TIME-FREQUENCY ANALYSIS OF HIGH-FREQUENCY ACTIVITY FOR SEIZURE DETECTION AND TRACKING IN NEONATE

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1. ABSTRACT

Time-frequency based methods have been shown to outperform other methods in dealing with newborn EEG. This is due to the fact that newborn EEG is nonstationary and multicomponent. This paper presents a new time-frequency based EEG seizure detection method. It uses the distribution of the interspike intervals of a high frequency slice of the time-frequency representation of an EEG epoch to discriminate between seizure and non-seizure activities. The seizure detected through this method is then tracked throughout all the available EEG channels by cross-correlating the binary encoded signals of both the detected seizure and the subsequent EEG epochs in all channels. This approach allows the study of the migrating behavior of seizure using EEG signals.

2. INTRODUCTION

Neonatal seizure is a common occurrence in newborn. Approximately one in every 200 newborn babies experiences some forms of seizure, indicating cerebral abnormalities or damage to the brain.

Seizure in adults is usually accompanied by some well-recognized clinical manifestations such as body jerking, repetitive winking or fluttering of eyelids. In newborns, however, the clinical signs are not as clear and can easily be missed without constant close observation. Monitoring brain activity through the electroencephalogram (EEG) has been a successful method for detecting seizure in adults. The onset of an EEG seizure is often identified in the EEG by sharp and repetitive waveforms (figure 1). The detection of these waveforms is complicated for the case of newborn since the brain of a normal neonate may produce spurious waveforms and sharp spikes which are the results of extra electrical activity associated with the maturing brain [3]. The problem is to differentiate between these waveforms. Figure 1 shows two different epochs of neonatal EEG signals associated with seizure and non-seizure activities. The spiky nature of the sharp waveforms can be seen as short time broadband events in the TF domain [4]. Experiments with such waveforms showed that their TF signature extend to frequencies higher than $75Hz$ [9] and that the distribution of the interspike intervals of the EEG seizure at these high frequencies are very different from that of the background. These findings formed the basis for the present proposed seizure detection method.

It has been observed that seizure activity migrates from one region of the brain to another, and this is reflected by transition of EEG seizure between different channels [10] [11]. In this paper, we propose to use a cross-correlation based method in order to track the seizure in different EEG channels.

3. HIGH FREQUENCY ACTIVITY OF EEG SIGNAL

In traditional analysis of EEG signals using polygraphic recording devices, the high frequency activity has been overlooked due to insensitive response of the mechanical pen. The analysis of EEG data recorded by digital systems with a high sampling rate shows that there is a high frequency activity in EEG signal that may be used to discriminate between seizure and lack of seizure (background) [9].

Spikes, which are often difficult to characterize in the time domain, can be identified as lines or ridges in the TF domain, where the height of the ridge depends on the power of the spikes. In figure 2, TF representations of the EEG signals associated with the first four second epochs of the signals is shown in figure 1. The time–frequency distribution (TFD) used is the exponential distribution (ED) with $\sigma = 0.1$ [2]. For the sake of clarity, the part of TF plot higher than $50Hz$ has been emphasized. From figure 2, we can see that the TF spikes during normal activity of EEG data are less frequent and less regular than those during seizure activity [4]. So, analyzing intervals between successive spikes in the TF domain allows one to distinguish the nature of spike firing patterns related to seizure and non-seizure activities. Based on this remark, one way to differentiate between the spike activity during seizure and non-

