Classification of Obsessive-Compulsive Disorder by Two-Dimension Convolutional Neural Network

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Abstract

Obsessive-compulsive disorder is a mental disorder that a person has uncontrolled, causing the patient to be high anxiety, which affects the daily life of the patient. EEG signal is one method used to diagnose brain diseases. In which EEG is a measure of changes in electrical charges in the brain. In this paper, we propose a two-dimension convolution neural network model, a popular way to distinguish between two categories by using images. The time-frequency image was created using the complex Morlet wavelet. Time-frequency images are used as an input of the 2-D convolution neural network model, which uses 2-D convolution to extract the characteristics of the image in each channel of the electrode. The experiment result of testing is 87.5 percent accuracy and 0.461 test loss value in the 2-D CNN model. Therefore, the power of time-frequency in two-dimension convolution neural network model provides a new method for the classification of obsessive-compulsive disorder in the Flanker task.

Keywords: Obsessive-Compulsive Disorder (OCD), Electroencephalogram (EEG), Two-Dimension Convolution Neural Network (2-D CNN)

1. Introduction

In present-day society, obsessive-compulsive disorder (OCD) is not a dangerous disease, but it affects life quite a lot. Obsessive-compulsive disorder is a mental disorder in which the patient has repeated thoughts and over again about the same subject, causing high anxiety. Sometimes have a responding to those thoughts by repeating the behavior to reduce the anxiety that occurs. The symptoms of obsessive-compulsive disorder can be divided into two types of obsession and compulsion. Obsession: The patients have thoughts and feelings that occur over and over again in your mind for no reason, which cannot control that idea, such as the patient repeatedly thinking about whether the door is locked yet. Compulsion: The patient must be repeated many times to relieve anxiety from repeated thoughts of obsession, such as going back to inspect the door house many times. Some patients may have severe symptoms to the point of repeatedly checking back and forth like that resulting in spending most of their time thinking and doing those actions, which affecting work, study, or various matters in daily life. The causes of obsessive-compulsive disorder caused by abnormal brain structure and function in the prefrontal cortex and genetic or hereditary factors [1].

Because of the work we do is related to brain diseases. Therefore, we choose to use the EEG signal for analysis to distinguish between patients and normal. Electroencephalography (EEG) is a measurement to record electrical activity in the brain at an area around the scalp. Recording EEG in the brain measures electrical fluctuations due to the flow of electric charges within the nerve cells of the brain.

In this study, we brought the EEG signal of both patient and normal to the preprocessing process to eliminate the interference signal and signals from the participant movement. The EEG signal is used to create time-frequency images from the convolution with complex Morlet wavelets [2]. After that, time-frequency images are imported into deep learning to distinguish between patients and normal.

Deep Learning is a branch of machine learning that mimics the functions of human neurons network. Deep learning is used in processing data and create patterns used in the decision. The deep learning model brings the neural network system stacked on multiple layers. Deep learning can be divided into two parts, feature extraction part and classification part. We used a convolution neural network in the feature extraction part, which is popular for image data analysis. Convolution is a mathematical calculation that serves to extract features of the image by multiplication or dot product between input and kernel of filter, and sub-sampling is reducing the dimensions of data obtained from the previous layer. The classification part is called a fully connected layer, connecting all the neuron nodes in each layer. In the output layer, there is one neural node for distinguishing between two categories. In training the model to find performance results, parameters must be changed within the model, such as the filter size of the convolution layer, size of kernel filters, size of pooling filters, number of nodes in the fully connected layer.

As little research has been done on obsessive-compulsive disorder patients's classification, we brought this previous study[3] to compare with our model. A method called support vector machines is used in a previous study on the classification of obsessive-compulsive disorder. It performs an analysis from EEG

The manuscript received July 12, 2020; revised November 1, 2020; accepted December 21, 2020; available online August 31, 2021.
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signal in a one-dimensional feature or all frequencies combined in one signal, in which this analysis may lose the specific feature of each frequency. Our proposed method uses the two-dimension convolution neural network method. It analyzes the time-frequency image in two-dimension, which can see the value of every frequency in every time interval.

