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EEG signal based Modified Kohonen Neural Networks for Classification of Human Mental Emotions

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Abstract

Identifying human emotions is very important in human machine interaction(HMI). These emotions will affect communication between people, and their mood.Emotion detection will give a clear idea aboutcustomer satisfaction in e-learning, marketing, entertainments and behavior of criminals in law. Artificial neural networksare essential for machine learning and emotion detection.The emotions are detected from EEG signals which can give better performance to audio and facial signals. In this work, several modified Kohonen neural networks are proposed for human emotion classification.EEG signals from DEAP Database are used asinput for ANN to detect the human emotions. Angry, Happy, Sad and Relax are the emotions classified using KohonenNeural Networks.Experimental results show promising results for the proposed approaches.

Keywords

Kohonen neural network, brain signals, human emotions, classification accuracy

1. Introduction

Human emotion recognition will improve the effective communication between human and machine interaction. Multi-model bio signals are used to classify the human emotions. Six human emotions are classified using back propagation artificial neural network. Accuracy of this model is good [1]. Emotions are recognized using physiological-data-driven approach by Multiple-fusion-layer based ensemble classifier of stacked autoencoder (MESAE).Three hidden layers and one filter is present in SAE to avoid the noise and stable features. DEAP dataset is given as an input to this classifier. Shallow emotion classifier and state-of-the-art deep learning models has lower generalization capability than MESAE [2].Emotion recognition using EEG signals is difficult but in Deep Neural Network (DNN), EEG-ER is more accurate than human's recognition capability. DEAP EEG data signal is given as an input to the DNN model. This will classify the emotion in two levels "positive" and the other one is "negative". Finally, CNN and conventional models are compared [3].

Affective states classification problem is addressed in two types Stacked denoising autoencoder (SDAE) and Deep Belief Networks (DBN). DEAP dataset EEG signals are given as an input to this model. In DPN 86.67%, 86.60% and 86.69% are the average F1 scores of arousals, valence and liking states. Small fraction of labeled data is applied for semi-supervised learning models. It will increase the state-of-the-art classification performance [4]. Here, emotions are identified using facial and brain signals. Feature extraction of both signals are calculated and given to artificial neural network for emotion recognition. Active Shape Model is used for facial feature extraction and Support Vector Machine method is used for emotion classification [5].

DEAP data set EEG brain signals features are extracted from Shannon Entropy and higher order auto-regressive model of statistical measures. These features are given as an input to multi-class Support Vector Machine for emotion classification. Accuracy of this algorithm is 94.097% [6]. Brain will produce different signals for every emotion. These changes are observed to reduce the noise and artifacts in EEG signal, modified adaptive filtering method is used. Feature extraction values of EEG signal is given to the adaptive neuro fuzzy inference system for emotion classification and analysis [7]. Facial expression, gesture, speech and text are the different ways to find the human emotions. Six emotions are classified by 4 classification methods SVM, NN, KNN, Naive Bayes and DWT. In neural network method 55.58% of accuracy is measured [8]. Feature extraction of EEG signal is calculated using discrete wavelet transforms. Extracted features are given to support vector machine and K-nearest neighbor classifiers to detect the emotional states. Arousal has the maximum accuracy of 86.75%and the valence accuracy of 84.05% [9].Feature extraction, dynamical reduction is calculated using Principle Component Analysis and Wavelet Transform. In accuracy Wavelet transform with ANN is having less accuracy than PCA with ANN. Various optimization techniques are used to improve the accuracy in Artificial Neural Network [10].

EEG signal frequency range is divided into five different levels according to their power spectrum density. 0 to 4 Hz EEG low frequency signals are avoided to reduce the EEG artifacts. Human emotions are detected by using inference and Bayesian network [11]. Real time EEG signals are recorded by Ground Truth Method. Extracted features are given to k-NN classifier then both sad and happy signals are classified. Training and testing data of different combinations are given to the classifier to calculate the accuracy level [12]. Recognizing functional autism patient emotion is very difficult using facial expression. Deep learning algorithm is used for both feature extraction and emotional classification. Three layers of restricted Boltzmann machines problems are cleared by Deep learning algorithm. Comparing to conventional algorithm, Deep learning algorithm has better emotion recognition accuracy [13].

