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Emotion recognition through EEG phase space dynamics and Dempster-Shafer theory

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ABSTRACT

Emotions play an important role in our life. Emotion recognition which is considered a subset of brain computer interface (BCI), has drawn a great deal of attention during recent years. Researchers from different fields have tried to classify emotions through physiological signals. Nonlinear analysis has been reported to be successful and effective in emotion classification due to the nonlinear and non-stationary behavior of biological signals. In this study, phase space reconstruction and Poincare planes are employed to describe the dynamics of electroencephalogram (EEG) in emotional states. EEG signals are taken from a reliable database and phase space is reconstructed. A new transformation is introduced in order to quantify the phase space. Dynamic characteristics of the new space are considered as features. Most significant features are selected and samples are classified into four groups including high arousal – high valence (HAHV), low arousal – high valence (LAHV), high arousal – low valence (HALV) and low arousal – low valence (LALV). Classification accuracy was about 90% on average. Results suggest that the proposed method is successful and classification performance is good in comparison with most studies in this field. Brain activity is also reported with respect to investigating brain function during emotion elicitation. We managed to introduce a new way to analyze EEG phase space. The proposed method is applied in a real world and challenging application (i.e. emotion classification). Not only does the proposed method describe EEG changes due to different emotional states but also it is able to represent new characteristics of complex systems. The suggested approach paves the way for researchers to analyze and understand more about chaotic signals and systems.

Introduction

During recent years, emotion classification has been receiving a lot of attention from numerous researchers in different fields. Emotions play a crucial role in human life. Thanks to emotion recognition systems, physicians and psychologists are now able to diagnose and treat people's mental disorders like depression, autism, etc. Moreover, different papers, which are related to Brain Computer Interfaces (BCI) and emotion assessment, have been published so far. Many scientists have tried to design a precise and fast emotion recognition system using biological signals with the aim of controlling robots or expressing real emotions online. Since there is no precise definition of emotion states, emotion recognition may solve problems in this field. Emotion states are key to designing video games and e-learning. These are just some interesting aspects of emotion recognition. We can easily conclude that emotion classification is of importance in our world [1–15].

There are two major views about emotions: one view considers emotions as general states of individuals and the other one knows emotions as physiological interactions [1]. The second view emphasizes on physical and physiological interactions. James introduced this approach for the first time in 1884. Feelings (like fear or anger and etc.) stem from the brain's responses to these physiological changes and not from the interpretation of the situation. Based on this approach we can distinguish emotions through processing biological signals such as EEG, Electrocardiogram (ECG), Electromyogram (EMG), etc. Since EEG has high temporal resolution and is simple to record, it seems to be a better source for emotion classification. Emotion recognition is carried out through EEG signals in this study. However, EEG has chaotic and non-stationary dynamics which suggests that nonlinear analysis can better describe this complex biological signal. Several studies such as [2–9]

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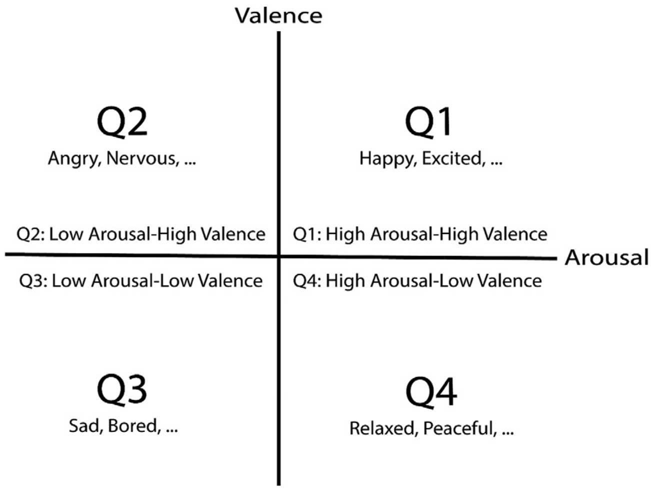

Fig. 1. Arousal-Valence Model of Emotions.

have reported the advantages to employing nonlinear analysis while processing EEG. Phase space of EEG contains reliable information about EEG dynamics and transitions. Therefore it seems that employing phase space reconstruction can help us to know more about EEG. In this study, phase space is utilized as a source of information to classify emotions.

Based on previous studies, human feelings can be described using two different approaches including discrete and dimensional models. Based on the first model, emotions are discrete and have unique physiological characteristics like fear, anger, happiness, surprise, etc. In contrast, dimensional model suggests that emotions are presented by two main factors; arousal and valence. Most recent studies in the field of emotion recognition have employed the dimensional model since more feeling can be represented in this model. Moreover, dimensional model is closer to the human perception about feelings. Similar to previous studies [2–15], in this study we use dimensional model. Considering the dimensional model, there are two coordinates to indicate feelings which lead to the arousal-valence plane. Fig. 1 shows the plane and some basic emotions on it.

As can be seen, this model consists of four quadrants which are named Q1 to Q4 in Fig. 1. These regions are correspondent to four main emotional states including high arousal-high valence (HAHV), low arousal-high valence (LAHV), low arousal-low valence (LALV) and high arousal-low valence (HALV). We also consider these four states and classify emotions into these groups. Since biological systems like CNS and their responses are nonlinear and non-stationary, it is necessary to take this fact into account that nonlinear analysis and features can indicate true changes in complex biological signals. Previous studies showed that nonlinear features can reflect emotions precisely [8–15]. Table 1 demonstrates some recent studies which have applied nonlinear analysis and features to classify emotions. Nonlinear features are mostly based on phase space reconstruction. Features like Lyaponouv exponents, correlation dimension, fractal dimension, etc. are highly dependent on the phase space of signals. In most studies including nonlinear analysis of EEG signals, phase space reconstruction is the first and most important part of signal processing. Nonlinear feature extraction is based on phase space reconstruction and mostly complicated and time consuming. It motivated us to employ phase space as a rich source of information to describe EEG dynamics while emotion elicitation with the aim of classifying emotions through EEG signals.

Committee machines have been widely used in artificial intelligence as they address most problems with mislabeling data or incomplete information in an appropriate way. Different models of classifier fusion such as voting, bagging and boosting have been employed recently. One of the most well-known fusion models is Dempster-Shafer theory (DST) of evidence. DST introduces a mathematical framework to combine experts or classifiers in order to decrease uncertainty and improve classification accuracy. Two basic but efficient classifiers including multilayer perceptron (MLP) and Naïve bayes are used and combined through DST in this study. Posterior probabilities are taken as the input of DST and classification is carried out. DST enables us to resolve some common problems in pattern recognition such as imprecise, uncertain and partial information. DST mostly results in better classification results.

