Patients' EEG Data Analysis via Spectrogram Image with a Convolution Neural Network

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Abstract. Electroencephalogram (EEG) recording is relatively safe for the patients who are in deep coma or quasi brain death, so it is often used to verify the diagnosis of brain death in clinical practice. The objective of this paper is to apply deep learning method to EEG signal analysis in order to confirm clinical brain death diagnosis. A novel approach using spectrogram images produced from EEG signals as the input dataset of Convolution Neural Network (CNN) is proposed in this paper. A deep CNN was trained to obtain the similarity degree of the patients' EEG signals with the clinical diagnosed symptoms. This method can evaluate the condition of the brain damage patients and can be a reliable reference of quasi brain death diagnosis.

Keywords: Deep learning · CNN · EEG · Spectrogram image · Brain death diagnosis

1 Introduction

Deep learning is a new method of training multi-layer neural network. Despite of the insufficiencies of shallow learning that are optimization difficulty and short in feature expression ability, deep learning has the unique hierarchical structure and the capability of extracting high-level features from low-level features which can solve these problems of shallow learning. [1] Back propagation (BP) is a typical algorithm of traditional shallow learning, it appears bad performance when the number of hidden layers increases [2]. In 2006, Hinton [3] and Bengio Y [4] proposed the unsupervised greedy layer-wise training algorithm based on Deep Belief Networks (DBN) which brings hope to solving multi-layer neural network optimization problems. From that time, deep learning has become a new area of machine learning and applied in the fields of speech recognition, computer vision, nature language processing and information retrieval. Lecun et al. [5, 6] proposed Convolutional Neural Networks (CNN) algorithm and applied it in MNIST handwritten digits recognition. Several methods were applied to the CNN to reduce the number of weights so the deep hierarchical structure can be trained in an acceptable time.

Electroencephalogram (EEG) is a recording of voltage fluctuations produced by ionic current flows in the neurons of brain and refers to the recording of the brain's spontaneous electrical activity over a period of time. EEG signal is applied to many fields such

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as brain-computer interface (BCI) [7], diagnosis of brain-related diseases like Epilepsy [8] and Alzheimer [9]. In our previous work, many algorithms were proposed to analyze EEG signal and evaluate the state of patients' brain activity [10–12]. EEG signal is acquired from human scalp by measuring electrical activities at different electrode positions. Raw EEG signals are the record of amplified voltage varies with time. Like other electric signals, EEG signals can be characterized by amplitude and frequency. Human brain EEG signals are classified according to four different frequency bands, Delta (0.5 to 4 Hz), Theta (4 to 8 Hz), Alpha (8 to 13 Hz) and Beta (13 to 30 Hz) [13]. The signal features of each band can reflect human's physical conditions. Raw EEG signal is time-domain signal format and needs to be processed in order to obtain useful features. It is usually analyzed by three methods, time-domain analysis, frequency-domain analysis and time-frequency analysis. For frequency-based analyze, Fourier Transform (FT) is often used to transform raw EEG signal into frequency-domain signal.

Spectrogram image is a visual representation of signals. The frequency spectrum of spectrogram image varies with time and different colors on the image represent different energy values. Spectrogram image is another form of raw EEG signal's feature representation. Comparing to using some feature extraction methods, spectrogram image contains more unknown features of EEG signals and may have a better performance in a classification network. In order to produce spectrogram images from EEG signals to represent the features of EEG, Short Time Fourier Transform (STFT) technique was applied as a time-frequency analysis method.

With the aim to using EEG to help clinical brain death diagnosis, this paper applied a novel method of using EEG signals to train a CNN to accomplish EEG signal classification work. Firstly the study of deep learning, EEG and spectrogram image was briefly introduced. Then several works of brain death diagnosis, signal classification and time-frequency analysis which are related to this paper's study was illustrated. Next, the basic principle of CNN was explained. Finally, the experiment method and result was elaborated, and the conclusion and future work was proposed.