In brain electrical activity of neurons are recorded by EEG. Support vector Machine (SVM), Linear Discriminant (LDA) classifiers are used to classify seven human emotions. Accuracy of both classifiers is 74.13% and 66.50% respectively. If the training sample increases it will increase the accuracy. While comparing both classifiers SVM has given a good accuracy of emotion recognition [14]. From EEG signals, sub-signals are plotted with the help of 3-D phase space diagram. From this diagram mean, standard deviation of Euclidian distance is calculated. Human emotions are classified with the help of multiclass least squares support vector machines (MC-LS-SVM).This classifier has an accuracy of 91.04% [15].

Three human emotions are classified with the help of hierarchical network structure with subnetwork nodes. Two EEG signal database is given to this system with both single and multiple modality. This classifier is compared with other state-of-the-art methods and shows that it performs better than them [16]. EEG signals are recorded from the object while they are watching a music video. This is given to the probabilistic network, which is simple, efficient, and easy to train. In order to reduce the number of channels Relief-based channel selection algorithm is used. Reducing the number of channels will not affect the accuracy of the system [17]. A simple Deep Neural network and convolutional neural networks are used for classification of emotions using DEAP EEG brain signals. This model has a state-of-the-art classification accuracy of 4.51 [18]. But, this method is computationally complex. Hierarchical convolutional Neural network is used to classify positive, neutral and negative emotions of EEG signals. And also stacked autoencoder (SAE), SVM and KNN classifiers also used for classification purpose. But accuracy of HCNN is higher than SAE. High frequency wave bands of EEG signals, Beta and Gamma waves used to read the emotions [19]. EEG signals of SEED dataset (SJTU Emotion Dataset) are used to find the time domain and time-frequency domain features. Artificial Neural network and Support Vector Machine (SVM) classifiers are used to classify three different human emotions with the accuracy rate of 91.2% [20]. But. Several methods have given better accuracy.

Training algorithm of Levenberg-Marquardt is used in the feed-forward neural network. Emotion-specific multichannel EEG dataset are given as input to this classifier. It has 60% of accuracy in emotion recognition [21].BDDAE and Bimodal-LSTM models are called denoising autoencoders. Features of temporal information and frequency-domain information are used in this classifier. Both SEED and DEAP data sets are given to this system. The mean accuracy is measured as 93.97% and 83.53 % respectively [22]. When the music is played, EEG brain signals are categorized by self-reported emotional states. With the help of support vector machine classifier four emotions (joy, anger, sadness, and pleasure) are classified with the average accuracy of 82.29% [23]. Russell's circumplex model, Higuchi Fractal Dimension (HFD) and support machine Vector are used to classify the emotions. Machine learning is done in two ways, one is for all subjects and another one is for a particular subject. In this first method is impossible for real time application and the second one is suitable for real time application and it has 70.5% of accuracy[24].In Support Vector Machine classifier emotion recognition is done based on Thayer's two dimensional model and accuracy of the classifier is increased from 72.14% to 87.27% with hierarchical classifier[25]. The novelty and the contributions of this work are:

- Two modified Kohonen neural networks are proposed in this work.
- The modifications are performed in the training algorithm. Specifically, the changes are made in the weight adjustment process of the conventional system.
- The proposed modified neural networks are independent of the difference between the inputs and old weights unlike the conventional Kohonen neural networks. This change has improved the performance of the proposed system

Since the current society is suffering from stress, depression, anxiety, the proposed work is highly suitable for practical applications. Smart watches can be developed with the proposed works as computational algorithms. People can use them daily to assess their emotional situation in workplaces. Similarly, phycologists can use these algorithms in their computers to assess the emotional conditions of their patients.

