

Emotion Recognition Based On Electroencephalogram Signals Using Deep Learning Network

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Deep learning networks have a high calculation volume, which is one of their problems. To solve this defect, the data of intrinsic modes obtained from the application of empirical mode decomposition to Electroencephalogram signals were used for the first time in this study. The present paper presents a method for emotion recognition using a deep learning network and electroencephalogram signal. Based on the non-stationary nature of the electroencephalogram, the intrinsic mode functions are extracted using empirical mode decomposition before selecting the first three intrinsic mode functions. Then, electrode positions are converted into pixel positions in images using suitable mapping, and the extracted features are interpreted as pixel color components. Using a deep learning network, all generated images are input into the network to determine whether they belong to the high or low valence class. Similarly, the class of arousal has been determined using the same method. This method was evaluated using the DEAP database to assess its efficiency. The results show that by selecting the image with the size of 17×17 , the proposed method can detect valence and arousal emotions with an accuracy of 82.3% and 78.4%, respectively, which is an acceptable superiority compared to previous research.

Keywords: Deep learning network, electroencephalogram signal, intrinsic mode functions, empirical mode decomposition, emotion recognition.

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1. Introduction

Emotional states significantly affect different parts of people's daily life, such as learning, making decisions, and communicating with others. With the advancement of technology, people's daily life is tied to the relationship between man and man and man and machine. Humans are skilled in deciphering the emotional signs that arise in their relationships with each other and can express appropriate responses following the situation [1]. Recent advances in machine learning in various sciences [2–4] have also helped design human emotion recognition methods [5–7]. Based on this, in recent years, the recognition of different human emotions has received much attention [8–10]

Various works have been done in the past that have

exactly handled emotion recognition through physiological signals and principally EEG as in [11–13]. Algorithms expending sample entropy [14], power spectral density [15], wavelet transform [16], differential entropy [17], and several other approaches have been applied for extracting features from the EEG signals. However, these prototypical driven approaches try to approximate the EEG data to a welldefined structured linear model and hence may not capture the non-linear statistics in the data. Majority of the state of the art models lately utilized machine learning-based classifiers [[18–20], PSD features with Naive Bayes classifiers in [21], PSD and holographic feature maps in [22], deep belief network-based features with support vector machine in [23], power spectral and statistical features with neural networks in [24], features extracted using a pyra-

midal convolutional neural network or autoencoders with fully connected networks as classifiers in [25]. Frequency domain-based feature extraction methods like short-time-Fourier transform [26] and complex wavelet transform [27] have also been used before.

There were various tools and methods to detect emotions, of which the electroencephalogram data is one of the most significant methods [13]. Emotion recognition by computer from EEG is a matter of machine learning and pattern recognition, which includes pre-processing stages of feature extraction and classification. Methods such as empirical mode decomposition (EMD), based on time-frequency property, are suitable for decomposing these signals [28]. Deep learning network is one of the new topics in the field of machine learning, which has recently been widely used.

In recent years, the use of artificial intelligence, machine learning, image processing [29–31], and optimization methods in numerous fields has involved the attention of many scientists. Also, the use of these methods to diagnose various diseases such as Covid-19 [32–34], Alzheimer's [35], cancer [36–38], etc. has been developed. Deep neural networks (DNNs) are neural networks that are made up of more layers. A support vector machine (SVM) was used by Aggarwal et al. [39] to classify emotions using features extracted from the wavelet packet transform. The average results obtained from the research for all people from the aspects of a class of arousal, dominance, and liking equal 64.3%, 66.2%, 98.3%, and 70.5%, respectively.

