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Comparison of EEG Data Processing Using Feedforward and Convolutional Neural Network*

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Abstract

EEG signals are the overall reflection of the physiological activities of brain nerve cells in the cerebral cortex and scalp. By classifying and processing EEG signals, it is possible to identify states that do not require conscious activity. This article mainly processes the raw data and uses the multi-layer perceptron (MLP) neural network to determine whether the subject's eyes are open or closed and compares the results of the convolutional neural network (CNN) network.

Keywords: EEG, signal processing, MLP neural network, classification, CNN

1. Introduction

Brain-Computer Interface (BCI) is a communication control system established between the brain and external devices (computers or other electronic devices)

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through signals generated during brain activity [10]. The aim of BCI is to create a communication link between the human brain and the computer. It provides a way to transform brainwaves into physical effects without using muscles [11]. In the decades since the birth of BCI technology, the research on electroencephalogram (EEG) signals classification methods have always been the driving force for the continuous development of BCI technology. EEG is a non-invasive acquisition method in the BCI system [1]. It detects weak EEG signals by placing electrodes on the scalp and records changes in electrical signals during brain nerve activity. However, since EEG will be greatly weakened when it travels through the cerebral cortex to the scalp, the signal-to-noise ratio of the extracted signal is extremely low, which increases the difficulty of subsequent feature extraction and classification [13]. It is difficult for traditional classification methods to find well distinguished and representative features to design a classification model with excellent performance. In recent years, however, the deep learning methods have made itself a great success in the field of image and speech such as good generalization capabilities, and layer-by-layer automatic learning of data features [12].

This study created a convolution neural network that can recognize and automatic extract the features of EEG signals and compare the accuracy of traditional methods of feature extraction and classification using data from the same public database. We used PhysioNet EEG data for this project, which are composed of over 1500 one- and two-minute EEG recordings, received from 109 subjects. The goal of our work is to explore Fast Fourier Transform (FFT) signal analysis techniques for distinction between two states, eyes open (EO) and eyes closed (EC), through the detection of EEG activity obtained from eight scalp channels.

2. Methods

2.1. PhysioNet EEG Database

PhysioNet EEG data set are composed of over 1500 one- and two-minute EEG recordings, received from 109 subjects [3]. They accomplished six different motor/imagery tasks while the EEGs were recorded from 64 electrodes using the BCI2000 system. Each volunteers completed 14 trials: two one-minute baseline runs (one with EO, one with EC), and three two-minute trials of each of the four following tasks:

- An object shows on either the left or the right hand side of the screen. The volunteer opens and closes the matching fist until the object vanishes. Then the volunteer unwinds.
- An object shows on either the left or the right hand side of the screen. The volunteer visions opening and closing the matching fist until the object vanishes. Then the volunteer unwinds.
- An object shows on either the top or the bottom of the screen. The volunteer opens and closes either both fists (if the target is on top) or both feet (if

the target is on the bottom) until the object vanishes. Then the volunteer unwinds.

- An object shows on either the top or the bottom of the screen. The volunteer visions opening and closing either both fists (if the target is on top) or both feet (if the target is on the bottom) until the object vanishes. Then the volunteer unwinds.[8]

The 64-channel EEG were recorded (each sampled at 160 samples per second) as per the international 10-10 system (excluding electrodes Nz, F9, F10, FT9, FT10, A1, A2, TP9, TP10, P9, and P10), as it is shown Figure 1.