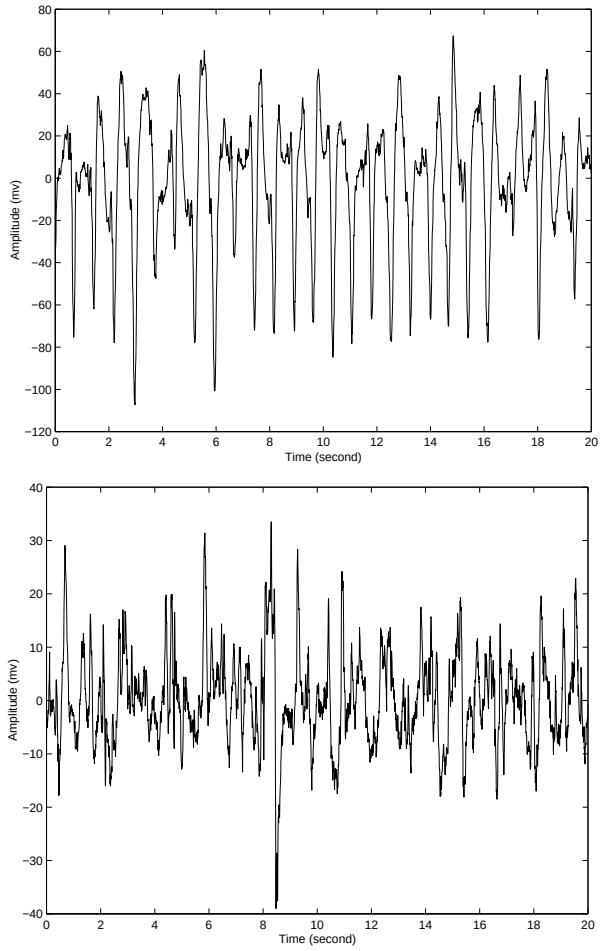

Fig. 1. Neonatal EEG signal (a) seizure activity (b) nonseizure activity

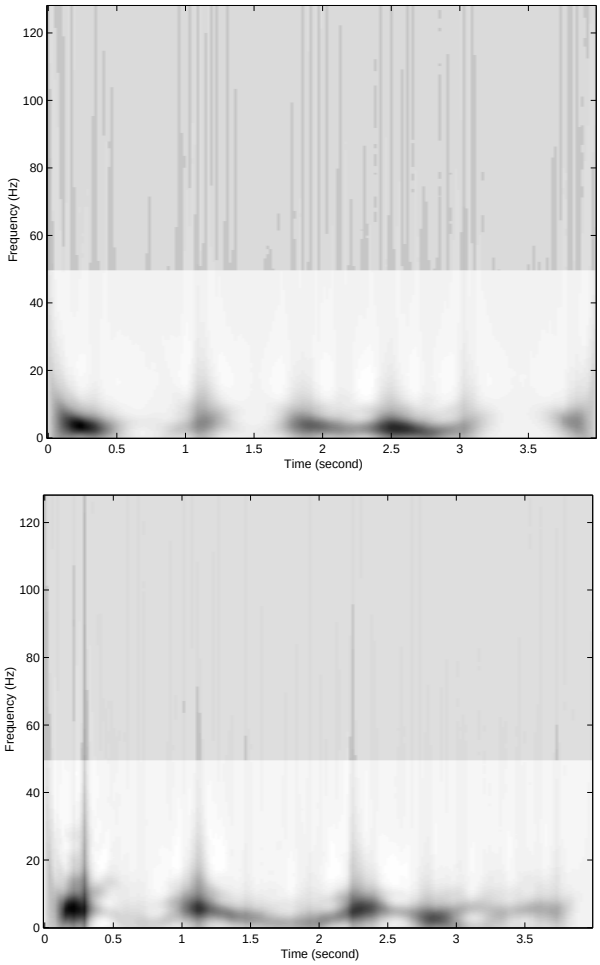

Fig. 2. 4-second epoch of newborn EEG signal in Time-frequency domain showing seizure (above) and nonseizure activities (below).

seizure is through the distribution of the interspike intervals (ISI) in the time-frequency domain.

The distributions of interspike intervals in TF domain related to signals in figure 2 are shown in figure 3. The distribution of the ISI is constructed by first extracting a slice of the time-frequency representation of an EEG epoch at the frequency $75Hz$. The amplitude of the obtained signal is then thresholded to eliminate the less energetic spikes. The thresholded signal is encoded such that the values of the signal amplitude larger than the threshold are assigned a value of 1 while the other are set to zero. A histogram of the intervals between the 1s of the encoded signal is finally constructed to obtain plots in figure 3. The value of threshold was set at 50. This value was found to give highest detection rate.

Figure 3 shows that there is a clear difference between the distribution of ISI during seizure and non-seizure activities. The histogram related to the seizure activity suggests a nearly exponential distribution. This remark agrees with the result reported in [7].

4. DETECTION OF EEG SEIZURE

The proposed TF based algorithm for seizure detection compares a reference histogram to a histogram of an EEG epoch using the Jensen function [5]. The seizure is said to have occurred if the Jensen function returns a value that is less than a given threshold. The algorithm of seizure detection comprises the following steps:

Step 1– Segmentation: It has been reported in the literatures [1] [8] that seizure can last from a few seconds to minutes. Based on this, we segment the EEG signal into 4-second epochs. This length also corresponds to the time windows that gives the best detection performance.

Step 2 – Time–frequency representation: The 4-second EEG epoch is mapped to TF domain using exponential distribution with $\sigma = 0.1$.

