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THEORETICAL ADVANCES

Emotion recognition from EEG signals by using multivariate empirical mode decomposition

Ahmet Mert[1] · **Aydin Akan**[2]

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Abstract This paper explores the advanced properties of empirical mode decomposition (EMD) and its multivariate extension (MEMD) for emotion recognition. Since emotion recognition using EEG is a challenging study due to nonstationary behavior of the signals caused by complicated neuronal activity in the brain, sophisticated signal processing methods are required to extract the hidden patterns in the EEG. In addition, multichannel analysis is another issue to be considered when dealing with EEG signals. EMD is a recently proposed iterative method to analyze nonlinear and nonstationary time series. It decomposes a signal into a set of oscillations called intrinsic mode functions (IMFs) without requiring a set of basis functions. In this study, a MEMD-based feature extraction method is proposed to process multichannel EEG signals for emotion recognition. The multichannel IMFs extracted by MEMD are analyzed using various time and frequency domain techniques such as power ratio, power spectral density, entropy, Hjorth parameters and correlation as features of valance and arousal scales of the participants. The proposed method is applied to the DEAP emotional EEG data set, and the results are compared with similar previous studies for benchmarking.

Keywords Empirical mode decomposition · Multivariate empirical mode decomposition · Emotion recognition · Electroencephalogram

✉ Ahmet Mert
ahmet.mert@btu.edu.tr

1 Department of Mechatronics Engineering, Bursa Technical University, 16330 Yildirim, Bursa, Turkey

2 Department of Electrical and Electronics Engineering, Istanbul University, 34320 Avcilar, Istanbul, Turkey

1 Introduction

Electroencephalogram (EEG) signal is the recording of electrical potentials of neurons in the brain. The signals from the electrodes placed on the scalp are generally used to acquire EEG recordings. By referring to the 10–20 electrode positioning system, a noninvasive and reproductive measurement of EEG signals is utilized. Brain computer interface (BCI) [27] is one of the most popular applications achieved by the analysis of EEG signals to control external devices or implement some actions. In addition to mentally controlling devices by using EEG signals, estimating the mental and emotional states is popular studies as well [23].

The emotional state is represented in a two-dimensional parameter space called valence and arousal [21]. This scale ranges from negative to positive to describe emotions quantitatively. While arousal state represents activity or inactivity in the range of high level (i.e. excited) to low level (i.e. bored), valence score states the positive and negative emotions from pleasant (i.e. happy) to unpleasant feelings (i.e. sad). Arousal scale is associated with the alpha and beta bands of the subject's EEG signal recorded from the scalp [2, 17]. Power spectral density (PSD) in the alpha band (8–13 Hz) is reported to be correlated with the level of inactivity of the brain, whereas the power in the beta band (14–30 Hz) is positively correlated with active brain states [11]. Therefore, the most frequently applied technique to estimate the level of arousal is to use the alpha/beta bands power ratio. Similarly, methods estimating the valence scale from EEG signals focus on the frequency domain methods such as PSD. Inactivation of the left and right hemisphere of the brain is observed as an indicator of valence level estimation [17]. Since the inactivation in the left hemisphere indicates the negative emotional state, PSD ratios of the symmetric EEG channels in the left and right hemispheres are proposed as a metric to predict valence level [17]. Generally, arousal level estimation is based on PSD band ratios of the EEG channels, while valence score estimation is based on methods focusing on asymmetric properties of the EEG signals in the left and right hemisphere [2, 10]. However, emotion recognition is still a challenging study due to complex neuronal structure of the brain, and many other subject-dependent parameters affecting the results.

A comprehensive research study on a publicly available EEG data set called "A database for emotion recognition analysis using physiological signals, (DEAP)" [10] deals with recognition of emotional state. The study explores the use of theta, alpha, beta and gamma spectral powers (SP) of 32 EEG channels with spectral power asymmetry (SPA) of the bands between the 14 channels in the left and right lobes. It has been reported that naive Bayes classifier (BC) with these spectral features and leave-one-participant-out (LOO) cross-validation achieves the accuracy rates of up to 62 and 57.6 % for high/low arousal and high/low valence level estimation, respectively. Deep learning network (DLN) and principal component analysis (PCA)-based emotion recognition using DEAP data set have the accuracy rates of 52.03 % $\pm$ 9.4 and 53.42 % $\pm$ 9.4 for three level (high, neutral and low) arousal and valence classifications [9]. It implements the same feature extraction methods and LOO with the original study of the DEAP data set for benchmarking. Another study [3] uses dual-tree complex wavelet packet transform (DT-CWPT) to decompose EEG signals into sub-bands, singular value decomposition (SVD) to reduce dimension and support vector machine (SVM) to classify. It has been reported that accuracy rates of 66.9 % for arousal and 65.3 % for valence are obtained, in case of high/low binary classification scheme for LOO cross-validation. Thus, level estimations are conducted on DEAP EEG emotional data set without using the participants EEG signals and extracted features of forty emotional states. On the other hand, there are a few studies which use their own data set and signal processing methods and validation strategies to recognize emotional states. Wang et al. [26] create a data set with six participant EEG recordings. The combination of power spectral and nonlinear dynamical features with linear discriminant analysis has suggested to classify positive and negative emotion with the accuracy rate of up to 91.77 %, when they have constructed a training set and a test set for each participant by using each participant EEG recordings, and also they have ignored the recordings which have dominance score less than three. Lin et al. [11] also have been recorded EEG signals of 26 volunteers induced by music to label the emotions as joy, anger, sadness and pleasure. SVM classifier with extracted PSDs of thirty channels and differential and rational PSDs of the symmetric twelve channels in left and right hemispheres is deployed using tenfold cross-validation, and obtained average accuracy rate of 82.29 %.

