Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2019) 27: 4070 – 4081
© TÜBİTAK
doi:10.3906/elk-1805-126

Application of multiscale fuzzy entropy features for multilevel subject-dependent emotion recognition

Hamze LOTFALINEZHAD, Ali MALEKI*
Department of Biomedical Engineering, Semnan University, Semnan, Iran

Received: 20.05.2018 • **Accepted/Published Online:** 17.03.2019 • **Final Version:** 26.11.2019

Abstract: Emotion recognition can be used in clinical and nonclinical situations. Despite previous works which mostly used time and frequency features of electroencephalogram (EEG) signals in subject-dependent emotion recognition issues, we used multiscale fuzzy entropy as a nonlinear dynamic feature. The EEG signals of the well-known Database for Emotion Analysis Using Physiological signals dataset was used for classification of two and three levels of emotions in arousal and valence space. The compound feature selection with a cost of average accuracy of support vector machine classifier was used to reduce feature dimensions. For subject-dependent systems, the proposed method is superior in comparison to previous works with 90.81% and 90.53% accuracies in two-level classification and 79.83% and 77.80% accuracies in three-level classification in arousal and valence dimensions, respectively.

Key words: Emotion recognition, multiscale fuzzy entropy, electroencephalogram, support vector machine

1. Introduction

All of our thoughts, actions and decisions are rooted in our emotions [1]. The proper construction of emotional human–computer interaction system depends on understanding of emotions [2, 3]. Emotion-based human–computer interaction systems can be used in many areas such as healthcare, driving, marketing, and even educational programs. Affective computing is a development of a system that can interpret and recognize human affects, it is an emerging field of science [4, 5]. In the last few decades, researchers have done many studies on affective brain–computer interface to recognize emotions through electroencephalogram (EEG) signals. Because of high temporal resolution of EEG signals, the emotional response of a user can be detected in milliseconds but still, due to the noise and low spatial resolution of EEG signals, the automatic emotion recognition in subject-dependent issues remains unresolved. The majority of previous studies stimulated user emotions through external stimulations such as international affective picture system (IAPS) [6] and international affective digital sounds (IADS) [7]. In some other works, another type of stimulation like movie clips, music videos, or emotional recall has been used; we will review some of these works here. In [8], authors used IAPS and IADS to stimulate emotional states of the users and then with the spectral coherence of EEG signal and Multilayer perceptron (MLP) classifier, they achieved an accuracy of 64% for classification among happy, natural, and unhappy. Spectral features of EEG signals with naïve Bayes classifier achieved 60% and 40% accuracies for two and three levels of arousal classification [9]. In [10], authors used music video clips as stimulation and extracted spectral features from EEG signals for classification among three levels of arousal and valence with support vector

*Correspondence: amaleki@semnan.ac.ir

machine (SVM) classifier. As a result, 62% and 50% classification accuracies have been reported in arousal and valence dimensions, respectively.

In [11], classification accuracy of five individual emotions (joy, anger, sadness, fear, and relax) reached 42% with SVM classifier. In [12], authors evoked positive, negative, calm, and excited states of the users with emotional recall stimulation. Finally, with frequency properties of EEG signals and SVM, they reported 56% classification accuracy. In [13], spectral EEG features with naïve Bayes classifier was also used, and the results showed 55.2% and 55.4% accuracies in arousal and valence dimension, respectively. In [14], a new technique is defined for classification of emotions in 4 binary classes in 2D arousal–valence space. In [15], the authors used 2400 different features for emotion recognition in both arousal and valence dimensions. They used many feature extraction techniques, and finally with 30 to 40 features they reported 89.84% and 89.61% accuracies in bilevel and 75.02% and 75.70% accuracies in multilevel arousal and valence classifications, respectively.

The nonlinear dynamic structure of the brain signals appears at several successive levels. Therefore, simple entropy calculated in one level such as sample or fuzzy entropy cannot fully define the nature of these signals [16]. To overcome this issue, multiscale entropy (MSE) was defined; it extracts multiple scales of original time series with a coarse-gaining method and then calculates the entropy of each scale separately [17, 18]. The concept of MSE spans a wide range of areas such as information theory, statistical mechanics, biology, sociology, ecology, and economics [19]. In biomedical-related researches, MSE usage improved diagnosis accuracy such as human heartbeat fluctuation under pathologic conditions [16], MEG and EEG analysis in patients with Alzheimer's disease [20, 21], complexity analysis of human gait under various walking conditions [22], EEG complexity changes with aging [23], and analysis of human red blood cell glimmering [24].

Multiscale fuzzy entropy has been introduced recently; it can measure multivariate complexity of complex and noisy signals such as physiological signals. In [25], the authors have used multiscale fuzzy entropy to find coupling between heart rate variability (HRV) and diastolic period variability (DPV). Results showed that coupling between DPV and short-term HRV is reduced in multitemporal scales in patients with heart failure compared with healthy subjects. Multiscale fuzzy entropy has shown great performance in real-time uterine EMG complexity analysis, especially when we have a short duration of signals [26]. The emotion classification accuracy will increase by increasing feature dimensions and using more EEG channels and also reducing irrelevant data from the dataset. The objective of this paper is to choose a small number of EEG channels without losing classification performance.

