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EEG signal processing and emotion recognition using

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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, Author_11 (FFT) and Author_12 (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 learning 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 to 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 valence-arousal model and the accuracy rate reaches 61.17% and 64.84%. Reference [2] extracted EEG signal features from the 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%. Reference [3] used an efficient feature selection method and a kernel-based classifier to classify emotions on the standard EEG data set, and the accuracy of the valence and arousal on the SVM preprocess the original EEG signal to filter out high-frequency clutter. Second, a fast Fourier transform (FFT) and continuous wavelet transform (CWT) perform feature extraction on EEG signals. Finally, through neural network learning and training, the classification results are output.

EEG signal
Preprocessing
FFT
Author_1
CWT
FFT CNN
CWT CNN
Classification
results
Classification
results
Feature extraction

Figure 1. Overall design framework

A. CNN Model with FFT Author_2, 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 80-20, apply one-hot encoding to the labels, and use a standard scalar to normalize the data in order to obtain better accuracy. 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 convolution part is shown in Fig. 2(a).

Conv
Relu
MaxPooling
Conv
Relu
MaxPooling
Softmax
Input
BN
BN
Author_6 ×3

Conv
Relu
MaxPooling
Conv
Relu
MaxPooling
Flatten

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

(a) (b)

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

(a) (b)

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

C. Analysis of the CWT CNN Author_1 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. Author_2/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.

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D. Comparison between FFT and CWT Author_1 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 Author_2 accuracy
FFT Model
CWT Author_3
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
Author_4/dislike