Empirical mode decomposition (EMD) is proposed as an alternative method to process nonlinear and nonstationary signals [7]. It is an completely adaptive and data-driven algorithmic approach. It decomposes signal into amplitude and frequency modulated (AM–FM) oscillations called intrinsic mode functions (IMFs) without any a priori assumption and defined a basis. Generally, the decomposed IMFs have overlapping limited bandwidth due to its dyadic filter bank structure [12, 19]. The bivariate [20], trivariate [24] and multivariate empirical mode decompositions [18] (BEMD, TEMD, MEMD) are the extended version of the mono EMD algorithm to analyze multivariate and multichannel data. First, the BEMD is proposed for two channels or complex signals, and TEMD is followed for three channels data. Finally, MEMD algorithm is suggested to generalize EMD algorithm for multivariate data with up to 32 channels, and filter bank properties of the EMD algorithms have been also investigated [5, 14, 25]. From this point of view, the EMD algorithm has been successfully applied to multivariate nonstationary signals for detailed analysis [4]. For EEG signals, higher order statistical values of the IMFs [1] and geometrical properties of the decomposed IMFs in complex plane [16] are used as feature vectors for epilepsy detection. In addition, SVD is computed for the first nine IMFs of electrocardiogram (ECG) signals to obtain robust feature vectors for arrhythmia classification [22].

In this paper, an EMD-based feature extraction method is proposed to identify emotional state as high/low arousal and high/low valence. Multichannel EEG signals are decomposed by MEMD, and extracted IMFs are analyzed using several signal processing methods namely PSD, entropy, Hjorth parameters [6], correlation and their asymmetrical properties on the left and right hemisphere for feature extraction. Thus, oscillations in the EEG signals are extracted, and detailed analysis are conducted on each IMF to increase accuracy rate of the recognition. The performance of the proposed classification is evaluated on the publicly available EEG recordings and the two-dimensional cognitive emotional scales of the DEAP emotional data set for benchmarking. The rest of the paper is organized as follows: The EMD and MEMD with their filter bank structures are summarized in Sect. 2. DEAP data set is described in Sect. 3. Proposed MEMD-based emotion recognition method is described in Sect. 4. Results and discussion of the proposed approach are presented in Sect. 5. Finally, Sect. 6 concludes the paper.

2 Empirical mode decomposition and its multivariate extension

Empirical mode decomposition (EMD) was suggested as a tool of adaptive and data-driven signal processing method by Huang et al. in 1998 [7]. EMD decomposes a multi-component signal into amplitude and frequency modulated intrinsic mode functions (IMFs) so that the sum of them is equal to the signal. The main part of the EMD algorithm is the so-called *Sifting* process that is based on envelope extraction using cubic spline. Steps of the algorithm are given in the following:

(i) Determine local maxima and minima as M_i, $i = 1, 2, \ldots$, and m_k, $k = 1, 2, \ldots$, in $x(n)$.
(ii) Find upper and lower envelopes by the interpolating signals $M(n) = f_M(M_i, n)$, and $m(n) = f_m(m_k, n)$ using cubic spline.
(iii) Compute the mean of the envelopes, $h(n) = [M(n) + m(n)]/2$.
(iv) If $h(n)$ satisfies IMF requirements, keep it as an IMF $\varphi(n) = h(n)$, and subtract $h(n)$ from the signal; $x(n) = x(n) - h(n)$.
(v) If $x(n)$ is trend or satisfies stopping criterion , the residue is kept as $r(n) = h(n)$.

