is selected on (n-1) sphere.
2. For all k's (all clusters of direction vectors), in order to give as the reflection cluster $\{p^{Q_k}(t)\}_{k=1}^{K}$, the reflection $\{p^{Q_k}(t)\}_{t=1}^{T}$ of input signal $\{v(t)\}_{t=1}^{T}$ along the direction vector x^{Q_k} is calculated.
3. $t_j^{Q_k}$ time constant which corresponds to maximum reflected signal is estimated.
4. So as to obtain multivariate envelope curves $\{e^{Q_k}(t)\}_{k=1}^{K}$, the interpolation is performed by utilizing $t_j^{Q_k}, v(t_j^{Q_k})]$
5. For a set of K direction vectors, envelope curves average, as $m(t)=\frac{1}{K}\sum_{k=1}^{K} e^{Q_k}(t)$, is computed.
6. To be "i" as a rank of IMF, "the detail" $c_i(t)$ is extracted by utilizing $c_i(t)= v(t) - m(t)$. If "the detail" $c_i(t)$ provides the stopping criterion of a multivariate IMF, above procedure is executed if not is executed to $c_i(t)$.

Algorithm 2: Noise Assisted Multivariate EMD

1. Create a series of uncorrelated white Gaussian noises with the same length (a channel) with the input signal.
2. Add the noise channel (a channel) obtained in step 1, the input multivariate signal (b channel), and obtain a signal of (a + b) channel.
3. The (a + b) channel multivariate signal generated by using the MEMD algorithm summarized in Algorithm 1 is processed.
4. "a" channel signal corresponding to the noise is subtracted from the resulting "a+b" channel signal.

Multivariate Empirical Mode Decomposition (MEMD) and its noise supported version Noise Assisted Multivariate Empirical Mode Decomposition (NA-MEMD) algorithms is given Algorithm 1 and 2 as above.

So, the noise will remain in a different subspace and be used in raising the filter bank structure, never interfering with the useful data channels, thereby reducing the problem of mode-mixing and providing a better definition of frequency bands belonging to data. Only the IMFs that correspond to the original input signal are preserved by subtracting the subspace of the IMF connected to the noise. Due to the noise subspace, the alignment of the IMFs aligns with dyadic filter bank structure, thus providing an important option for non-stationary analysis of narrowband biomedical signals, and aligning IMFs with relevant input signal. The behavior of the NA-MEMD algorithm depends on the power level of the added noise channels. The algorithm performs similarly to the standard MEMD for infinitesimal small noise amplitudes. Increasing the noise power will further strengthen the structure of the dyadic filter bank property on the input data, however over-noise levels reinforce the data adaptive capability of the M(EMD)-based algorithms. A fundamental rule is to choose a variance (power) of 2-10% of the variance of the input. Noise above this range of power can result in an unnecessary mode-mixing problem at the output [5].

2.2. Classification

In this study, for high/low valence, activation, dominance levels, the selected version (linear) of Support Vector Machine (SVM), which is included in MATLAB Classification Learner Tool as a classifier is utilized. SVM transforms the classification problem into a quadratic optimization problem, and core function selection and parameter optimization play an important role in the implementation process. Estimated speed in MATLAB Classification Learner Tool is medium for linear SVM. Interpretability is difficult for linear SVM, which is easy for other kernels. Memory usage is medium for linear SVM, middle for multiple classes, and wide for others [17] [18] [19]

