Convolutional neural network with binary moth flame optimization for emotion detection in electroencephalogram

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ABSTRACT

Electroencephalograph (EEG) signals have the ability of real-time reflecting brain activities. Utilizing the EEG signal for analyzing human emotional states is a common study. The EEG signals of the emotions aren't distinctive and it is different from one person to another as every one of them has different emotional responses to same stimuli. Which is why, the signals of the EEG are subject dependent and proven to be effective for the subject dependent detection of the Emotions. For the purpose of achieving enhanced accuracy and high true positive rate, the suggested system proposed a binary moth flame optimization (BMFO) algorithm for the process of feature selection and convolutional neural networks (CNNs) for classifications. In this proposal, optimum features are chosen with the use of accuracy as objective function. Ultimately, optimally chosen features are classified after that with the use of a CNN for the purpose of discriminating different emotion states.

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1. INTRODUCTION

Brain-computer interfaces (BCI) are devices allowing the users to mentally manage a computer program or Neuro prosthesis by translating brain activity into sequences of commands for the computer [1]. Human computer interaction became part of the daily life. In a similar way, the emotions are significant and they constantly exist in the daily lives of the people. Emotions could provide numerous prospects in the enhancement of interactions with the emotion-based computers, for example, the affective interactions for the epileptic or autistic patients [2] It facilitates communication, particularly for physically challenged individuals [3]. Emotions have an important impact on many tasks, including decision making, communication, and human-computer interactions [4]. Emotion is a type of the unconscious or conscious feeling for a work or phenomenon. Emotions are expressed by a variety of the physical and biological reactions, which include text, voice, gestures, bio signals and facial expressions.

The people can't hide their emotions although they do not want to show them. The reactions to the emotions are a very significant key for communications amongst people [5] the detection of the emotions represents one of the very important sub-areas of the affective computing, focusing upon the recognition of the human emotions that are based upon various modalities, such body language, audio-visual expression, physiological signals, and so on. In comparison with other Emotion detection is a significant affective computing sub-area, focusing on the recognition of the human sentiments based upon various modalities, like physiological signals, body language, audio-visual expressions, and so on. In comparison with other modalities, physiological signals, like the EEG, electromyography (EMG), electrocardiogram (ECG), galvanic skin response (GSR), and so on, have a benefit of being hard to disguise or conceal [6]. Compared to other outward appearance indicators like the facial expression and gesture, the method based on EEG data is more dependable among numerous approaches to emotion identification due to its objective evaluation and high accuracy [7]. There are several techniques for detecting brain activity, including magnetic resonance imaging (MRI) [8], [9] magnetoencephalography (MEG) [10]. Off grid communication has been implemention in [11] and electroencephalogram [12].

However, because the EEG has a quick reaction time and is less costly than other techniques, it is commonly employed to monitor brain activity in brain-computer interfaces (BCI) research [12], [13]. By inserting electrodes on the scalp, the EEG signals are captured as a weak potential and analyzed to create a BCI system. The study has been based upon the recording and analyses of EEG brain activity, as well as the recognition of EEG patterns linked with mental states [14]. Several strategies for designing a BCI system based on EEG signals have been proposed, including event-related synchronizations [15] and event-related de-synchronization [16]. A variety of EEG-based BCI systems were lately created in which feature extraction and classification algorithms may identify EEG patterns in different mental states for information transmission [17].

Understanding brain's reactions to the variety of the emotional states could considerably develop the computer models for the identification of the emotions. Numerous psychophysiology investigations [18]–[20] showed relationships between human emotions and EEG patterns. In addition to that, with rapid development of wearable devices and dry electrode approaches [21]–[24], there is now a possibility to transfer EEG-based emotion recognitions from the laboratory to the real-world applications like the driving fatigue detections and monitoring of the mental states [25]–[29].