These iterations continue until the following stopping criterion is reached:

$$\mathrm{SD} = \sum_{i=0}^{N-1} \left[\frac{|\, h_{(k-1)}(n) - h_{(k)}(n)\,|^2}{h^2_{(k-1)}(n)} \right] \tag{1}$$

where k and N indicate the iteration number of consecutive *Sifting* processes and total number of samples, respectively. Finally, the original signal can be represented by the IMFs as follows:

$$x(n) = \sum_{i=1}^{L} \varphi_i(n) + r(n) \tag{2}$$

The stopping criterion related to the steps (v) is originally suggested as standard deviation (SD)-based technique to detect the retained signal changes or not. There are a few approaches for envelope extraction [28, 29], but IMF conditions are valid for all EMD algorithms. At least, IMFs have to satisfy two criteria: First, the number of the extrema and the number of zero crossings must be equal or must differ by one at most. Second, the mean of the envelopes determined by the local maxima and minima, namely upper and lower envelope should be zero [7]. Therefore, IMFs have limited bandwidth and instantaneous frequency (IF) fluctuations [19].

The extended versions of the EMD for multivariate signal decomposition are called bivariate [20], trivariate [24] and multivariate empirical mode decomposition [18] (BEMD, TEMD, MEMD). The steps of these extensions are similar to the mono EMD. However, they use multidimensional envelope extraction. The graphical representation of the multidimensional envelope extraction for two signal originated from the study [5] is given in Fig. 1.

The multivariate extensions of the EMD have advantages of processing multichannel signals more practically and conveniently over processing each channel by mono EMD. For multivariate extensions, the decomposed IMFs of the each channel have close properties in time and frequency domains. In other words, the first IMFs of the EEG channels have similar frequency fluctuations, bandwidths, or autocorrelation properties. When mono EMD is deployed for each EEG channel separately, the number of IMFs varies over each channel and IMFs have different statistical properties.

The filter bank properties of the EMD and MEMD are also data-driven, and it is dependent on the statistical properties of the signal(s). Moreover, they have dyadic filter bank structures, but the bandwidths of the IMFs and overlapping properties are data dependent. This filter bank structure has been investigated by decomposing white Gaussian noise, and shown in Fig. 2.

Consequently, EMD and MEMD extract the signal into a set of IMFs. Band-limited spectral properties of the decomposed oscillations, namely IMFs, of the EEG signals are the main principles of the proposed EMD-based feature extraction for emotion recognition.

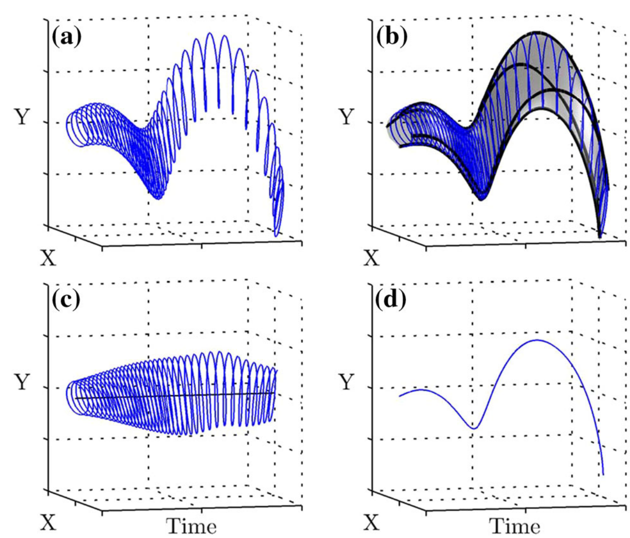

Fig. 1 Graphical representation of the bivariate extensions. **a** Two-dimensional rotating signal. **b** Three-dimensional Envelope. **c** Rapidly rotating component. **d** The mean of the three-dimensional tube in (**b**) [5]

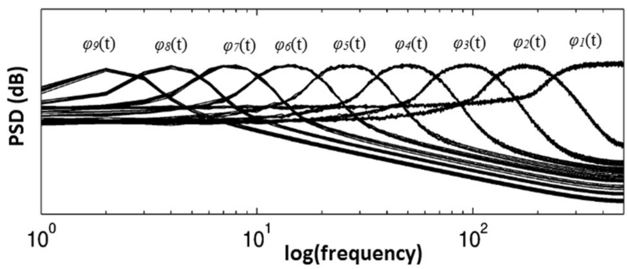

Fig. 2 Multivariate empirical mode decomposition filter bank structure [25]

3 DEAP EEG database

DEAP is a multimodal data set [10] consisting of EEG recordings while watching the selected video clips to analyze human affective states. Before the experimental and recording procedure, 40 of 120 video clips were selected depending on their inducing level of emotions. Volunteers performed the self-assessment of the valence and arousal scale using a web application after watching the 120 music clips. After that, the 40 clips having the closest ratings to the corners of the two-dimensional cognitive emotional map have been gathered as the best stimulus.