Based on the reviewed studies, we encouraged the use of multiscale fuzzy entropy as a nonlinear dynamic feature to extract entropy of original EEG in different successive scales and to see how it can increase the performance of emotion recognition problems. Despite previous studies which used various time and frequency features with high feature dimensions, we expect better accuracy in arousal and valence classifications with lower feature dimension and small number of EEG channels by using multiscale fuzzy entropy. The structure of the present paper is as follows. In Section 2 we explain dimensional model of emotions. Section 3 presents an emotion recognition model and the details of the proposed method. Results and discussion are explained in Section 4. Finally, comparison with previous works and conclusion are given in Sections 5 and 6.

2. Dimensional model of emotions

Dimensional model of emotions was proposed by Russell [27] in 1980. It defines a variety of emotions in two dimensional arousal–valence space. Valence dimension divides emotions into positive and negative parts and arousal dimension in vertical axis defines emotions as low and high awakens (see Figure ??).

In Russell's emotion model, each discreet emotion will be mapped at a certain place in the 2D arousal and valence space. For example, neutral emotion will be placed in the central part of the 2D space between the arousal=5 and valence=5. Positive emotions with high arousal like happiness or joy will be mapped at the top-right corner of this 2D space and negative emotions with low arousal like depression or sadness will be placed at the bottom-left side of the 2D arousal and valence space.

3. Emotion recognition method

In this paper, a novel method which combines compound feature selection and kernel classifier is proposed. The model takes one EEG channel signal and binds relevant features for recognition of several emotions.

3.1. DEAP dataset

We used EEG signals of publicly available Database for Emotion Analysis Using Physiological signals (DEAP) [28]. The DEAP dataset consists of 32 EEG channels and other 8 peripheral signals including electrodermal activity, body temperature, blood volume pulse, respiration, two-channel electrooculogram, and two-channel surface electromyogram. In the stimulation procedure, each volunteer watched a 60-s stimulation of 40 different affective music videos. At the end of the stimulation, the subject labeled each video in arousal, valence, dominance, liking, and familiarity spaces with a score from 1 to 9. At the end of each trail, 32 EEG channels (and other peripheral signals) which hold 60-s emotional content were obtained. These EEG channels have a specific label (label provided by the subject at the end of trial) in arousal and valence dimensions which will map them at a specific point in the 2D space of Russell's emotion model. In arousal or valence classification, we will divide arousal or valence dimensions into 2 or 3 classes such that each class has its own sets of EEG signals. In Figure 1, all 32 EEG channels of DEAP dataset are illustrated with gray and green colors (green color indicates the five selected channels for further analysis).

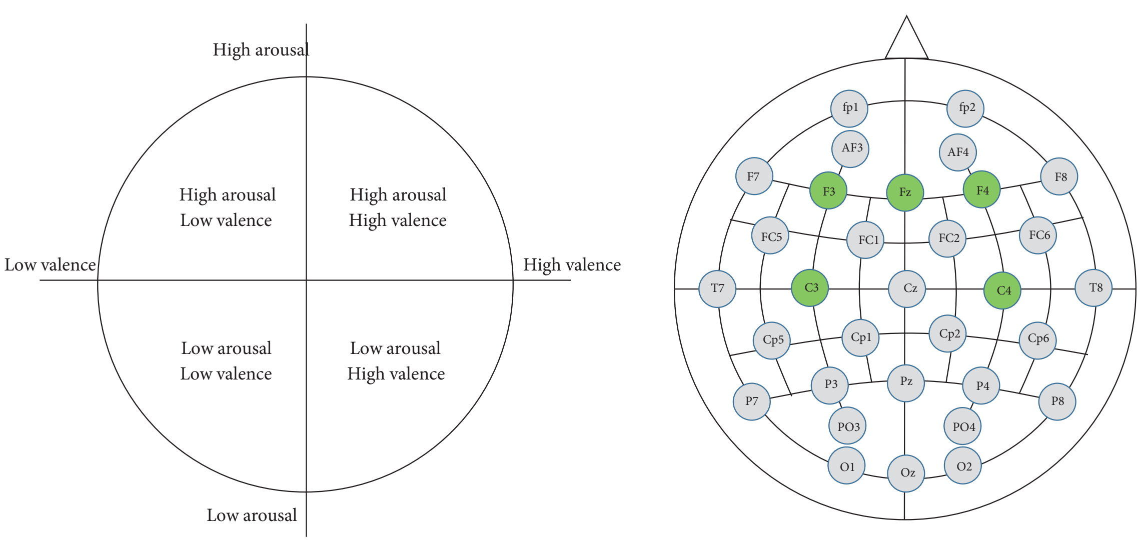

Figure 1. Russell's emotions model (left) and 32 EEG channels (gray and green colors) of the DEAP dataset (right).

3.2. Multiscale fuzzy entropy

Multiscale fuzzy entropy of a given time series can be calculated by using coarse gaining method (see Figure 2). In this method, we divide the original EEG signal into nonoverlapped subwindows with S (scale) number of samples in each subwindow. Here we will define a new time series by calculating the samples average in each subwindow [16] and the fuzzy entropy of this new time series is called S-scale fuzzy entropy of the original EEG signal.