Mert and Akan [40] multi-channel EMD (MEMD) was used on 18 signal channels. Then, the signal was decomposed into its intrinsic modes, and the characteristics of power, entropy power spectral density, Hjorth parameters, and correlation were extracted from the intrinsic mode functions (IMFs). Another study by Chen et al. [41] has been conducted on the DEAP database, using Pearson and phase correlation, by separating 4 frequency bands of theta, alpha, beta, and gamma on 32EEG channels to detect emotions in high and low classes. The average accuracy of classes of valence and arousal using the SVM classifier and the leave-one-trial-out technique was obtained as 76.12% and 73.59%, respectively. Jirayucharoensak et al. [42] considered the power spectral density of 32 EEG channels on DEAP data as a feature. The important features were separated using PCA and using the leave-one-trial-out technique. These features were classified into three classes: high, low, and neutral. Bahari and Janghorbani [43] reached an regular accuracy of 58.05% and 67.64% for arousal and valence, respectively, by using the spectral power of different frequency bands in EEG samples on all EEG channels. Arnau-González et al. [44] recognized emotions by using

channel-based and correlation-based features, support vector machines, and simple Bayes classifiers. The best accuracy was obtained with the support vector machine classifier, whose valence and arousal value was 69.6% and 67.7%, respectively. Liang et al. [45] extracted features in the time-frequency and wavelet domains in 32 EEG channels and labeled the data using large-scale clustering. Olamat et al. [46] selected convolutional neural networks (ResNet-101, DenseNet-201, AlexNet, and ResNet50) and AutoKeras framework for image organization. Cizmeci and Ozcan [47] presented a technique including the collection of suitable channels from EEG data, feature extraction by Welch power spectral density estimation of selected channels, and an enhanced capsule network-based classification model. The technique was established with DEAP and DREAMER EEG datasets.

There are several difficulties associated with deep learning networks, including the high volume of calculations involved. Hence, providing solutions with optimal accuracy in the shortest time and using the least data has attracted the attention of many researchers. In this study, for the first time, intrinsic modes have been applied to EEG signals to reduce the number of features for emotion classification. For this purpose, in the present study, emotions categorizing has been conducted into two classes, high and low, about valence and arousal. To extract the features, the signal is first decomposed into intrinsic modes using EMD. In the following, the first three IMFs are selected, and then each IMF is converted into smaller parts by windowing. The power of each part is considered a feature. The features are converted into images using the mapping corresponding to the 10-20 system, and these images, which express emotions, are classified by designing a deep learning network.

The rest of the study is organized as follows. In Section 2 we will discuss the methodology framework and database. In Section 3 we will present the proposed results and discussion. This work will be concluded in Section 4 followed by funding and references.

2. Methodology

First, this section introduces the database used in the present research. Then the various stages of the proposed method, including feature extraction using EMD, feature mapping to the image, and deep learning network, are described.

2.1. Database

DEAP database is used in this study [48]. This database contains signals recorded by 32 people while watching 40

one-minute music videos. The recorded signals include 32-channel EEG (based on a 10-20 electrode system) and 8 physiological signals (skin galvanic, respiratory amplitude, skin temperature, heart rate, blood pressure of neck and smile muscles activity, and EOG). At the end of each music video, the person is asked to use the selfassessment mannequin method to express his/her emotions in the aspects of valence, arousal, dominance, and liking as quantitative values from 1 to 9 and to describe liking the video with 3 states of liking, neutral and disliking. EEG signals are sampled at a rate of 512 samples per second. These signals are passed through a band-pass filter with a pass band of 4 to 45 Hz to remove possible noises and artifacts and to maintain a suitable frequency range. After that, the sampling rate was reduced from 512 to 128. In this way, including 3 seconds of additional time for rest and concentration of the person, the examined data in each EEG channel for each person-music video equals 8064 samples. By referring to the 10 – 20 system, the subjects could be compared to each other. Human brain wave is the composition of five main frequency bands called delta (1 – 3 Hz), theta (4 – 7 Hz), alpha (8 – 13 Hz), beta (14 – 30 Hz), and gamma (31 – 50 Hz), as shown in Fig. 1. The features of each band can be used to estimation the emotion states.