Thirty-two-EEG channels according to international 10/20 electrode placement were acquired with 512 Hz sampling frequency while the participants were watching the selected 40 music video clips. After that, they performed their levels of arousal, valence, dominance and liking using self-assessment manikins (SAM) [15] as shown in Fig. 3 [9].

Participants selected the numbers 1–9 for emotional state for each clip. The arousal scales extends from passive to active (e.g. from calm to excited), and valence ranges from negative to positive (e.g. from sad to happy). The other scales of the SAM are not required for two-dimensional cognitive emotion state. Liking should not be confused with the valence scores. It is related with the taste, not feeling as well. The original study of the DEAP database maps these scales into two level of arousal and valance states. High/low arousal and high/low valence states were recognized as a binary classification scheme. Thus, the four quadrants of the two-dimensional cognitive valence/arousal scales giving in Fig. 4 [10] are adopted to high/low states.

The date set contains an preprocessed version of the original EEG signals. The recordings were downsampled to 128 Hz, EOG artifacts were removed, and a bandpass filter with cutoff frequencies of 4.0–45.0 Hz was applied. Finally, these are reorganized for classification without the hassle of processing all the data. We use this preprocessed multichannel EEG recordings and the performed valence and arousal scales in the form of high/low levels to recognize emotion state using the suggested EMD-based method. The results are also compared to the method deployed in DEAP study.

4 Proposed MEMD-based emotion recognition

We propose an emotion recognition method based on filter bank property of the MEMD. The MEMD algorithm is capable of decomposing multichannel signals simultaneously, and dyadic filter bank structure yields to obtain band-limited multicomponent IMFs. Their spectral, entropy and correlation-based properties with asymmetrical changes are extracted as feature vector. We also use recordings of 18 channels (eight left, eight right and two central channels in the frontal lobes) instead of 32 channel for computational efficiency, since the emotional and motivational parts of the brain exist in these lobes [2]. The selected channels are highlighted in the international 10/20 electrode placement scheme[1] in Fig. 5.

Various analyzing methods including power, power ratios, PSDs, Hjorth parameters and entropies of the 18 channels IMFs are computed to extract arousal state. Similarly, asymmetrical properties are also extracted computing power differences, power ratios, relative entropies, correlation coefficients and coherence between eight left and eight right channels. Moreover, eight virtual channels are generated subtracting the signals acquired from left channels from the symmetrical pairs in the right lob to enhance asymmetrical analysis. Finally, the proposed MEMD-based emotion recognition scheme is given in Fig. 6.

When the EEG signals are formed as

$$X = [\mathrm{LeftCh},\ \mathrm{RightCh},\ \mathrm{CentralCh},\ \mathrm{VirtualCh}]^T,$$

the multivariate IMFs are obtained, and they are normalized in the range of 0.1 and 0.9 to extract accurate and reliable power ratios. The implemented techniques from left to right in Fig. 6 can be formulated as

$$P_i^m = \frac{1}{N}\sum_{n=0}^{N-1} \varphi_i^m(n)^2 \tag{3}$$

$$P_i/P^m = \frac{\frac{1}{N}\sum_{n=0}^{N-1} \varphi_i^m(n)^2}{\frac{1}{N}\sum_{n=0}^{N-1} x^m(n)^2} \tag{4}$$

$$\widehat{P}_i^m(f) = \frac{1}{2\pi N}\left|\sum_{n=0}^{N-1} \varphi_i^m(n)e^{-j\omega n}\right|^2 \tag{5}$$

[1] http://www.mariusthart.net/downloads/eeg_electrodes_10-20.svg.