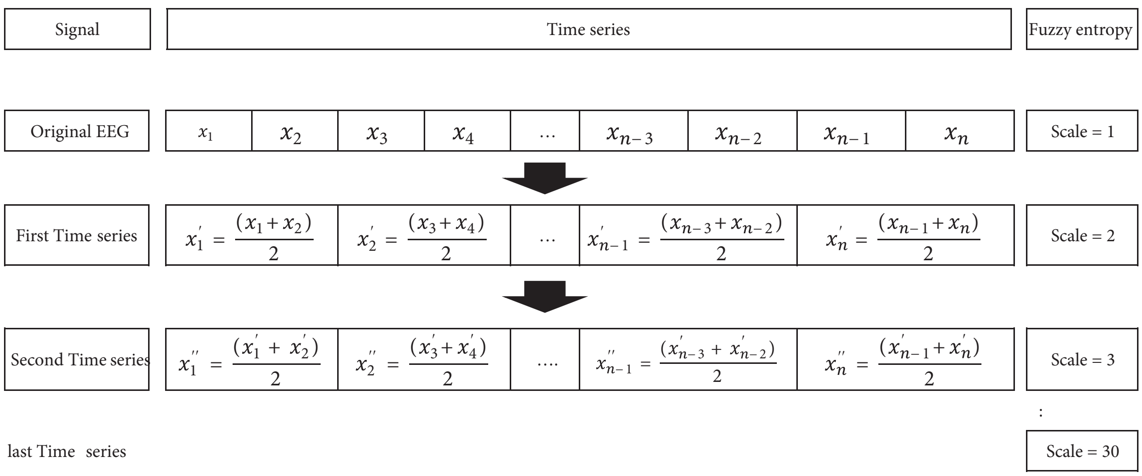

Figure 2. Multiscale (scale = 30) fuzzy entropy with coarse gaining method.

In our study, we used 30 scales ($S = 1, 2, , 30$) and in each scale the fuzzy entropy was calculated. For a given EEG signal, entropy is calculated as follows. Assume that we have an EEG signal with N-point samples ($u(i) : 1 \leq i \leq N$). For this time series, we proceed as follows to calculate the fuzzy entropy.

1. Perform phase space reconstruction on $u(i)$ according to the sequence orders. At the end of this step, we obtain a set of m-dimensional vectors ($m \leq N-2$). The reconstructed vector is given in Eq.1. Moreover, i is equal to $i = 1, 2, , N - m + 1$ and $u_0(i)$ is the mean value in Eq.1 and Eq.2.

$$X_i^m = u(i), u(i+1), , u(i+m-1) - u_0(i), \tag{1}$$

$$u_0(i) = 1/m \sum_{j=0}^{m-1} u(i+j). \tag{2}$$

2. Calculate the distance between the two vectors, X_i^m and X_j^m. The distance is defined as the maximum difference values between the corresponding elements of the two vectors.

3. Fuzzy membership function $\mu(D_{ij}^m, n, r)$ is an exponential function and in this function, r and n are width and gradient. The similarity degree D_{ij}^m of the two vectors, X_i^m and X_j^m, is defined in Eq. 3:

$$D_{ij}^m = \mu(D_i j^m, n, r) = \exp(-(D_{ij}^m)^n / r). \tag{3}$$

4. By defining the function $\phi(n,r)$ as Eq. 4 and repeating steps from (1) to (4), a set of $(m+1)$-dimensional vectors are constructed.

$$\phi(n,r) = \frac{1}{(N-m)} \sum_{i=1}^{N-m} [\frac{1}{N-m-1} \sum_{j=1, j \neq i}^{N-m} D_{ij}^{m}]. \tag{4}$$

5. Finally, Eqs.5 and 6 which is the fuzzy entropy of given signal are described.

$$\phi^{+1}(n,r) = \frac{1}{(N-m)} \sum_{i=1}^{N-m} [\frac{1}{N-m-1} \sum_{j=1, j \neq i}^{N-m} D_{ij}^{m+1}], \tag{5}$$

$$FuzzyEntropy(m,n,r) = \lim_{N \to \infty} [ln\phi^{m}(n,r) - ln\phi^{m+1}(n,r)]. \tag{6}$$

If the number of given time series samples (N) is limited (like EEG signals), the fuzzy entropy can be defined as $ln\phi^{m}(n,r) - ln\phi^{m+1}(n,r)$. For details about fuzzy entropy, see [29]. See Figure 3 for an example of multiscale fuzzy entropy of EEG signal.