In this study, EEGs are taken from a reliable emotion recognition database named Database for Emotion Analysis using Physiological Signals (DEAP) [16]. More information about this database is provided in the following sections. Since the preprocessed version of data is employed, no primary processing is required. EEG phase space is reconstructed for each channel and then transformed into a new state space called angle space (AS). In this paper, an attempt is made to quantify AS and its characteristics. Simulations show that this new space has valuable information about EEG dynamics in different emotion classes. Nonlinear features are extracted from AS and fed to classification step. Results show that determined, random, quasi-periodic and chaotic time series can be appropriately described through AS. Some geometrical characteristics and nonlinear features are calculated in order to analyze the dynamics of AS. Extracted features are statistically examined and most significant features are fed into the classification process. Two basic and common classifiers including MLP and Bayes are used to identify emotions and their outputs are combined through DST to improve the classification accuracy. Ten-fold cross validation is performed and results are reported. Fig. 2 shows the block diagram of the proposed method. More information about the proposed method is provided in the following sections.

Different features related to AS are introduced in this study and results show that these features are effective. Processing time is low and comparable to previous studies. To the best of our knowledge, transformation of phase space into this new state space and the proposed features have not been studied yet. Also simulations demonstrate some special features of the angle space whereby determined and chaotic signals can be easily classified. So this motivated us to propose the above-mentioned method. This paper is organized as follows: "Section 2" represents material and methods. Database, processing methods and suggested features are explained in this section. In "Section 3" results are reported and compared with other related studies. In "Section 4" you can find the discussion. Finally, the paper is concluded in "Section 5".

Table 1
Some recent studies in emotion classification using EEGs ([1] International Affective Picture System).

Ref.	Authors	Year	Database	Elicitation	Features
[5]	Zangeneh Soroush et al.	2018	DEAP	Video clips	Correlation dimension, fractal dimension, recurrence quantification analysis, approximate entropy
[6]	Zangeneh Soroush et al.	2018	DEAP	Video clips	20 nonlinear features from EEG phase space
[9]	Fan and Chou	2018	DEAP	Video clips	Recurrence quantification analysis
[10]	Tong et al	2017	Recorded	IAPS[1] pictures	Power spectrum entropy, correlation dimension
[11]	Song et al	2018	SEED, DREAMER	Video clips	Dynamical graph convolutional neural networks (DGCNN)
[14]	Xu and Plataniotis	2016	DEAP	Video clips	Power spectral density
[15]	Jie et al	2014	DEAP	Video clips	Sample entropy

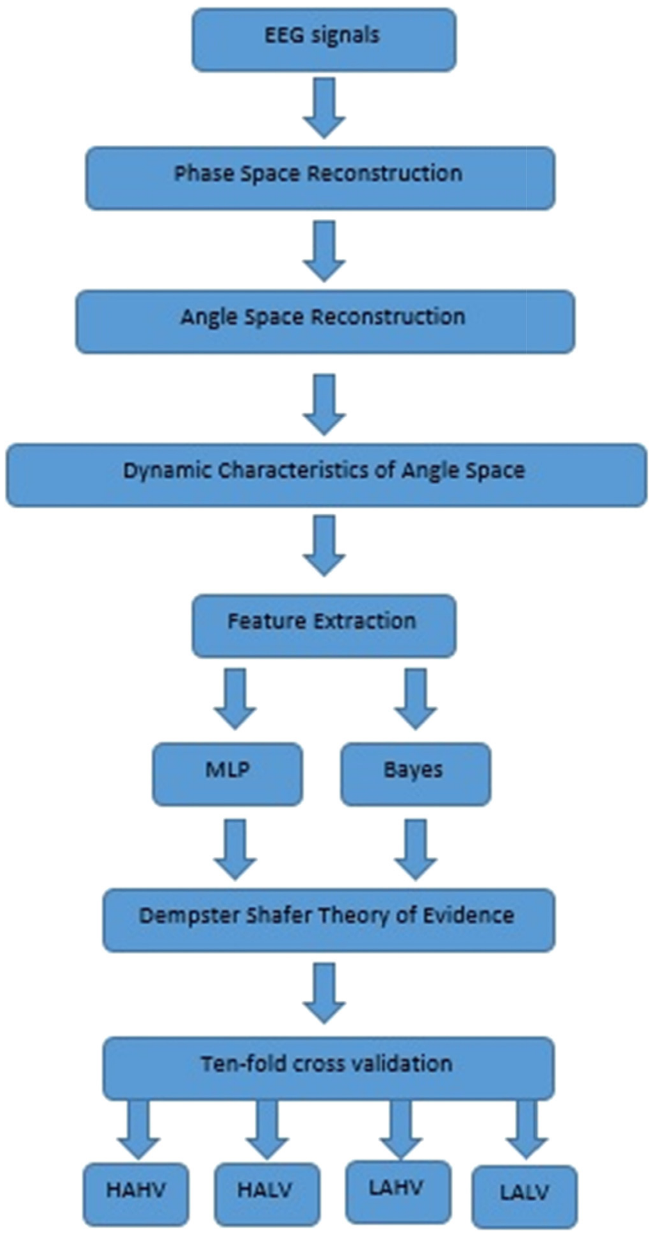

Fig. 2. Block diagram of the proposed method.

Materials and methods

Database

EEG signals from DEAP database are used in this study. This dataset is a reliable collection of bio-signals in response to emotion elicitation. Numerous studies have been conducted using this database [9,12–15]. Thirty-two healthy individuals (50% female, aged 19–37) participated in the experiment. Volunteers filled a consent and were informed about the experiment. 40 one-minute video clips were shown to participants, meanwhile they were requested to express their feelings through a self-assessment process using some factors including arousal, valence, dominance and liking in a continuous scale (from 0 to 9). EEG and some peripheral signals were recorded. The sampling frequency was 512 Hz first and was down-sampled to 128 Hz after preprocessing. 32 EEG channels (based on international 10–20 system) were recorded using Ag-AgCl electrodes. Based on what was just mentioned, 1280 samples (32 people, each one 40 trials) with one-minute 32-channel EEG signals and subjective values for arousal and valence are available in this dataset. For more information, the reader can refer to the online description of DEAP dataset at: http://www.eecs.qmul.ac.uk/mmv/datasets/deap and also refer to the published paper [16].

Phase space reconstruction

Phase space has received more attention in nonlinear dynamic signal processing during recent years. Many characteristics of a given signal can be described through the phase space. Phase space of a time series, here named x(t), is a set of vectors which is represented by X(i). We can reconstruct $N - d + 1$ vectors in the phase space as:

$$X(i) = [x(i)x(i+\tau)x(i+2T)\cdots x((i+(d-1))T)]i = 0, 1, \cdots,(N-(d-1))T \quad (1)$$

where d and T are the embedding dimension and time delay respectively. d and T are important parameters while reconstructing phase space. T stands for time delay and is estimated using mutual information algorithm. Embedding dimension is considered two for further analysis in this paper. It is also common to reconstruct EEG phase space in a 2D space [17–19].

Angle space reconstruction

After phase space reconstruction, we can consider the angle between each three points (in row) as a geometrical characteristic of the phase space. In other words, each line connecting points in the phase space is considered a vector and the angles between vectors and also the length of these vectors are calculated in order to transform the phase space into a new state space called AS. Fig. 3 illustrates the process of reconstructing AS from the phase space. In addition, the length of the vectors is calculated and used as a feature later. Estimated angles are transformed from the Cartesian coordination to Polar coordination. We calculate angles and vectors and then transform them into the new space. In other words, each point in the phase space (expect the first and the last points) is described by two geometrical characteristics including the angle and the radius in the polar coordination. These values can be considered as two time series describing the dynamics of the original signal (i.e. EEG in this study). It is a transformation from phase space to a new state space. This transformation lets us describe a signal (like EEG) in a new way.

