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An efficient detection of epileptic seizure by differentiation and spectral analysis of electroencephalograms

Jae-Hwan Kang [a], Yoon Gi Chung [a], Sung-Phil Kim [b,*]

[a] Department of Brain and Cognitive Engineering, Korea University, Seoul, Republic of Korea
[b] Department of Human and Systems Engineering, Ulsan National Institute of Science and Technology, Ulsan, Republic of Korea

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ABSTRACT

Epilepsy is a critical neurological disorder resulting from abnormal hyper-excitability of neurons in the brain. Studies have shown that epilepsy can be detected in electroencephalography (EEG) recordings of patients suffering from seizures. The performance of EEG-based epileptic seizure detection relies largely on how well one can extract features from an EEG that characterize seizure activity. Conventional feature extraction methods using time-series analysis, spectral analysis and nonlinear dynamic analysis have advanced in recent years to improve detection. The computational complexity has also increased to obtain a higher detection rate. This study aimed to develop an efficient feature extraction method based on Hjorth's mobility to reduce computational complexity while maintaining high detection accuracy. A new feature extraction method was proposed by computing the spectral power of Hjorth's mobility components, which were effectively estimated by differentiating EEG signals in real-time. Using EEG data in five epileptic patients, this method resulted in a detection rate of 99.46% between interictal and epileptic EEG signals and 99.78% between normal and epileptic EEG signals, which is comparable to most advanced nonlinear methods. These results suggest that the spectral features of Hjorth's mobility components in EEG signals can represent seizure activity and may pave the way for developing a fast and reliable epileptic seizure detection method.

1. Introduction

The symptoms of epilepsy are characterized by recurrent and unpredictable seizures, called epileptic seizures, resulting from excessive neuronal activity in the brain [1]. Epileptic seizures negatively affect physical and psychological behavior, resulting in significant social maladaptation and even death [1,2]. The etiology of epilepsy is known to include lesions in the brain and genetic abnormalities, leading to impaired neuronal regulation; however, epilepsy can also be caused by unknown factors that are difficult to identify [1]. The prognosis and diagnosis of epilepsy are highly dependent on the interpretation of neuronal activity in the brain. Consequently, the detection of epileptic signs embedded in neural activity is of great importance.

Due to its simplicity and efficiency, electroencephalography (EEG) has been widely used in epilepsy research [3]. EEG signals during seizures show distinct patterns that reflect excessive neuronal activity; hence, epilepsy can be diagnosed by monitoring epileptic characteristics by EEG. However, this monitoring process is often time consuming, burdensome, and dependent on visual inspection [4]. To overcome these limitations, various computational models have been developed for automated epileptic seizure detection. A number of studies have proposed computational models to extract epileptic EEG features using time-series analysis with correlation [5], autoregressive (AR) model parameters [6], and Hjorth's parameters [7], or the use of frequency analysis with the Fourier transform [8] and wavelet transform [9]. More complicated features have also been extracted using nonlinear dynamics properties, including correlation dimension [10], wavelet entropy [11], approximate entropy, and Kolmogorov–Sinai entropy [12]. Once specific features are determined, a classifier is built and used to detect epileptic EEG patterns. Many epilepsy classifiers have been designed using machine learning models such as artificial neural networks (ANNs). To date, a variety of ANNs and other machine learning methods have been developed for seizure detection, including probabilistic neural network (PNN) [13], multilayer perceptron neural network (MLPNN) [14], spiking neural network (SNN) [15], recurrent Elman network (REN) [11], and Gaussian mixture model (GMM) [16].

Efforts to improve epileptic seizure detection by identifying more reliable features and employing further advanced machine learning algorithms have demonstrated quite accurate detection results. Despite their successful results, these approaches can suffer from great computational complexity, particularly when

* Corresponding author. Tel.: +82 52 217 2727; fax: +82 52 217 2708.
E-mail address: spkim@unist.ac.kr (S.-P. Kim).

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nonlinear features/models are used. The models using nonlinear features and/or nonlinear classifiers require multiple processing steps and complex computational procedures, rendering them inappropriate for real-time diagnoses. To reduce the computational burden while maintaining accuracy, this study sought a new approach for epileptic seizure detection. The goal is to maximize computational simplicity without sacrificing detection accuracy compared to current nonlinear models.

Toward that end, features were created using one of Hjorth's parameters, mobility [7], which has been widely used in time-series analyses of electroencephalograms. Mobility was estimated by time-domain differentiation and was then transformed to the frequency-domain using fast Fourier transform (FFT). Once a spectral mobility feature space was created, a classifier based on Fisher discriminant (FD) analysis or MLPNN was built to detect seizure activity. Using the same dataset, the detection performance of the new method was compared to those of previous nonlinear methods to determine whether it could provide state-of-the-art detection accuracy.

