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Neonatal Seizure Detection Combining Sparse Representation and Deep Learning

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Abstract. Neonatal seizures are a common emergency in neonatal intensive care unit (NICU). Neonatal epilepsy detection is generally the doctor through the naked eye reading electroencephalogram (EEG) to judge, this way is more subjective easy to produce differences. In this paper, a novel algorithm combining sparse representation and deep learning for automatic detection of neonatal seizures is proposed. After the EEG data is preprocessed, the features are extracted and sent to the Deep Sparse Representation Classification (DSRC) network. The performance of the algorithm was evaluated by sensitivity (sen) and specificity (spe) values in a publicly available dataset of 36 neonates with continuous EEG signals. Testing is done using cross-validation, so performance accurately represents the ability to classify architectures and test generalizations in a clinical setting. The sensitivity and specificity of cross detection were 89.33 and 90.2, respectively.

Keywords. electroencephalogram (EEG), Neonatal seizures detection, Deep learning, Sparse representation

1. Introduction

Neonatal seizures are a common emergency for infants admitted to neonatal intensive care unit [1]. Recent clinical studies show that infants experiencing seizures are at a high risk of death and morbidity. Up to one-third of the new-borns who suffer neonatal seizures are likely to die, while the survivors can be at risk for long-term neurodevelopmental impairments [2]. Therefore, accurate detection of seizures in neonates is essential to identify a dedicated therapy and prevent the risk of adverse conditions in later life. Interpretation of neonatal EEG signals requires highly trained medicinal professionals. Moreover, the process is time-consuming and energy-consuming. Therefore, it is of great importance to explore a method that can voluntarily detect the EEG signal of newborn epilepsy.

The technology of automatic detection of neonatal epilepsy has aroused the interest of many researchers. So far, several automatic detection technologies of neonatal

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epilepsy have been developed. Karoliina et al. used summative EEG measures/features to represent EEG (electroencephalogram); Support vector machine is used to combine features to form decision statistics [3]. Asison et al. used only the convolutional layer to process multi-channel time domain signals and used the full convolutional architecture to detect neonatal epilepsy from the original multi-channel EEG [4]. Asison et al. used only the convolutional layer to process multi-channel time domain signals and used the full convolutional architecture to detect neonatal epilepsy from the original multi-channel EEG [5].

Deep learning is a machine learning method that is a major driver of the development of artificial intelligence. Xaunjie Qiu et al. introduced the channel attention module in the network, it can make the model focus on information related to seizures, and prove the classification ability in two and five seizure detection tasks [6]. XinghuaYao et al. solved the problem of seizure changeability by using the attention mechanism and BiLSTM (two-way long and short-term memory) to distinguish features [7].

Sparse coding has shown excellent application performance in some computer vision fields such as image classification and pattern recognition, and has attracted more and more researchers' attention. Meng Yang et al. proposed a discriminant semi-supervised learning (DSSLDDR) algorithm based on depth and dictionary representation. In this algorithm, the final classification is realized by the error of sample reconstruction with class-specific dictionary [8].In the robust sparse representation method for medical image classification proposed by Majid et al., sparse coding and dictionary learning are iterated until a dictionary close to the optimal appears [9]. HongPeng et al. focus on homotopy dictionary learning (DLWH) to solve classification problems. They studied a sparse representation-based epilepsy classification method based on dictionary learning homotopy algorithm (DLWH), which has a high classification rate and recognition speed [5].

In recent years, the automatic detection of neonatal epilepsy has been further developed. However, the processing process of EEG data is very tedious, which is easy to cause overfitting phenomenon. Therefore, this paper proposes a neonatal epilepsy detection network that combines sparse representation and deep learning. In particular, the sparse coding layer introduced by the network lies between the encoder and the decoder, and the sparse coding output is used to estimate the sample class.

2. Materials and methods

Figure 1 shows the flow of the proposed method. These processes are described in detail below.

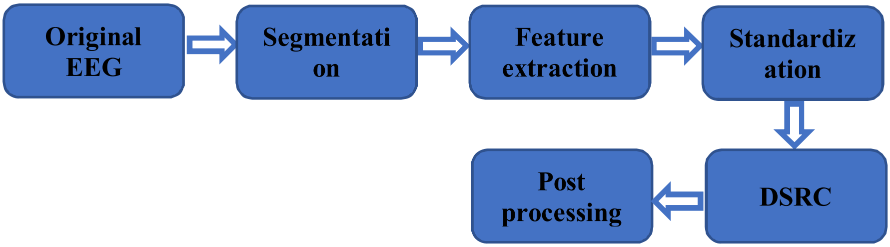

Figure 1. The process of the proposed EEG signal classification method.