In Fig. 3, P_0, P_1, P_2, $\cdots$ are points in the phase space of a hypothetical signal. The first and last points are ignored. θ_1, θ_2, θ_3, $\cdots$ and L_1, L_2, L_3, $\cdots$ are calculated and transformed into the angle space. By this new description, signals can be classified according to their representation in their AS. This transformation results in a 2D state space called AS and if we set the radius to 1 we have angle plot (AP). As it was mentioned before, two time series (angle and radius) are taken from AS. In this study, some common features in the field of nonlinear analysis are extracted from these two signals. These quantifiers help us to quantify signal dynamics in a new way. So, as it was mentioned above, angles and length of the vectors are achieved first. Suppose that $x(t)$ is a signal with N time samples and M points in the phase space. Angle values cannot be calculated for the first and last points in the phase space. Therefore $M - 2$ angles and vector length can be estimated. If we consider these parameters as two signals called length signal and angle signal, we can define length variability (LV) and angle variability (AV) as bellow:

$$\theta_V = \theta_{i+1} - \theta_i, \ \ i = 1, \cdots, M-3 \quad (3)$$

$$L_V = L_{i+1} - L_i, \ \ i = 1, \cdots, M-3 \quad (4)$$

where θ and L are angle and length values taken from the AS respectively. These two signals show dynamics of the angle space and also can describe characteristics of the original signal. The relative and difference values can show the changes along the signal trajectory. We can also illustrate length at a constant angle and also demonstrate angle

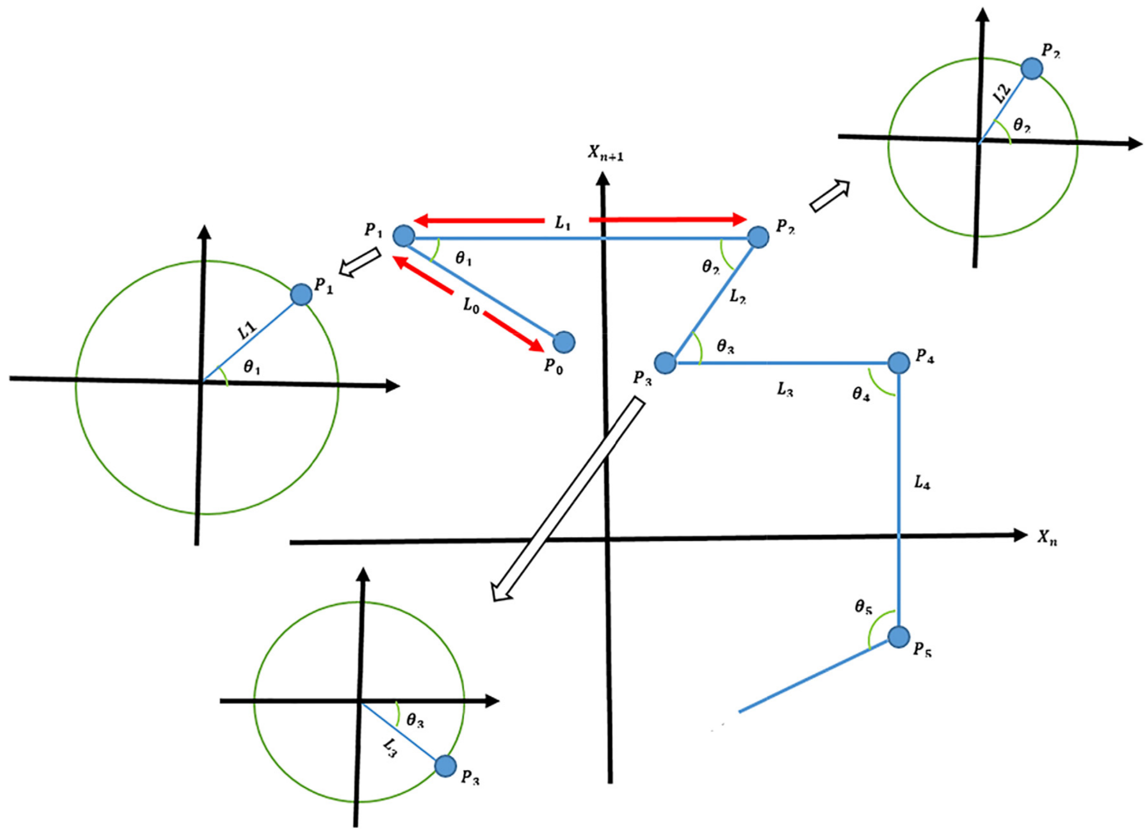

Fig. 3. Part of the phase space of a hypothetical signal and illustration of the angles for P1, P2 and P3 in the new state space called angle space.

values at a constant radius which is AP. These illustrations can be considered as sources of information and some nonlinear methods such as Poincare intersections can describe them in further studies. They are not studied in the current work. Fig. 4 represents a signal, its length and angle variability.

Fig. 5 shows the AS of some well-known signals. Taking a closer look at the angle space, we can easily realize that signals are describable and comparable through this new state space. Fig. 4 implies that the proposed state space can be an effective tool to analyze signals visually and qualitatively. For instance, the representation of a deterministic time series like *sin* signal is totally different from that of a chaotic logistic signal's. In the following sections some features are introduced in order to analyze the proposed state space in a quantitative way.

To go further we decided to study the logistic map through its AS. The logistic map is defined as follows:

$$r(n+1) = A * r(n) * (1 - r(n)) \tag{2}$$

where A is the parameter and usually varies from 3 to 4. $r(n)$ indicates the logistic map time-series. In this study, $r(0)$ is chosen 0.4 for all simulations and the simulation length is 300 samples. Logistic map, which is a model of complex systems, has different dynamics with respect to its parameter (i.e. A in Eq. (2)). Fig. 5 illustrates the bifurcation diagram of the logistic map, its AS, angle variability (AV) and length variability (LV). Taking a closer look at bifurcation diagram we can easily witness periodic, quasi-periodic and chaotic dynamics. The correspondent AS plots show that these dynamics can be recognized through AV and LV signals. Some differences can be visually noticed while analyzing logistic map through AS. This has motivated us to evaluate the proposed method in processing complex signals like EEG while emotion elicitation. We can conclude that emotional changes can be distinguishable through this analysis. Having been mentioned before, it is reported that almost all biological systems like brain and emotion regulation system consist of several components and are completely and inherently complex, nonlinear, non-stationary and non-Gaussian [20]. It suggests that to analyze these kinds of systems and their behavior, it is imperative to employ nonlinear time series descriptors like what has been done in this study. Not only do these characteristics describe signals and systems in the course of time but also they can reflect the interaction between components. This approach leads to extracting meaningful information from biological signals such as EEG [21]. Logistic map is just introduced to show the abilities of the proposed method. Similar to the logistic map, EEG has chaotic and nonlinear dynamics. Therefore, EEG is reconstructed into its AS and two time series including AV and LV are taken as information sources in order to classify emotions into four groups.