This paper is arranged as follows: we explain about data of participants in section 2. Then preprocessing, time-frequency image generation, and deep learning is described in section 3. After that, the result is shown in section 4. The conclusion is in the final section.

2. Materials

2.1 Participants

All participants were given written informed consent and the research ethics committee of the University of Arizona approved this experiment [4]. Participants were excluded if they are a history of neurological diseases, head injuries, or currently using psychoactive drugs.

Participants were recruited by completed the obsessive-compulsive inventory-revised [5], which consists of 18 items covering six dimensions of obsession and compulsion: checking, obsessing, washing, neutralizing, ordering, and hoarding. In a group, the analysis recommended a significant cutoff score of 21 was used to discriminate between low and high groups. After testing the flanker task, the post-test was made to ensure that the OCI-R score was not different from the pre-test. If the experiment results were different (High to low or low to high), the participant data would be excluded in the analysis.

2.2 Flanker Task

Participants have already joined the modified Erikson Flanker task. Each trial (400 trial total) in this speeded response task, required to press one of two response buttons with the thumb to identify the center letter in string either congruent (i.e., KKKKK, RRRRR; FFFFF, EEEEE; 200 trials) or incongruent (i.e., KKRKK, RRKRR; FFEFF, EEFEE; 200 trials) from the Flanker task. Errors tend to occur on incongruent trials due to rapid response competition [2].

2.3 Electroencephalography Data Recording

All participants' EEG signal information was taken from the website supported by the University of New Mexico Office of the Vice President for Research. EEG signals were recorded from measurements using 62 Ag/AgCl scalp electrodes by a Neuroscan Synamps and arranged according to the international 10-20 electrode system. Besides, signals were also recorded from two mastoid channels. Two electrodes for measuring the Electrooculography (EOG) signal of vertical and horizontal eye movement. EEG signals were recorded continuously in ac mode with bandpass filter 0.5-100 Hz. Data were recorded sampling rate at 500 Hz, and impedances were kept under 10 kΩ [6].

3. Methods

3.1 Data Preprocessing

In the process of preprocessing, EEG signal data were re-referenced to Cz and Cpz channels. After that, the EEG signal was filtered bandpass frequency at 0.5-45 Hz to filter various signals such as the 50 Hz power-line interference and noise signals. Then EEG signal was extracted the epoch by baseline-correct from -100 to 0 milli-second [6], in which each epoch has a period between -1 to 2 seconds. The zero-second position of each epoch was determined by tracking of button presses in speeded response experiments. After that, we applied the epoch trial data to the independent component analysis (ICA) process. ICA is an imperceptible source separation method, which separated the mixed signal into sub-component signals. ICA process is used to eliminate artifacts such as vertical and horizontal eye movements. Finally, we transform them into time-frequency images by complex Morlet wavelet.

3.2 Time-Frequency Image Generation

Time-frequency images were generated from custom-written MATLAB (The MathWorks). The time-frequency domain was calculated from the multiplication between the EEG signal and the set of complex Morlet wavelets in the frequency domain by Fourier transform. The complex Morlet wavelet [7] was defined with a gaussian-window complex sine wave (w):

$$w = e^{2i\pi ft} \cdot e^{\frac{-t^2}{2s^2}} \tag{1}$$

Where i: imaginary operator ($i = \sqrt{-1}$), t: time in second, f: frequency in Hz (increased from 0.5 to 30 Hz), s: width of the Gaussian, which is defined as:

$$s = \frac{n}{2\pi f} \tag{2}$$

The multiplication results are converted into the time domain by the Inverse-Fourier transform, the power of time-frequency is calculated by an equation:

$$Z(t) = real[z(t)]^2 + imag[z(t)]^2 \tag{3}$$

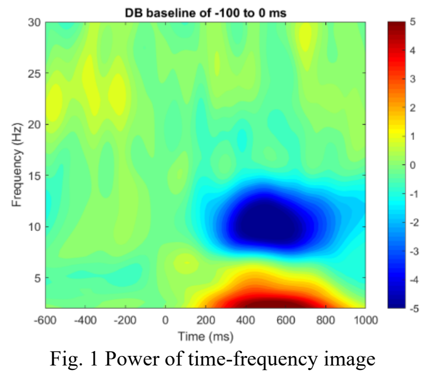


Fig. 1 Power of time-frequency image

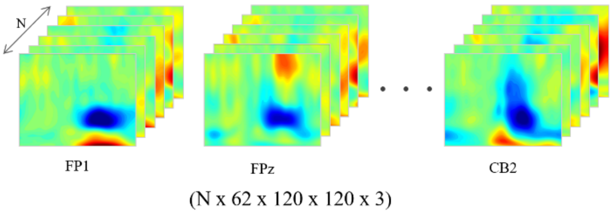


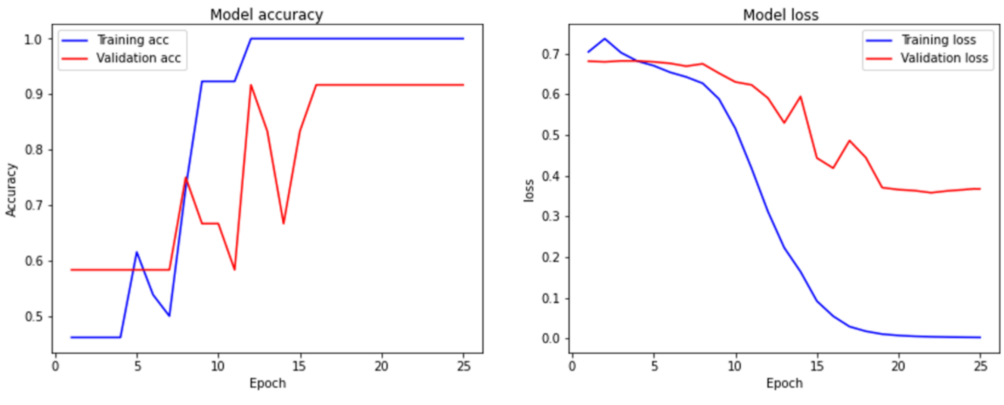
Fig. 2 Cube of Time-frequency image (N: All participant)

The time-frequency image as shown in Fig.1, is created from the average power of time-frequency in all epoch and cropped the time interval between -0.6 seconds to 1 second for observing the response post-stimulus.

3.3 Convolution Neural Network

Time-frequency images are resized to 120x120x3 pixels, which 120x120 means width and length of the image, 3 represents the RGB values of the image. Images are re-arranged separately in each channel of electrodes (total 62 channels). Finally, we receive a cube of the time-frequency image, which shape is N x 62 x 120 x 120 x 3 shown in Fig.2.

In this study, we propose the architecture of the two-dimension convolution neural network model in Fig 3. The feature extraction has 62 inputs separately according to the number of channels from the time-frequency image. 2-D convolution layer consists of 4 kernel filters with 2x2 in size. The activation function was defined with a rectified linear unit or ReLU. The max-pooling layer comprises a pooling size of 2x2. According to the classification part, data must re-arrange the dimension from the two-dimension images to one-dimension or called flatten. The number of neural nodes is set to 64, 32, and 16 in each layer, by using the ReLU as the activation function. The output layer uses the sigmoid activation function. The loss function uses binary cross-entropy, where the loss value was calculated from loss class in the output layer with optimizer Adam in 0.0003 learning rate.