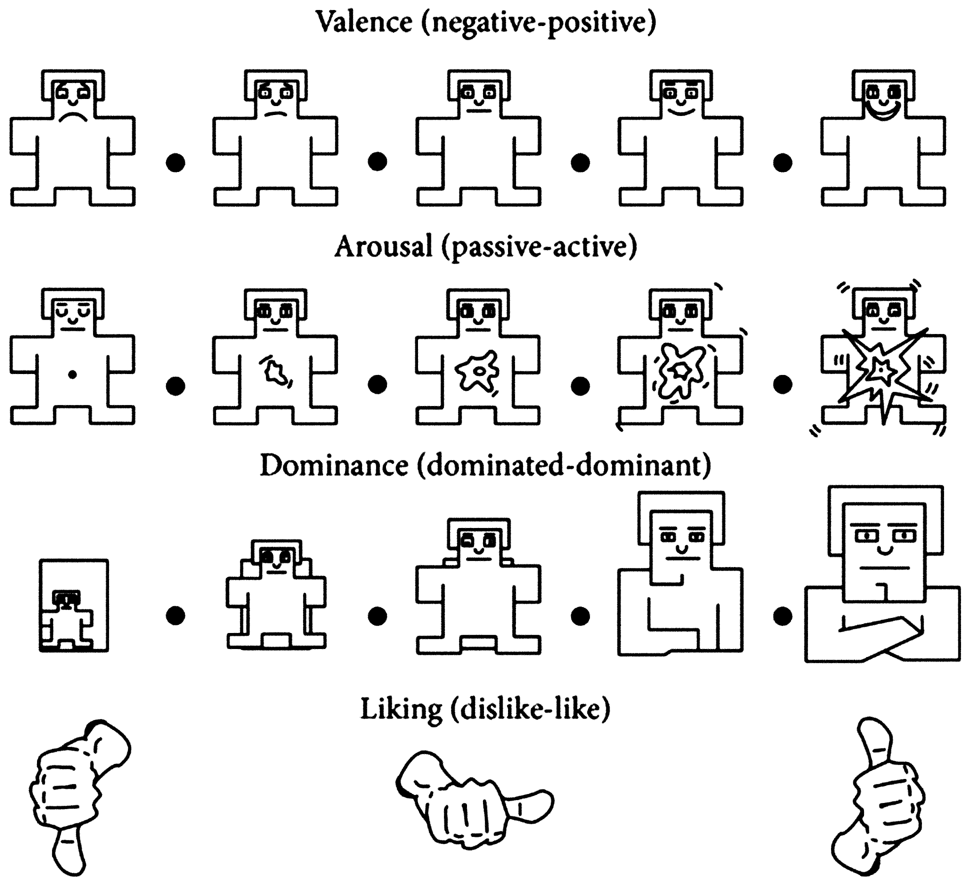

Fig. 3 Self-assessment manikin for emotion state

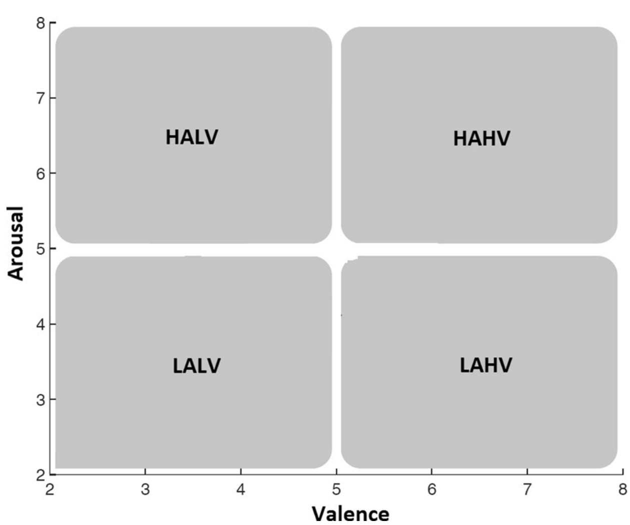

Fig. 4 Valence–arousal scale for two-dimensional cognitive emotional representation (e.g. high arousal and high valence is denoted as HAHV)