Feature extraction

As explained above, EEG signals are reconstructed in phase space and then in angle space. Two signals called angle variability and length variability are also calculated from the angle space. Features including correlation dimension, fractal dimension, etc. are extracted from these two signals. Statistical attributes like average, variance, skewness, kurtosis and Shannon's entropy of those signals are also estimated and used as features. A quantitative description of angle space is performed using Poincare map. In this paper, Poincare sections including horizontal and vertical coordinate, bisectors of the first and second quadrant are selected to represent features of EEG signals. A circle with radius equal to 0.01 is also selected as a Poincare section. Number of intersections is calculated and used as mathematical characteristics and features for further analysis and classification. Table 2 represents the features and the abbreviations.

Classification

In this paper, we used the statistical test analysis of variance

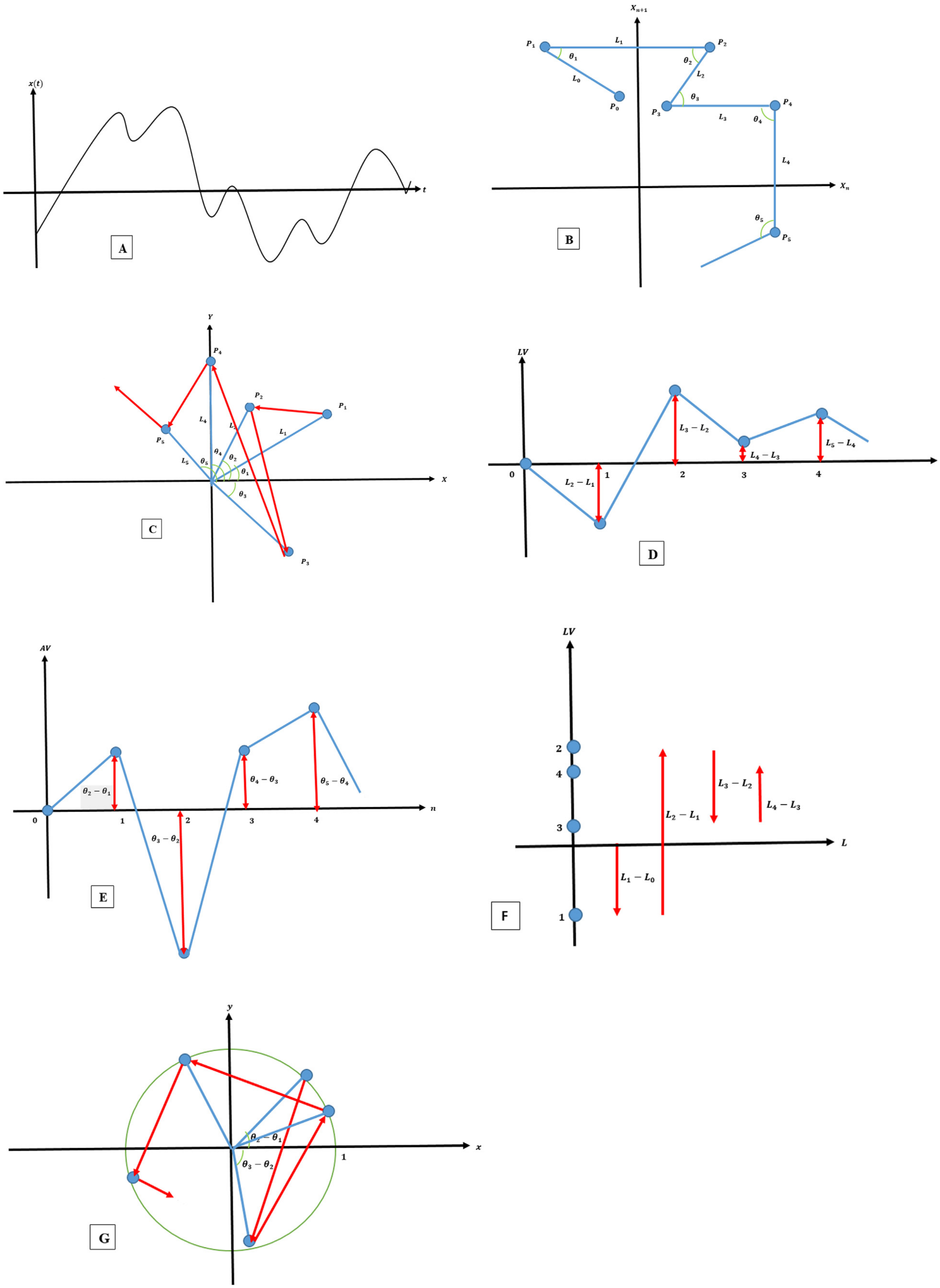

Fig. 4. Representation of a hypothetical (A) signal, (B) phase space, (C) angle space, (D) length variability signal, (E) angle variability signal, (F) length variability at a constant angle, (G) angle variability at a constant radius.