2. Proposed approach

The proposed approach is shown in Figure 1.

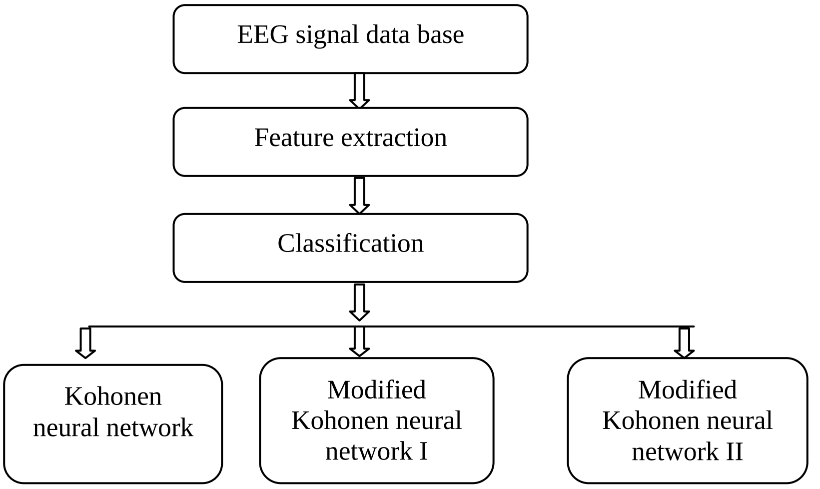

Figure 1. Framework of the proposed approach.

EEG brain signal will give an accurate emotion while comparing to facial,speech,gesture signals. Feature extraction of these signals is tabulated. Kohonen neural network is used to classify the human emotions. In order to improve the accuracy some modification is made in Kohonen neural network.

2.1. EEG signal database

Emotion recognition of human is more accurate when we use EEG brain signal because participants can hide their feeling in speech and facial signals. But it will not happen in brain signal. Here DEAP dataset [26] is used for emotion classification. In this dataset 32 participants are asked to watch a 40, one minute videos and their EEG brain signals are recorded in a noise free environment. Arousal and valences are responsible for classification of human emotion. If both the values are high it will be happy or relax, if both the values are low it will be angry or sad.

2.2. Feature extraction

Feature extraction is used to extract the information from the signals. Mean, Variance, standard deviation, skewness, kurtosis, mobility and complexity are the features taken to analysis the EEG brain signal.

Mean:

Mean value of the entire EEG signal is measured by the given formula.

$$Mean = \frac{1}{N}\sum_{i-1}^{N} X_i \tag{1}$$

Variance:

Variance is also one parameter in the feature of the signal. This is calculated by the given formula

$$Variance = \sigma^2 \tag{2}$$

Median:

Median value of a EEG signal is tabulated using the below equation

$$\begin{Bmatrix} Y_{(N+\frac{1}{2})} & if \quad N\, is \quad odd \\ 1(Y(N/2)+Y2+N/2) & if \quad N \quad is \quad even \end{Bmatrix} \tag{3}$$

Where Y1 and Y2 are two different EEG signals.

Mobility:

Ratio between first derivative of variance and variance is measured as mobility of the signal.

$$Mobility = \frac{First \quad derivative \quad of \quad Varience}{Varience} \tag{4}$$

Complexity:

Ratio between first derivative of mobility and mobility is called complexity of the EEG signal.

$$Complexity = \frac{First \quad derivative \quad of \quad Mobiligy}{Mobility} \tag{5}$$

Skewness:

Symmetry of the EEG signal is calculated using skewness formula. It always depends on mean and variance of the EEG signal.

$$Skewness = \frac{E(\mathrm{x}-\mu)^3}{\sigma^3} \tag{6}$$

Kurtosis:

Kurtosis of the signal gives the information about the peaks present the EEG signals. This is measured by the given formula where ‘m’ corresponds to the moments.

$$Kurtosis = \frac{m_4}{m_2^2} \tag{7}$$

3. Classification

Human emotions are classified using Kohonen neural network. Angry, happy, relax and sad are the four human emotions classified using valence an arousal value. If both valence and arousal values are high then it will be a positive emotion happy, relax. If both are low then it will be a negative emotion angry or sad.

