EEG signal processing and emotion recognition using ANONIM Network

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Abstract—As an important task in the advanced stage of artificial intelligence, the research of emotional EEG has received more and more attention in recent years. In order to improve the accuracy of EEG signal emotion recognition, in this paper, Fast ANONIM (FFT) and ANONIM Transform (CWT) are used to extract the features of EEG signals on the DEAP data set and build two CNN models for emotion recognition. The results show that the proposed algorithm is effective for EEG signal emotion recognition. The average recognition accuracy of emotion valence can reach 75.9%; the arousal can reach 79.3%; the like/dislike can reach 80.7%. This research can provide practical application reference for continuous dimension emotion automatic analysis and machine recognition.

Keywords-component; EEG; FFT; CWT; CNN; emotion recognition

I. Introduction

Emotion recognition is a multidisciplinary research field integrating cognitive science, psychology, computer science, and neuroscience. It is a difficult and hot spot in the field of cognitive science. With the enhancement of computer computing power, the cost of implementing machine learning algorithms is greatly reduced, and building a machine learnin algorithm model can effectively improve the accuracy and robustness of emotion recognition. At the same time, with the development of non-invasive sensing technology and human computer interaction technology, EEG signals are gradually introduced into the field of emotion recognition research due their strong objectivity and high accuracy of classification and recognition.

Emotion recognition of EEG signals has achieved good classification results under traditional machine learning classifiers. Reference [1] used linear kernel least squares support vector machines (LS-SVM) and back propagation artificial neural network (BP-ANN), which are effective the two-category emotion recognition is performed on the valenc arousal model and the accuracy rate reaches 61.17% and 64.84%. Reference [2] extracted EEG signal features from th DEAP data set by combining maximum correlation, minimum redundancy and principal component analysis, and fused high-dimensional features, using support vector machines (SVM) for classification, and accurate classification in terms of valence and arousal the accuracy were 72.45% and 76.1%. Referenc used an efficient feature selection method and a kernel-base classifier to classify emotions on the standard EEG data set, and the accuracy of the valence and arousal on the SVM classifier reached 73.06%, 73.14%.

The increase in computer processing speed and computing power provides the possibility for the design and implementation of deep learning networks. Reference [4] extracted the median, mean, variance, and kurtosis of the EEG signal on the DEAP data set, and used a convolutional neural network (CNN) as the classifier to achieve valence-valence. Emotion recognition was performed on the degree of emotion model, and the average classification accuracy rates of 81.40% and 73.36%. Reference [5] divided the EEG signal into multiple time periods on the DEAP data set and extracted its features and used the Long-Short term memory (LSTM) algorithm for dimensional emotion classification, and the accuracy rates were 73.9% and 73.5% respectively; Reference [6] introduced the deep belief networks with glia chains (DBN-GC) model to extract high-level abstract features in the time domain, frequency domain, and time-frequency domain of the EEG signal and used restricted Boltzmann machines (RBM) to achieve emotion classification accuracy rates of 81.40% and 73.36%.

At present, in EEG signal emotion recognition, the accuracy of continuous emotion recognition based on the dimensional emotion model is generally not high, especially for the four-category emotion recognition research, which cannot meet the application needs, and the individual emotional physiological characteristics vary greatly. The characteristics of physiological signals related to emotions are not sufficient and the differences are not significant. Therefore, in response to these problems, this article uses two types of feature extraction tools on the dimensional emotional data set: fast Fourier transform (FFT) and continuous wavelet transform (CWT), and constructs two CNN models for classifying EEG signals. By comparing the experimental results of the two proposed models with other emotion classification task models, the FFT CNN model obtained a better recognition accuracy, which laid a solid foundation for the automatic emotion analysis and recognition of physiological signals.

II. Materails and Methods

The steps of emotion recognition based on EEG signals generally include: emotion induction, EEG signal collection, signal preprocessing, EEG feature extraction and emotion learning classification.

In this paper, the data set is DEAP [7]. The overall design framework is shown in Fig. 1. First, a bandpass filter is used to

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preprocess the original EEG signal to filter out high-frequency clutter. Second, a fast Fourier transform (FFT) and continuou wavelet transform (CWT) perform feature extraction on EEG signals. Finally, through neural network learning and training, the classification results are output.

