Epileptic Seizure Detection Using Multi-Channel EEG Wavelet Power Spectra and 1-D Convolutional Neural Networks

Roneel V. Sharan, *Senior Member, IEEE*, and Shlomo Berkovsky

***Abstract*—The use of feature extraction and selection from EEG signals has shown to be useful in the detection of epileptic seizure segments. However, these traditional methods have more recently been surpassed by deep learning techniques, forgoing the need for complex feature engineering. This work aims to extend the conventional approach of epileptic seizure detection utilizing raw power spectra of EEG signals and convolutional neural networks (CNN). The proposed technique utilizes wavelet transform to compute the frequency characteristics of multi-channel EEG signals. The EEG signals are divided into 2 second epochs and frequency spectrum up to a cutoff frequency of 45 Hz is computed. This multi-channel raw spectral data forms the input to a one-dimensional CNN (1-D CNN). Spectral data from the current, previous, and next epochs is utilized for predicting the label of the current epoch. The performance of the technique is evaluated using a dataset of EEG signals from 24 cases. The proposed method achieves an accuracy of 97.25% in detecting epileptic seizure segments. This result shows that multi-channel EEG wavelet power spectra and 1-D CNN are useful in detecting epileptic seizures.**

I. Introduction

Globally, an estimated 50 million people suffer from epilepsy [1] and about 2.4 million people are diagnosed with epilepsy every year [2]. Epilepsy is one of the most common neurological disorders having social and psychological effects [3]. As such, accurate diagnosis and subsequent treatment of epilepsy can lead to improvement in quality of life [4].

Epilepsy is marked by short disturbance to the normal patterns of neuronal activity of the brain leading to seizures. Electroencephalogram (EEG), neuroimaging, and neuropsychological tests are amongst the techniques used to help diagnose epilepsy [5]. Over the past decades, the use of EEG signal analysis for detection of epileptic seizures has gained significant attention. This has been supported by the availability of relevant databases such as the CHB-MIT scalp EEG database (https://physionet.org/content/chbmit) and the EEG database from the seizure prediction project Freiburg (http://epilepsy.uni-freiburg.de/database), now superseded by the European Epilepsy Database (http://epilepsy-database.eu).

The availability of robust EEG signal analysis algorithms has the potential to automate detection of epileptic seizure segments. This could save clinicians significant time in manual or semi-automated detection and analysis of seizure segments in EEG signals recorded over several hours.

Frequency domain analysis of EEG signals has shown to be useful in epileptic seizure detection [6, 7]. Various feature extraction, feature selection, and classification strategies have been proposed in this regard. In [6], subband energies are used for epileptic seizure onset detection. In [7], frequency domain features, such as peak frequency, median frequency, etc., are considered in combination with various feature selection methods, such as statistical significance, principal component analysis, and linear discriminant analysis. Also, support vector machines have proven to be accurate in feature classification, as seen in [6-8].

Deep learning techniques have recently produced encouraging results in various classification tasks, without the need for complex feature extraction and selection. One such method is convolutional neural networks (CNN). Originally developed as an image classification method [9], it has been successfully applied to audio signal classification tasks [10]. Similar techniques have also been applied to EEG signal classification [11, 12]

In this work, the use of CNN for detection of epileptic seizure segments as manifested in EEG signals is explored. In particular, it is proposed to represent each EEG epoch or segment in frequency domain using wavelet transform (WT), which has been shown to be more useful than fast Fourier transform (FFT) based frequency domain analysis of EEG signals, for epileptic seizure detection [13]. This yields a one-dimensional (1-D) feature vector, thereby, utilizing 1-D CNN. It is also proposed to use EEG signals from multiple channels for this purpose requiring the use of a multi-channel 1-D CNN. Spectral information from the previous and following epochs is also utilized to improve the classification performance [14]. The proposed method achieves robust seizure detection performance when compared to several baseline methods.

The rest of the paper is organized as follows. Section II describes the dataset used in this work and overviews the proposed method. The results are presented in Section III and discussions and conclusions are given in Section IV.

II. Method

A. Dataset

This work utilizes the CHB-MIT scalp EEG dataset [6, 15]. The dataset was collected at the Children's Hospital Boston and consists of EEG recordings from pediatric subjects with intractable seizures. The recordings were collected from 23 subjects and have been grouped into 24 cases, chb01 – chb24. Cases chb01 and chb21 were obtained from the same subject 1.5 years apart.