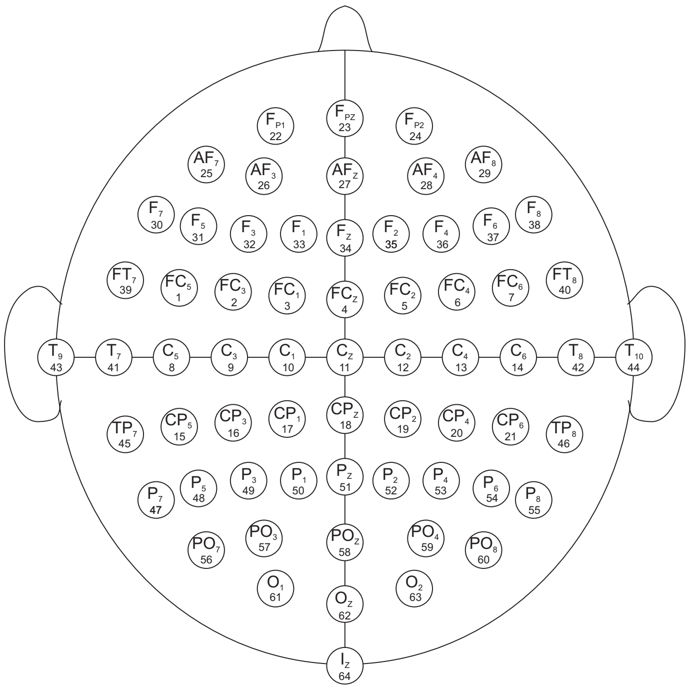

Figure 1. The 10-10 system with PhysioNet EEG database.

2.2. Data acquisition

A trained neural network will be planning to use to implement real-time classification in the future by our own device, which is an Ultracortex Mark IV biosensing headset from OpenBCI. In this case, only these eight channels were taken into account that are C3, C4, Fp1, Fp2, P7, P8, O1, and O2.

Since the data from eight channels original scalp are around two minutes long with 160 samples per second sampling frequency. In order to increase the number of samples, we expanded the data cut every 4 seconds as a segment (640 points).

2.3. Signal analysis by EEGLAB

EEGLAB is an interactive MATLAB toolbox for processing continuous and event-related EEG, MEG, and other electrophysiological signals [2].

EEG signals can be analyzed in the frequency domain. We name 8-14 Hz for alpha, 14-30 Hz for beta, 30-80 Hz for gamma, 1-4 Hz for delta, 4-8 Hz for theta band, however frequency ranges are lightly dissimilar in various articles [4, 6, 11]. The Power Spectral Density (PSD) of EC and EO for the first eight seconds of the first volunteer is shown in Figure 2 and Figure 3 respectively. Each colored trace represents the spectrum of the activity of one data channel. The leftmost scalp map indicates the scalp distribution of power at 10.3 Hz, which in these data is concentrated on the occipital regions and parietal midline respectively. The other scalp maps show the distribution of power at 15.5 Hz and 20.6 Hz. We can see easily that the alpha wave power is significantly higher in the EC state than in the EO state with obvious differences in frontal, parietal and occipital regions.

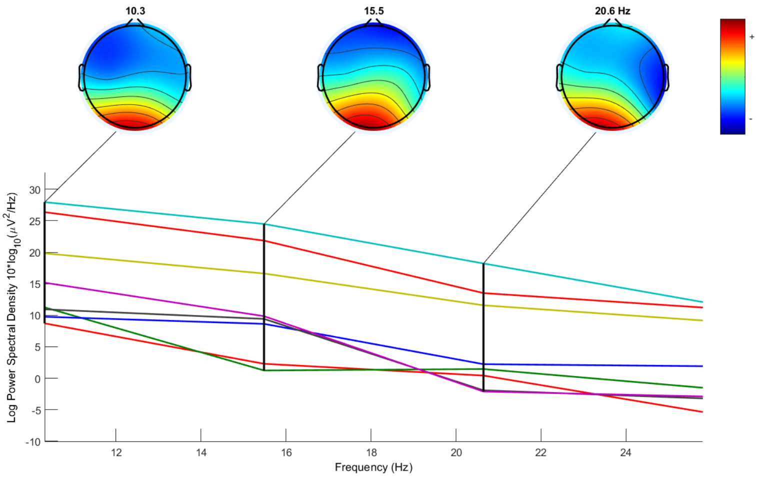

Figure 2. Eight seconds window PSD of EC.