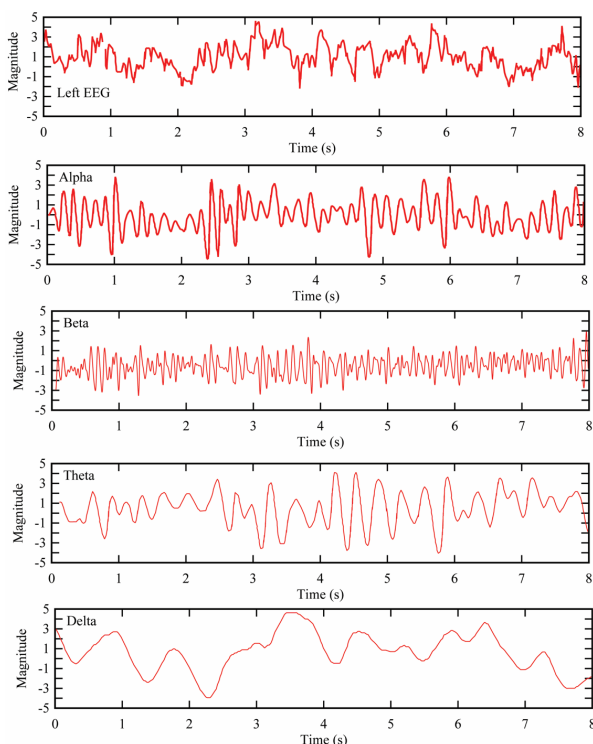


Fig. 1. Alpha, beta, theta, and delta EEG shapes obtained from the left hemisphere EEG signal

2.2. Feature extraction

First, the data of each video person is decomposed into intrinsic modes by applying EMD. The number of samples of each IMF equals the number of samples of the input signal; each IMF has 8064 samples. The instantaneous frequency of each IMF is calculated using the Hilbert transform, and only the first 3 IMFs are used to calculate the feature. In the next step, IMF signals are broken into smaller parts by applying 2-second windows and 0.5 -second overlaps. The signal power is calculated as a feature for each of the windows. In this way, according to the three extracted IMFs, a matrix with dimensions of 125×3 has been attributed as a feature matrix for a video-person channel.

2.3. Image generation

In this step, by combining the extracted features for each channel, a 2D color image is constructed for every 0.5 seconds of the EEG signal. After calculating the 125×3 feature matrix for each EEG channel, a $32 \times 32 \times 125$ matrix is obtained for each video-person, interpreted as 125 two-dimensional color images. It should be noted that only the values of 32 pixels of each image are known, and to determine the position of these pixels, a square map is used in which the position of the electrodes relative to each other is defined based on the 10-20 system [49].

As demonstrated in Fig. 2, this maps the position of the electrodes on the head to the point of a 9×9 square grid and forms the desired image. In this way, only the values of 32 pixels out of 81 pixels of the image are known. Cubic interpolation has been used to determine the values of the pixels between two pixels with a known value. For other pixels, which correspond to the outer points of the 10-20 system, extrapolation with initialization to zero has been used. In general, the dimensions of the image or square grid are equal to $(n \times 8) + 1$.

After performing these steps, 125 images were obtained for each video person, and according to the number of 40 music videos, the total number of images for each person is equal to 5000. In the next step, these images are used to learn and test the deep learning network. The obtained color image can be converted into a gray image by averaging the 3 color components of each pixel. An example of the gray image generated in this step is shown in Fig. 3.

2.4. Deep learning network

The model presented for the classifier is a convolutional deep-learning network model inspired by the ZF Net method [52]. The final design of this model, along with its general specifications, is shown in Fig. 4. The structure of the model is sequential, and the outputs of each layer are