R. V. Sharan and S. Berkovsky are with the Australian Institute of Health Innovation, Macquarie University, Sydney, NSW 2109, Australia (e-mail: roneel.sharan@mq.edu.au and shlomo.berkovsky@mq.edu.au).

978-1-7281-1990-8/20/$31.00 ©2020 IEEE

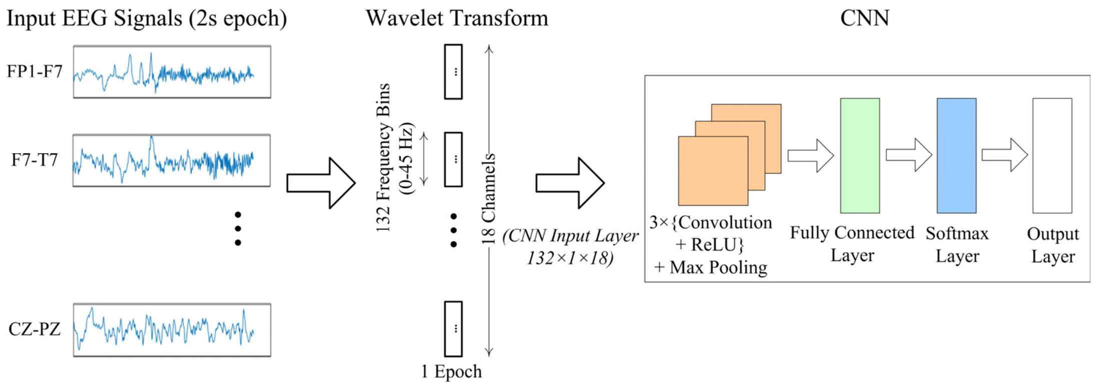

Figure 1. An overview of the proposed method.

The demographic data is available for 22 subjects of which 5 are male, aged 3 to 22 years, and 17 are female, aged 1.5 to 19 years. Each case has 9 to 42 EDF recordings that are mostly 1 to 4 hours long. The sampling frequency of the signals is 256 Hz with 16 bit resolution. Each recording has 23 or more channels. The EEG electrode positions and nomenclature follow the international 10-20 system.

In total, the dataset contains 686 EDF files. Of these, 141 files contain one or more seizures with a total of 198 seizures. Four files were excluded due to different channel montages or corrupt data. As such, the useable dataset for this study contains 682 EDF files with a total of 185 seizure files. For the problem of seizure/non-seizure epoch classification, data over the following 18 common channels, as given in the dataset, are analyzed: FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, P8-O2, FZ-CZ, and CZ-PZ.

B. *Proposed Method*

An overview of the proposed EEG based epileptic seizure segment detection method is shown in Fig. 1. The EEG signals are divided into short time-windows or epochs. The filtered time-domain epochs are transformed to frequency domain. The 1-D feature vectors from all the channels form input to a CNN for seizure/non-seizure prediction.

Similar to [7], the signals are filtered using a second order Butterworth filter and up to a cutoff frequency of 45 Hz [16]. Epochs of different durations have been used in earlier works. For example, 1 second epochs are used in [17], 2 second epochs in [18], and 60 second epochs in [7]. In this work, non-overlapping epochs of 2 seconds are used. Due to the scarcity of the seizure segments, the use of short duration epochs of 2 seconds yields more seizure epochs for training the CNN model.

An epoch containing seizure, regardless of the duration, was marked as a seizure epoch. Otherwise, it was labeled as a non-seizure epoch. This results in a total of 5,748 seizure epochs and 1,424,564 non-seizure epochs. The number of non-seizure epochs is significantly higher than the number of seizure epochs. In this work, all seizure epochs are used and an equal number of non-seizure epochs are randomly selected for training and validation. As such, the final dataset contains 5,748 seizure epochs and 5,748 non-seizure epochs for training and validation.