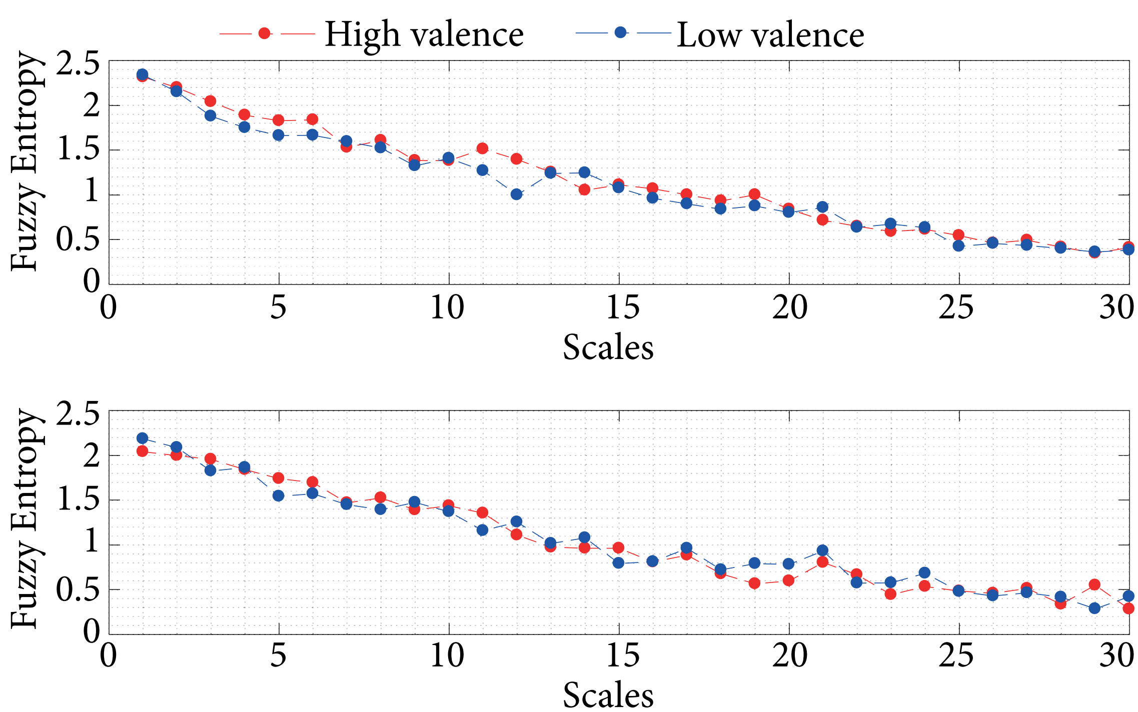

Figure 3. Example of 30-scale fuzzy entropy of arousal and valence in bilevel (high and low) emotions of channel Fz.

3.3. Compound sequential search

Large feature dimensions can cause curse of dimensionality for most of the classifiers [30]. There are many proposed methods in the literature for feature selection. Compound sequential feature selection is a wrapper-based method which is a combination of sequential forward selection and sequential backward selection techniques. In this method, first, we run the L consecutive forward selection on all features to find L optimal subset of features and then after the L steps were finished, we apply R backward elimination steps on these L features. We continue this L and R steps until the algorithm reaches a stopping criterion [31]. By early analysis, we set the optimal steps of forward and backward search to $L = 5$ and $R = 2$.

3.4. SVM classifier and classification levels

SVM is binary and well-known supervised classifier [32]. In an SVM network, the classifier trains with a training set with predefined features and then is tested with unknown test samples. There are many proposed methods for multiclass SVM classification among which one versus all (OVA) [33] and one versus one (OVO) [34] are the two common approaches. In this paper, we use the OVO method because of its advantages in comparison to OVA in terms of performance [35]. In OVA and OVO, we consider C and C(C-1)/2 SVM classifiers, respectively. Each classifier is trained with samples of train data and finally with majority voting strategy [35], we test the classifiers with unknown test samples. In this work, the k-fold (k is an integer number) cross-validation (rotation estimation) technique was used for our model validation [36]. We set the k-fold cross-validation average accuracy as a feature selection criterion which can prevent the overfitting of the kernel-SVM classifier. For kernel-SVM, we used radial basis function (RBF) as a kernel function.

To increase the accuracy of the SVM classifier, RBF-sigma (γ) as a kernel parameter was set to the value of 1 and a penalty factor (C) was set to its optimal value by using grid search [37]. The range of grid search was set to $[0.1, 2^8]$ with the interval of 0.1. For unbalanced data, we set the misclassification cost of minority classes to a higher value to prevent overfitting of classifier to majority classes.

In bilevel arousal–valence recognition, the range of arousal and valence (from 1 to 9) was divided into two equal classification classes ([1,5), [5,9] high arousal (valence) versus low arousal (valence)), respectively, and in multilevel emotion recognition, this range was divided into three equal classification classes ([1,3.66), [3.66,6.33), [6.33,9]) which divides the arousal and valence dimensions into 3 classes of high arousal (valence), neutral, and low arousal (valence), respectively.

3.5. The proposed method

3.5.1. Channel reduction

For each subject, we have 32 available EEG channels. To reduce the complexity of subject-dependent classification and processing time, among 32 available channels, we manually chose a set of channels which was used in previous studies as the best channels for emotion recognition tasks. Here we will review the papers which inspired us in the channel reduction step. The frontal lobe of the brain is related to negative and positive emotions and also sudden change of emotions [38–40]. In [41], eleven channels (P8- P7- AF3-AF4-FC5-FC6-PO3-FC6-F3-F4-C3) in the valence dimension and 9 channels (F7-F8-F3-P4- Oz- C3-C4- PO3-PO4) in the arousal dimension are reported as the best channels with better results. In [42], the authors chose 12 pairs of channels from the left and right hemispheres of the brain ((FP1,FP2), (AF3,AF4), (F3,F4), (F7,F8), (FC3,FC4), (FC1,FC2), (C3,C4), (T7,T8), (CP5,CP6), (CP1,CP2), (P3,P4), (P7,P8), (PO3,PO4), (O1,O2)) for classification of emotions in the arousal–valence space. In [43], F3-F4-C3-C4-P3-P4-O3-O4-Fp1-Fp2 were 10 best channels which were used in classification of emotions in both arousal and valence dimensions. In [28, 44], the authors showed that among 32 channels of the DEAP dataset, 8 channels (AF3-FP1-P7-FC2-C4-T8-CP6-PO4) are best channels for emotion recognition in arousal and valence space. In [14], initially 4 channels (F3, F4, C3, and C4) were considered, and finally, two channels (F3 and C4) were selected as the best two channels. By reviewing the results of the mentioned papers, we used five channels (Fz, F3, F4, C3, and C4) which are located in the frontal and central parts of the brain for classification of emotions in the arousal and valence space.