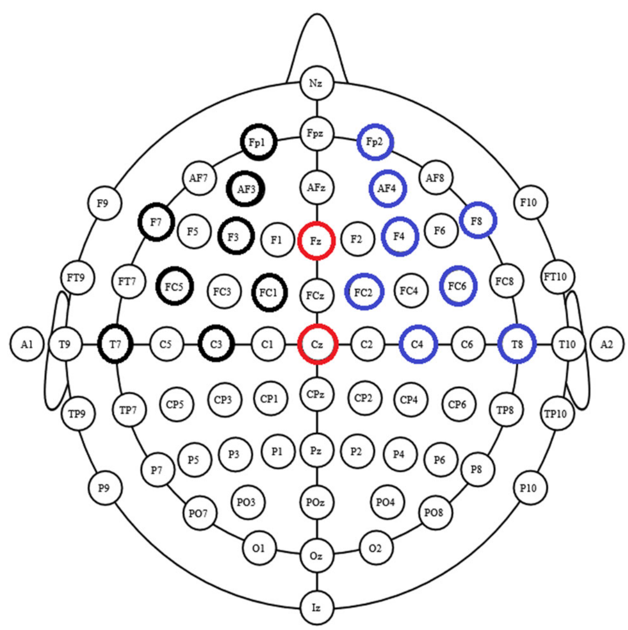

Fig. 5 Selected channels for MEMD-based feature extraction

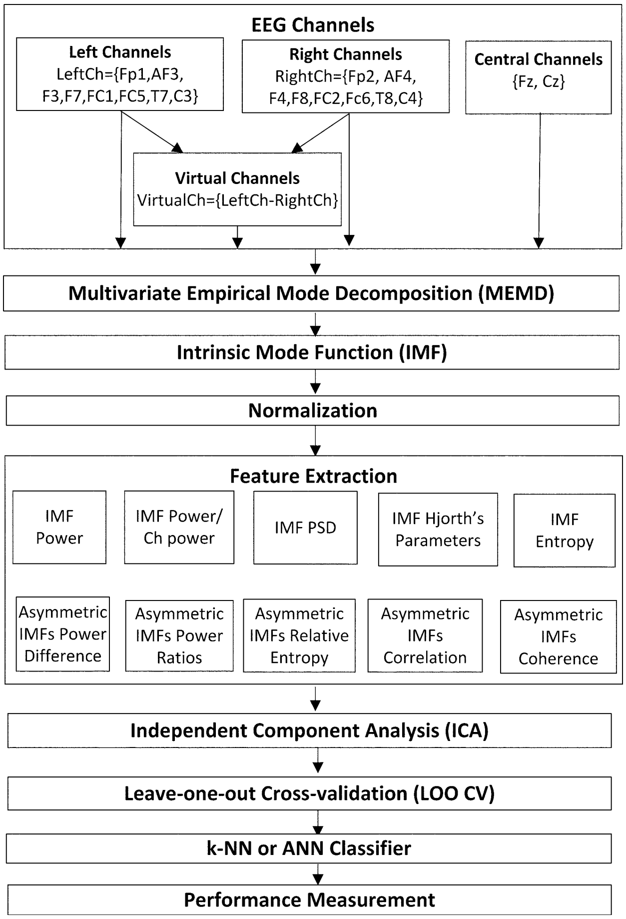

Fig. 6 Proposed MEMD-based emotion recognition

$$\text{Activity}_i^m = \frac{1}{N}\sum_{n=0}^{N-1}\left[\varphi_i^m(n) - \bar{\varphi}_i\right]^2 \tag{6}$$

$$\text{Mobility}_i^m = \sqrt{\frac{Activity\left(\frac{d\varphi_i^m}{dt}\right)}{Activity_i^m}} \tag{7}$$

$$\text{Complexity}_i^m = \sqrt{\frac{Mobility\left(\frac{d\varphi_i^m}{dt}\right)}{Mobility_i^m}} \tag{8}$$

$$H_i^m = -\sum_j P_j\left(\varphi_i^m\right)\log P_j\left(\varphi_i^m\right) \tag{9}$$

$$Pdif_i^m = \frac{1}{N}\sum_{n=0}^{N-1}\varphi_i^m(n)^2 - \frac{1}{N}\sum_{n=0}^{N-1}\varphi_i^{m+8}(n)^2 \tag{10}$$

$$P_i^m/P_i^{m+8} = \frac{\frac{1}{N}\sum_{n=0}^{N-1}\varphi_i^m(n)^2}{\frac{1}{N}\sum_{n=0}^{N-1}\varphi_i^{m+8}(n)^2} \tag{11}$$

$$D_{\mathrm{KL}}\left(\varphi_i^m \| \varphi_i^{m+8}\right) = -\sum_j P_j\left(\varphi_i^m\right)\log\frac{P_j\left(\varphi_i^m\right)}{P_j\left(\varphi_i^{m+8}\right)} \tag{12}$$

Table 1 Number of features for a participant

Valence/arousal state	40
Total features	7419
Reduced features	250

$$C\left(\varphi_i^m, \varphi_i^{m+8}\right) = \frac{\frac{1}{N}\sum_{n=0}^{N-1}\left(\varphi_i^m(n) - \bar{\varphi}_i^M\right)\left(\varphi_i^{M+8}(n) - \bar{\varphi}_i^{M+8}\right)}{\sqrt{\frac{1}{N}\sum_{n=0}^{N-1}\left(\varphi_i^m(n) - \bar{\varphi}_i^M\right)^2\frac{1}{N}\sum_{n=0}^{N-1}\left(\varphi_i^{m+8}(n) - \bar{\varphi}_i^{m+8}\right)^2}} \tag{13}$$

$$\text{Coherence}\left(\varphi_i^m, \varphi_i^{m+8}\right) = \frac{\left|\widehat{P}_{\varphi_i^m\varphi_i^{m+8}}(f)\right|^2}{\widehat{P}_i^m(f)\widehat{P}_i^{m+8}(f)} \tag{14}$$

where $1 \leqslant i \leqslant 8$ and $1 \leqslant m \leqslant 16$ refer to the IMF number and the channel number, respectively. P_i^m and P_i/P^m are IMFs power and their power ratios to channels power. PSDs ($\widehat{P}_i^m(f)$) are estimated using periodogram with the choice of 16 points FFT to obtain a smooth envelope and not to increase dimension of the feature set. Activity, mobility and complexity are Hjorth parameters of each IMF. In addition, entropy (H_i^m) are computed to estimate arousal state. On the other hand, asymmetric or unbalanced scores of the signal processing methods used for arousal state estimation are implemented to predict valence state. Power difference ($Pdif_i^m$), power ratio (P_i^m/P_i^{m+8}), relative entropy ($D_{\mathrm{KL}}\left(\varphi_i^m\|\varphi_i^{m+8}\right)$), correlation coefficient ($C\left(\varphi_i^m, \varphi_i^{m+8}\right)$), and coherence ($Coherence\left(\varphi_i^m, \varphi_i^{m+8}\right)$) between eight channels in the left and right hemisphere are extracted. Consequently, the number of features for a participant is given in Table 1.