FFT and WT are used for transforming the time-domain EEG signal to frequency domain. FFT is applied to the windowed signal as

$$S(k,r)=\sum_{n=0}^{N-1} x(n)\,w(n)\,e^{\frac{-2\pi ikn}{N}}, \qquad k=0,\ldots,N-1 \quad (1)$$

where N is the length of the window, $x(n)$ is the EEG signal, $S(k,r)$ is the k^{th} harmonic corresponding to the frequency $f(k)=kF_s/N$ for the r^{th} epoch, F_s is the sampling frequency, and $w(n)$ is the window function. The window function in this case refers to a 2 second non-overlapping rectangular window.

The spectrogram values are then obtained by

$$S_{Log}(k,r)=\log\left(\left|S(k,r)\right|^2\right). \quad (2)$$

A 768-point FFT is computed for each epoch for each of the 18 channels. Frequency bins in the range 0-45 Hz are considered for classification using CNN. A total of 135 frequency bins were present in this frequency range.

For the time-domain EEG epoch signal $x(t)$, the continuous wavelet transform at scale s and position u can be computed as [19]

$$W_\psi(u,s)=\int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi*\left(\frac{t-u}{s}\right)dt \quad (3)$$

where ψ is the mother wavelet (complex). The Morlet wavelet is used in this work which was shown to produce the best classification results in [20]. The number of voices per octave is set to 28. There are 132 continuous wavelet transform complex values in the frequency range 0-45 Hz. These values are transformed in similar to (2).

The layout of the CNN, shown in Fig. 1, was determined via offline experiments. The raw spectral data from the 18 channels forms the input layer of the CNN. As such, the input layer is of size 135×1×18 using FFT and 132×1×18 using WT. In addition, combining spectral information from the current, previous, and next epochs for predicting the label of the current epoch, the input layer size is 135×1×54 with FFT and 132×1×54 with WT.

The CNN model is trained using adaptive moment estimation [21]. The network contains three convolution layers, each of which includes a rectified linear unit (ReLU) [22], and a max pooling layer [23] in the final layer. The filter size for the three convolution layers is 15×1, 10×1, and 5×1, each with stride 1×1. The number of filters in each layer is 128 and the max pooling layer size is 2×1 and stride 2×1. This is followed by a fully connected layer, a softmax layer [24], and an output layer.

The settings for other parameters are as follows: initial learn rate = 0.005, learn rate schedule = piecewise, learn rate drop factor = 0.6, learn rate drop period = 5, L2 regularization = 0.5, mini batch size = 1/10 of training data, data shuffle = every-epoch, and max epochs = 50. The parameters were optimized based on the training/validation performance. The training stops after the maximum number of epochs is reached.

C. Performance Evaluation

The classification performance of the proposed method is evaluated using 10-fold cross-validation using the following metrics: sensitivity, specificity, accuracy, and area under the ROC curve (AUC). In each fold, the optimal cut-off point on the ROC curve was determined as the intersection of the sensitivity and specificity on the training performance. The corresponding threshold was then applied to the validation data in the fold.

III. Results

The overall results for seizure and non-seizure epoch classification using FFT and WT and 1-D CNN are given in Table I. First, the spectral information from the current epoch only (1 epoch) is used for predicting the label of the current epoch. Next, spectral information from adjacent epochs is combined with the spectral information from the current epoch (current, previous, and next epochs, 3 epochs in total) for predicting the label of the current epoch.

An accuracy of 93.01% is achieved using FFT data from the current epoch only. With WT this increases to 94.76%, an increase of 1.75%. The classification performance improves further when the spectral data from adjacent epochs is also included in predicting the label of the current epoch for both the FFT and WT methods. The classification accuracy increases to 96.31% with FFT and 97.25% with WT, an increase of 3.30% and 2.49%, respectively. The classification results using WT are superior to those using FFT in both cases. The best overall sensitivity, specificity, and accuracy of 97.25%, 97.25%, and 97.25% in seizure and non-seizure epoch detection are achieved using WT when combining with spectral data from adjacent epochs.

To further evaluate the performance of the different techniques, the ROC curves for the validation data output from all 10 folds are shown in Fig. 2. An AUC of 0.9723 is achieved using the best performing method, combined epochs using WT and 1-D CNN.

