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Motor imagery recognition based on CWT-CNN*

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Introduction

Electroencephalography, or EEG, is a non-invasive technique used to measure brain activity via electrodes placed on the scalp[7]. This technique is often used as an important component of brain-computer interfaces (BCI) to detect signals of electrical activity in the brain due to various conditions, such as imagined movements. EEG can also be used to evaluate brain function and can provide valuable insights for the diagnosis and treatment of neurological disorders. However, manual analysis of these brain waves is also complex and time-consuming. CNN, as one of the important research outcomes of machine learning in recent years, has achieved a lot in the field of EEG recognition[8]. With its end-to-end learning capability, it allows researchers to perform feature extraction without the necessity of deep understanding of EEG data and manually. EEG data has both time domain and frequency domain features, and many related researches nowadays use either time domain signal or frequency domain signal as input to CNN, which may ignore other important features. Continuous wavelet transform (CWT) is a popular time-frequency signal analysis tool that can map EEG signals to time-frequency images[2]. We propose a model combining CWT and CNN and test it on a public dataset. Since 2001, several international BCI competitions have been organized to provide a reliable source of data for researchers in this field. In this study, a public dataset (2008 BCI Competition IV Data base 2b[10]) was selected to validate the proposed algorithm, which contains two types of (left- and right-handed) motion imagery data.

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Proposed CWT-CNN Method

In the field of motor imagery EEG signal classification, related studies have found that Event-related desynchronization (ERD) / Event-related synchronization (ERS) phenomena in motor imagery EEG signal tasks typically occur between frequency alpha rhythms (7–14 Hz) and beta precepts (14–30 Hz) (varying slightly in different articles)[4][6]. The proposed model is shown in Figure 1. We transform the original signals into CWT mapping images of alpha precept and beta rhythm, respectively. Then they are passed as input through two CNN networks respectively. The 2D features extracted by the two networks are expanded into a 1D vector by the fully connected layer. Then, we concatenate all the 1D features from the two branches into a 1D vector and use the vector as the input of the classifier. Three popular classification algorithms, decision tree (DT), softmax, and support vector machine(SVM), are compared as classifiers for this model. In this paper, the pooling layer is removed from the standard CNN in order to optimize the network structure and prevent the loss of effective features[3].

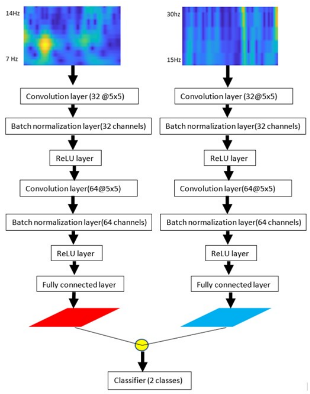

Figure 1. The proposed CWT-CNN framework.

Result

Due to the size of the convolution kernel, different mother wavelet functions and types of classifiers can have an impact on the EEG signal classification accuracy. We have concluded through extensive experiments that Morlet wavelets, 5x5 convolution kernels, and SVM classifiers are the most suitable for our purpose, respectively. In this work, we obtained an average accuracy of 84.1% for 9 subjects. To demonstrate the superiority of the proposed method, we compare this result with the state-of-art research results [9][5][1][11] and compare other deep learning models (e.g., VGG16, EEGNet) for analysis.

Conclusion

Because of the constraints such as the complexity of EEG signals, manual feature extraction or the use of a single domain of feature makes it very challenging to classify EEG signals. The improvement of this method is to design a novel CNN model for CWT mapping maps and CNN features, which makes feature extraction more comprehensive while improving classification accuracy. For the BCI Contest IV 2b dataset, our proposed EEG motion imagery classification method achieves an average classification accuracy of 84.1%. This is 12.8% higher than the winner of this dataset. It also has the highest average classification accuracy compared to other state-of-art methods. It is our hope that this technique can be applied to other machine learning and MI-EEG analyzing tasks, and we look forward to further exploring its potential.

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