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Application of Convolutional Neural Network Method in Brain Computer Interface

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Application of Convolutional Neural Network Method in Brain Computer Interface

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Abstract. Pattern Recognition is the most important part of the brain computer interface (BCI) system. More and more profound learning methods were applied in BCI to increase the overall quality of pattern recognition accuracy, especially in the BCI based on Electroencephalogram (EEG) signal. Convolutional Neural Networks (CNN) holds great promises, which has been extensively employed for feature classification in BCI. This paper will review the application of the CNN method in BCI based on various EEG signals.

1. Introduction

In decades, brain computer interface (BCI) has already become a investigation hotspot in the following fields, including brain science, rehabilitation engineering, biomedical engineering, and automatic control of human-machine. The reason is that BCI does not need to rely on the peripheral nerves and muscles of the brain to output information but establishes direct communication channels to make up for some defects or deficiencies of human beings. BCI system involves signal acquisition, feature classification and control devices, and so on, among which pattern recognition may stand out. Deep learning is the method to realize the internal procedures and interpretation levels of sample data and as-obtained information during learning, which is conductive to interpret data. The outcome is that the tested machine can get the goal which is similar to being analytical and created by human beings. Not only can it handle texts, but it also recognizes the images or sounds. More and more deep learning methods were applied in BCI to improve the overall quality of pattern recognition accuracy, especially in the BCI based on Electroencephalogram (EEG) signal.

Convolutional Neural Networks (CNN) is a critical class of feedforward neural network among all those deep learning models. It includes convolutional calculation and has deep structure, widely applied to BCI for feature extraction and classification in BCI.

This paper will review the traditional BCI feature classification method and other machine learning methods, especially neural network models like CNN and RNN. We will mostly focus on the application of these classification methods in BCI pattern recognition.

2. BCI system

Note that Brain-Computer Interface (BCI) is able to interpret activity forms of the human brain into communications or instructions to interconnect with the outer world [1]. The major limitation of BCI is to accurately identify human intentions at weak signal-to-noise ratios (SNR) of brain signals.

2.1 Pattern Recognition

Despite the huge achievements of conventional BCI systems, it is still tough to develop BCI. Various biological and environmental artifacts easily corrupt brain signals. Whereas some signal preprocessing and feature selection and extraction techniques have been established, feature engineering is extremely dependent on human expertise in a particular field [2].

2.2 Interface Application

The applications of the BCI system may replace the natural output that is lost due to injury or disease, such as a person who has lost the ability to speak by writing through a BCI or by speaking through a speech synthesizer. Secondly, the output of the brain-computer interface can restore lost function. For example, cochlear implants have helped hundreds of thousands of deaf patients reestablish hearing, and synthetic eyeballs is able to assist blind patients to see again, etc. Brain computer interface (BCI) technology can also train the brain's motor cortex to help stroke patients recover after they have lost control of their limbs. Furthermore, mainly for healthy people, to achieve functional expansion. In engineering psychology, cognitive load, fatigue degree and other states of personnel in special work positions. They play an incredibly crucial role in job performance and job safety. In education, brain-computer interfaces do matter in assessing students' dynamic attention level and optimize teachers' education arrangement.

3. BCI feature classification method

This section presents a thorough introduction of pattern recognition methods used in BCI systems. Figure 1 demonstrates a taxonomy of the BCI feature classification method, including EEG feature extraction, machine learning method, and deep learning method, namely Neural Network Model. EEG feature extraction (Section 3.1); Machine learning method includes Decision Trees, Naive Bayesian Classification and Support Vector Machine (Section 3.2); Neural network model including Convolutional Neural Networks, Recurrent Neural Network and Bi-directional LSTM RNN (Section 3.3).