2.3. The Progress of Proposed Methods

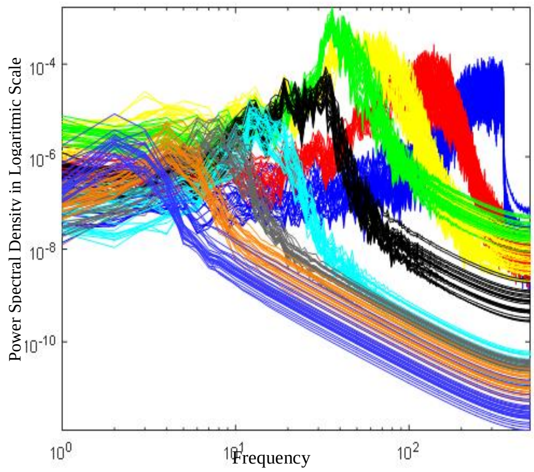
Firstly, considering the EEG signals of the first 10 songs of 6 subjects of data set on the EEG signals recorded in the DEAP data set used in the study, as a total of 26 data (26*10*8000) for each subject (for each song 26*1*8000), consisting of left frontal lobe (Fp1, AF3, F3, F7, FC1, FC5, T7, C3), right frontal lobe (Fp2, AF4, F4, F8, FC2, FC6, T8, C4), right and left frontal lobe differences, 2 central channels (Fz, Cz) [13] is given as input to the MEMD algorithm, then acquired IMFs are evaluated in terms of their oscillations. As a result, the acquired data size is approximately 26*15*8000. Here, the middle value shows the number of IMFs. In this study, our IMFs' number ranges from14 to 17, however in general, it is 15. Then, in the same way, NA-MEMD algorithm is applied, however for this time, before the algorithm operation, on the EEG signals recorded during every song of each subject, the fundamental rule is executed to choose a variance (power) of 2-10% of the variance of the input. In the noise subspace of NA-MEMD, two noise channels corresponding to SNR ranging from 0.2 to 0.5 dB are used, l = 2 (noise channel number) and N = 8000 independent noise sets are used. Number of direction in MEMD is 128 and stopping criteria is [$\sigma 1 = 0.05$, $\sigma 2 = 0.5$, $\alpha = 0.05$]. But there is no limit on the number of noise channels to add to data. MEMD algorithm is started for each song of each subject, after the data set is expanded from (26*1*8000) to (28*1*8000) by adding noise channel. Consequently, the acquired data is approximately (28*15*8000), similarly our IMFs' number ranges from 14 to 17, however in general, it is 15. IMFs' number do not change because of the NA-MEMD algorithm application. Last two channels are removed because of basic rule of NA-MEMD algorithm. At last, the data as (26*15*8000) is acquired again. At this point, to indicate how NA-MEMD algorithm has an improvement on the mod-mixing problem, its filter bank property is investigated comparing to the filter bank property of MEMD and shown in Results and Discussion section.

Before the classification steps, these three-dimensional data set for each song of each subject was turned into one dimensional data set by using "reshape" function in MATLAB. Then, Singular Value Decomposition (SVD) algorithm is applied for the data of each song of each subject as dimension reduction. At the end of SVD algorithm, it is acquired as (390*1) double matrix. It is obvious to say that, if it is needed to take into consideration at this point, for the classification steps, for simplicity only the amplitudes of IMFs were utilised in contrast to the references [10] and [13] in which further operations were performed on the IMFs. After this stage, for the data of 6 subject used in the study, an input data of (60 * 390) created (each song of each subject is in sub-altitude), therefore and the input matrix is created. As an output, for each label (valence-activation-dominance) scale, it is determined that the values varying from 1 to 9 is separated as high and low label whether its value is > 5 or not. And the label values are set to 0 or 1. After the label values are adjusted as three different (60*1) matrix for valence-activation-dominance scale, the performance of the selected classifier in the MATLAB Classification Learner Tool has been evaluated as {data = [output (label data (60 * 1) (e.g. valence label) input (processed EEG signal (60* 390)).

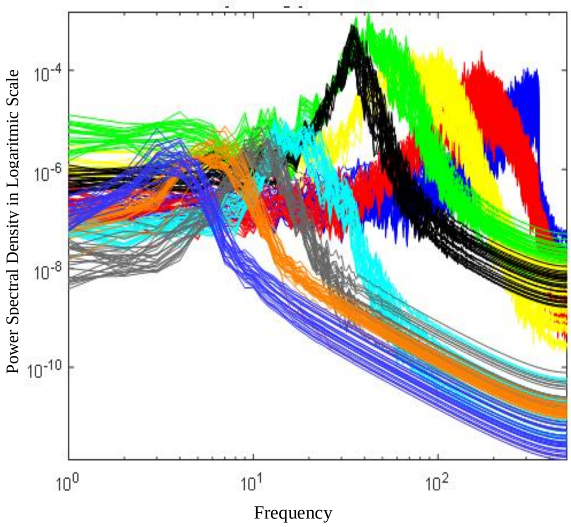
3. Results and Discussion

In this study, using the DEAP data set for emotional state analysis, valence, activation, and dominance levels are classified as high and low from the EEG signals. The classification results are compared with the studies using EEG signals for emotion recognition via MEMD algorithm. Table I depicts the results for classification of MEMD and NA-MEMD algorithm, as high and low for valence, activation and dominance levels respectively. Figures 1 and 2 show respectively, when using MEMD and NA-MEMD as a filter bank, well-defined instantaneous frequencies for each of the 26 channels according to Power Spectral Density in Logarithmic Scale and the mode-mixing state solution on each of the IMFs.