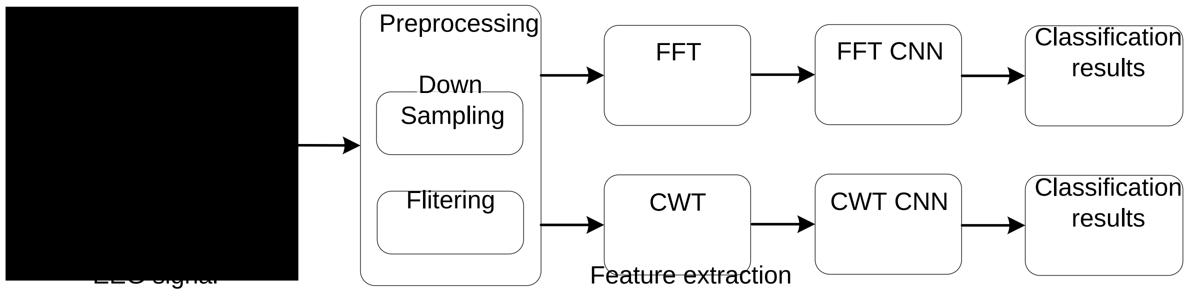

Figure 1. Overall design framework

A. CNN Model with FFT ANONIM

First, the raw EEG signal is preprocessed, and feature extraction is performed through the FFT algorithm. Split the processed data and labels into a training-test set at a ratio of 20, apply one-hot encoding to the labels, and use a standard scalar to normalize the data in order to obtain better accurac

Maximum pooling is implemented for the convolution part, and the rectified linear unit (Relu) activation function is used for the dense layer. Several batch normalization and dropout layers were inserted to prevent overfitting. For the final classification layer, use the softmax activation function to output the probability estimate for each class. The convolutio part is shown in Fig. 2(a).

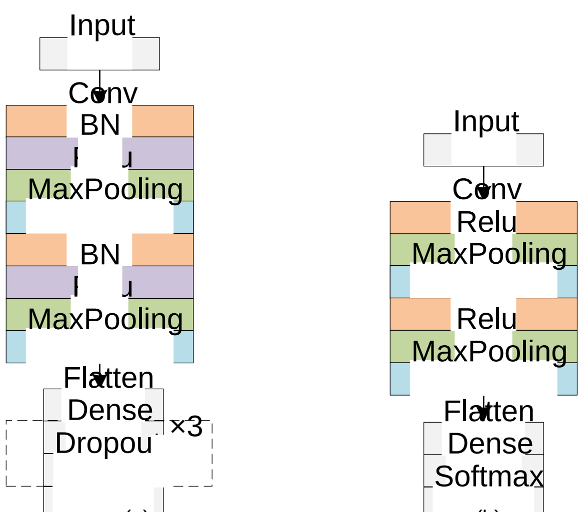

Figure 2. FFT model (a); CWT model (b)

B. CNN Model with CWT ANONIM

The CWT model utilizes the CWT algorithm from PyWavelets. This method uses the mother wavelet and the scale list of the inspection signal as the input signal. The mother wavelet is a "Morlet" wavelet.

Similar to the FFT model, the CWT model is implemented through One-Hot and other methods of encoding, standard scalar normalization, and k-fold cross-validation. The model architecture is redesigned as shown in Fig. 2(b). In order to better adapt to the DEAP data set and produce better results. The CWT model reduces the number of dropout layers and the number of batch normalization layers to prevent large peaks and fluctuations in the verification loss.

III. EXPRIMENTAL RESULTS AND DISCUSSION

This experiment was trained and tested on the windows10 system and the ANONIM P5000 platform. Considering computing resources and computing time, this experiment uses the original EEG data of 3 subjects (subjects 01, 02 and 03).

A. DEAP data set and preprocessing

The DEAP data set contains 32 channels of EEG signals of 32 subjects and 8 channels of peripheral physiological signals. This article only uses 32-channel EEG signals as experimental data: EEG signals are first sampled at 512Hz, then the sampling rate is reduced to 128Hz, and the bandpass frequency filtering of 40-45.0Hz is used to remove EOG artifacts, as shown in Fig. 3. Each participant watched 40 emotional music videos, each with a duration of 1 minute. After the subjects watched each video, they scored the degree of arousal, valence preference and dominance, with a score of 1-9. The evaluation value from small to large indicates that the various indicators are from negative to positive, from strong to weak.

B. Analysis of FFT CNN Model

The CNN model with FFT feature extraction was trained with k-fold cross-validation (k=5) over 200 epochs, and the model was confirmed to converge. Fig. 4 shows a pair of training and testing accuracy and loss curves of the model during 5 folds. From the results, it can be seen that the FFT model produces good results, and the accuracy value is significantly higher than the chance level. This shows that the fast Fourier transform model is also very versatile for invisible data, because the training and testing results are comparable. Among the 4 classes, the performance of the FFT model is quite stable, with like/dislike classes, resulting in the best test accuracy result of 81.2%.