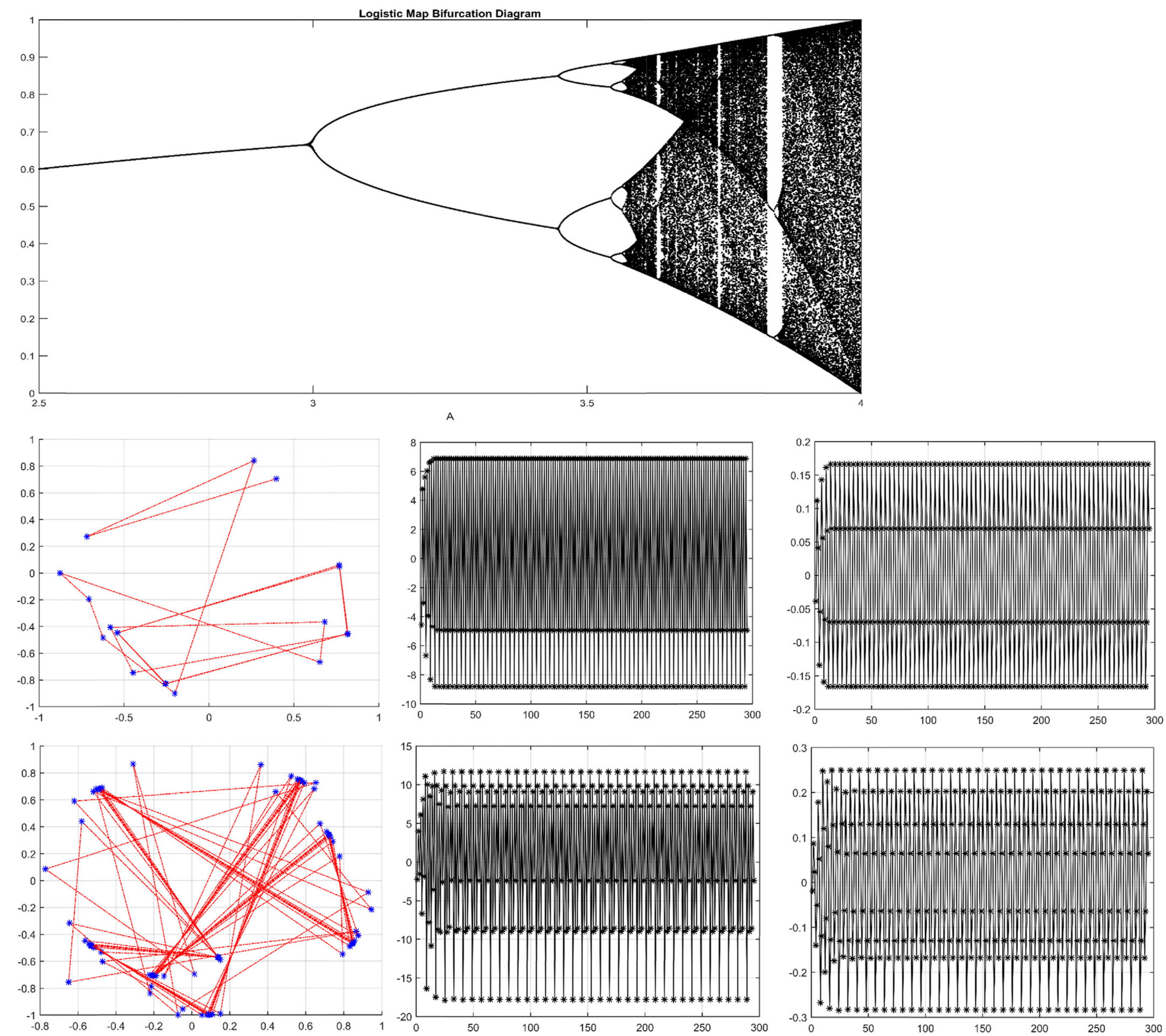

Fig. 5. Bifurcation diagram of the logistic map (the first row). Angle space, AV and LV are represented for different nonlinear dynamics including 4-cycle periodic (the second row), 8-cycle periodic (the third row), chaotic (the fourth row) in the logistic map and white noise (the fifth row). The first, second and third columns show AS, AV and LV for aforementioned dynamics respectively. The first row demonstrates bifurcation diagram of the logistic map. The values of the parameter A for the 4-cycle, 8-cycle and chaotic dynamics are taken as A = 3.50, A = 3.63 and A = 3.90 respectively. Simulation length is 300 samples.

(ANOVA) to determine the significant differences between the four emotional classes. Before using this measure, normal distribution was checked with Kolmogrov-Smirnov (K-S) test, then this measure was employed. Also, these features are tested based on correlation analysis in order to avoid data redundancy. Correlated features are eliminated. Selected features are fed into the classification procedure.

Bayes classifier is one of the most useful and well-known classifiers which minimizes the probability of misclassification. The main classification method is based on Bayes theorem. The Bayesian classifier is optimal due to minimizing the classification error probability. For more information, refer to [22]. This classifier uses prior probability of samples and generates the posterior probability for each sample. Posterior probability could be used as decision criteria and also in fusion of classifiers.

Neural networks have become quite effective in pattern recognition field. Among different kinds of neural networks, multi-layer perceptron (MLP) has a wide usage. MLP has been stated in many text books and papers [23–25]. Like several classification models, there are two major phases while using MLP as a classifier. The first step is training phase which means to adapt weights according to input data to have less classification error and more generalization abilities. The second phase is testing the model. Since implementation of MLP is really simple and there are several toolboxes to train and test it, we decided to use it in this study. A 3-layer MLP neural network with nonlinear (sigmoid) activation functions is used. Number of hidden neurons is set by trial and error method. The output of MLP is considered as the posterior probability.

The Dempster-Shafer theory (DST) of evidence is a mathematical framework which is able to handle imprecision of data. Uncertain and partial information could be analyzed using this theoretical framework. A mixture of classifiers can be designed by this mathematical framework. DST has been addressed in numerous studies and used in several

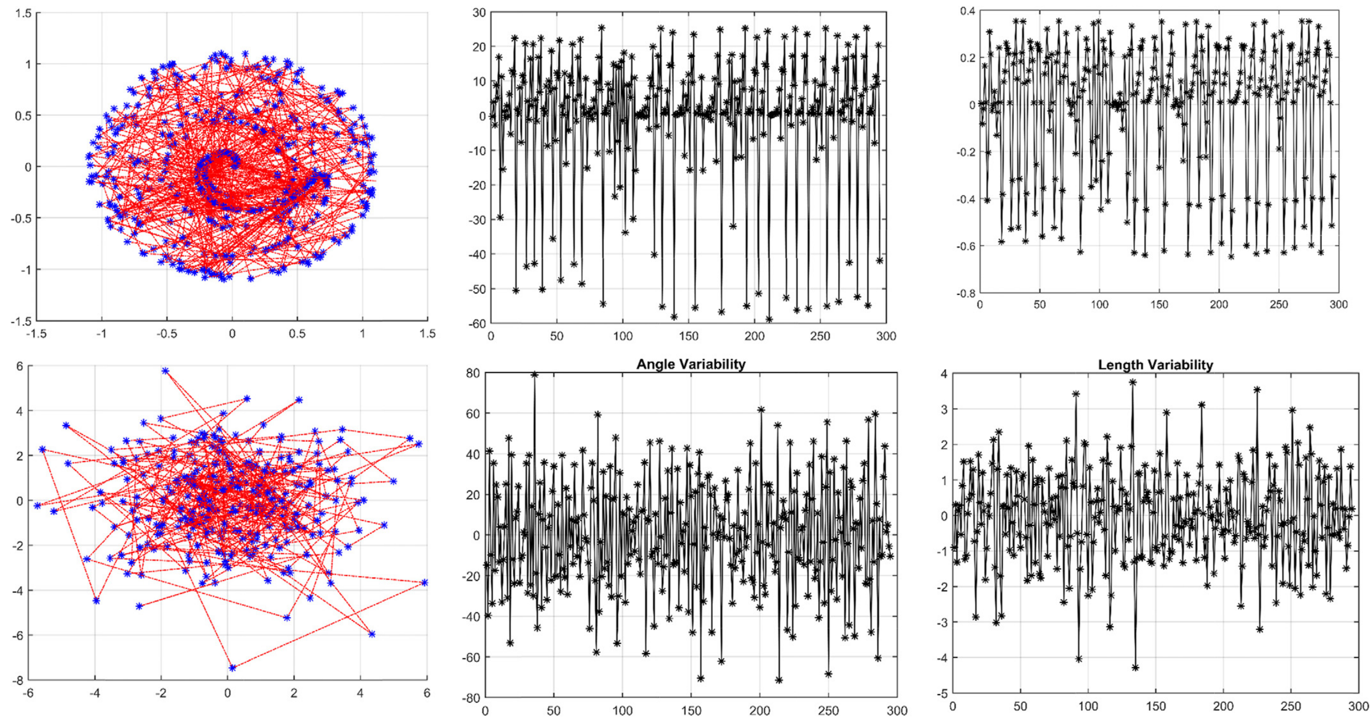

Fig. 5. (*continued*)

Table 2
Features and abbreviations.