To show the success for the MEMD and NA-MEMD used in the proposed emotional state model, it is obvious that the dyadic filter bank structure in the NA-MEMD method is more successful than the MEMD dyadic filter bank structure. It appears that the mode-mixing phenomenon has decreased and the mode alignment became more visible and IMF oscillations behaved in a more orderly fashion after IMF5 (shown as black in Firgures 1 and 2) due to noise added MEMD approach. When the MEMD is used as shown in Figure 1, further mode mixing problem appears starting with IMF5 and IMF6, moreover IMFs' expansions from different channels overlap in IMF5, IMF6, IMF7, IMF8 and IMF9. On the other hand, the application of the NA-MEMD to the same data set resulted in frequency-aligned IMFs, each containing a single temporal mode as it is shown in Figure 2. Especially, IMF5's information content became more visible . For this reason, in classification step, the contribution of first 9 IMFs are evaluated and participated in the feature vector. As mentioned earlier, it is a prerequisite for NA-MEMD to select suitable variance range for the "l" noise channels to operate successfully. However, we have discovered some disadvantages of NA-MEMD as well. Although both are run on the same computer, the calculation time of NA-MEMD algorithm took more than three times compared to MEMD. Additionally, adding noise to extra channel is time consuming in terms of calculation and finding the suitable variance (power) of 2-10% of the variance of the input. We have observed that noise addition did not cause any significant differences for some subjects' data analysis. Here, we come up with the result that inherent features of data are also important in terms of application for NA-MEMD and MEMD algorithm. Even so, both MEMD and NA-MEMD algorithms are better options to decompose the signal compared to classical time-frequency methods.



Figures 1. IMFs alignment using MEMD as a filter bank.



Figures 2. IMFs alignment using NA-MEMD as a filter bank.

When it comes to how the solution of the mode-mixing problem influences the classification step, it is shown in Table 1. Accordingly, since the signal is decomposed at v = 128 direction vector, the results have been successful even in results of MEMD algorithm, however, the classification results have improved thanks to the solution of the mode-mixing problem via NA-MEMD algorithm.

Table 1. Classification results obtained by IMFs' contribution via MEMD and NA-MEMD algorithm by using linear Support Vector Machine (SVM).

High-Low	Valence	Activation	Dominance	Method
Linear SVM	79.4%	75.0%	71.7%	MEMD
Linear SVM	85.3%	76.7%	75.0%	NA-MEMD

The DEAP database results [4] (high / low activation is 62%, high / low valence is 57%, in the study [13] high / low activation is 75%, high / low valence is 72%, in [20] high / low valence is 72% , and high / low activation is 74.20% respectively. When compared to these results, it is seen that it is successful to a considerable extent. Since we think that the results obtained using our proposed model are based on data-driven methods and that the NA-MEMD algorithm can change the results depending on the data itself, it is predictable that the results can change when we present the classification results as whole data of DEAP data set for all songs and subjects.

4. References

[1] Ekman, P., Friesen, W. V, O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., Ricci-Bitti, P. E., Tomita, M."Universals and cultural differences in the judgments of facial expressions of emotion", *Journal of personality and social* , vol 53, p. Journal of personality and social, 1987.

[2] Bakker,I., Voordt, T.V.D, Vink,P., Boon J.D, "Pleasure, Arousal, Dominance: Mehrabian revisited", *Curr Psychol,* cilt 33, p. 405–421, 2014.

[3] Othmana, M., Wahaba, A., Karima, I., Dzulkiflib,M.A, Alshaiklia, I.F.T."EEG emotion recognition based on the dimensional models of emotions", *Procedia - Social and Behavioral Sciences* , vol 97, pp. 30-37, 2013.