2.1. Dataset

The experimental objects of this study were the EEG dataset of 79 newborns recorded by Helsinki University Hospital [10]. Among these 79 newborns, 39 experienced seizures. However, due to the duplication of EEG recordings in some patients, we studied the EEG of the remaining 36 neonates. Neonatal electroencephalography was recorded using 19-channel electroencephalography located by the international 10-20 system, with a sampling frequency of 256HZ. EEG signals in the dataset were preprocessed by six-order Butterworth filtering, and seizure and non-seizure fragments were recorded in the dataset. 0 and 1 were used as labels for seizure and non-seizure fragments respectively. The definition of epileptic seizures and non-epileptic seizures comes from a joint note by three experts. EEG data totaling about 48 h were used in this work.

2.2. Data Preprocessing

2.2.1 Segmentation

Because the Helsinki database used in this study is a long-term EEG signal, a sliding window with a length of 4s was used for segmentation to facilitate processing.

2.2.2 Feature Extraction

To improve the classification ability and reduce the amount of computation, feature extraction was carried out on the segmented EEG signal. The statistical characteristics selected in this experiment include maximum, minimum, median, mean, standard, mean absolute deviation, root mean square, skewness, kurtosis.

2.2.3 Standardization

In order to eliminate different orders of magnitude effects between features, we standardized each feature. The features are denoted as

$$y_i = \frac{x_i - \bar{x}}{s}, \ \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

while $s = \sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2}$, y_i is the output of this step.

2.3. Deep Sparse Representation-Based Classification Network

Our model consists of an encoder, a sparse coding layer and a decoder. The purpose of sparse coding is to find sparse representation under a given basis while minimizing construction errors [11]. Based on the assumption that samples from each class are located in a linear subspace, the test samples are represented as a linear combination of the training samples. Given a training sample matrix $y_{train}=[y_{train}^1 \cdots y_{train}^A] \in R^{B\times C}, y_{train}^A \in R^{B\times C_A}$ and a test sample $y_{test} \in R^{B\times 1}$, the linear representation of y_{test} can be written as:

$$y_{test}=[\mathrm{y}_{\mathrm{train}}^{1}\cdots\mathrm{y}_{\mathrm{train}}^{\mathrm{A}}]\begin{bmatrix}\mathrm{U}^{1}\\ \cdot\\ \cdot\\ \cdot\\ \mathrm{U}^{\mathrm{A}}\end{bmatrix}=\mathrm{yU} \tag{2}$$

Where, A represents the number of classes, the number of training samples in class A, $\mathrm{C}=\sum_{n=1}^{\mathrm{A}}\mathrm{C}_{\mathrm{A}}$, and B represents the dimension of samples.

Assuming, respectively, the encoder picks up the signal $\mathrm{y}=[\mathrm{y}_{\mathrm{train}},\mathrm{y}_{\mathrm{test}}]$, where it develops its abstract features $T=[\mathrm{T}_{\mathrm{train}},\mathrm{T}_{\mathrm{test}}]$, Between the encoder and the decoder is sparse coding layer. Sparse coding layer restores test samples through sparse linear combination of training samples to find sparse representation, for y_{test}, sparse representation coefficient can be obtained by solving the following optimization problems:

$$\arg\min_{\mathrm{U}}\{\|\mathrm{T}_{\mathrm{test}}-\mathrm{T}_{\mathrm{train}}\mathrm{U}\|_{\mathrm{E}}^{2}+\lambda_0\|\mathrm{U}\|_1\} \tag{3}$$

Where U is the coefficient matrix containing sparse code and λ_0 is the regularization parameter.

In view of the sparsity limitation, the optimization problem (3) can be modeled in a fully connected layer neural network with sparse parameters. After sparse representation is obtained, sends it to decoder, which reconstructs features generated by encoder to make input and output the same. Sparse coding layer output $\hat{\mathrm{T}}_{\mathrm{train}}$ and $\hat{\mathrm{T}}_{\mathrm{test}}$, namely the input of the decoder. The end-to-end training targets of both sparse coding and encoder-decoder find both sparse codes and features, which are used to predict class labels. and finally predicts the final category through the combination of sparse representation and features of test set. the prediction label of $\mathrm{y}_{\mathrm{test}}$ is determined by the following:

$$\mathrm{class}(\mathrm{y}_{\mathrm{test}})=\arg\min_{\mathrm{A}}\|\mathrm{T}_{\mathrm{test}}-\mathrm{T}_{\mathrm{train}}^{\mathrm{A}}\mathrm{U}^{\mathrm{A}}\|_2^{2} \tag{4}$$

The network structure consists of four convolutional layers, sparse coding layer and three deconvolutional layers. The proposed DSRC framework and its network parameters are shown in Figure 2.