3.1. Kohonen neural network

Kohonen neural network is also called self-organized map. It is a single layer, unsupervised, feed forward artificial neural network. Only one hidden layer is present in the Kohonen neural network. It uses "winner take –all" training rule for the training algorithm. Complexity of this network is less in comparison to Back Propagation Neural Network.

Training algorithm of Kohonen neural network:

Step1: Supply first input(x), randomly initialized weight matrix (w), learning rate(α).

Step2: Determine the Euclidean distance for every output layer.

$$d(j) = \sum_{i \neq 1}^{N} (x_i - w_{old})^2 \tag{8}$$

Step3: Determine the neuron (j) for which the distance value is minimum.

Step4: Adjust only the weights of the winner neuron

$$w_{ij}(new) = w_{ij}(old) + \propto [x_i - w_{ij}(\text{old})] \tag{9}$$

Step5: Repeat step 2 to step 4 with the new set of weights.

Step6: Repeat the algorithm for a specified number of iterations (100 to 200 times).

3.2. Modified Kohonen neural network I

In Kohonen neural network is an unsupervised network, so accuracy level is low while comparing to BPN. In order to increase the accuracy level some modification is introduced in the training algorithm. In Kohonen neural network new weight value is strong dependence of the initialization. So, in this modified Kohonen neural network new weight value will not dependent on the previous weight values.

Training algorithm of modified kohonen I:

Step1: Supply first input(x), randomly initialized weight matrix(w),learning rate(α).

Step2: Determine the Euclidean distance for every output layer.

$$d(j) = \sum_{i \neq 1}^{N} (x_i - w_{old})^2 \tag{10}$$

Step 3: Determine the neuron (j) for which the distance value is minimum.

Step4: Adjust only the weights of the winner neuron

$$\vartriangle w_{ij} = 2 \propto x_i + \propto \tag{11}$$

Step5: Repeat step 2 to step 4 with the new set of weights.

Step6: Repeat the algorithm for a specified number of iteration.(150).

The value of alpha used in this work is 0.6. The weight adjustment process is different from the conventional system. In the proposed method, the weight adjustment process is independent of the difference between the inputs and the old weights. Since this difference can never be zero, the conventional system performance is relatively poor. This is overcome in the proposed method.

3.3. Modified Kohonen neural network II

In modified kohonen neural network II, few other changes are made to increase the accuracy level in comparison to normal Kohonen neural network. Accuracy level of this network is higher than normal Kohonen and lesser than modified Kohonen neural network II.

Training algorithm of modified Kohonen II:

Step1: Supply first input(x), randomly initialized weight matrix(w),learning rate(α).

Step2: Determine the Euclidean distance for every output layer.

$$d(j) = \sum_{i \neq 1}^{N} (x_i - w_{old})^2 \tag{12}$$

Step 3: Determine the neuron (j) for which the distance value is minimum.

Step4: Adjust only the weights of the winner neuron

$$\vartriangle w_{ij} = 2 \propto x_i - \propto^2 \tag{13}$$

Step5: Repeat step 2 to step 4 with the new set of weights.

Step6: Repeat the algorithm for a specified number of iterations. (150)

The value of alpha used in this work is 0.6

4. Experimental Results and Discussions

The tests are completed in an Intel Core(TM) i3 processor with 4 GB RAM. The product utilized for the execution is MATLAB. Four human emotions of angry, happy, relax and sad are classified using Kohonen neural network.384 EEG signals are taken as an input to this test. There are 96 signals in each category. Among these, 30 signals are used for training process and the remaining 66 signals are used for testing process