#	Feature description	Information source	Abbreviation
1	Correlation Dimension	angle variability	CDA
2	Fractal Dimension	angle variability	FDA
3	Largest Lyaponouv Exponent	angle variability	LLEA
4	Recurrence Rate (RQA)	angle variability	RRA
5	Determinism (RQA)	angle variability	DETA
6	Entropy (RQA)	angle variability	ENTA
7	Diagonal Line Length (RQA)	angle variability	LA
8	Mean	angle variability	MA
9	variance	angle variability	VA
10	skewness	angle variability	SA
11	kurtosis	angle variability	KA
12	Shannon's entropy	angle variability	SHA
13	Correlation Dimension	Length variability	CDL
14	Fractal Dimension	Length variability	FDL
15	Largest Lyaponouv Exponent	Length variability	LLEL
16	Recurrence Rate (RQA)	Length variability	RRL
17	Determinism (RQA)	Length variability	DETL
18	Entropy (RQA)	Length variability	ENTL
19	Diagonal Line Length (RQA)	Length variability	LL
20	Mean	Length variability	ML
21	variance	Length variability	VL
22	skewness	Length variability	SL
23	kurtosis	Length variability	KL
24	Shannon's entropy	Length variability	SHL

fields [5]. This theory, which was first introduced by Dempster and then modified by Shafer, can decrease uncertainty and incompleteness and lead to higher accuracy of classification by applying a combination rule to combine mass values of different information sources. These sources could be some experts or classification models trained by subsets of features. Different classifiers can be combined by this theory. Combination of classification models leads to better results. In this study, MLP and Bayes are employed and the posterior probabilities are fed to DST to be combined and classify emotions. In this study we used DST for emotion recognition, for more details about the implementation of DST please refer to [26–30]. Also, we decided to consider the maximum value of mass function. For sake of simplicity maximum mass value is chosen to determine selected hypothesis [28–30].

Results

EEG signals are represented in phase space. According to what was mentioned, each channel is transformed into the phase and angle space. Then two signals including angle variability and length variability are extracted from the angle space. Moreover, differential angle space at unit vector length and differential length space at constant angle are constructed. 24 different features are extracted from each channel and finally 20 most statistically significant features are selected. After feature extraction, ANOVA is performed and 20 features are selected as final features. Table 3 shows the most significant features. As

Table 3
Statistically significant features identified by ANOVA.

#	feature	channel	*p*-value
1	CDA	Fp1	$1.03 * 10^{-2}$
2	FDL	FC6	$1.26 * 10^{-2}$
3	RRA	O1	$1.47 * 10^{-2}$
4	DETL	Fp2	$1.63 * 10^{-2}$
5	SHL	Fp1	$1.76 * 10^{-2}$
6	LLEA	T7	$1.89 * 10^{-2}$
7	LA	FC2	$2.19 * 10^{-2}$
8	DETA	O2	$2.33 * 10^{-2}$
9	FDA	C3	$2.46 * 10^{-2}$
10	RRL	P3	$2.52 * 10^{-2}$
11	FDL	Fp2	$2.88 * 10^{-2}$
12	DETL	PO4	$3.11 * 10^{-2}$
13	ENTA	T7	$3.20 * 10^{-2}$
14	LLEL	Fp2	$3.26 * 10^{-2}$
15	CDL	F7	$4.27 * 10^{-2}$
16	LLEA	Fp1	$4.39 * 10^{-2}$
17	ENTL	FC5	$4.54 * 10^{-2}$
18	CDA	T8	$4.62 * 10^{-2}$
19	CDA	O1	$4.73 * 10^{-2}$
20	SHL	AF4	$4.85 * 10^{-2}$

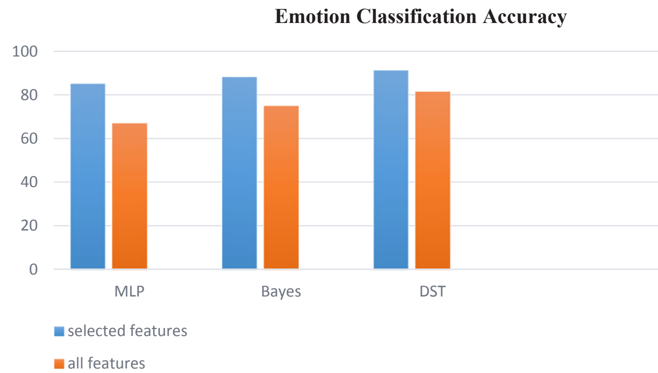

Fig. 6. Accuracy of classification methods before and after feature selection.

mentioned, also, features are tested based on correlation analysis; in order to avoid data redundancy, correlated features are eliminated and ignored.

As mentioned before, based on arousal-valence plane there are 4 regions (classes) in classifying emotions which are HAHV, HALV, LALV, LAHV. Taking a closer look at the block diagram of the proposed method in Fig. 2, we can easily realize that selected features are fed into MLP and Bayes classifiers. Ten-fold cross validation is used to evaluate the proposed method. Posterior probability values for test samples go through the softmax operator and then are combined by DST. Then final decision is made based on the fusion of classifiers. Finally, the proposed method is tested with respect to classification accuracy ratio. Fig. 6 shows the results of classification before and after feature selection.

Discussion

Due to EEG being chaotic and non-stationary, nonlinear methods should be taken into account in order to process such signals and time series. Nonlinear analysis is not limited to EEG processing or emotion recognition. Several studies like [31–33] have also employed nonlinear features to extract meaningful information from biological signals in different applications. Based on Table 3, nonlinear features are more effective in this study as the 20 most significant features include nonlinear features and statistical features are not as effective as nonlinear ones. Phase space reconstruction is a useful method to transform signals into a new space. In phase space new information about signals can be achieved. Phase space characteristics like geometrical features are valuable. Angle space can be extracted from phase space to better study its geometrical features. In this study angle space is reconstructed for EEG phase space with the aim of emotion recognition. Considering comparable results, it is obvious that emotion recognition could be handled using the angle space and its characteristics. Also, a relative view in signal processing is presented in this paper. Variations in angle and vector length are considered as new information and then nonlinear features are extracted from these two signals. Nonlinear features can successfully extract small changes in non-stationary signals like EEGs. In other words, it could be interpreted that absolute values are not important and differential values are more significant features while processing nonlinear and biological signals. That is why differential angle and vector length signals are estimated from angle space and then nonlinear features are extracted from these signals. Based on the previous sections, 24 features are extracted from each channel. 20 most statistically significant features are selected with respect to ANOVA. Selected features are classified by two well-known classifiers called MLP and Bayes. These classification models are combined using DST. Posterior probabilities of these two classifiers are fed into DST and based on the Dempster-Shafer rule of combination they are mixed and the maximum mass function is considered as the class label. Finally, 10-fold cross validation is used to ensure reliable classification. Samples are classified into four groups including HAHV, HALV, LALV and LAHV. Table 4 shows the classification performance of the proposed method and some recent studies using the same database.