3.5.2. Feature extraction, selection, and classification

For each subject, we have five selected channels (F3, F4, C3, C4, and Fz) and 40 EEG signals each of which refers to a specific emotion in the arousal and valence space. We applied feature extraction, selection, and classification as follows. The feature extraction, selection, and classification steps for each subject is as follows:

1. Select one channel among five channels (F3, F4, C3, C4, and Fz).

2. The selected channel has 40 EEG signals and each signal has 7068 samples (60-s signal with a sampling frequency of 128 Hz).

3. Extract 30 features from these 40 EEG signals with the 30-scale fuzzy entropy method. At the end of this step, we have a feature matrix with 40 samples and 30 feature dimensions.

4. To reduce the feature dimensions, we use compound sequential search. In compound sequential search, features are selected in sequence. In the first step, the best single feature is selected among all the features. The criterion for this selection is the average k-fold cross-validation accuracy obtained using the SVM classifier. In the next step, the best combination of features is obtained by combining the feature obtained from the previous step with other features. This forward and backward search allows the classifier to choose the best combination of features which can lead to the best accuracy. See Figure 4 for the block diagram of the proposed method.

4. Results and discussion

There are 31 available participants in the DEAP dataset which have two and three levels of labeling in the arousal–valence space. Furthermore, 30 features (thirty-scale fuzzy entropy) were extracted from five different channels (Fz, F3, F4, C3, and C4) in both the arousal and valence dimensions. The classification results were divided into three sections, including the classification without any feature selection by providing the classifier with all of the thirty features in order to observe whether the feature selection has any effect on the obtained results, the classification using a single channel in order to observe which channel had the best results, and the classification using all five channels to observe whether the accuracy improves. For each channel, the mean classification accuracy of subjects with or without feature selection is reported in Table 1. Considering the five channels in question (Fz, C3, C4, F3, and F4), channel Fz had a higher accuracy of about 1–4% in the two-level arousal-valence classification and three-level valence classification. Furthermore, channel C3, which is primarily located in the central and left side of the brain, had the highest level of accuracy compared to other channels in the three-level valence classification. The classification accuracy of all five channels is reported in Table 1. As indicated by the results given in Table 1, when five channels were used instead of one, the classification accuracy increased in both the two-level and multilevel classifications.

According to the results given in Table 1, channel Fz has a higher level of performance in emotion classification when we merely compare single channels, regardless of their classes. In the case of utilizing

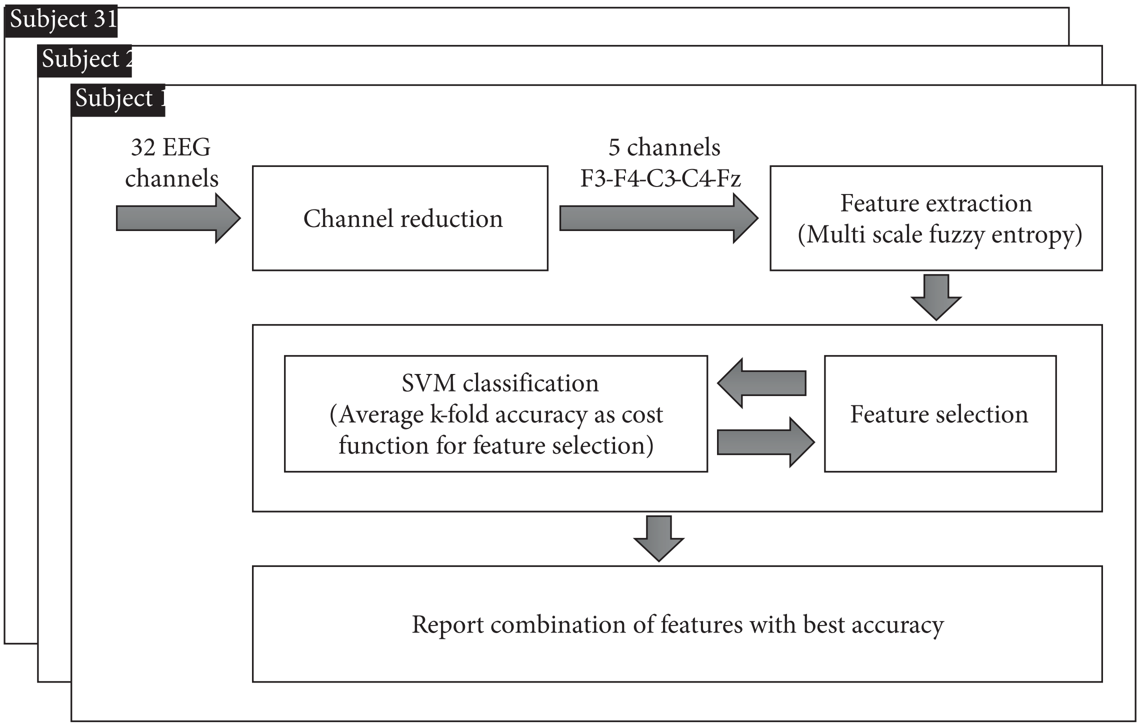

Figure 4. Block diagram of the proposed emotion recognition method.