Figure 4 and Figure 5 respectively showed the activity spectrum at O2 position of EC and EO state. We can see a distinct peak at 8-14hz on Figure 4 compared to Figure 5. Alpha waves appear when people are awake, quiet and with their eyes closed. As soon as subjects open their eyes, think, or receive other stimuli, alpha waves disappear and turn into fast waves. It reappears when the person becomes quiet again and closes his eyes. This phenomenon is called “alpha blocking” [5]. So alpha waves are the main manifestation of electrical activity of the cerebral cortex in awake, quiet and EC state.

At the same time, alpha wave activities are unstable according to the Figure 4 and 5. When analyzing the same EEG signal, the amplitude of the beta waves are much less than that of the alpha waves. It may be more reasonable to use beta waves as an analytical indicator than alpha waves for identifying the EO state.

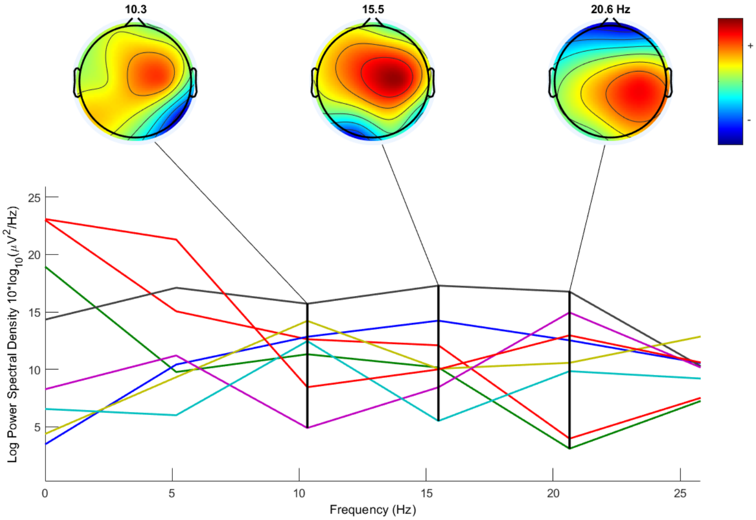

Figure 3. Eight seconds window PSD of EO.

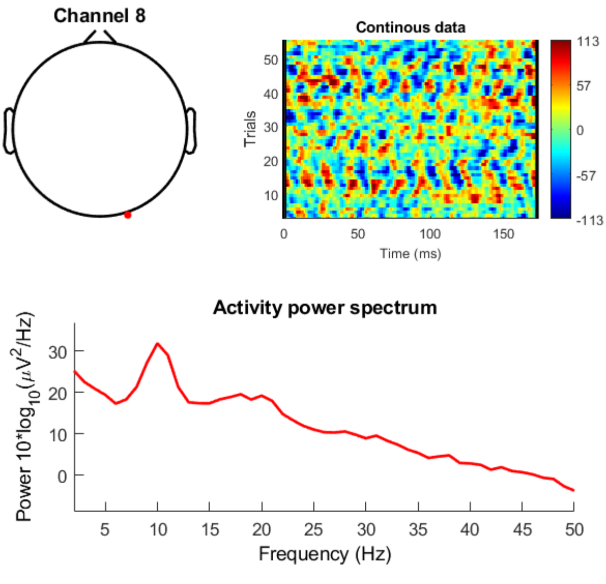

Figure 4. Power spectrum of EC on channel 8.

Most of the researches [7, 9] focus on the amplitude and power variation of wave in different states. The study of alpha and beta wave does not involve the correlation and mutual comparison between the two waves. Therefore, beta waves are added as the features for comparison in this paper.