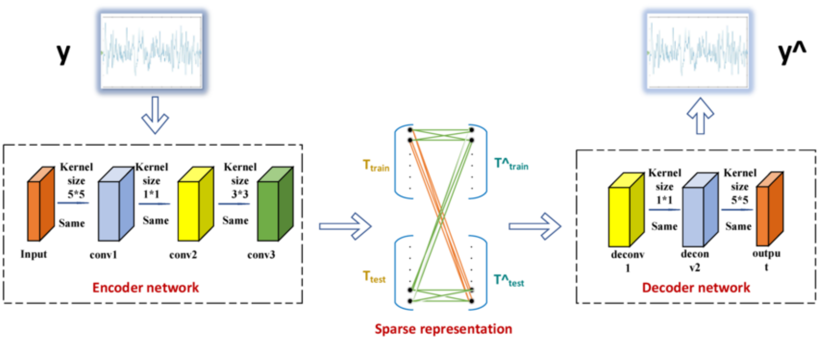

Figure 2. The proposed DSRC network structure.

2.4. Post-processing

For signals in the same data segment, 19 binary decision results are output. If the number of temporally parallel channels labeled as 'seizure' is larger than 10,(Half of the total number of channels) the time segment will be ultimately marked as 'seizure', otherwise, it will be marked as 'non-seizure'. A time segment will be also labeled as 'seizure' when its previous and next segment are both labeled as 'seizure'. And a time segment will be also labeled as 'non-seizure' in a similar way.

3. Results and Discussion

The method in this paper is implemented by tensorflow-1.4. The learning rate is 10^{-3}, the language is python3.6, the code platform is pycharm and the loss minimization function is realized by Adam.

The performance of the experimental model presented in this paper was evaluated by cross-validation. data from each patient was used half for training and half for testing, and then the training and testing set were exchanged for validation again. so that the neonatal EEG test data would be independent of the training data and facilitate the evaluation of emerging data. Because neonatal epilepsy detection is an unbalanced classification problem, we evaluated the performance of the model adopted in this study by sensitivity and specificity.

Sensitivity is the percentage of correctly classified positive samples to all positive samples:

$$\text{Sensitivity} = \frac{\text{true positives}}{\text{total number of actual seizure segments}} \tag{5}$$

Specificity is the percentage of correctly classified negative samples to all negative samples:

$$\text{Specificity} = \frac{\text{true negatives}}{\text{total number of actual non-seizure segments}} \tag{6}$$

The sensitivity、specificity obtained by the method proposed in this paper are shown in Figure 3.

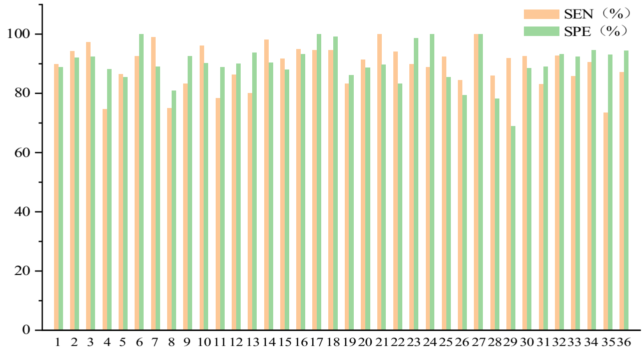

Figure 3. Neonatal seizure detection results from the Helsinki dataset.

According to the deep sparse network model used in this paper, control variable method is adopted to change the network parameter kernel_size in convolutional layer 1 to compare the network performance. Figure 4 shows the classification results of patient5, patient 40 and patient 44 of the deep sparse network model used in this paper under the condition that other network parameters remain unchanged and different kernel sizes of convolutional layer 1 are changed. The horizontal data in this figure are the different kernel size: 1, 3, and 5 used in this comparison test. It can be seen that when kernel_size in convolutional layer 1 is 1, the classification effect is basically the best, so our experiment uses the deep sparse network model when kernel_size is 1.

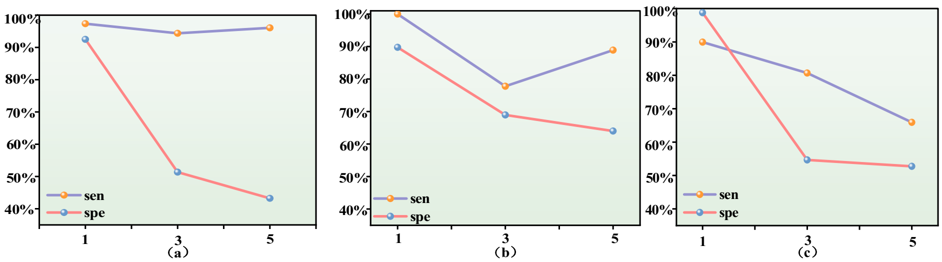

Figure 4. The classification results of patient 5(a), patient 40(b)and patient 44(c)under different kernel size in convolution layer 1.

4. Conclusions

In this paper, a novel method combining sparse representation and deep learning for neonatal seizure detection is proposed. Firstly, EEG data is filtered and truncated. Then, in order to reduce the amount of computation and remove the redundant information of EEG signal, the statistical characteristics of EEG signal are extracted. Eventually, the EEG features were sent to the DSRC network. The experimental results show that this method has a good effect on the classification of EEG signals in newborn epilepsy, so as to quickly realize the targeted and effective treatment of epilepsy disease.

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