Table 1. Average accuracy of 31 available subjects of all five channels and compound feature selection.

channel	2-classes accuracy				3-classes accuracy			
	Compound feature selection		All features		Compound feature selection		All features	
	Arousal	Valence	Arousal	Valence	Arousal	Valence	Arousal	Valence
F3	80.59	81.28	66.59	69.82	69.00	68.60	50.94	50.67
F4	80.8	78.99	67.21	66.41	72.33	67.54	52.84	51.69
C3	78.38	80.56	64.33	65.46	70.93	70.54	51.09	52.66
C4	80.35	80.45	66.13	66.57	69.83	68.90	50.47	50.29
Fz	85.04	81.84	69.37	68.04	72.58	69.93	51.73	50.18
All channels	90.81	90.53	–	–	79.83	77.80	–	–

all channels, the accuracy increases about 5–10% compared to a single channel (Fz) with a maximum of 10 features. The accuracy of subjects when all of the five channels (two- and three-level classification) are being used is illustrated in Figure 5. With respect to the arousal dimension, the mean accuracy was determined at 90.81% in the two-level labeling and 79.83% in the three-level labeling. As for the valence dimension, a mean accuracy of 90.55% and 77.80% was reached for the two- and three-level labeling, respectively.

5. Comparison with previous studies

A comparison was made between our proposed method and previous studies using the same dataset and threshold in the two- and three-level classifications, as shown in in Table 2. In a three-level recognition using a maximum of 10 features and five channels, an accuracy of 90.81% for the arousal dimension and 90.53% for the valence

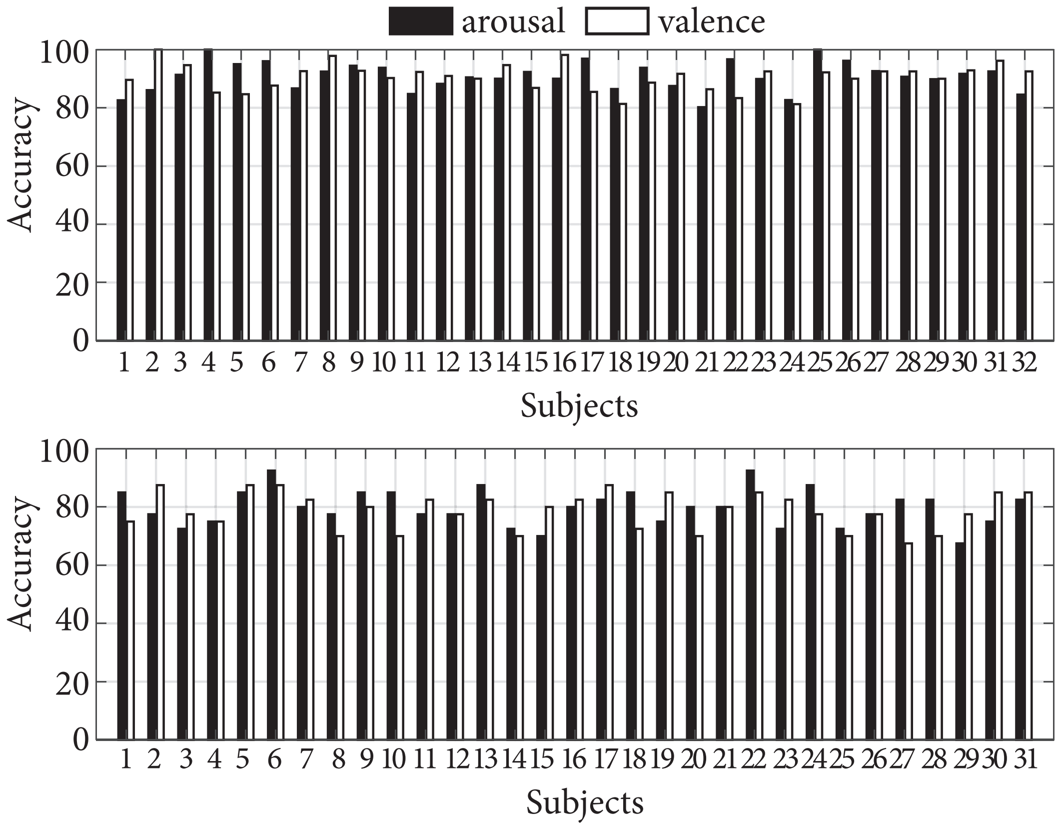

Figure 5. The average accuracy for each subject in two- (top) and three-level (bottom) classification.

dimension was reached, which is approximately 17% higher compared to values obtained in other studies [10] and [45]. In another research [45], more than 20 different features (time and frequency features) were employed for the two- and three-level classification, which is exactly twice the number of features used in our study.

For the two- and three-level subject-dependent emotion recognition, a more significant improvement was observed by using much smaller feature dimensions (a maximum of 10 features) and only five EEG channels. This, in turn, indicates that our proposed method plays a positive role in emotion recognition applications. In another research [15], the highest percentage of accuracy among the studies conducted on emotion recognition was achieved. In other words, accuracy levels of 89.61% and 89.84% were reached in a two-level classification for the valence and arousal dimensions, respectively, while accuracy levels of 75.02% and 75.70% were achieved in a three-level classification for the arousal and valence dimensions, respectively. Moreover, the reported accuracy was about 1–3% lower compared to our study even though 30 to 40 features were used. Therefore, a higher accuracy with a maximum of 10 features and five EEG channels was obtained in our research.