According to Tables 1 and 4, it can be seen that the accuracy of our work is higher than the reported studies. Results indicate that the proposed method is quite effective and useful. This work could be extended to study angle space characteristics in other applications. Physiological meaning of proposed features can be analyzed in further studies. Other biological signals such as ECG can be analyzed through AS in future. Stability of the method and features is an important criterion. Stability at different noise levels for example, can be investigated in future studies. Moreover, this paper suggests that valuable information exists in a signal while employing relative and differential signals extracted from the angle space. In other words, by reconstructing angle space we process EEG signals' phases independently. Then signal amplitude is processed in vector length representation at a constant angle of zero. This view could be analyzed in other signal or image processing applications. Similar to other works, our study has some benefits and drawbacks. A new relative approach is introduced based on the phase space dynamics of EEG while emotion elicitation. In addition, we managed to classify emotions into four main emotional states using a new mathematical framework which is based on DST. A new method for analyzing nonlinear signals is proposed. In addition, the classification process, which takes advantage of DST, can successfully classify samples into emotional classes. The proposed classification method is used to decrease the uncertainty which exists in most pattern recognition studies. Since there are numerous samples which lay on the borders of emotional classes, previous studies had trouble recognizing emotions precisely. That is why most studies report lower classification performance for this dataset [13,35,37]. As it is mentioned in Table 4, most previous works have used basic classifiers which usually fail to classify data with imperfect labels. Therefore, this weakness might lead to uncertainty in the classification step and lower accuracy in those studies. It suggests that since samples are not separated in practical studies, it is necessary to employ classifiers whereby we can overcome uncertainty. DST can appropriately solve this problem and decrease uncertainty by mixing classifiers like what is carried out in this study. As can be seen, in recent studies like [12–15], researchers have tried to apply classification models such as deep learning which are based on decreasing uncertainty. In addition, the lack of samples might lead to incompleteness and consequently lower accuracy and generalization in classification. Some studies like [30] have introduced the benefits to employing DST as a solution while working on insufficient data with imperfect labels. Additionally, it is reported that combining different sources of information might yield better results. Employing DST in the current study not only enhances the classification accuracy but also leads to accelerating the progress of related research. DST is a flexible fusion theory and mathematical framework that is able to overcome the imprecision and incompleteness present in data and the uncertainties in different information sources [26]. Like every single study, our work has some weak points as well. One of the disadvantages is the number of samples, which is not large enough. Richer databases can be produced by researchers in the future. Also computation time, which is not efficient, is a drawback of this study as well. Our proposed method is computationally intensive. Faster algorithms could be developed in further studies to resolve this problem.

Detection of brain lobes which are correspondent to emotional changes is of importance from neuro-scientific point of view. Fig. 7 shows the share of each brain region with respect to 100 most significant features. As it was mentioned before, four classes named Q1 to Q4 are considered and significant features are determined using ANOVA. Taking a closer look at Fig. 7, we can conclude that all brain lobes participate while emotion elicitation. This means that neural circuits associated with emotional changes exist in almost all brain lobes. Although selected features are from all regions the frontal, temporal and occipital lobes are the most significant ones in all classes. As mentioned before, it is interpreted that there are complex and

Table 4
Summary of studies using the same database.

Ref	Authors	Year	Method	Classification Accuracy (%)
[5]	Zangeneh Soroush et al.	2018	EEG nonlinear features and modified Dempster-Shafer theory	91%
[6]	Zangeneh Soroush et al.	2018	EEG nonlinear features and combination of features selection approaches and machine learning methods	88%
[9]	Fan and Chou	2018	Recurrence quantification analysis, logistic regression	75%
[12]	Zhong et al	2017	Spectral and time features, multiple-fusion-layer based ensemble classifier of stacked autoencoder (MESAE)	78%
[13]	Atkinson and Campos	2016	Statistical and spectral features, Hjorth parameters, fractal dimension, minimum-Redundancy-Maximum-Relevance, support vector machine	62%
[14]	Xu and Plataniotis	2016	Power spectral density, stacked denoising autoencoders, deep belief network	89%
[15]	Jie et al	2014	Sample entropy, support vector machine	82%
[34]	Yin et al	2017	spectral and time features, multiple-fusion-layer based ensemble classifier of stacked autoencoder	77%
[35]	Tripathi et al	2017	convolutional neural networks, deep neural network	67%
[36]	Alam et al	2016	convolutional neural networks	81%
[37]	Kumar et al	2016	bispectrum, least square support vector machine, radial basis function, linear neural network	65%
–	**Our work**	**2019**	**The proposed method**	**91.37%**

nonlinear interactions between components while eliciting emotions.

To go further, 100 most statistically significant features are considered and the separability index is calculated based on the p-values for each channel. Lower p-values are correspondent to higher separability indices. The results suggest that some specific EEG channels including Fp1, Fp2, T7, FC2, FC6, O1 and O2 play a crucial role and can reflect emotions more effectively in comparison with other channels. These important channels, which are valuable sources of information, are mostly from frontal, temporal and occipital lobes. To approve of this finding, we compute the average brain activity over brain lobes for each class using EEGLAB [38]. Brian activity is achieved through the activation of the brain sources which are obtained using second order blind identification (SOBI) as it is recommended in some previous studies such as [5,6]. Fig. 8 shows the average components' activity over brain lobes. In other words, Fig. 8 represents the brain activity correspondent to each brain region in four emotional states. As it can be seen, the frontal, temporal and occipital lobes have the most activity in comparison with other brain regions. The results from Figs. 7 and 8 are almost similar to each other and approve of our results. This approves of our findings which was mentioned above in terms of significant EEG channels.