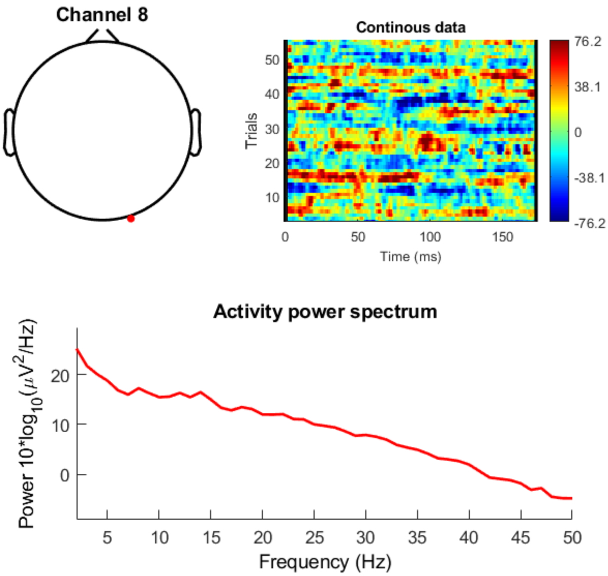

Figure 5. Power spectrum of EO on channel 8.

2.4. Data processing by Matlab

In our case the data processing includes data import, normalization, segmentation, feature extraction, neural network creation, training and test steps.

To facilitate the activity classification, the raw data was divided into small segments (windows). The main challenge in this task is the find the proper window size. In order to improve the accuracy, we made different degrees of linear enhancement according to the correlation of each channel. In case of PSD calculation, multiple FFT window sizes were tested. Windows were overlapping, at each sample the window contained the current sample and the previous N-10 samples. Before classification, a 5-Fold Cross-Validation was used for randomly shuffled the training and testing data set.

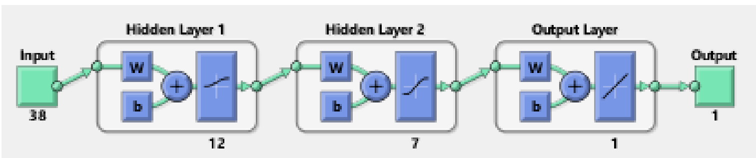

Figure 6. Used MLP neural network architecture.

We tested and compared the performance of feedforward MLP networks and CNN in this step. In case of MLP, training function was Levenberg-Marquardt (trainlm). We achieved the best results with the two hidden layers network contained 12 and 7 neurons using log-sigmoid transfer functions (as shown in Figure 6). Output layer had only one neurons as it is two states (EO and EC) to be recognized. On the layers the initial weights came from a normal Gaussian distribution. In the training algorithm the epoch limit was 1000 cycles.

The advantage of deep learning algorithm classification accuracy is usually reflected when the number of sample sets is large enough. And the more complex the network, the more parameters to be trained, the more training set samples are needed. Therefore, the high complexity of the network model cannot be pursued blindly in the design of neural networks. Layers of the used CNN is shown in Table 1. The raw data were converted to grayscale images and these images were used as inputs for the CNN. Image size was $64 \times 1 \times 8$ (64 measurement points, 8 channels).

Table 1. Structure of CNN.

Layer number	Layer type
1	Image input layer (64x1x8)
2	Convolution layer (13x1 64)
3	Batch normalization layer
4	ReLU layer
5	Convolution layer (13x1 128)
6	Batch normalization layer
7	ReLU layer
8	Convolution layer (39x1 256)
9	Batch normalization layer
10	ReLU layer
11	Fully connected layer (2)
12	Softmax layer
13	Classification layer

In addition to the design of network structure, many hyperparameters still need to be determined manually in the training process of a CNN classifier. We created a set of options for training a network using stochastic gradient descent with momentum.

We used a mini-batch with 64 observations at each iteration. If the batch size is set too small, it will be difficult for the network to converge and under-fitting. If the batch size is set too large, it will result in reduced efficiency or memory overflow.

Learning rate is a very important hyperparameter in network training. On the on hand, if the learning rate is set too small the error curve drops too slowly. On the other hand, too large learning rate will lead to error explosion, and the network cannot find the correct direction of gradient descent. We reduced the learning rate by a factor of 0.1 every 10 epochs with 0.2 initial learning rate and set the maximum number of epochs for training to 50.