[4] Koelstra, S., Mühl, C., Soleymani, M., Lee, J. S., Yazdani, A., Ebrahimi, T., Patras, I., "DEAP: A database for emotion analysis; using physiological signals", *IEEE transactions on affective computing,,* vol 3, pp. 18-31, 2012.

[5] Rahman,N.U., Park,C., Huang,N.E, Mandic,D.P., "Emd via Memd:Multivariate Noise Aided Computation of Standard Emd", *Advances in Adaptive Data Analysis,* vol 5, 2013.

[6] Khasnobish,A., Bhattacharya,S., Singh,G., Jati,A., Konar, A., Tibarewala,D.N., Janarthanan, R., "The role of Emprical Mode Decomposıtıon on Emotıon Classificatioın Using Stimulated EEG signals", *Advances in Computing and Information Technology* ,vol 178, no. Advances in Intelligent Systems and Computing, pp. 55-62, 2013.

[7] Santillan-Guzman,A., Fischer,M., Heute,U., Schmidt, G."Real-time Empirical Mode Decomposition for EEG signal enhancement", *Signal Processing Conference, 2013 Proceedings of the 21st European*, Marrakech, Morocco, 2013.

[8] Shahnaz,C., Masud,S.B., Hasan, S.M.S, "Emotion recognition based on wavelet analysis of Empirical Mode Decomposed EEG signals responsive to music videos" *IEEE Region 10 Conference (TENCON),* Singapore, Singapore, 2016.

[9] Maity,A.K, Pratihar,R., Mitra,A., Dey,S., Agrawal,V., Sanyal,S., Banerjee,A., Sengupta, R., Ghosh,D., "Multifractal Detrended Fluctuation Analysis of alpha and theta EEG rhythms with musical stimuli",*Chaos, Solitons & Fractals,* vol 81, no. Part A, p. 5267, 2015.

[10] Zhuang,N., Zeng,Y., Tong,L., Zhang, C., Zhang,H., and Yan,B., "Emotion Recognition from EEG Signals Using Multidimensional Information in EMD Domain", *BioMed Research International,* vol 2017, pp. 1-9, 2017.

[11] Xu,H., "Towards Automated Recognition of Human Emotion using EEG", Toronto,Canada: University of Toronto, 2012.

[12] Tonoyan,Y., Looney,D. Mandic, ,D.P., Hulle, V.M.M., "Discriminating Multiple Emotional States from EEG Using a Data-Adaptive,Multiscale Information-Theoretic Approach", *International Journal of Neural Systems,* vol 26, 2016.

[13] Mert,A., Akan,A., "Emotion recognition from EEG signals by using multivariate empirical mode decomposition", *Pattern Analysis and Applications,* pp. 1-9, 2016.

[14] Guitton,C.,"Emotions Estimation from EEG Recordings",, London: Imperial Collage of Science, Technology & Medicine Department of Electrical& Electronic Engineering, 2010.

[15] Xu,H., Plataniotis,K.N, "Application of Multivariate Emprical Mode Decomposition in EEG signals for Subject Independent Affective States Classificaition",*International Journal of Communications,* vol 9, pp. 91-97, 2015.

[16] Rehman, N.U, Mandic, D. P., "Filter bank property of multivariate empirical mode decomposition", *IEEE transactions on signal processing* , p. 2421–2426., 2011.

[17] Ayhan,S. , Erdoğmuş,Ş., "Destek Vektör Makineleriyle Sınıflandırma Problemlerinin Çözümü için Çekirdek Fonksiyonu Seçimi", *Eskişehir Osmangazi Üniversitesi IIBF Dergisi,* pp. 175-201, 2014.

[18] Karakoyun,M., Hacıbeyoğlu,M., "Biyomedikal Veri Kümeleri ile Makine Öğrenmesi Sınıflandırma Algoritmalarının İstatistiksel Olarak Karşılaştırılması", *DEÜ Mühendislik Fakültesi Mühendislik Bilimleri Dergisi,* vol16, pp. 30-42, 2014.

[19] https://www.mathworks.com/help/stats/choose-a-classifier.html.

[20] Hatamika, S., Maghooli, K., Nasrabadi., A.M, "The emotion recognition system based on autoregressive model and sequential forward feature selection of electroencephalogram signals", *Journal of Medical Signals and Sensors,* vol 4(3), pp. 194-201, 2014.