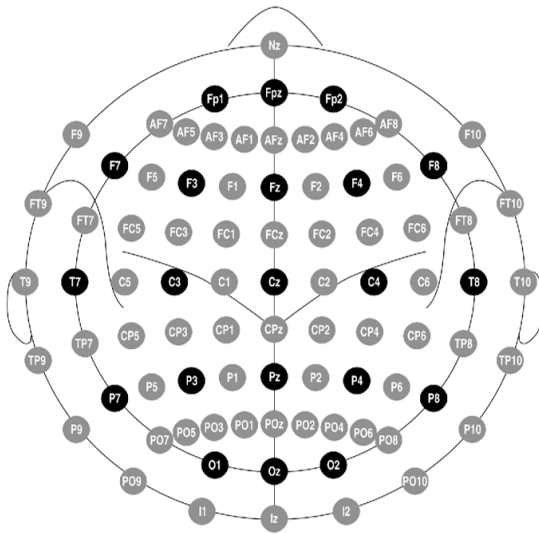


Fig. 2. Electrode locations and markers in 10-20 scheme. Black circles show locations of the original 10-20 system, and gray circles show additional locations introduced in the 10-10 extension [50]

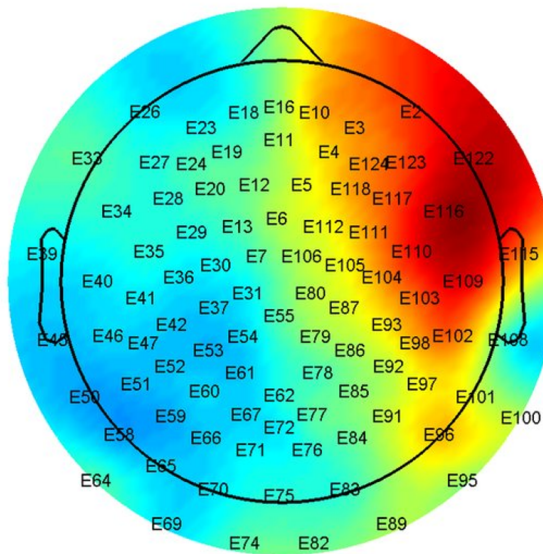


Fig. 3. Typical topographical EEG scalp map [51]

connected to the input of the next layer. At first, there are two convolution layers where the image is twisted with a kernel. The size of the kernel is equal to a 3×3 window, which has 32 different kernels in each layer. Then the output Relu activation function is applied. Next, there is the max-pooling layer, which is used to reduce the image dimensions while maintaining the main features. A dropout layer is used to avoid overfitting the model [53], in which 25% of the neurons are randomly set to zero in the training

phase. In the end, there are two completely connected layers with 10 neurons, like a multi-layer perceptron artificial neural network. The softmax function is used to assign data to a class, which generates a value with a possible meaning between 0 and 1. Adam optimizer and cross-entropy cost function have been used to train the model. The batch size is set to 128, equivalent to the number of entries in each round of training. After defining the model, all weights have been initialized using the Glorot method [54].

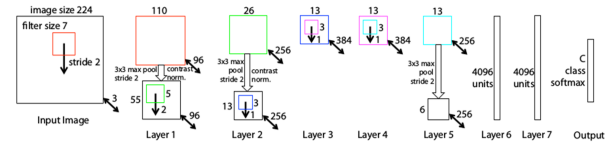


Fig. 4. Final design of the model used in this research, along with its general specifications

3. Results and discussion

In this section, the results of using the proposed method have been investigated. At first, 80% of all data were considered as the training set and the remaining 20% as the test set, and the evaluation was also performed on these two sets. After that, the performance of the designed network in emotion recognition was investigated. The leave-one-trial-out technique is used to prepare training and test data at this stage. For each person, one music video has been left out of the test, and 39 other music videos are considered for training. In other words, from the set of 5000 images generated for one person, 125 images are for testing, and the rest are intended for training. This task is repeated 40 times for each person until all the music videos are used as a test for one time. Then, the average and standard deviation of the accuracy of the 40 tests is reported for each person. The result of the regression analysis for the ZF Net multi-layer deep neural network can be seen in Fig. 5.

This study uses the power parameter as a feature for selected intrinsic mode functions in windows of 0.5 seconds. The time signal without feature extraction is usually considered the network input in deep learning networks. Of course, the main goal of this work is to prevent the complexity of the network and reduce the volume of calculations. By selecting a part of the data in which emotion stimulation occurs, a higher correlation between the computed features and emotion is established. Thus, the classification performance is expected to improve. In addition, in the case of identifying the channels that are more impacted by emotions, it is possible to increase the classification accuracy and reduce the amount of processing by removing the

other channels.

