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Analysis of spike-wave discharges in rats using discrete wavelet transform

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ABSTRACT

A feature is a distinctive or characteristic measurement, transform, structural component extracted from a segment of a pattern. Features are used to represent patterns with the goal of minimizing the loss of important information. The discrete wavelet transform (DWT) as a feature extraction method was used in representing the spike-wave discharges (SWDs) records of Wistar Albino Glaxo/Rijswijk (WAG/Rij) rats. The SWD records of WAG/Rij rats were decomposed into time–frequency representations using the DWT and the statistical features were calculated to depict their distribution. The obtained wavelet coefficients were used to identify characteristics of the signal that were not apparent from the original time domain signal. The present study demonstrates that the wavelet coefficients are useful in determining the dynamics in the time–frequency domain of SWD records.

1. Introduction

The Wistar Albino Glaxo/Rijswijk (WAG/Rij) strain is an inbred strain of Wistar rats in which all animals present generalized non-convulsive epileptic seizures [1]. These seizures appear as a sudden interruption of consciousness and are characterized in the cortical electroencephalogram (EEG) by the occurrence of bilateral and synchronous spike-wave discharges (SWDs) [2].

SWDs seen in WAG/Rij rats share many clinical characteristics with typical human absence epilepsy and exhibit a similar pharmacological reactivity to drugs [1,3,4]. Therefore, WAG/Rij strain of rats is considered to be a valid animal model of human absence epilepsy [5,6]. Nowadays this genetic model of absence epilepsy is commonly used for studying the efficacy of new antiepileptic drugs on the occurrence of SWD and the pathogenesis of absence epilepsy [2,7]. However, the mechanisms underlying SWDs, still remain unclear [8]. Although the analysis of the time–frequency structure of SWDs may contain important information about the mechanisms of this type of brain paroxysmal activity and can play a significant role in the investigation of antiepileptic drugs, the dynamics of SWDs in rodent models have been poorly investigated [9,10]. It is usually indicated that in animals with the absence epilepsy the typical SWDs have a mean frequency of 8.7 Hz [3]. In addition, by means of the fast Fourier procedure it was shown that the frequency of the SWD is approximately 10–11 Hz at the beginning of and 7–8 Hz at the end of the discharges [11].

Until now, only a few studies have used modified wavelet transform (WT) for the analysis of the time frequency of SWD. Bosnyakova et al. used a modified Morlet WT to describe significant parameters of the dynamics in the time–frequency domain of the dominant rhythm of SWD [9]. In a recent paper, analysis of the time–frequency pattern of SWD in patients with absence seizures and WAG/Rij rats revealed that time–frequency dynamics of SWDs had similar properties but in a different frequency range [10].

A feature extraction is the determination of a feature or a feature vector from a pattern vector. In order to make pattern processing problems solvable one needs to convert patterns into features, which become condensed representations of patterns, ideally containing only salient information. Feature extraction methods could be based on either calculating statistical characteristics or producing syntactic descriptions. The feature selection process usually is designed to provide a means for choosing the features which are best for classification optimized against on various criteria. The feature selection process performed on a set of predetermined features [12–14].

Features are selected based on either (1) best representation of a given class of signals or (2) best distinction between classes. Therefore, feature selection plays an important role in classifying systems such as neural networks. For the purpose of classification problems, the classifying system has usually been implemented with rules using if–then clauses, which state the conditions of certain attributes and resulting rules. However, it has proven to be a difficult and time consuming method. From the viewpoint of managing large quantities of data, it would still be most useful if irrelevant or redundant attributes could be segregated from relevant and important ones,

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although the exact governing rules may not be known. In this case, the process of extracting useful information from a large data set can be greatly facilitated [12–14].

In the feature extraction stage, numerous different methods can be used so that several diverse features can be extracted from the same raw data. The discrete wavelet transform (DWT) provides very general techniques which can be applied to many tasks in signal processing. Wavelets are ideally suited for the analysis of sudden short-duration signal changes. One very important application is the ability to compute and manipulate data in compressed parameters which are often called features [15]. Thus, the time-varying signals, consisting of many data points, can be compressed into a few parameters by usage of the DWT. These parameters characterize the behavior of the time-varying signals. This feature of using a smaller number of parameters to represent the time-varying signals is particularly important for recognition and diagnostic purposes [16–23]. The objective of the present study in the field of detection of changes in time-varying signals is to extract the representative features of the signals under study. In this study the dynamic parameters in the time–frequency domain of SWD were analysed and results represent good additional tool (wavelet coefficients) for discriminating this epileptic event and new perspective for future investigations.

2. Data description

Eight male WAG/Rij rats, weighing 230–300 g were used in this study. Animals were maintained on a 12–12 h light/dark cycle and access to food and water *ad lib*. All experimental procedures were carried out with the approval of the Kocaeli University Ethics Committee.

