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Bayesian approach to identify spike and sharp waves in EEG data of epilepsy patients

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ABSTRACT

Electroencephalography (EEG) is the most common test being used to diagnose epilepsy. Most abnormal EEG patterns in epilepsy are interictal epileptiform discharges (IEDs), which consist of spike and sharp waves. These two types of waves can be detected in detail by using the Walsh transformation. In this technique, training data consisting of the original data from EEGs and the results of the first- and second-order Walsh transformation are collected to construct IED profiles. In this paper we propose two Bayesian classification models based on the dependence of the IED profiles. Bayesian classification is applied to classify spike and sharp waves resulting from the Walsh transformation. In our case study, the classification model with dependent features assumption gave better results than the model with independent features assumption.

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1. Introduction

Epilepsy is a condition characterized by recurrent seizures as a result of brain abnormalities. Electroencephalography (EEG) is the most commonly used method to support an epilepsy diagnoses. The phenomenon of epilepsy is identified by abnormal EEG patterns that represent epileptiform activites and consist spike and sharp waves. A spike wave has a duration of 20–70 *ms*, while a sharp wave which is followed by a slow wave [1–3] has a duration of 70–200 *ms*. Manual detection of interictal epileptiform discharges (IEDs) requires the ability of an experienced electroencephalographer (EEGer). In order to avoid misdiagnosis of epilepsy, mathematical modeling is sometimes needed to confirm and classify IEDs.

Digital signal analysis can be used to extract features allowing detection of epileptiform activities with high accuracy. Many approaches towards detection of this epileptiform activity have been presented. Nenadic et al. [4] studied spike detection using the continuous wavelet transform. Bayesian classifier was used here to determine whether ICA components represent EEG activity or artifactual signals. It is shown that the falsely detected spikes from the method resemble the actual spikes.

A system for automatic artifact removal from ictal scalp EEGs based on independent component analysis and Bayesian classification has been proposed in [5]. Tzallas et al. [6] studied epileptic seizure detection in EEGs using time-frequency analysis. With the use of artificial neural network, classification of EEG segments was obtained from time-frequency analysis. Epileptic seizure detection for multichannel EEG signals with Support Vector Machines based on approximate entropy (ApEn) and statistic value features is proposed in [7]. Liu et al. in [8] constructed a model-based spike detection of epileptic EEG data. They used k-point nonlinear energy operator (k-NEO) to detect all possible single spike and spike with slow wave candidates and then Adaptive Boost (AdaBoost) classifiers are applied to classify EEG patterns into single spike, spike with slow wave or non-spike class. A genetic algorithm tuned expert model for detection of epileptic seizures from EEG signatures has been developed by Dhiman et al. in [9]. They selected optimal features based on discrete wavelet packet transform using genetic algorithm (GA) with support vector machine as a classifier for creating objective function values for the GA. While in [10] automatic feature extraction using genetic programming was applied in epileptic EEG classification with the purpose of improving the discrimination performance of K-nearest neighbor. Automatic EEG seizure detection using dual-tree complex wavelet-Fourier features

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is reported in [11]. The author here used nearest neighbor classifier to classify the EEG signal into seizure or normal class. In contrast to previous studies, this study proposes a model for classifying spike and sharp waves that has not been explored previously for this propose. Jaseja et al. in [12] reported a difference in the duration of spike and sharp waves related to a difference in clinical significance in epilepsy. The authors found that an increased sharpness or spiky nature corresponds to a decrease in the size of the epileptogenic zone. Therefore, the classification of spike and sharp waves is very important.

An integrated algorithm based on the Walsh transformation to identify the criteria that defines the morphological characteristics of interictal spike in epilepsy patients using recorded EEG data has been reported in [13–15]. The sharpness of the spike wave was characterized with the rising and falling slopes of the wave. Results in [13] revealed that the precision and sensitivity of this algorithm were 92% and 82%, respectively. Therefore, this transformation should be a good choice for IED detection.

The novelty of the present study is to classify IEDs as spike or sharp waves using a Bayesian model. In this model we present an observed EEG wave as a profile vector. As a profile vector obtained from a continuous EEG wave, a natural assumption is that it has a dependency structure between its elements. Therefore, we assume that the profile vector follows a distribution with dependency properties. In this study, a multivariate Normal distribution is chosen as the distribution of the profile vector. The advantage of choosing this distribution is that the dependency of the elements of the profile vector can be easily expressed in the covariance matrix, which is the important parameter in the multivariate Normal distribution. To see the effect of dependency on the classification of the two wave types, we compare the classification resulted from a dependent multivariate Normal distribution with those from an independent multivariate Normal distribution.