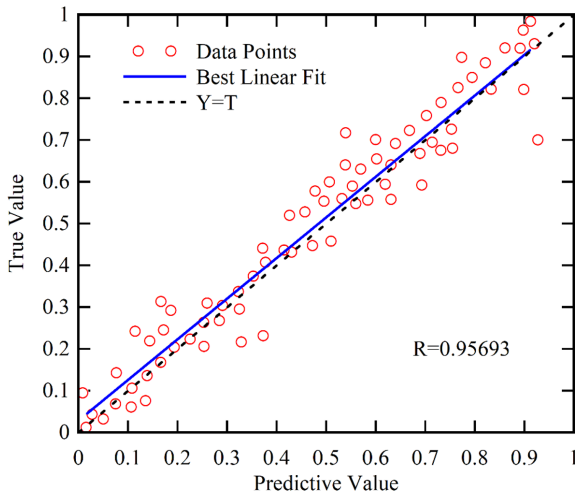


Fig. 5. The result of regression analysis for multi-layer deep neural network

In this investigation, images of different sizes are generated, and the accuracy of the results is examined. In this case, 80% of the data is separated for training, while 20% is used for testing. The training and test sets have been saved, and all the methods have been performed on the same set to compare the methods. The results obtained for images with dimensions of 9×9 , 17×17 , and 25×25 in two classes of valence and arousal are presented in Table 1. As observed, the accuracy of 17×17 images is the highest, and these dimensions are used in the present study.

Table 1. Accuracy ratio for images with different sizes

Picture size	Valence feature	Arousal feature
original	53.6%	56.4%
9×9	68.9%	67.9%
17×17	79.7%	76.8%
25×25	78.2%	72.5%

One of the problems associated with deep learning networks is the high volume of their calculations. In the presented method, despite summarizing the signal, it is observed that the network input is in the form of 125 color images of 17×17 . Each image has undergone convolution twice, using 32 different 3×3 kernels each time. Next, there are two completely connected layers with the number of 10 and 2 neurons. This complex structure will increase the number of adjustable parameters in the training phase, thus lengthening the training time and having a heavy computational load in the execution phase.

In the following, the results of using the proposed method are presented. These results were obtained using

17×17 images and selecting training and test data using the leave-one-trial-out method. The results are reported as the average accuracy for all people in the classes of valence and arousal. To evaluate the presented method, its results are compared with those of other similar works conducted on the DEAP database, presented in Table 2. It should be noted that the compared researches are among the best in terms of results. Just like the proposed method, in all of them, the leave-one-trial-out method was used for training and testing. It can be seen that the performance of the proposed method in both valence and arousal classes is higher compared to the methods presented in the previous research. Although the results of [41] demonstrate performance close to the proposed method in the valence class, its performance is much weaker in the class of arousal.

4. Conclusion

The present study uses empirical mode decomposition to extract features from the electroencephalogram signal to recognize emotions. A suitable intrinsic mode function has been selected using Hilbert transform and instantaneous frequency calculation due to the insignificant effect of emotions in the low-frequency bands of electroencephalograms. Among the important innovations of this study is the mapping of selected intrinsic mode functions to a large number of colored images, where each pixel of the image is determined based on its electrode location. Then, a deep learning network was employed for emotion recognition with the help of the obtained color images. Compared to previous research, the proposed method can recognize emotions in two classes of valence and arousal, with an accuracy of 82.3 and 78.4, respectively.

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Table 2. Comparison of the proposed method with another research

Study	Arousal Accuracy	Valence Accuracy
Koelstra et al. [48]	57.6	62.3
Naser and Saha [55]	64.3	66.2
Mert and Akan [40]	72.8	75.0
Chen et al. [41]	76.1	73.6
Arnau-González et al. [44]	69.7	67.7
Proposed method	78.4	82.3

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