2. Methods

2.1. EEG dataset

Epileptic and normal EEG signals analyzed in this study were obtained from the publicly available EEG database created by Andrzejak et al. [17], which contains five subsets denoted as Sets A, B, C, D, and E. Set A was extracranially recorded from five healthy subjects who did not show any epileptic symptoms. Set B was also extracranially recorded from five healthy subjects, but it contained eye blinking artifacts. Sets C and D were intracranially recorded from five epileptic patients during interictal periods. Set C was recorded from the hippocampal formation on the opposite side of the epileptogenic zone, and Set D was recorded from the epileptogenic zone. Set E was intracranially recorded from all of the recording zones in Sets C and D during ictal periods. Among these five sets, only Set E contained seizure activities. All of the EEG signals were recorded using a 128-channel amplifier system with a sampling rate of 173.61 Hz. Signals were filtered with a 0.53–40 Hz bandpass, and artifacts resulting from muscle and eye movements were removed by visual inspection. Each set consisted of 100 single-channel segments, each of which spanned 23.6 s. In this study, Sets A and D were selected as a normal set and an interictal set, respectively. Set E was selected as an epileptic set and compared to Sets A and D. While the primary focus was on analyzing Sets A, D, and E, Sets B and C were also analyzed for the purpose of confirming that the method could be applied to data with diverse characteristics.

2.2. Feature extraction

The approach to epileptic feature extraction was based on two basic signal processing schemes: mobility and Fourier transform. Mobility is one of Hjorth's parameters used for time-series analysis [7]. Activity, the first Hjorth's parameters, is defined as the variance of the EEG amplitudes in a given time frame. Mobility, the second Hjorth's parameters, is defined as the square root of the ratio of activity of the first derivative of the EEG amplitudes to activity of the EEG amplitudes in a given time frame

$$\text{Mobility} = \sqrt{\frac{\sigma'^2}{\sigma^2}} = \frac{\sigma}{\sigma} \tag{1}$$

where σ denotes the standard deviation of the EEG amplitudes and σ' denotes the standard deviation of the first derivative of the EEG amplitudes. The characteristic of mobility is highly dependent on the first derivative, which indicates the instantaneous slopes of EEG signals. This study modified mobility such that the first order time-domain differentiation was applied to the EEG signals, but no further computation (i.e., the standard deviation) was performed. Instead, the short-time Fourier transform (STFT) was performed to generate time-varying spectral features of the differentiated EEG signals. In the STFT analysis, the parameters of the sliding window were optimized, including the window size and the step size. Window sizes of 0.737, 1.475, 2.949, and 5.898 s were sampled, along with step sizes of 0.092, 0.184, 0.369, and 0.737 s. As each EEG segment contained 4096 discrete samples lasting 23.6 s, the parameters could be translated into seconds as follows: 128, 256, 512, and 1024 samples for the window size corresponding to 0.737- to 5.898-s windows and 16, 32, 64, and 128 samples for the step size corresponding to 0.092- to 0.737-s step sizes. After applying the STFT analysis to both the original and differentiated EEG signals, we extracted the averaged powers ranging from 2 to 55 Hz with 2-Hz frequency resolution. For each frequency-bin, we calculated the ratio of the averaged power of differentiated signals to that of the original signals. Those calculated ratios of all frequency-bins were constructed as a feature vector into classifiers.

2.3. Classification

The goal of classification was to discriminate the epileptic EEG signals from non-epileptic signals. Among the many classifiers that can be used for this purpose, a FD-based classifier was chosen because of its computational simplicity. The classifier used in this study was built based on quadratic discriminant analysis (QDA) (see [18] for details).

QDA discriminates two or more classes using a decision boundary estimated from the data with quadratic functions. QDA is more general than the linear discriminant analysis (LDA) method because QDA does not require that each class has the same covariance as in the case of LDA. Due to this computational advantage, QDA generally provides a better classification outcome than LDA [19]. In QDA, the spectral feature vector, x, was projected into the subspace spanned by H, maximizing between-class scattering while minimizing within-class scattering: $y = H^T x$. The quadratic discriminant function, $d_i(y)$, classified the spectral feature vector projected into the subspace based on the Mahalanobis distance, defined by

$$d_i(y) = (y - \bar{y}_i)^T \Sigma_i^{-1} (y - \bar{y}_i) + \ln|\Sigma_i| - 2 \ln \pi_i \tag{2}$$

where i represents a class, y represents the spectral feature vector projected into the subspace spanned by H, $\bar{y}_i$ represents a mean of class i, Σ_i represents the sample covariance of y in class i, and π_i represents the a priori probability of class i. We assumed that the π_i values were equal for every class. As we had two classes, class 1 (interictal or normal) and class 2 (epileptic), we chose class 1 if $d_1(y) < d_2(y)$ and vice versa.

Classification accuracy was evaluated with 10-fold cross-validation. Data was divided into 10 equal-size subsets. One of these subsets was used as a test set and the remaining nine subsets were used to train the QDA classifier. The training and testing operations were iterated 10 times. In each iteration step, accuracy was measured as a ratio of the number of correctly classified short-time subsets to the total number of subsets. In addition, sensitivity measured how well a classifier discriminated the target class (e.g., epileptic class) whereas specificity measured how well a classifier discriminated the control class (e.g., normal class). Specificity and sensitivity were defined by

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}) \tag{3}$$

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN}) \tag{4}$$