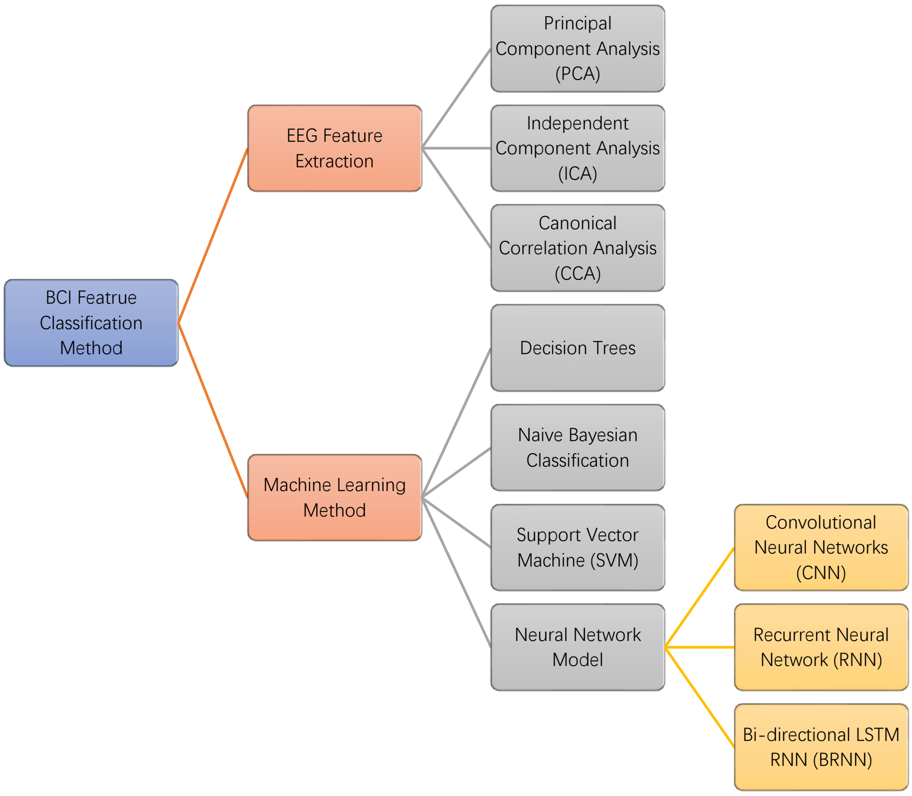

Fig.1. The BCI feature classification method is used in the BCI system.

3.1 EEG feature extraction

In the field of BCI, it is highly desired to examine data with many differences. If each indicator is investigated separately, the assessment tends to be unique. Therefore, the following common feature extraction methods are generated.

3.1.1 Principal Component Analysis (PCA)

PCA is the most broadly applied data dimension reduction algorithm. Celine uses an online database of active EEG signals containing left and right-hand motion images (Glass dataset B). These data are studied with extracted features by PCA.[4] In this case, MI information. The dimensionality reduction of the signal can be achieved by using the projection method to create a suite of linear/nonlinear conversions of the input variables. Anticipated MI outcomes were one hundred percent faithful to the supposed classification, i.e., right-handed MI executions were classified as Category 2, and left-handed MI executions were classified as Category 1. Through the experiment, the accuracy is 100%. The obtained signal has sufficient correlation to ensure that the motor image is correctly classified using the LR method, but the size is reduced.

3.1.2 Independent Component Analysis (ICA)

ICA is a calculation means to separate multiple signals into additive sub components. This is accomplished by assuming that the subcomponents are non-Gaussian and statistically self-determining of each other. PCA shows that the principal components are orthogonal to each other, and the samples are Gaussian distribution; ICA does not require samples to be Gaussian distribution. Nguyen utilized neurophysiological to estimate whether auditory cue were able to acquire identical data compared to visual did and denoise signal through band pass filter.[5]

3.1.3 Canonical Correlation Analysis (CCA)
CCA is to correlate a linear relationship between 2 multidimensional variables. CCA serves as complicated tags to direct feature selection to the underlying semantics. Shao successfully applied CCA and its extension method to frequency identification of BCI system based on SSEP and proposed TCCA and an improved filter bank frequency identification method based on TCCA, Filter Bank Time Local Specification Correlation Analysis (FBTCCA).[6] Lin et al. used the SSEP data set of 10 healthy subjects (three women, aged eighteen to thirty-one, all right-handed) to participate in the offline test. The time information of the CCA method is considered for the first time to reduce the artifacts and improve the algorithm's accuracy under a short time window. Combined with the filter library and TCCA to improve the classification accuracy, the final accuracy is 91.16% when the processing time is 1.5s.