Independent component analysis (ICA) [8, 13] is deployed to reduce dimension of the proposed feature set. After that, 40 valence/ arousal levels of a participant are used as testing data, while the levels of the other participants are used for training. This LOO cross-validation scheme is evaluated to find out the accuracy of the proposed method with k-NN and ANN classifiers.

5 Results and discussion

The performances of the proposed MEMD-based methods are evaluated using the publicly available DEAP data set for benchmarking. High/low arousal and high/low valence states of participants are recognized using the MEMD-based features with k-NN or ANN classifier, and then the results are compared to the studies which use DEAP data set to evaluate the suggested method.

A total of 7419 dimensional feature set is extracted using the suggested MEMD method. After computing the aforementioned signal analysis techniques, this large

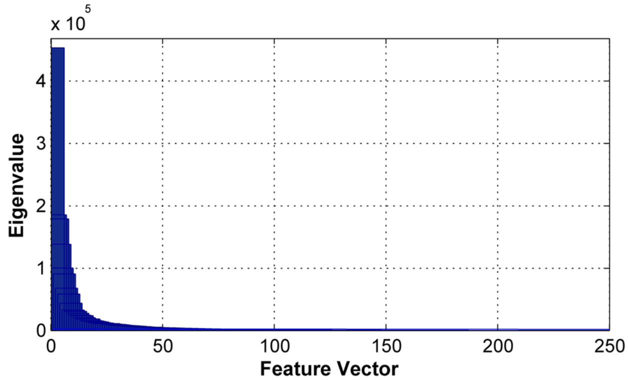

Fig. 7 Corresponding eigenvalues of the extracted feature set

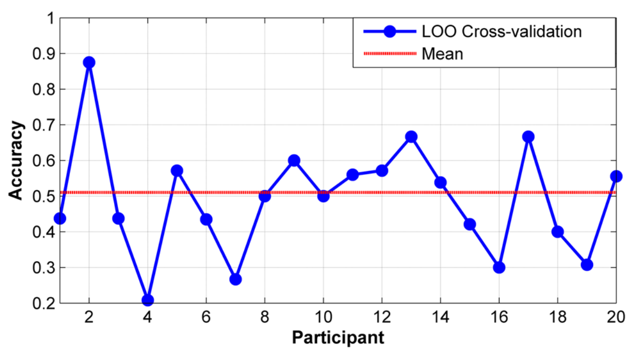

Fig. 8 High/low arousal classification results of k-NN with LOO cross-validation

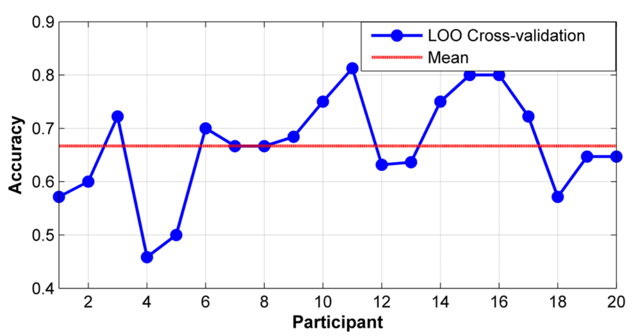

Fig. 9 High/low valence classification results of k-NN with LOO cross-validation

dimensional feature vectors are reduced to 250 independent components (ICs), and they are used for testing and training data in the rest of the study. Thus, 97.24 % of eigenvalues are retained as shown in Fig. 7.

Forty arousal and valence states of a participant as given in Fig. 4 are implemented as testing data and classified by k-NN and ANN trained by the rest of the arousal and valence states. k-NN classifier with LOO cross-validation scheme is evaluated using the proposed feature extraction method, and the accuracy results of high/low arousal and valence are given in Figs. 8 and 9.