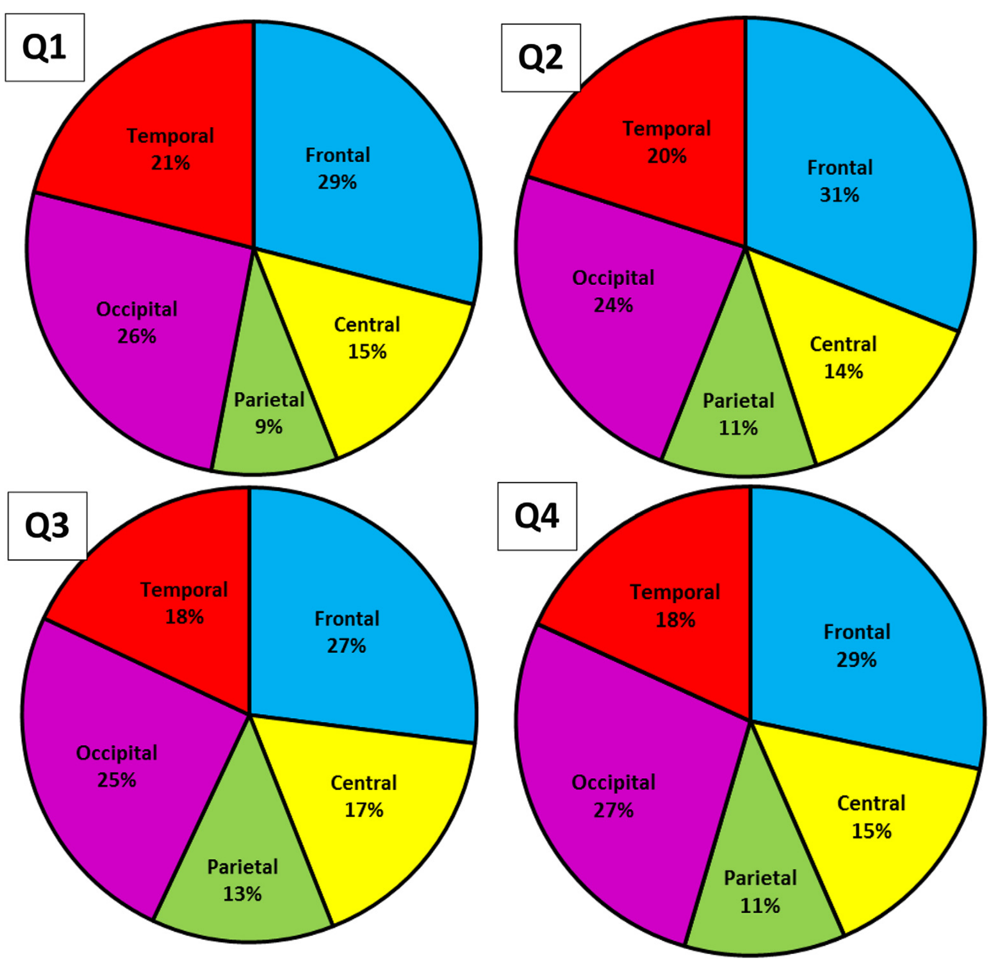

Fig. 7. Share of feature presence of each brain lobe for emotion classes.

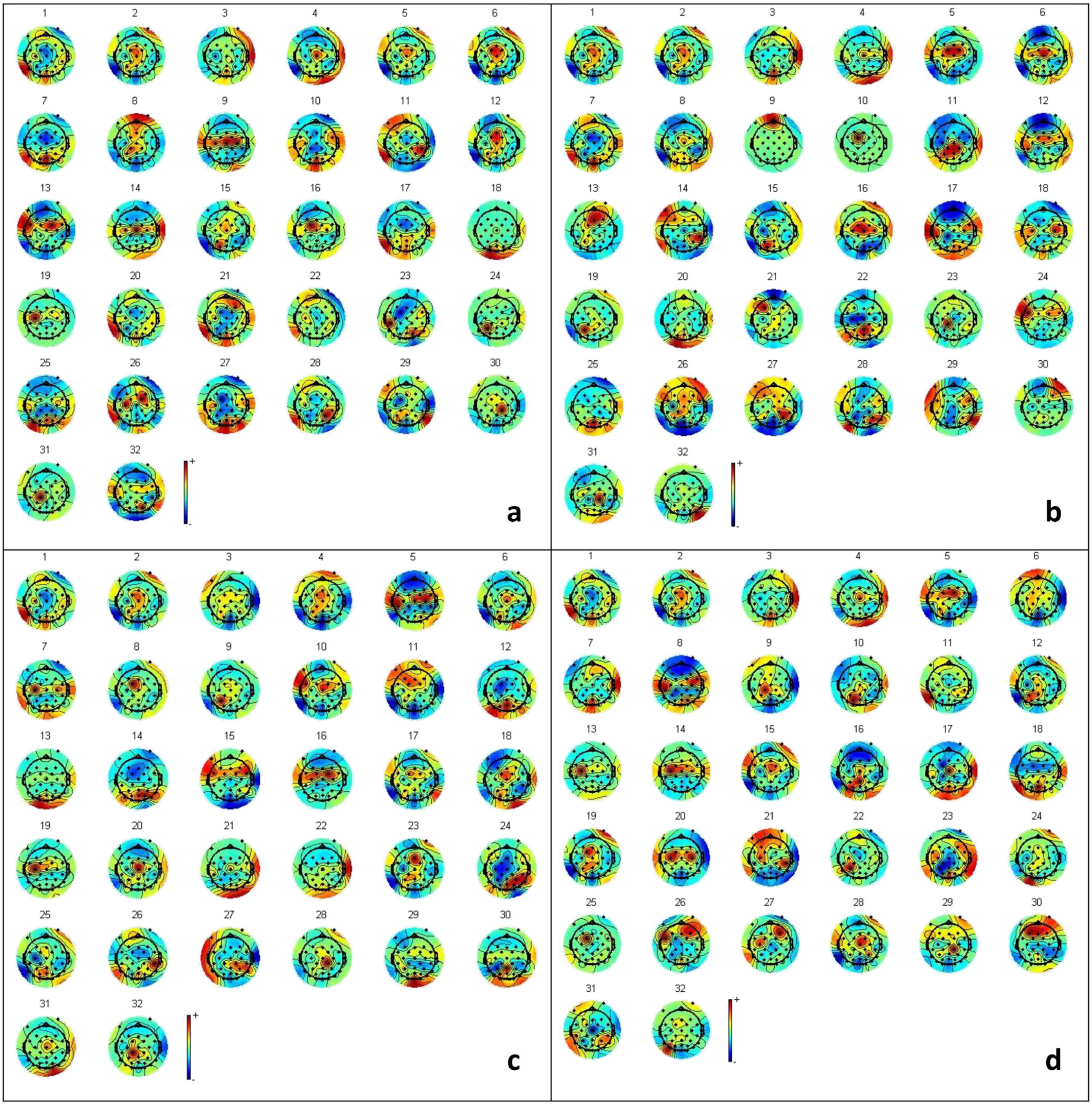

Fig. 8. Average brain activity in four emotional states including (a) HAHV, (b) HALV, (c) LALV and (d) LAHV [5].

Conclusions

Emotion recognition has become a very controversial subject in human computer interfaces. A lot of studies have been published with the aim of improvement in classification accuracy. In this paper, we introduce a new method using angle space of EEGs. Angle space of EEG signals is constructed and nonlinear features are extracted from the angle and the radius signals of AS. The proposed method leads to considerable results. Statistically significant and independent features are fed into two classification models including MLP and Bayes. Classifiers are combined through DST and final decision is made. Inspired by the success of the suggested method, we decided to use this method to classify emotions into four groups. Results show that the proposed method including the new state space, mentioned features and classification model is effective. Considering previous studies, it is clear that the proposed method is successful in emotion recognition. Also, it should be noticed that the processing time is quite short and advantages of the proposed method outweigh the disadvantages. This study has motivated us to employ this method in our future studies such as processing other biological signals.

Compliance with ethical standards

Declarations.

Consent for publication

Individual Person's Data: Not applicable.

Availability of data and materials

The data that support the findings of this study are available from [16] but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of [16]. The datasets analyzed during the current study are available in the DEAP repository, http://www.eecs.qmul.ac.uk/mmv/datasets/deap

Competing interests

The authors declare that they have no competing interests.

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Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Authors' contributions

Morteza Zangeneh Soroush and Keivan Maghooli conceived of the presented idea. Morteza Zangeneh Soroush developed the theory and performed the computations. Ali Motie Nasrabadi and Seyed Kamaledin Setarehdan verified the analytical methods. Morteza Zangeneh Soroush wrote the manuscript with support from Keivan Maghooli. All authors provided critical feedback and helped shape the research, analysis and manuscript. Keivan Maghooli supervised the project.

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