2 Related Work

Chen Z, Cao J, Cao Y, et al. [12] did a series of work related to brain death diagnosis. They firstly applied independent component analysis (ICA) and Fourier and time-frequency analysis to EEG signals processing. Then they used several methods to do statistical complexity measures in order to evaluate the difference between coma EEG and brain death EEG. Significant differences of the two kinds of samples were obtained from the preliminary experimental results.

There are several studies related to EEG-based signal classification. Koelstra et al. [14] applied a support vector machine (SVM) classifier to realize emotion classification by single trail EEG signals. Power spectrum density (PSD) of EEG signals was used as input features of the classifier and two levels of valence states and two levels of arousal states were classified. Junhua Li and Andrzej Cichocki [15] used a multi-fractal attributes extraction method to extract useful features from EEG signals. Then the extracted features were put into a deep network initialized by a block of denoising auto encoder (DAE) to recognize the subjects' motor imagery.

Although time-frequency analysis is applied to EEG signal processing [16] and other areas [17], very few are in image processing area. Mustafa [18] trained an Artificial Neuron Network (ANN) for brainwave balancing application. Spectrogram images were produced by spectrum data of EEG signals and Gray Level Co-occurrence Matrix (GLCM) features of the images was extracted as the input of the ANN.

3 Convolution Neural Network

Convolution Neural Network (CNN) is a deep learning algorithm which achieves high performance especially in image classification area. CNN uses relative space position relations to reduce the number of training parameters by a large margin in order to increase training speed and training performance. As shown in Fig. 1, a normal CNN consists of image input layer, convolution layer, sub-sample layer, and classification layer. Different CNNs vary in different algorithms of convolution layer and sub-sample layer and different structures of the network.

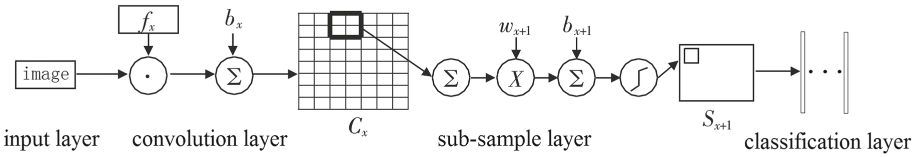


Fig. 1. Structure diagram of a typical CNN

3.1 Image Input Layer

Image input layer receives raw images from training samples and transforms the data into a unified form in order to deliver the data into next layer correctly. This layer also defines the initial parameters such as the scale of the local receptive fields and different filters.

3.2 Convolution Layer

Convolution layer processes the input data by convolution algorithm and produces several layers called feature map which consist of the convolution calculation results from the previous layers. The output equation of the convolution calculation is as follows:

$$x_j^l = f\left(\sum\nolimits_{i \in M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right) \tag{1}$$

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

Where x is the output value of the convolution layer, k is the kernel (or called the filter), l is the number of output layers which is decided by the number of kernels, i is the stride that the kernel moves in every step of calculation, M_j is the jth feature map produced by different kernels, b is the bias and f is an activation function usually defined as a sigmoid function showed in Eq. (2). Though every output neuron has different receptive fields, every neuron of the same feature map shares the same weights and bias. In this way, training parameters are greatly decreased.

3.3 Sub-sample Layer

This layer sub-samples every feature map from the previous convolution layer. The sub-sample method is weighted summation calculation or taking the maximum value in an $n \times n$ area of every feature map. The output of sub-sample layer is as follows:

$$x_j^l = f\left(\beta_j^l downsample\left(x_j^{l-1}\right) + b_j^l\right) \tag{3}$$

Where x^l is the output value of the l th sub-sample layer, *downsample* is the sub-sample function, β is the bias of the sub-sample function, f and b are the activation function and the bias respectively. Sub-sample layer reduces the number of training parameters, filters noises and avoids over-fitting of the network.

3.4 Classification Layer

After the data goes through several convolution layers and sub-sample layers, the size of output feature maps continuously decreases. For the classification layer, every feature map consists of only one neuron and becomes a 1D feature vetor. The vector is fully connected with a classifier. Usually the classifier is a traditional fully connected neural network.