6. Conclusion

This research introduced a multiscale fuzzy entropy based on compound sequential feature selection in order to increase the accuracy of two-level and multilevel subject-dependent emotion recognition. The EEG channels in the front and central parts of the brain have been repeatedly used in previous studies, and their positive effect in emotion recognition have been confirmed. Moreover, it should be noted that our results are not far from what

Table 2. Comparison among previous subject-dependent studies with the same DEAP dataset.

Authors	Classification class	Arousal	Valence
Atkinson [45]	3	60.7	62.33
Soleymani [10]	3	62.1	50.5
Yoon [13]	3	55.2	55.4
Piho [15]	3	75.70	75.02
The proposed method (70% train, 30% test)	3	78.52	75.22
The proposed method (10-fold cross-validation)	3	79.83	77.80
Atkinson [45]	2	74.51	72.98
Yoon [13]	2	70.9	70.1
Piho [15]	2	89.84	89.64
The proposed method (70% train, 30% test)	2	89.43	89.91
The proposed method (10-fold cross-validation)	2	90.81	90.53

has been achieved in previous studies. We individually employed five different EEG channels (F3, F4, C3, C4, and Fz) and the Fz channel, located in the front part of the brain, had slightly higher accuracy in comparison with the other four channels. We also utilized all five channels at the same time in order to observe whether they can enhance the final results. Overall, simultaneous application of all five channels in the front and central parts of the brain had the highest level of accuracy in terms of both the arousal and valence dimensions.

Using the smallest number of EEG channels in the emotion recognition problems can, in fact, increase user comfort and reduce the associated computational costs. In the subject-dependent emotion recognition, a classification model should be individually developed for each subject since the training time is a key factor. In [15], 12 h was needed for one subject to be fully trained; however, the training time was around 20 min for both the two-level and three-level classifications in our proposed method. Finally, our method outperformed those in previous works in both the two-level and multilevel arousal-valence classifications.

References

[1] Dalgleish T, Dunn BD, Mobbs D. Affective neuroscience: past, present, and future. Emotion Review. 2009; 1(4): 355-368.

[2] Bajaj V, Pachori RB. Detection of human emotions using features based on the multiwavelet transform of EEG signals. Journal of Brain-Computer Interfaces: Springer 2015; 74: 215-240.

[3] Verma GK, Tiwary US. Affect representation and recognition in 3d continuous valence–arousal–dominance space. Journal of Multimedia Tools and Applications 2016:1-25.

[4] Tao J, Tan T, Picard R. Affective computing and intelligent interaction. First International Conference, ACII 2005; Beijing, China; 2005, Proceedings; 2005: Springer.

[5] Salmeron JL. Fuzzy cognitive maps for artificial emotions forecasting. Journal of Applied Soft Computing 2012; 12(12): 3704-3710.

[6] Lang PJ, Bradley MM, Cuthbert BN. International Affective Picture System (IAPS): Instruction Manual and Affective Ratings. The Center for Research in Psychophysiology, University of Florida, 1999.

[7] Bradley MM, Lang PJ. The International Affective Digitized Sounds (IADS-2): Affective Ratings of Sounds and Instruction Manual. University of Florida, Gainesville, FL, Tech Rep B-3. 2007.

[8] Zhou F, Qu X, Jiao JR, Helander MG. Emotion prediction from physiological signals: A comparison study between visual and auditory elicitors. Journal of Interacting with Computers 2014; 26(3): 285-302.

[9] Gao J, Zheng C, Wang P. Online removal of muscle artifact from electroencephalogram signals based on canonical correlation analysis. Journal of Clinical EEG and neuroscience 2010; 41(1): 53-59.

[10] Soleymani M, Pantic M, Pun T. Multimodal emotion recognition in response to videos. IEEE Journal of Transactions on Affective Computing 2012; 3(2): 211-223.

[11] Takahashi K. Remarks on SVM-based emotion recognition from multimodal bio-potential signals. 13th IEEE International Workshop on Robot and Human Interactive Communication; Kurashiki, Okayama Japan; 2004. pp. 1-25.

[12] Chanel G, Kierkels JJ, Soleymani M, Pun T. Short-term emotion assessment in a recall paradigm. International Journal of Human-Computer Studies 2009; 67(8): 607-627.

[13] Yoon HJ, Chung SY. EEG-based emotion estimation using Bayesian weighted-log-posterior function and perceptron convergence algorithm. Journal of Computers in Biology and Medicine 2013; 43(12): 2230-2237.

[14] Zhang Y, Zhang S, Ji X. EEG-based classification of emotions using empirical mode decomposition and autoregressive model. Journal of Springer Science & Business Media, LLC, part of Springer Nature 2018; 20(77): 26697-26710.

[15] Piho L, Tjahjadi T. A mutual information based adaptive windowing of informative EEG for emotion recognition. IEEE Journal of Transactions on Affective Computing 2018; 1-1. doi: 10.1109/TAFFC.2018.2840973

[16] Costa M, Goldberger AL, Peng CK. Multiscale entropy analysis of complex physiologic time series. Journal of Physical Review Letters 2002; 89(6): 068102.