3.2 Machine learning method for feature classification
Machine learning requires a computer and contributes to model real-time human learning. Since the 1950s, artificial intelligence (AI) has experienced the "reasoning period", "knowledge period", "knowledge engineering bottleneck," and "machine learning period". This has led to various machine learning methods, three of which are common in the following sections.

3.2.1 Decision Trees
Decision Trees are in the light of the identified probability of manifestation of different circumstances. Joadder proposed a new method of computer-assisted feature selection to clarify the most excellent feature set for differentiating motor images instead of the manual feature selection used in previous studies. [7] A decision tree classifies the functions selected by this method to verify the overall performance. During the process of recording, the subjects were requested to conduct a motion image task of their left, right, or right foot, but the competition only provided clues for the right and right foot categories [8]. There are 280 trials per subject, of which there are 140 trials per subject. Using a single feature is the most accurate feature "combination" in the test object. However, despite these results, the algorithms used still have independent success due to their precision and the reduced computational load.

3.2.2 Naive Bayesian classification
The Bayesian technique is in line with Bayesian theory and categorizes the dataset by probability and statistics. Then, Naive Bayes approach is a simplified method according to Bayes algorithm.

3.2.3 Support Vector Machine (SVM)
SVM represents one regulated learning model associated with concerned learning algorithms in machine learning. One SVM training algorithm determines a model and allocates new instances to one class or other classes to make it a nonprobabilistic binary linear classification. Its core is the kernel function. After establishing the kernel function, since the recognized data of determining the kernel function also have a variety of inaccuracies, considering the problem of generalization, two-parameter variables.

Ghumman proposed a feature classification method in line with SVM and improved its performance by optimizing polynomial kernel parameters.[9] In accordance with the standardized global EEG 10-20 system, electrodes are positioned on different parts of the scalp to record the brain's electrical activity.[10] These signals from the electrodes reflect the subject's motion image (MI) activity.[11] Then, EEG signals were recorded while performing various MI tasks such as hand, foot, and tongue movements.[12] A polynomial kernel (SVM-PK) support vector machine method for EEG signal classification in a BCI system on the basis of MI is proposed in this work. Using the network search means to select the best value of the polynomial kernel, the performance is improved. This experiment is to select the kernel and then optimize it. At the same time, the steps of regularization parameter (C) were changed from 0.1 to 100[0.1,10,20,-,90,100] by coarse grid search. Under all these C values, the classification accuracy reaches 0.664.

4. Neural network Model

Deep learning is one rising technique that utilizes neural networks to transform or represent the input nonlinearly. Deep neural networks (DNN) are the foundation of deep learning. To understand DNN, we must first understand the DNN model. Through the construction of deep neural networks, numerous analysis activities are carried out.

4.1 Convolutional Neural Networks

Under the framework of the biology of the visual cortex, the idea that specific elements of the system have specific tasks is applied to the machine, which is the basis of CNN. The reason why CNN can work is that computer can categorize images by looking for low-level features, and then build more abstract concepts through a series of convolutional levels.

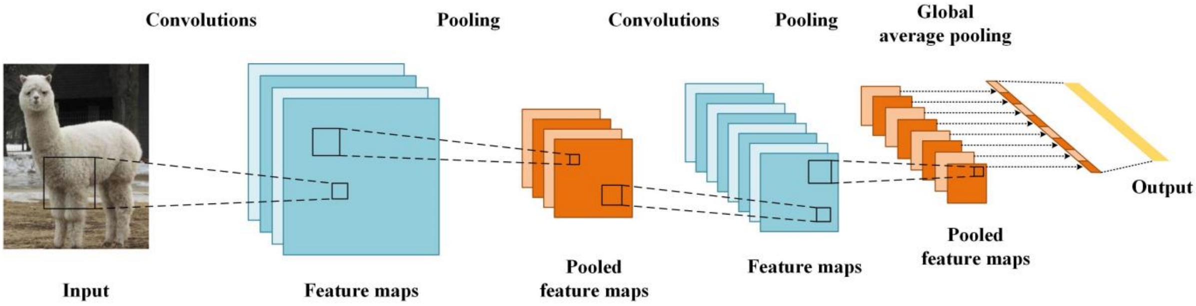

Fig.2. The basic structure of CNN.