TABLE I. Classification results for seizure detection using multi-channel 1-D CNN with different frequency transformation techniques and epoch combinations

	Sensitivity (%)	Specificity (%)	Accuracy (%)
FFT - 1 Epoch	93.30	92.71	93.01
FFT - 3 Epochs	97.03	95.60	96.31
WT - 1 Epoch	95.25	94.28	94.76
WT - 3 Epochs	**97.25**	**97.25**	**97.25**

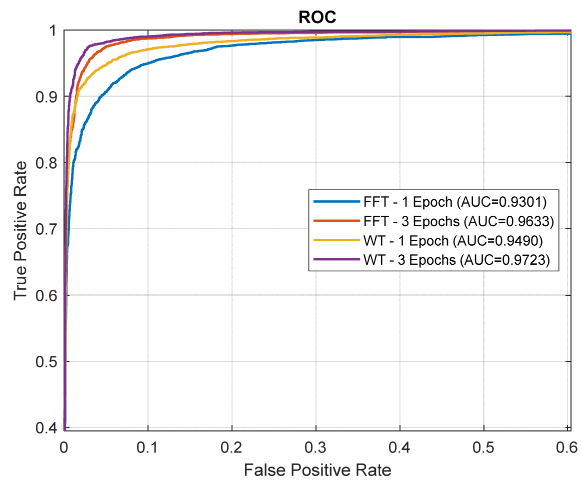

Figure 2. ROC curves for seizure and non-seizure epoch classification using multi-channel 1-D CNN with different frequency transformation techniques and epoch combinations.

IV. Discussion and Conclusion

This work proposes the use of wavelet power spectra of multi-channel EEG signals and 1-D CNN for detecting epileptic seizure segments. When combined with data from adjacent epochs, a classification accuracy of 97.25% is achieved on the CHB-MIT scalp EEG database. This shows the robustness of the proposed method in automatic detection of epileptic seizure segments.

Results from three other studies which utilize the same dataset are summarized in Table II. Although the method and experimental setup of these works was different from ours, they allow for an indicative comparison of results. A classification accuracy of 93% is achieved in [12] with spectral data computed using FFT and CNN. This is similar to the 93.01% we achieved using FFT and CNN. However, we could achieve substantially improved accuracy of 97.25% using WT and epoch combination.

Another close comparison to the method proposed here would be [25] where a classification accuracy of 88.67% was achieved using CNN. However, their work utilized the EEG database from the seizure prediction project Freiburg. This database has since been superseded by the new European Epilepsy Database which is not freely available. As such, the proposed method could not be evaluated on another dataset.

TABLE II. A SUMMARY OF RESULTS FROM SOME OTHER STUDIES UTILIZING THE CHB-MIT DATABASE

Ref.	No of Samples	Method	Results
[7]	Seizure: 171 Non-seizure: 171	Several features, LDA backward feature selection, KNN classifier Epoch length=60s Val: 80% holdout	Sens. = 93% Spec. = 94%
[12]	Not known	FFT and CNN Epoch length=1s Val: 6-fold cross-val.	[a]Acc. = 93%
[20]	[b]Not known	Wavelet transform, PCA, SDAE Epoch length=3s Val: 4:1 holdout	Acc. = 95.71%
This work	Seizure: 5748 Non-seizure: 5748	Wavelet transform, 1D-CNN Epoch length=2s Val: 10-fold cross-val.	Acc. = 97.25%

a. Results for the problem of interictal vs preictal vs ictal classification.

b. Data from 9 subjects is used.

Sensitivity and specificity of 93% and 94%, respectively, were achieved in [7] with the CHB-MIT scalp EEG database. However, they find only 171 seizure recordings useable compared to the 185 used in this work. They also utilize a different validation technique and 60 second epochs compared to 2 second epochs in this work, which collectively prevents us from directly comparing the obtained results.

Our work, however, has limitations. The dataset used in this work has only 24 cases. Epileptic seizure affects millions of people worldwide and having data from more subjects may help improving the generalizability of the models. Also, various EEG devices are available on the market with different number of channels. It is not clear how well the model developed here would perform with a different EEG device or with the same EEG device in a different setting.

Furthermore, the method proposed here is best suited for offline analysis of EEG signals for epileptic seizure detection. This would be beneficial to clinicians in analyzing several hours of EEG signals automatically for epileptic seizure diagnosis. While this could also be extended to detect seizures in real-time, epileptic seizures can be detected by clinical observations, such that it would be more beneficial to epileptic subjects if seizures could be detected before onset. We plan to focus on this in the future, building on earlier work in this area, such as in [26].

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