(a)Training and validation accuracy (b)Training and validation loss

Fig.4 Accuracy and loss of 2-Dimension Convolution Neural Network model

4. Results

The 2-D CNN model in this study was designed using the following equipment; CPU: AMD Ryzen5 3600 3.6 GHz, RAM: DDR4/3200 32 GB, GPU: GeForce GTX 1070 Ti. We have adjusted the several parameters in the 2-D convolution neural network model until obtaining a training result that is shown effective. The graphs have a tendency of accuracy and loss in Fig.4a and Fig.4b, respectively. The curve in the loss graph shows that the model did not occur overfitting and received the validation loss value is approximately 0.37. After getting the desired model, the model is tested with time-frequency images of the participants that are not included in the training model and received a test accuracy of 87.5% and a 0.461 test loss value.

Table 1 shows a comparison of the 2-D CNN model to machine learning such as decision tree and k-nearest neighbor classifier. To evaluate performance, we introduce statistical parameters such as accuracy,

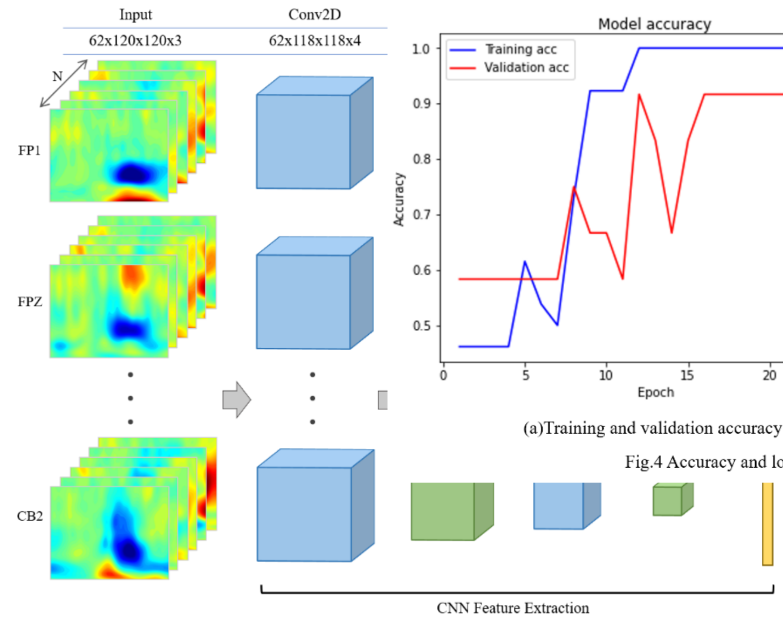


Fig.3 The architecture of the proposed 2-Dimension Convolution Neural Network model

precision, sensitivity, and specificity for assessment of the model. Finally, the result shows that the 2-D CNN model has better performance than machine learning. The limitation of this research lacks participants in Flanker's experiment.

Table 1 Classification results of DT, KNN, and 2-D CNN.

	Accuracy	Precision	Sensitivity	Specificity
DT	0.75	0.67	0.80	0.71
KNN	0.67	0.71	0.71	0.75
2-D CNN	0.88	0.80	1.00	0.75

A comparison of the proposed model to S.Aydin's article [3] is shown in Table 2. S.Aydin's article did use machine learning such as support vector machine (SVM). The proposed model is more accurate than the support vector machine because we analyze the time-frequency image in two-dimension, which can see the value of each frequency in every time interval, providing the specific feature of each frequency.

Table 2 Comparison

reference	Accuracy
S.Aydin [3]	0.850
Proposed	0.875

5. Conclusion

Obsessive-compulsive disorder is not a dangerous disease but can affect everyday life. In this paper, we proposed a two-dimension convolution neural network model for obsessive-compulsive disorder. The input of the 2-D CNN model is the time-frequency image of the EEG signal obtained from the convolution with a complex Morlet wavelet. The results of this experiment show that the essential characteristics of the time-frequency image extracted from the 2-D CNN model can separate between obsessive-compulsive disorder patients and normal people. Therefore, the time-frequency power in the two-dimension convolution neural network model provides a new method for the classification of obsessive-compulsive disorder in Flanker task.

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