Nijisha Shajil et al. used CNN for the classification of MI signals.[13] EEG signals are obtained through 16 channels and filtered using a bandpass filter with a frequency range of 1 to 100 Hz. The spectrogram of the spatially filtered signal was provided to CNN as input. Monoconvolutional layer CNN is constructed for classifying MI EEG signals of the left hand, right hand, hands, and feet.

4.2 Recurrent Neural Network

In the CNN mentioned above, the input and output of training samples are relatively determined. The idea of RNN is to use sequence information. It is proposed that all inputs and outputs are independent of each other. But for many other tasks, this idea is very bad. If you need to predict the next word in a sentence, it's helpful to know the preceding word. In theory, RNN can use the information of any length sequence, but it can only deal with very limited information of the first few steps in practice.
Sumanto Dutta has proposed a new data-enhancement approach to address the challenges posed by the scarcity of EEG data for training deep learning models (e.g., RNN).[14] Flow EEG data were collected from 16 participants using the Emotiv EPOC+ 14-channel headset. To sort out EEG data, the system using NVIDIA's GeForce Titan XP GPU has 12GB of memory to implement the deep learning algorithm. The verification accuracy of the enhanced data is better than that of the unenhanced data. Solid experimental results indicates that the performance of the mental state estimator is improved by data enhancement, and the accuracy rate is 98%.

4.3 Bi-directional LSTM RNN

Normally, RNN is only able to foresee the output of the next time in proportion to the time sequence information of the preceding time. Still, the current time's output is related to the original state and may be associated with the future state. BRNN has two RNN superimposed together, and the states of the two RNN determine the output. The basic idea of BRNN is to propose that every training sequence is two RNN forward and backward, and these two RNN are connected with an output layer.
Cai, CNN, and BRNN were combined for facial expression recognition.[15] Cheavd, the challenge data set, consists of 140 minutes of spontaneous emotion clips extracted from movies, TV shows, and

talk shows. The database includes 238 speakers, ranging from children to the elderly. It consists of eight emotions: anger, anxiety, disgust, happiness, neutrality, sadness, surprise, and worry. In contrast, the dataset is extended using two forms of data enhancement. This method acts well in recognizing emotions such as anger (74.07%), happiness (46.27%), surprise (54.48%), worry (33.33%), anger (22.37%), and sadness (26.88%), suggesting its big role in multi-emotion recognition. The highest recognition rate was 74.07%, compared to only 4.76% at baseline, demonstrating that this method seems to be very effective in identifying aversive manifestations. However, the neutral recognition rate was 27.51%, lower than baseline (61.97%), nothing that the lowest recognition rate in this work was 15.79%.

5. Convolutional Neural Networks in BCI

The commonly used BCI-EEG paradigm includes visual evoked potential, motor imagination, emotion, and so on. Next, the investigations in every BCI signal and the deep learning method related to the feature classification will be summarized.

5.1 Application in Visual Evoked Potentials based BCI

5.1.1VEP

In general, the ERP signals are examined by the P300 phenomenon. Cecotti et al.[16]attempted to improve the recognition correctness of P300 to obtain more accurate word spellings. A new-found model in line with CNN is proposed. The model includes five low-level CNN classifiers with various feature sets, and the low-level classifiers vote the final high-level results. In the third BCI competition, the highest accuracy of Dataset II was 95.5%. Liu and co-workers [17] created a Batch Normalized Neural Network (BN3), a variant of CNN in the P300 speller. The method is divided into six layers, and each batch is normalized. Maddula et al. [18] filtered the P300 signals with visual stimulation through a bandpass (2~35Hz).

5.1.2 SSVEP

Most deep learning-based researches in SSEP concentrate on SSVEP like [19, 20]. Waytowich et al. [21] applied a compact CNN model to process raw SSVEP signals directly without any hand-crafted features. The average accuracy of the reported cross-subjects was about 80%. Atia et al.[22] aimed to determine a suitable intermediate interpretation of SSVEP. Aznan et al.[23] explored SSVEP classification of signals collected through dry electrodes. Thomas et al.[24] The original SSVEP signal is triggered by a band signal (5~48Hz), and then the discrete FFT is operated on 512 consecutive points. The processed data were independently classified by CNN (69.03%) and LSTM (66.89%). Gao et al. [25] designed a SSMVEP signal-based trolley control system and introduced a deep learning method. They then constructed a convolutional neural network (CNN-LSTM) framework with a long and short memory.