[17] Grassberger P. Toward a quantitative theory of self-generated complexity. International Journal of Theoretical Physics 1986; 25(9): 907-938.

[18] Goldenfeld N, Kadanoff LP. Simple lessons from complexity. Journal of Science 1999; 284(5411): 87-89.

[19] Manson SM. Simplifying complexity: a review of complexity theory. Journal of Geoforum 2001; 32(3): 405-414.

[20] Escudero J, Abásolo D, Hornero R, Espino P, López M. Analysis of electroencephalograms in Alzheimer's disease patients with multiscale entropy. Journal of Physiological Measurement 2006; 27(11): 1091.

[21] Hornero R, Abásolo D, Escudero J, Gómez C. Nonlinear analysis of electroencephalogram and magnetoencephalogram recordings in patients with Alzheimer's disease. Journal of Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences. 2009; 367(1887): 317-336.

[22] Costa M, Peng CK, Goldberger AL, Hausdorff JM. Multiscale entropy analysis of human gait dynamics. Physical A: Statistical Mechanics and Its Applications 2003; 330(1-2): 53-60.

[23] Takahashi T, Cho RY, Murata T, Mizuno T, Kikuchi M et al. Age-related variation in EEG complexity to photic stimulation: a multiscale entropy analysis. Clinical Neurophysiology 2009;120(3):476-483.

[24] Costa M, Ghiran I, Peng CK, Nicholson-Weller A, Goldberger AL. Complex dynamics of human red blood cell flickering: alterations with in vivo aging. Physical Review E. 2008; 78(2): 020901.

[25] Li P, Ji L, Yan C, Li K, Liu C et al. Coupling between short-term heart rate and diastolic period is reduced in heart failure patients as indicated by multivariate entropy analysis. Age (years). 2014; 56(7.6): 59.8-10.6.

[26] Ahmed MU, Chanwimalueang T, Thayyil S, Mandic DP. A multivariate multiscale fuzzy entropy algorithm with application to uterine EMG complexity analysis. Entropy 2016; 19(1): 2.

[27] Russel J. A circumplex model of affect. Journal of Personality and Social Psychology 1980; 39: 1161-1178.

[28] Koelstra S, Muhl C, Soleymani M, Lee J-S, Yazdani A et al. Deap: A database for emotion analysis; using physiological signals. IEEE Journal of Transactions on Affective Computing 2012; 3(1): 18-31.

[29] Xiang J, Li C, Li H, Cao R, Wang B et al. The detection of epileptic seizure signals based on fuzzy entropy. Journal of neuroscience methods 2015; 243: 18-25.

[30] James G, Witten D, Hastie T, Tibshirani R. An Introduction to Statistical Learning, vol. 112. NY, USA: Springer, 2013.

[31] Molina LC, Belanche L, Nebot À. Feature selection algorithms: A survey and experimental evaluation. In: Proceedings 2002 IEEE International Conference on Data Mining; Maebashi City, Japan; 2002. pp. 1-19.

[32] Cortes C, Vapnik V. Support-vector networks. Journal of Machine learning 1995; 20(3): 273-297.

[33] Vapnik V. The Nature of Statistical Learning Theory. NY, USA: Springer Science & Business Media, 2000.

[34] Knerr S, Personnaz L, Dreyfus G. Single-layer learning revisited: a stepwise procedure for building and training a neural network. Neurocomputing Journal of Springer 1990; 3(68): 41-50.

[35] Hsu CW, Lin CJ. A comparison of methods for multiclass support vector machines. IEEE Journal of transactions on Neural Networks 2002; 13(2): 415-425.

[36] Geisser S. Predictive Inference. New York, NY, USA: CRC Press, 1993.

[37] Kaya GT, Kaya H. Optimization of SVM parameters using High Dimensional Model Representation and its application to hyperspectral images. Signal Processing and Communications Applications Conference (SIU); Trabzon, Turkey; 2014. pp. 1-20.

[38] Fox NA. If it's not left, it's right: electroencephalograph asymmetry and the development of emotion. American Psychologist 1991; 46(8): 863.

[39] Fox NA. Dynamic cerebral processes underlying emotion regulation. Journal of Monographs of the Society for Research in Child Development 1994; 59(2-3): 152-66.

[40] Schmidt LA, Trainor LJ. Frontal brain electrical activity (EEG) distinguishes valence and intensity of musical emotions. Journal of Cognition & Emotion 2001;15(4): 487-500.

[41] Naser DS, Saha G, editors. Recognition of emotions induced by music videos using DT-CWPT. Medical Informatics and Telemedicine (ICMIT), 2013 Indian Conference; Kharagpur, India; 2013. pp. 53-57.

[42] Matiko JW, Beeby SP, Tudor J. Fuzzy logic based emotion classification. Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference; Hong Kong, China; 2014. pp. 6974-6980.

[43] Chen J, Hu B, Moore P, Zhang X, Ma X. Electroencephalogram-based emotion assessment system using ontology and data mining techniques. Journal of Applied Soft Computing 2015; 30: 663-674.

[44] Zheng WL, Lu BL. Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. IEEE Journal of Transactions on Autonomous Mental Development 2015; 7(3):162-75.

[45] Atkinson J, Campos D. Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers. Journal of Expert Systems with Applications 2016; 47: 35-41.