We set L2 regularization to 0.0005. It ensures that feature weights are not too large, and the processed feature weights are relatively average.

3. Result

All the following experimental results are from the same computer(CPU: Intel Core i5-7300HQ, RAM: 16 GB,GPU: GeForce GTX 1050 Ti) with MATLAB R2020a.

Classification model evaluation metric was accuracy, calculated the following way:

$$\text{Accuracy} = \frac{\text{No correct predictions}}{\text{No all predictions}}.$$

To determine a proper window size for band power calculation, different window sizes were used, training and testing were repeated 1000 times to decrease statistical uncertainty. Used neural network in this case was the 2-layer MLP with 12-7 neurons in hidden layers. The Mean and best accuracy on test data using different windows are summarized in Table 2.

Table 2. Accuracy at different window sizes.

Window size(samples)	Mean accuracy	Best accuracy
20	84.46%	91.92%
40	84.23%	94.23%
60	81.00%	90.00%
80	80.87%	90.00%
100	80.26%	88.85%
120	79.66%	86.54%
140	78.71%	84.62%
160	78.94%	85.00%
180	78.57%	86.54%
200	78.50%	85.38%

In case of real-time data processing, we hope to find a window small enough.

We found window size of 40 samples a best choice as we are able to identify the activities of the subjects from the EEG signal in approximately 0.25 second. It is an acceptable latency and gives significantly better accuracy than other windows. Therefore, all of the following experiments are based on this window.

In order to further improve the accuracy of the network, we enlarged the data set. Each segment has 40 points that overlap the previous segment.

The best result obtained after enlargement was 96.63% for test data. The comparison of training time and mean accuracy are showed in Table 3. In Table 3, the suffix with A represents only alpha waves considered as feature. The suffix with B represents only beta waves considered as feature. The suffix with A and B represents the feature combined by alpha waves and beata waves. The suffix with L represents using expanded data set. All the accuracy results are the average values of 100 time 10-fold cross-validation.

Table 3. Comparison of training time and accuracy.

Type of Neural Network	Traing Time	Accuracy
MLP_A	0.76s	81.95%
MLP_A_L	14.09s	88.47%
MLP_B	0.64	80.46%
MLP_B_L	12.03s	92.66%
MLP_A_B	1.10s	84.23%
MLP_A_B_L	4.25s	94.85%
CNN	4m50s	88.00%
CNN_L	7m14s	91.00%

4. Conclusion

In this paper we proposed two artificial neural network approaches for EO and EC tasks recognition from EEG data. We used data from 50 volunteers and tried to recognize their activities with feedforward MLP network and CNN in combination with different data processing approaches. Our results demonstrated that the determination of the activity from the EEG signal is possible with high classification accuracy.

In the case of MLP, the results obtained show that the accuracy obtained using only alpha or beta waves are not significantly different, but using the extended data set makes a significant difference. So it would be more reasonable to use beta wave as an analytical indicator than alpha wave for this this purpose. This can provide some reference for studying the EEG signal of the subject's eye state.

We reached the higher accuracy rate and shorter training time of using MLP instead of CNN for this purpose. Compared with MLP, however, CNN combines signal preprocessing, feature extraction and classification. It prevents the blindness and cumbersomeness of EEG signal processing, and it also has a good accuracy rate. It is essential to produce a CNN construction with high robustness performance and accuracy rate for EEG signals.

The data set in this project was subjected to a simple preprocessing (bandpass filter and the normalized processing) without special processing for ECG, EMG and noise. The data set itself has much room to improve, and then makes the accuracy of the model also have great potential for ascension. Due to the limited research time of the project, more details in parameter adjustment have not been studied. However, the efficiency of deep neural network models such as CNN is largely dependent on parameter adjustment. Therefore, the further improvement of model performance needs to be further improved in parameter adjustment.

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