5.2 Application in Motor Imagine based NCI

Extreme Learning Machine (ELM)[26] has shown superiorities on the classification of MI EEG and real-motor EEG [27, 28]. Uktveris et al.[29]extracted many EEG features, such as mean channel energy (MCE), mean window energy (MWE), channel variance (MWE, CV), mean band power, etc. All extracted features are sent to 2D CNN for classification. Lee et al.[30] deal with the MI EEG signals by wavelet transform and manually extracted the PSD from the Mu and Beta bands for the first time. Wang et al.[31] designed a fast convolutional feature extraction method based on CNN to learn potential features from MI-EEG signals. Several weak classifiers are applied to select important features for the final classification. Hartman et al.[27] studied EEG signals induced by real motor effects. They studied how CNN represented spectral features through network intermediate phase sequences, showing high sensitivity to EEG phase features at the early stage and high sensitivity to EEG amplitude features later. Some studies have proposed a mixed model of electroencephalography for the identification of myocardial infarction[32].Tan et al.[33] proposed a complex system to achieve multimodal EEG classification. DE-noising AE was used to reduce dimension. A method combining multiple views CNN and RNN is proposed to discover the potential temporal and spatiotemporal information of low dimensional representations. They obtained the IIA dataset from BCI Competition IV with an average accuracy of 72.22%.Fadel et al.[34]proposed a chessboard image transformation method, which converts EEG signals of moving images into images for classification using hybrid deep learning models. The network model is composed of DCNN to extract spatial and frequency features, LSTM to extract time features, and finally, divided into five categories (four motion image tasks and one motion image task).The results are encouraging, and the classification accuracy of checkerboard method is 68.72%. Lun et al.[35] proposed a deep CNN structure with time and space filter separation. Echtioui et al.[36]compared two models, CNN and LSTM, on the same basic data set, an optimal classification method based on the deep learning method is proposed. The BCI Competition IV dataset 2A was used as the base dataset to test both classification methods.

5.3 Application in Emotional BCI

Of great note, one person's emotion could be identified by three factors, namely valence, arousal, and dominance, where each one can be rated by an integer between 1 to 9 or recognized positive and negative [37, 38]. Wang et al. [39] used the CNN algorithm to classify single EEGs. Interestingly, they enhanced the training set by adding Gaussian noise to the original sample to generate new EEG samples. Li et al.[40] proposed a new hierarchical convolutional neural network (HCNN) to identify subjects' emotions (positive, neutral, negative) and achieved an accuracy rate of 88.2%.In the HCNN structure, each convolution kernel has only a local acceptance field. The kernel can capture the correlation between adjacent electrodes, which may be of great value for the recognition task. Sheykhivand et al.[41]proposed an automatic two-stage (negative, positive) and three-stage (negative, positive, neutral) classification of emotions based on EEG signals. In this method, EEG raw signals are directly applied to Convolutional Neural Network (CNN-LSTM) and Short and Long Term Memory Network (CNN-LSTM).

6 Conclusion

In this paper, we introduce some data processing methods in machine learning and focus on the latest application of CNN in deep learning. Compared with traditional methods, CNN can improve the accuracy of image feature extraction. Through the flexible use of the convolutional layer and the combination of the convolutional layer, the basic structure of CNN can be transformed to improve the processing accuracy. The combination of CNN and LSTM has a prominent effect of improving the processing accuracy in MI, SSMVEP, and Emotional directions. In this paper, we introduce some data processing methods in machine learning and focus on the latest application of CNN in deep learning. Compared with traditional methods, CNN can improve the accuracy of image feature extraction. Through the flexible use of the convolutional layer and the combination of convolutional layer, the basic structure of CNN can be transformed to improve. The combination of CNN and LSTM has a prominent effect of improving the processing accuracy in MI, SSMVEP, and Emotional directions.

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