Convolutional neural networks (CNNs) are a type of end-to-end model. End-to-end models that are based upon the deep neural networks (DNNs) learn to map effectively from the main input to expected output through the DNN. This prevents design and selections of complex manual features. However, utilizing the CNNs for detecting the EEG emotions cannot directly accomplish the ideal results. The reason for this is that the order of the input channels entering the CNNs must be meaningful. None-the-less, the main EEG channels aren’t sorted according to their features. Channel proximity does not indicate the amount of channel information. Which is why, the strategy of the increase of the amount of the information in the adjacent channels through adjusting the channels one more time helps CNNs to learn effectively [30].

When the number of classified emotions is increased, the accuracy of EEG-based emotion detection system is decreased. Since EEG contains noise and artifacts, emotion detection by EEG is still challenging. In this paper, authors paid attention to emotion detection in EEG signals based of a binary moth flame optimization (BMFO) algorithm for feature selection and CNN for classifications. In this proposed study, optimum features have been selected with the use of the accuracy as objective function. Finally, optimally chosen features will be classified after that with the use of the CNN for discriminating different emotion states.

2. PROPOSED METHOD

The emotion may be recognized mainly with a variety of the modalities such as the face images, gestures and speech. Nonetheless, those methods of recognition have a susceptibility to person’s age, language, culture, habit and appearance, which is why, they’re not universal and they lack the accuracy of the recognition. In the present paper, the focus has been directed towards the recognition of emotions and connectivity analyses with the CNNs. The suggested approach has 3 stages. In pre-processing stage, independent component analysis (ICA) approach was used for removal of noise that is fundamentally induced electroencephalogram (EEG), signals. For the purpose of achieving enhanced accuracy and high true positive rate the suggested system introduced a binary moth-flame optimization (BMFO) [31] for feature selection and CNN for classification as can see Figure 1. The emotion recognition performed by CNN with subject-independent connection features. CNN can be defined as an End-to-End model type. End-to-end models that are based upon DNN effectively learn mapping from original inputs to expected outputs via DNN. It avoids complicated manual feature design and selections. However, directly utilizing the CNNs in the EEG emotion recognitions could barely accomplish optimal results. It is because the channels’ order of inputs that are fed into the CNNs must be meaningful. None-the-less, original EEG channels’ orders aren’t arranged based their characteristics. The channels’ proximity doesn’t reflect relevant information value between channels. Which is why, the strategy of the increase of information amount on the adjacent channels through the rearrangements of the channels will help the CNNs to learn in a more effective way. In the meantime, the features of the Pearson correlation coefficient could be representing information of the connectivity between the variety of the channels of the EEG signal.

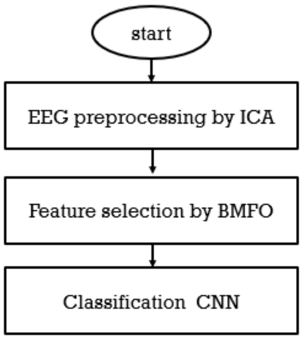

Figure 1. The flowchart of the classifications of the emotional states from the EEG data

2.1. Feature selection by BMFO algorithm

The moth flame optimization (MFO), which has been suggested by S. Mirjalili in 2015 [32], can be defined as a new algorithm of optimization that has been inspired by moths' special navigation approach in the nature, which is referred to as the transverse orientation. The moths can be considered as fancy insects, attracting towards an artificial light or the moonlight. Based on the MFO algorithm, the main MFO algorithm moth modules (i.e., the actual search agents) and flames (i.e., optimal moth position). The distinct moth position is updated based on the flame based on [31]. M_i can given in (1):

$$M_i = S(M_i, F_j) = D_i * e^{bt} * \cos(2\pi t) + F_j \quad (1)$$

where Mi represents ith moth, S represents logarithmic spiral function, Fj denotes jth flame, Di represents distance from Mi to Fj, b represents a constant value that defines logarithmic spiral shape and t represents some random number in [−1, 1]. For the binary search space, moth positions are limited to binary variable. Which is why, a sigmoidal function has been utilized for the purpose of transforming the position of every one of the moths updated based on a flame (1) into the new position in the binary search space (2) for the BMFO.

$$M_i = \begin{cases} 1 \; if \; r \, and \; < \frac{1}{1+e^{-(X(I+1))}} \\ 0 \;\; otherwise \end{cases} \quad (2)$$

Where X(I+1) represents real-value location update of moth for (I+1) th iteration and rand represents some random number which is chosen in the (0, 1) interval.