Under the ketamine (100 mg/kg, ip)–chlorpromazine (1 mg/kg, ip) anesthesia, tripolar EEG recording electrodes (Plastic One Products Company, MS 333/2A) were placed into the cortex; one in the frontal region (coordinates with skull surface flat and bregma zero-zero: A2.0, L-3.5) and a second one in the parietal region (bregma zero-zero: P-6.0, L4.0). The reference electrode was placed in the cerebellum. Following surgery, animals were allowed to recover for 10 days. After the rats habituated to the recording conditions, EEG recordings started at 09.00 and lasted for 1 h (MP100 data acquisition unit EEG100; Biopac System, St Barbara, CA, USA. www.biopac.com). Artifact-free condition was obtained in Faraday cage. EEG recordings were amplified, filtered between 1 and 60 Hz, digitalized with sample rate frequency of 500 Hz and stored for off-line analysis. The EEG data were pre-processed by an automatic routine, which searched in the EEGs for the presence of high-voltage activity with duration of 4–8 s. By this routine, the selected periods of aberrant EEG phenomena were visually inspected by a trained expert who determined, on the basis of the published criteria [3], whether these aberrant EEG phenomena were SWDs. The number of SWDs was counted and its duration was determined. Minimally 4, maximally 12 SWDs per animal were analyzed using the DWT. Example of the cortical EEG of a typical SWD in WAG/Rij rat is shown in Fig. 1.

3. Wavelet transform

WT is designed to address the problem of nonstationary signals. It involves representing a time function in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. Dilation, also known as scaling, compresses or stretches the mother wavelet and translation shifts it along the time axis.

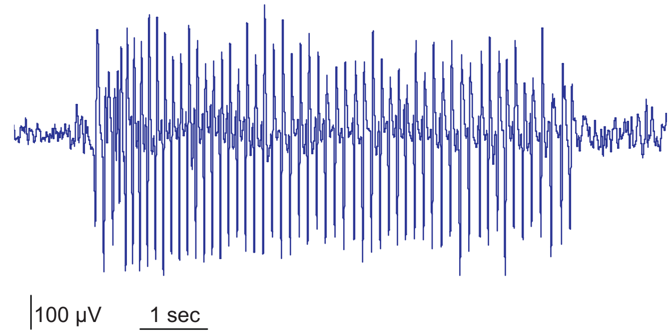

Fig. 1. Example of the cortical EEG of a typical spike-wave discharges in WAG/Rij rat.

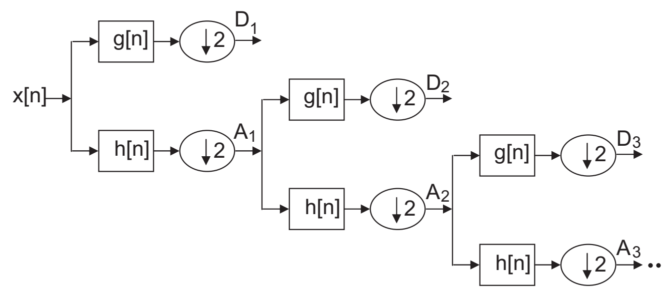

Fig. 2. Subband decomposition of discrete wavelet transform implementation; $g[n]$ is the high-pass filter, $h[n]$ is the low-pass filter.

The WT can be categorized into continuous and discrete. Continuous wavelet transform (CWT) is defined by

$$\mathrm{CWT}(a,b) = \int_{-\infty}^{+\infty} x(t)\psi^*_{a,b}(t)\,\mathrm{d}t, \tag{1}$$

where $x(t)$ represents the analyzed signal, a and b represent the scaling factor (dilatation/compression coefficient) and translation along the time axis (shifting coefficient), respectively, and the superscript asterisk denotes the complex conjugation. $\psi_{a,b}(\cdot)$ is obtained by scaling the wavelet at time b and scale a:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right), \tag{2}$$

where $\psi(t)$ represents the wavelet.

Continuous, in the context of the WT, implies that the scaling and translation parameters a and b change continuously. However, calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data. Therefore, the DWT is often used. The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The procedure of multi-resolution decomposition of a signal $x[n]$ is schematically shown in Fig. 2. Each stage of this scheme consists of two digital filters and two downsamplers by 2. The first filter, $g[\cdot]$ is the discrete mother wavelet, high-pass in nature, and the second, $h[\cdot]$ is its mirror version, low-pass in nature. The downsampled outputs of first high-pass and low-pass filters provide the detail D_1 and the approximation A_1, respectively. The first approximation A_1 is further decomposed and this process is continued as shown in Fig. 2.

All WTs can be specified in terms of a low-pass filter h, which satisfies the standard quadrature mirror filter condition:

$$H(z)H(z^{-1}) + H(-z)H(-z^{-1}) = 1, \tag{3}$$