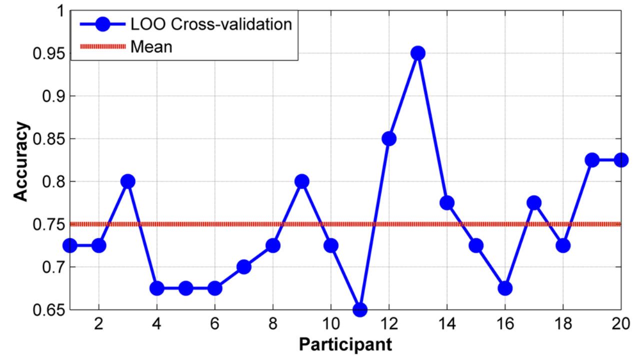

Fig. 10 High/low arousal classification results of ANN with LOO cross-validation

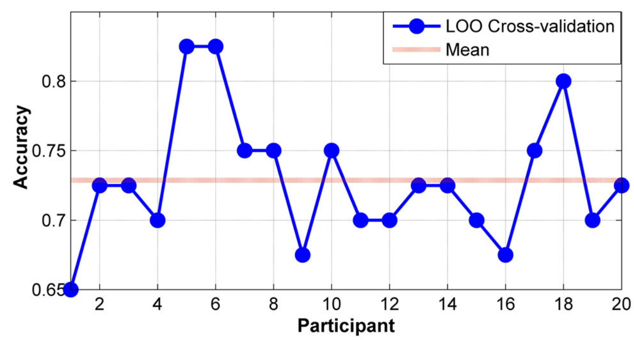

Fig. 11 High/low valence classification results of ANN with LOO cross-validation

k-NN with LOO cross-validation method yields accuracy rates of 51.01 % $\pm$ 15.69 and 67 % $\pm$ 9.60 for high/low arousal and high/low valence, respectively. Similarly, the feature extraction method is also evaluated using ANN classifier with two hidden layers up to 20 neurons. Emotion recognition results of the ANN classifier are shown in Figs. 10 and 11.

ANN with LOO cross-validation method yields accuracy rates of 75 % $\pm$ 7.48 and 72.87 % $\pm$ 4.68 for high/low arousal and high/low valence, respectively. In addition, the highest arousal accuracy level of 95 % is obtained for the 13th participant, while the lowest score is 65 % for the 11th participant. The highest and lowest valence scores are 82.5 and 65 % for the 5th and 1st participants. On the other hand, the classifications of k-NN and ANN for valence and arousal state recognitions have the lowest accuracy for the 4th participant. Our suggested MEMD-based emotion recognition methods are compared to the original study of the DEAP data set and the other studies which use this data set, and the results are given in Table 2.

Referring the comparison table, our suggested methods have higher accuracy rates than previous studies. From the point of classifiers, if k-NN is selected as classifier, accuracy rates reduce from 75 and 72.87 to 51.01 and 67 %

Table 2 The comparison of the MEMD-based emotion recognition with previous studies

Study	Recognition	Accuracy (%)	Methods
Koelstra et al. (DEAP) [10]	High/low arousal	62.00	SP, SPA, BC, LOO
	High/low valence	57.60	
Jirayucharoensak et al. [9]	High/neutral/low arousal	52.03 ± 9.74	SP, SPA, PCA, DLN, LOO
	High/neutral/low valence	53.42 ± 9.64	
Daimi and Saha [3]	High/low arousal	66.90	DT-CWPT, SVD, F-ratio, SVM
	High/low valence	65.30	
This study	High/low arousal	51.01 ± 15.69	MEMD-based features, ICA, k-NN
	High/low valence	67.00 ± 9.60	
This study	High/low arousal	75.00 ± 7.48	MEMD-based features, ICA, ANN
	High/low valence	72.87 ± 4.68	

when compared to emotion recognition using ANN in this study. MEMD-based method in this study and DT-CWPT method [3] are more successful than the others due to their advanced signal processing capabilities. On the other hand, the proposed MEMD-based feature extraction requires 123.23 s to decompose 18 EEG channels, while DWT takes only 3.45 s on a computer running at 2.27 GHz.

6 Conclusion

In this paper, we suggest multivariate empirical mode decomposition (MEMD)-based feature extraction method for emotion recognition as high/low arousal and high/low valence states. Multichannel EEG recordings of publicly available DEAP emotional EEG data set are used for benchmarking, and the results of previous studies are compared to the proposed MEMD-based method. The decomposed multivariate IMFs of the EEG signals are analyzed using band power ratios, power spectral density, Hjorth parameters, entropy, spectral power asymmetry, correlation and coherence. Independent component analysis (ICA) is implemented to reduce MEMD-based feature to 250 dimensions, and then arousal and valence states of the participants are recognized using k-nearest neighbor (k-NN) and artificial neural network (ANN) classifiers. The results indicate that our method outperforms the previous studies which use the same EEG data set. Extracted features with k-NN have accuracy rates of 51.01 and 67 %, while ANN yields the accuracy of 75 and 72.87 % for arousal and valence states, respectively. Therefore, nonlinear and non-stationary decomposition and signal processing capabilities of the MEMD with ANN provide more appropriate analysis to detect emotion form nonstationary EEG signals.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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