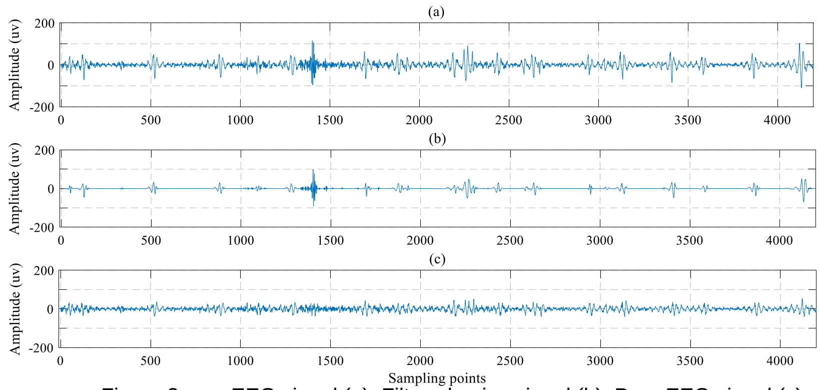

Figure 3. raw EEG signal (a); Filtered noise signal (b); Pure EEG signal (c)

[redacted]

Figure 4. FFT CNN model accuracy (a); FFT CNN model loss (b)

[redacted]

(a) (b)

Figure 5. CWT CNN model accuracy (a); CWT CNN model loss (b)

C. Analysis of the CWT CNN Model

Similar to FFT CNN model, CNN model with CWT feature extraction has been trained on 200 epochs. Fig. 5 shows a pair of training and testing accuracy and loss curves of the model. It can be seen that CWT model produces good results, with training and testing accuracy higher than the opportunity level and impressive training accuracy and loss. ANONIM/Dislike class shows the best results, with the test accuracy of 66.5% and the training accuracy of 95.6%.

However, it is worth noting that the model shows a high level of verification loss, which indicates that CWT model over-fits the training data. The loss graph confirms this finding. With the increase of epoch, the verification loss is different from the training loss.

D. Comparison between FFT and CWT Models

The results of FFT and CWT models are shown in table 1. It can be seen that FFT model outperforms CWT model in every emotion category of the DEAP data set, with an average test accuracy of 78%, while CWT model has an average test accuracy of 65%. Among the three different emotions, it is worth noting that FFT and CWT models have the best results on Like/Dislike class, followed by Arousal and Valence class. This may indicate that compared with other types of emotions (such as arousal), there is a higher correlation between likes and dislikes and individual EEG signal frequency.

TABEL 1. Results from the FFT and CWT Models

Classes	Test accuracy	
	FFT Model	CWT Model
Arousal	79.4%	63.9%
Valence	76.0%	63.0%
Like/dislike	81.2%	67.5%

E. Compared with other classification methods

The comparison between FFT and CWT models and other recognition models were completed and shown in table 2, all the datasets utilized the DEAP datasets. Reference [5] used LSTM recurrent neural network, and accurate classification in terms of valence and arousal the accuracy were 73.9% and 73.5%. Reference [6] used DBN network model, and the accuracy of the valence and arousal reached 78.2%, 77.1%. Reference [8] used dual-tree complex wavelet packet transform for three-dimensional emotion recognition and classification, the classification accuracy rates of arousal, valence, and like/dislike are 66.2%, 64.3%, and 70.2%, respectively. This paper proposes two three-dimensional emotion classification models. The classification accuracy of CWT CNN Model in valence, arousal, and like/dislike were 63.9%, 63.0%, and 67.5% respectively; and the FFT CNN Model is in valence, arousal, and like/dislike were 79.4%, 76.1%, and 81.2%. It can be seen from the summary of the results that although the performance of CWT CNN Model is inferior to other recognition models, it is still considerable compared with LSTM model in [8]. On the other hand, the FFT CNN Model is not inferior to other classification recognition models. It has achieved very impressive experimental results in both the two-class and three-class experiments, especially in the category of like/dislike, reaching 81.2%. This shows that the FFT CNN Model is indeed well generalized to EEG data.

TABEL 2. Accuracy comparison with other models

Classes/models	Arousal	Valence	Like/dislike
Reference [5]	73.9%	73.5%	-
Reference [6]	78.2%	77.1%	-
Reference [8]	66.2%	64.3%	70.2%
CWT CNN Model	**63.9%**	**63.0%**	**67.5%**
FFT CNN Model	**79.4%**	**76.1%**	**81.2%**

IV. CONCLUSION

In this paper, basing on the DEAP data set, fast Fourier transform and continuous wavelet transform are used to extract the features of EEG original signals, and input the extracted shallow features into the convolutional neural network for learning and training. Emotions are classified and identified in three dimensions: arousal, valence and likes/dislike. By comparing two different feature extraction algorithms, it is proved that the fast Fourier transform CNN model achieves better classification and recognition effect. Comparing with other methods, FFT feature extraction algorithm has achieved higher recognition accuracy and is more suitable for emotion classification tasks. This research can be applied to EEG emotion recognition in medical treatment, education, human-computer interaction and criminal investigation.

ACKNOWLEDGMENT

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