3. EVALUATION

3.1. Data-set

The data-set that has been used in the experimentations is Shanghai Jiao Tong University (SJTU) emotion data-base [33], containing 15 subjects' EEG data (8 females + 7 males). In this data-set, EEG signals have been recorded with the use of a 64 channel AgCl electrode at a 1,000 Hz sampling rate with the use of international 10−20 system. Every electrode's impendence has been < 5kΩ. SEED data-set was denoised by a band pass filter and artefacts removal approach. And those denoised EEG signals have been divided to 5 brain waves that correspond to frequency bands for all of the 62 channels. After that, brain waves have been separated to 1 sec. fragments and DE features have been extracted. Based on the theory that higher bands of frequency like β are more powerful and crucial in the detection of the EEG emotions. Figure 2 shows an example of binaural and noise signals.

3.2. The initialization of parameters

For checking the quality of the suggested algorithm, we adjusted CNN parameters. We did this task by considering 30 for maximum iteration, training percentage was considered for 80% of the data, and test percentage was taken into account for 20% of the data. Table 1 shows the settings of the parameters (CNN).

3.3. The evaluation criteria

The choice of criterion for evaluating the efficiency of the approach is dependent upon the problem that needs being solved. We assume that some data samples are available. These data are given separately to the model and a class is received as output for every one of them. The predicted class of the model and the actual class of data have been listed in a Table 2 that has been referred to as the confusion matrix.

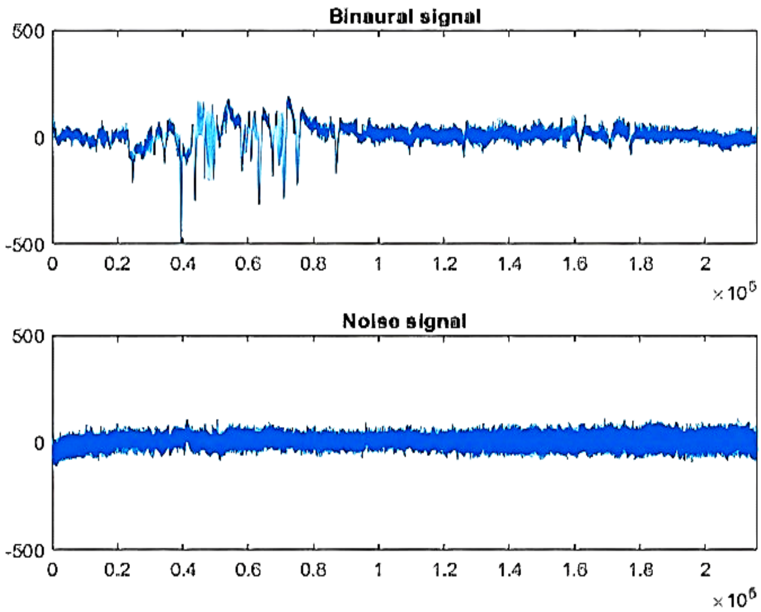

Figure 2. Plot of binaural and noise signals

Table 1. Initial values for parameters on CNN

Parameter	Initial parameters
Maximum iteration	30
Training percentage	80%
Test percentage	20%
Input layers	[64,128,1]
Learning rate	0.001

Table 2. Confusion matrix

	P	N	
PP Predicted positives	TP True positives	FP False positives	$\frac{TP}{PP}$ precision
PN Negative predictions	FN False negatives	TN True negatives	
	$\frac{TP}{P}$ Recall/sensitivity	$\frac{TN}{N}$ feature	

Section, it provides an exact description and definition of the confusion matrix. From this table, four simple criteria can be obtained directly: TP (i.e., true positive) and TN (i.e., true negative) denote the number of the positive and negative samples which have been accurately classified, while FP (false positive) and FN (false negative) are the number of the positive and negative samples which have been incorrectly classified,

- True positive rate: TPR (true positive rate) = TP/(TP+FN). Rate of the positive samples that are correctly classified in positive class. It is also called a recall or sensitivity.
- True negative rate: TNR (correct negative rate) = TN/(FP+TN). Rate of the negative samples that are correctly classified in the negative class are also called feature.
- False Positive Rate: FPR (false positive rate) = FP/(FP+TN). Rate of the negative samples that are incorrectly classified in the negative class.
- False negative rate: FNR (false negative rate) = FN/(TP+FN). Percentage of the positive samples that are incorrectly classified in the negative class.

