A Novel Multi-scale 3D CNN with Deep Neural Network for Epileptic Seizure Detection

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***Abstract*-- Accurate and timely detection of seizure activity during continuous EEG monitoring either in epilepsy monitoring unit or in neuro-intensive care unit is crucial for both physician and paramedical personnel. However, it is laborious work and required special training for epilepsy and EEG interpretation. In order to detect automatically seizure, we propose a Multi-scale 3D-CNN with Deep Neural Network (DNN) model for non-patient-specific seizure detection. We considered spectral, spatial and temporal features. The EEG signals are transformed to frequency domain using Short Time Fourier Transform (STFT) to extract spectral features. The spectral features are mapped to 2D images to preserve the position of the electrodes. The proposed model is composed of 3D-CNN and bidirectional Gated Recurrent Unit (GRU) to extract spatial and temporal features from the 2D mapped images. We evaluated the proposed model using CHB-MIT and Seoul National University Hospital (SNUH) Scalp EEG database. Our proposed model achieves the sensitivity of 89.4% and 97% and a false positive rate of 0.5/hours and 0.6/hours on the CHB-MIT database, and the SNUH database, respectively.**

I. Introduction

Epilepsy is a disease that affects 1% of the world's population [1]. The EEG is very useful for diagnosing epilepsy and monitoring brain activity. However, neurologist usually diagnoses the patient by directly visualizing the patient's EEG. It is extremely laborious for a neurologist to review each patient every day. Many automatic seizure detection studies have been conducted to reduce the laborious work of the neurologist and improve the quality of patient's life.

The deep learning shows superior performance in various fields such as image processing and speech recognition than hand-crafted approach. Some studies show that the deep learning is suitable for extracting seizure patterns that are extremely variable each patient [3,6]. Recent studies used deep learning to automatically detect epileptic seizures using a Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) [2-8]. These approaches used only square convolution filters.

3D-CNN is superior to 2D-CNN architecture because it keeps temporal features as well as spatial features in video analysis [8]. In this paper, we propose DNN with temporal and spatial features based on regions of the brain.

II. EEG Database

A. CHB-MIT Scalp EEG database

The first database is the CHB-MIT Scalp EEG database collected from the Children Hospital Boston. This database consists of 23 patients containing 198 seizure events. The EEG signals each patient contains 23 channels with a 10-20 international system, and with a sampling rate of 256 Hz. We used 184 seizure events.

B. SNUH Scalp EEG database

The first database is the SNUH Scalp EEG database collected from the Seoul National University Hospital. This database consists of 25 patients containing 53 seizure events. The EEG signals each patient contains 21 channels with a 10-20 international system, and with a sampling rate of 200 Hz. We used total seizure events.

III. Proposed Methods

The overall process for seizure detection consists of preprocessing and DNN. the process is shown in Figure 1.

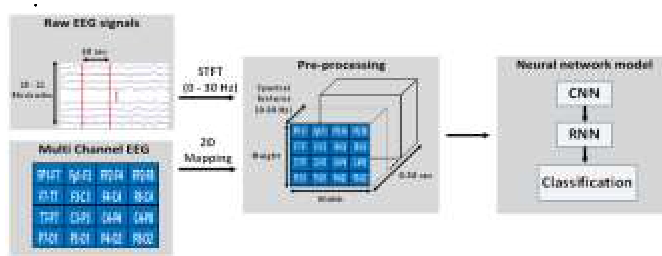

Fig. 1. Overall process for seizure detection

A. Pre-processing

The pre-processing has two steps. The first step, we extract raw EEG signals of 30 seconds with electrodes between 18 and 21, and this transform to the frequency domain with the frequency band of 1-30Hz using STFT. The second step, we applied 2D-mapping to preserve electrode positions [3,9].

B. 3D-CNN Module

The CNN module consists of three 3D-CNN filters. As shown in Figure 2, The 3D-CNN filters extract spatial features of three regions in the brain. We concatenate the total features after average-pooling and up-sampling.

C. RNN Module and Classification

The result of the CNN module uses the RNN module of input. The RNN module consists of one layer of bidirectional GRU to extract the temporal feature of the epileptic seizure, and we classified whether seizure or non-seizure using fully connected layer with 1 layer.

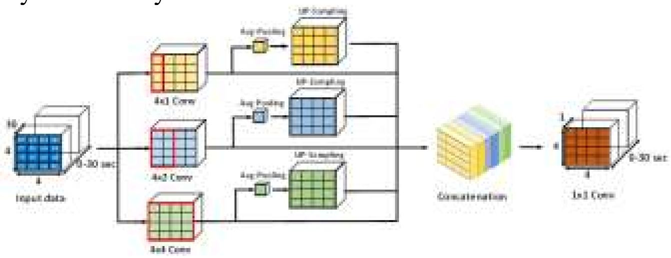

Fig. 2. 3D-CNN Module process

IV. Experimental Designs

A. Training and test database

We created a training set with the patients except the test patient. When a test patient changed, this process was repeated. Test set was created for each test patient. We trained the proposed model using a training database and evaluate performance of each patient using the test set. The process was repeated for all patients.

B. Performance measurement

The seizure detection performance is measured using standard metric. The standard metrics is show in the (1),(2),(3),(4). The sensitivity (Sen) is computed using True Positive (TP) and False Negative (FN). The TP is the number of correctly detected seizures. The FN is the number of incorrectly detected seizures. The specificity (Spe) is computed using True Negative (TN) False Positive (FP). The TN is the number of correctly detected non-seizures. The FP is the number of incorrectly detected non-seizures.

$$Sensitivity = \frac{\sum TP}{\sum TP + \sum FN} \quad (1)$$

$$Specifiticy = \frac{\sum TN}{\sum TN + \sum FP} \quad (2)$$

$$Accuracy = \frac{\sum TN}{\sum TN + \sum FP + \sum TP + \sum FN} \quad (3)$$

$$FPR = \frac{\sum FP}{Total\ recording\ time} \quad (4)$$

C. Hyper-parameters

We used the following hyper-parameter values to optimize the proposed model. Batch size is 128, Optimizer is Adam, a Learning rate is 0.001, Dropout is 0.5, Recurrent dropout is 0.5.

V. Experimental results

A. Performance of seizure detection

The proposed model correctly detected seizures with a sensitivity of 89%, and a false positive rate (FPR) of 0.5/hours for CHB-MIT Scalp EEG database. For Seoul National University Hospital (SNUH) Scalp EEG database, we achieved a sensitivity of 97% and the FPR of 0.6/hours.

TABLE I

Performance comparison of non-patient-specific approaches

Seizure detection algorithms	Database	Sen (%)	Spe (%)	Acc (%)	FPR (hours)
Samiee et al. [8]	CHB-MIT	72	97.2	84.6	-
Thodoroff et al. [3]	CHB-MIT	85	99.2	-	0.8
Proposed methods	CHB-MIT	**89**	**99.5**	**99.4**	**0.5**
Proposed methods	SNUH	**97**	**99.3**	**99.2**	**0.6**

VI. Conclusion

In this paper, we propose multi-scale 3D-CNN with DNN model for non-patient-specific detection using multi-channel scalp EEG signals. The proposed model was considered spectral, spatial and temporal features using STFT, multi-scale 3D-CNN and bidirectional GRU. The proposed model reaches to state-of-the-art performance in the CHB-MIT Scalp EEG database. The result of visualizing epileptic seizure activity will facilitate the analysis of the patient conditions.

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