4.1 Classification Accuracy of the classifiers

The proposed classifiers are analyzed by the terms accuracy, sensitivity and specificity. Formulae for measuring these terms are given below:

$$Classification \quad Accuracy(CA) = \frac{TP + TN}{(\mathrm{TP+TN+FP+FN})} \tag{14}$$

$$Sensitivity(SN) = \frac{TP}{(TP + FN)} \tag{15}$$

$$Sensitivity(SP) = \frac{TN}{(TN + FP)} \tag{16}$$

Where TP=True Positive, TN=True Negative, FP= False Positive, FN=False Negative. The detailed information about the performance measures and TP, FP, FN and TN are available in [27]. More information is available in [28-34].
The confusion matrix values are shown in Table 1, 2 and 3

Table 1. Confusion Matrix of Normal Kohonen network

.

	ANGRY	HAPPY	RELAX	SAD
ANGRY	40	0	0	26
HAPPY	0	47	0	19
RELAX	0	17	26	23
SAD	0	0	21	45

Table 2. Confusion Matrix of Modified Kohonen network I

	ANGRY	HAPPY	RELAX	SAD
ANGRY	40	0	0	26
HAPPY	0	47	0	19
RELAX	0	8	34	24
SAD	0	0	21	45

Table 3. Confusion Matrix of Modified Kohonen network II

	ANGRY	HAPPY	RELAX	SAD
ANGRY	40	0	0	26
HAPPY	0	47	0	19
RELAX	0	16	27	23
SAD	0	0	21	45

From the above table, it is evident that the misclassification of emotion is less in modified Kohonen neural network and more in normal Kohonen neural network. Then accuracy, sensitivity and specificity values are calculated using above formulae with the help of confusion matrix. These values are shown in Table 4,5 and 6.

Table 4. Performance measures of Normal Kohenen neural network

	TP	TN	FP	FN	CA	SN	SP
ANGRY	40	198	0	26	0.9015	0.6060	1
HAPPY	47	181	17	19	0.8636	0.7121	0.9141
RELAX	26	177	21	40	0.7689	0.3939	0.8939
SAD	45	130	68	21	0.6628	0.6818	0.6565
Average values					0.7992	0.5984	0.8661

Table 5. Performance measures of Modified Kohonen network I

	TP	TN	FP	FN	CA	SN	SP
ANGRY	40	198	0	26	0.9015	0.6060	1
HAPPY	47	190	8	19	0.8977	0.7121	0.9595
RELAX	34	177	21	32	0.7992	0.5151	0.8939
SAD	45	129	69	21	0.6590	0.6818	0.6515
Average values					0.8143	0.6287	0.8762

Table 6. Performance measures of Modified Kohonen network II

	TP	TN	FP	FN	CA	SN	SP
ANGRY	40	198	0	26	0.9015	0.6060	1
HAPPY	47	182	16	19	0.8674	0.7121	0.9191
RELAX	27	177	21	39	0.7727	0.4090	0.8939
SAD	45	130	68	21	0.6628	0.6818	0.6565
Average values					0.8011	0.6022	0.8673

The Kohonen neural networks have high specificity values than sensitivity values. The proposed method of neural networks has high accuracy in comparison to normal Kohonen neural networks. It may be noted that the modified Kohonen networks will not depend on the old weight values. A comparative analysis with other works is given in Table 7.

Table 7. Comparative analysis with other works

Author	Method	Accuracy (%)
Youjun Li et al [28]	K-NN	46
	Random decision forest	39
	SVM	65
	CNN+RNN	61
D. Jude Hemanth	Conventional Kohonen network	86
D. Jude Hemanth	Modified neural network I	87
D. Jude Hemanth	Modified neural network II	86

It is evident from the table that the proposed methods perform in an efficient way for practical applications.

5. Conclusions

Modified Kohonen neural networks are proposed in this work to improve the accuracy level of human emotion classification process. An improvement of 1-2% is achieved in modified Kohonen neural networks I and II. Even though the value is marginal, it is highly significant in case of affective computing applications. As a future work, different modifications can be used to improve the performance of the system. Different neural networks and feature set can be used to enhance the performance of the human emotion classification system.

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