3.3.1. Accuracy criterion

The most common criterion for classifying accuracy and vice versa is the error rate. This one is the ratio of positive samples that are actually positive and shows the accuracy of the learning model. Mathematically, this ratio can be described in (3),

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{3}$$

3.4. The evaluation of results

Emotions are characterized by the EEG signal with a variety of the feature extraction approaches and classification algorithms. The accuracy of the emotions could vary from one extract method to the other. After the implementation of the proposed approach in MATLAB 2018b environment and using the sama plot program, the results of both accuracy and detection rate were plotted, and the sorted results from the proposed improved neural network are shown in Table 3. CNN, have been compared. We compared the accuracy of current and proposed approaches for discriminatory emotion state. Compared with the existing methods, the error rate is reduced and the accuracy is superior to the existing approaches. In addition, the proposed network structure is simple and the memory consumption parameters are few. We also confirm that the shallow network also has a relatively good detection effect. In Figures 3 and 4, the trend of increasing accuracy and decreasing losses over 50 epochs.

Table 3. The comparison accuracy results of the suggested approach with the level of various techniques

S .no	Feature Selection	Classify method	Accuracy
1	BMFO	CNN	99.4%
2	Firefly Algorithm	ISO-FLANN Classification	95 %
3	DWT	K-NN	83.26%
4	Dynamic features and PCA	SVMs	64.70 _ 82.91%
5	WT	SVMs	82.38 %
6	HOC	SVMs	82.33%
7	STFT	SVMs	80%
8	HOC	NN	80.50%
9	Connectivity Features And PCA	RBF	84.60%
10	DWT	LDA	75.21%
11	HOC	QDY	62.3 %

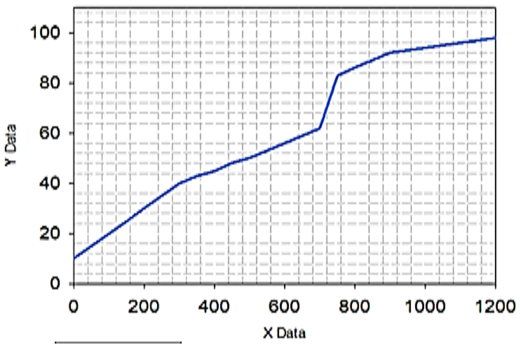

Figure 3. The accuracy results of the proposed approach during 50 epochs

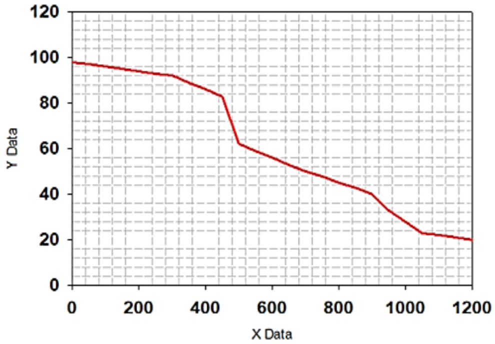

Figure 4. The loss results of the proposed approach during 50 epochs

4. CONCLUSION

We introduced emotion recognition based on EEG algorithm. In this algorithm, emotion is associated with the EEG signals. were the proposed system introduced a binary moth flame optimization (BMFO) algorithm for feature selection and convolutional neural networks (CNN) for classification. In the suggested study, optimum features had been chosen with the use of the accuracy as objective function. Finally, optimally chosen features will be classified after that with the use of a CNN for discriminating a variety of the states of emotions. We compared the accuracy of current and suggested approaches for discriminatory emotion state. Compared with the existing methods, the error rate is reduced and the accuracy is better than the existing approaches. In addition, the suggested network structure is simple and the memory consumption parameters are few.

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