In the Bayesian model, we constructed a profile derived from the original EEG data and the Walsh transformation results. Authors in [16] used another machine model approach (artificial neural networks, ANN) to classify epileptic or non-epileptic patients.

The organization of the rest of this paper is as follows. Section 2 proposes the methods for IED classification. Section 3 presents the results and discussion. Finally, Section 4 presents the conclusions.

2. Methods

2.1. Pre-proccessing

The EEG data of epilepsy patients used for this study were taken from Hasan Sadikin Hospital, Bandung, Indonesia. The EEG data were recorded following the 10–20 electrode placement system using 23 electrodes with bipolar montage. The recording duration was minimal 30 min. The sampling frequency of the EEG signals was 500 Hz.

We took the EEG data from the time duration containing the spike and sharp waves (about 1 s) based on the observation of a certified EEGer. We partitioned the chosen time duration into 500 subintervals of equal length. From the i^{th} subinterval we obtained a value of the EEG signals, namely f_i, $i = 1, 2, \ldots, 500$. We used three types of data, the first type was the original signal, the second was the first-order Walsh transformation and the third was the second-order Walsh transformation. For each type of data we divided the interval containing the IEDs into five subintervals, and then calculated the average value of a discrete signal $f(t)$ on each subinterval. Let $f_{t_1}^{(j)}, f_{t_2}^{(j)}, \ldots, f_{t_h}^{(j)}$ be the values of discrete signals in the observed time interval $[a, b]$, where $a = t_1 < t_2 < \ldots < t_h = b$ and $f_{t_\ell} \in \mathbb{R}$. The values $f_{t_\ell}^{(0)}, f_{t_\ell}^{(1)}$ and $f_{t_\ell}^{(2)}$, $\ell = 1, 2, \ldots, h$ represent the original data from the EEG recording, the first order Walsh transformation and the second order Walsh transformation, respectively.

The Walsh transformation that we used in our model will be described in detail in the following subsection.

2.2. Walsh transformation feature extraction

Walsh transformation is an orthogonal transformation that decomposes an EEG signal into a set of orthogonal function called the Walsh function. This method is quite simple because the Walsh function has only two values, +1 and −1 [17–19].

The algorithm of the Walsh transformation is discussed in detail in [13–15]. Let $f(t)$ be an EEG data. We use the length of Walsh operator $N = 4$, 8 and 16 to detect all potential spikes from the background signal under different scaling. The first and second order of the Walsh transformation can be written respectively as:

$$W1 = W_2^1 \cdot \left[W_4^1 + W_8^1 + W_{16}^1\right] \quad \text{and}$$

$$W2 = W_4^2 \cdot \left[W_4^2 + W_8^2 + W_{16}^2\right],$$

where $\cdot$ denotes point-by-point multiplication and W_N^r, $r = 1, 2$, denote the Walsh transformation with the length of Walsh operator N and the derivative order r [13]. Two peaks and one peak, respectively resulting from the absolute value of the first and the second order Walsh transformation, are used as profile for IED identification in the Bayesian approach. These criteria are explained in [13–15].

2.3. Profile modelling

We divide time interval $[a, b]$ into n equal length subintervals $[a_1, a_2], [a_2, a_3], \ldots, [a_{n-1}, a_n]$ with $a = a_1 < a_2 < \ldots < a_n = b$, as explained in Section 2.1 and illustrated in Fig. 1. The average value of each subinterval is given by

$$x_j^{(k)} = \frac{\sum_{\ell=1}^{m_j} f_{t_{\ell_j}}^{(k)}}{m_j}; \tag{1}$$

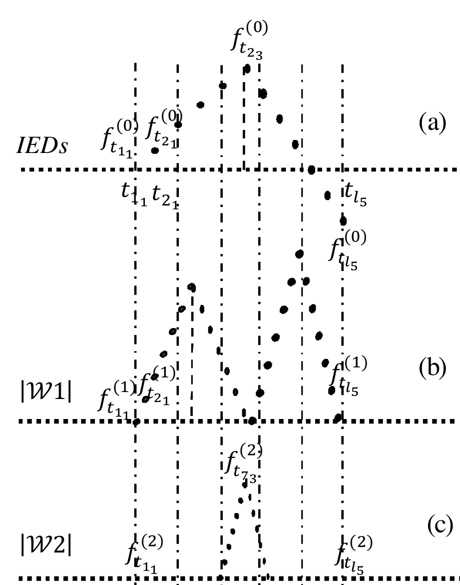

Fig. 1. Simulation of IEDs divided into five subintervals with Walsh transformation results. (a) Original data ($k = 0$). (b) The first order of the Walsh transformation in absolute values, $|W1|$, ($k = 1$). (c) The second order of the Walsh transformation in absolute values, $|W2|$, ($k = 2$).

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