4 Experiment Method and Results

The EEG signals used in this paper were obtained from the brain damage patients of a hospital in Shanghai. Each of the patients was diagnosed by clinical doctor. As for the experiment, firstly Short Time Fourier Transform (STFT) technique was applied as a time-frequency analysis method and spectrogram images were produced to represent the features of EEG signals. Then the images were labeled by patients' symptoms and used as the training samples in a deep convolutional neural network proposed in paper [19]. Finally the trained network was used to evaluate the similarity degree of the other patients' EEG signal with the two symptoms.

The experiment procedure is shown in Fig. 2 Firstly raw EEG signals of the patients were extracted from the data file by EEGLab Toolbox of Matlab software. The EEG data were pre-processed to prepare for producing spectrogram images. Then spectrogram images were labeled by the clinical diagnosed symptoms and the labeled images were used as the dataset to train a deep CNN. Finally, a set of raw EEG data from several other patients was put into the trained network to evaluate the state of the patients' conditions.

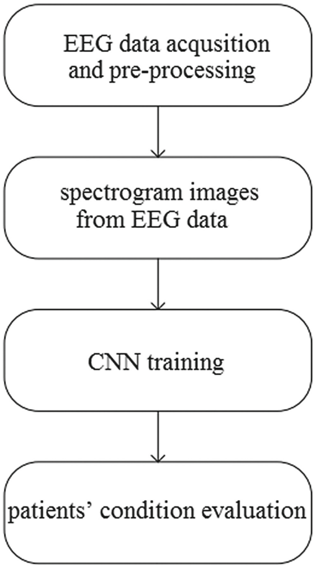


Fig. 2. Experiment method

4.1 EEG Data Acquisition and Pre-processing

The EEG data used in this paper was obtained from the brain damage patients in the intensive care unit (ICU) of a hospital in Shanghai. And the symptoms of the patients had been clinical diagnosed by the doctors before the record of the data. A total of 36 patients including 19 coma diagnosed patients and 17 brain death diagnosed patients with their age ranging from 18 to 85 years old were examined.

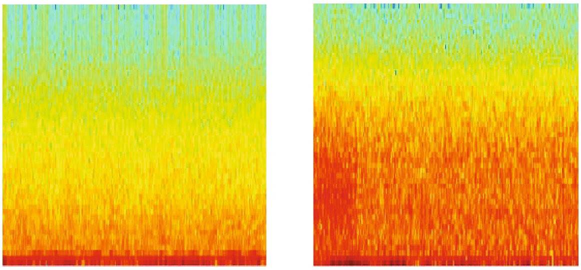
A portable EEG device named NEUROSCAN ESI was applied to measure EEG signals of the patients. Nine electrodes including six exploring electrodes (Fp1, Fp2, F3, F4, F7 and F8), one ground electrode (GND) and two reference electrodes (A1, A2) were used to record the EEG signals. The sampling rate was set as 1000 Hz and the resistance of the electrodes was set as less than 1000 kΩ. The recoding time of every patient ranged from 314 s to 1576 s.

The raw EEG signals used in this paper were obtained from the above method. Pre-processing including filtering specified voltage range (–150 μV to 150 μV) and frequency range (0.5 Hz to 30 Hz was done to filter the noise.

4.2 Spectrogram Images from EEG Data

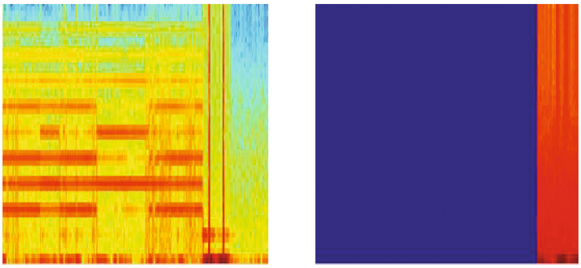
The spectrogram images were produced from pre-processed EEG signals using STFT method at Matlab software platform. According to time sequence, every 20 s of the EEG signals was sampled and produced one spectrogram image. In order to increase the number of produced images, six channels of the EEG signals were used to produce spectrogram images respectively. The individual differences of the patients were ignored so the images produced from different patients were taken as one dataset. And to make the most use of the data, every window of STFT overlapped 20% with the adjacent windows. Finally every produced spectrogram image was resized to 256×256 pixels for the purpose of matching the input format of the deep CNN.

Figure 3 (a) and (b) are the spectrogram images of coma patient and brain death patient respectively. However, the EEG signals used to produce spectrogram images are raw signals so they may contain some noises. Obviously some images like Fig. 4 (a) and (b) were produced by noise signals so they were removed manually. Totally, the EEG data of 15 coma patients and 15 brain death patients was used and 6000 spectrogram images including 2400 images produced from coma patients and 3600 images produced from brain death patients were produced, labeled and disorganized to be used as the dataset of the deep CNN.



(a) (b)

Fig. 3. EEG spectrogram images for coma patient (a) and brain death patient (b)



(a) (b)

Fig. 4. Spectrogram images (a) and (b) produced from noise signals

4.3 CNN Training

In the training step, a computer with a Core (TM) i7-2600 K (3.40 GHz), a 16.0 GB DDR3 and a GTX 1060 Graphics Processing Unit (GPU) was used. The operating system is Linux-Ubuntu 14.04.

A deep learning framework named Caffe which is developed by Yangqing Jia [20] was used to build the deep convolution neural network. The deep CNN from paper [12] in ImageNet classification and we used this network directly to train our spectrogram image dataset. This deep CNN has many convolution layers and has a large-scale input which can receive data from a high pixel image. By using this network, every single image can contain the data of a long period of time of EEG signals, and this is good for feature expression of time sequence data. The number of output unit of the classifier should be equal to the category of the class label so only the classification layer of the network was modified.

As for the dataset, 80% was used as training samples and 20% was used as testing samples. The max iteration was set as 12000 and GPU was used for training the network. The training time was 26 min and the test accuracy of this network is 99.8%.

4.4 Patients' Condition Evaluation

The EEG data from the other 6 brain damage patients which was not used in training the deep CNN model was used to evaluate the trained network. For every patient, 100 spectrogram images were extracted from the EEG data. Then according to the clinical diagnosis results, the images were put into the trained network to validate the recognition accuracy.

Table 1 shows the accuracy of every patient's validation result. Different from the test accuracy obtained from the training process, this accuracy is the recognition accuracy of samples from every single patient. Hence this can be regarded as the similarity degree of a patient's EEG signal with coma or brain death symptom.

Table 1. Experiment results

Diagnosed results	Samples	Accuracy (%)
Coma	100	95
Coma	100	89
Coma	100	96
Coma	100	88
Brain death	100	94
Brain death	100	92

5 Conclusion and Future Work

According to the experiment results, based on the trained deep CNN, the highest accuracy of coma and brain death diagnosed patients' samples are 96% and 94% respectively.

It proves the method this paper proposed is feasible and the method of converting a time-domain signal into several discrete spectrogram images is a good way of applying EEG signal to deep learning classification.

Using spectrogram images as the feature expression of EEG is a novel approach of EEG signal processing. Compared to the former brain death diagnosis studies which used many signal processing and feature extraction methods, we used raw signals to express more EEG features. Instead of working out some quantitative analysis results from processed EEG signals, we obtained the similarity between the symptoms and the patients' samples, which is more reliable in symptom evaluation. The method proposed in this paper can help evaluate the state of quasi brain death patient and be a reliable reference of the clinical diagnosis of brain-related illness.

In future work, instead of training the existing network which is initially used in other fields, we will build and test a specialized deep neural network of brain death diagnosis in order to raise calculation speed and classification accuracy. And an automatical denoising method should be proposed instead of picking out noising spectrogram images manually in case of processing mass data. In addition, more patient samples should be tested by the trained network in order to raise the reliability of the method.

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