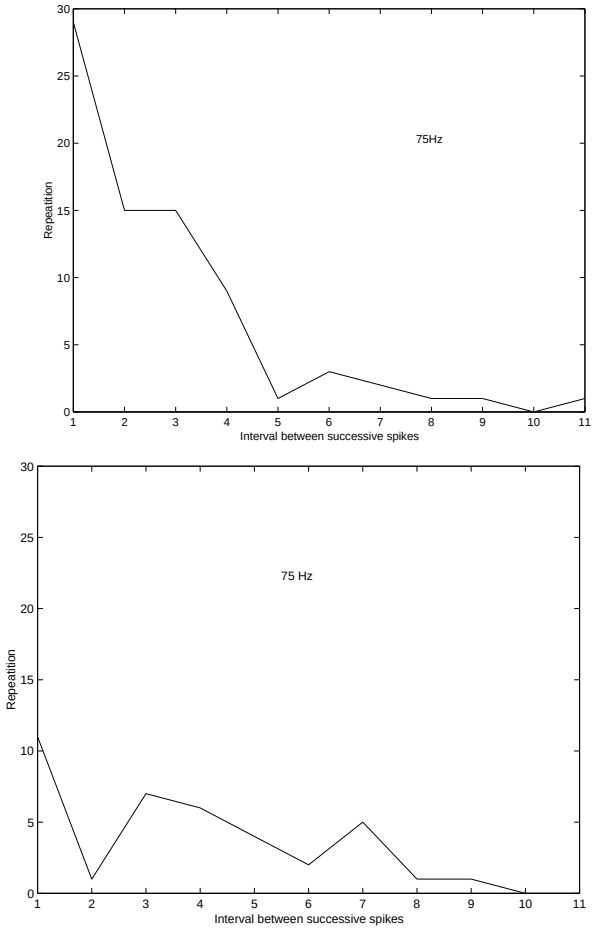

Fig. 3. Histogram of successive spikes event interval (a) Seizure ; (b) Nonseizure

Step 3 – Sample extraction: A time–frequency slice from the TFD of the EEG epoch at $75Hz$ is extracted. Experimentally a TFD slice around this frequency corresponds to the best discrimination between seizure and nonseizure.

Step 4 – Thresholding: The extracted signals, in step 3, thresholded to keep only the most significant components, and converted into a vector of 0 and 1. As discussed before, the value of the threshold has been selected experimentally as 50.

Step 5 – Encoding: The signal obtained from step 4 is encoded whereby the amplitude larger than the threshold is assigned a value 1 while the other amplitudes are assigned a value 0.

Step 6 – Histogram construction: A histogram of the time intervals between the ones of the encoded signal is constructed.

Step 7 – Histograms comparison: The histograms computed from step 6 is compared to a reference histogram using the Jensen function. The reference histogram was constructed by averaging a given number of histograms of seizure epochs from our EEG database.

Step 8 – Decision: The output of the Jensen function, which is between 0 and 1, is compared to a threshold value. The EEG epoch is declared to have a seizure if the output is smaller than the threshold value (the value was experimentally chosen at 0.2).

The seizure detection method has been assessed using the EEG data of three newborn babies who were admitted at the Royal Women's Hospital Prenatal Intensive Care Unit in Brisbane, Australia. In the assessment, we made a database of 290 four-second epochs of EEG signals containing seizure activity labeled by the neurologist. Half of them (145 epochs) were used to construct the reference histogram. Applying the proposed detection scheme to the EEG data resulted in a correct detection of 136 seizure epochs out of the total of 145; that is a correct detection rate of 94%

5. TRACKING SEIZURE ACTIVITY

It has been reported that seizure activity travels from one section of the brain to another [6] [11]. This is for example the case of multifocal seizures. So, once the seizure has been detected using the above scheme, it is tracked along the different EEG channels. The tracking process uses the cross–correlation between encoded signals of the detected seizure and that of the subsequent EEG epochs from different channels. By using the encoded signals, instead of the real signals, we are aiming at reducing the computational time.

To keep track of the seizure, we used the highest value above a certain threshold of the cross–correlation between encoded signals corresponding to the detected EEG seizure and the 4–second epochs in different channels. In other words, only the EEG seizure with the highest similarity to the detected one is considered.

Figure 4 shows the result of applying the seizure tracking process for a duration of 80 seconds (20 epochs of 4-second epoch). The seizure can be seen traveling from one channel to another. This observed behavior correlates very well with the labeling performed by the neurologist.

There are some types of seizures that tend to start from a local area of the brain and spread to multiple areas. For this type of seizures, all the values from the cross–correlator larger than a predefined threshold are to be considered. The result of applying our proposed scheme to this type of seizures will appear elsewhere. The results of this research will be very helpful in localizing the source of the seizure.

6. CONCLUSION

This paper presents a new method for seizure detection and tracking using newborn EEG signal. This method uses the

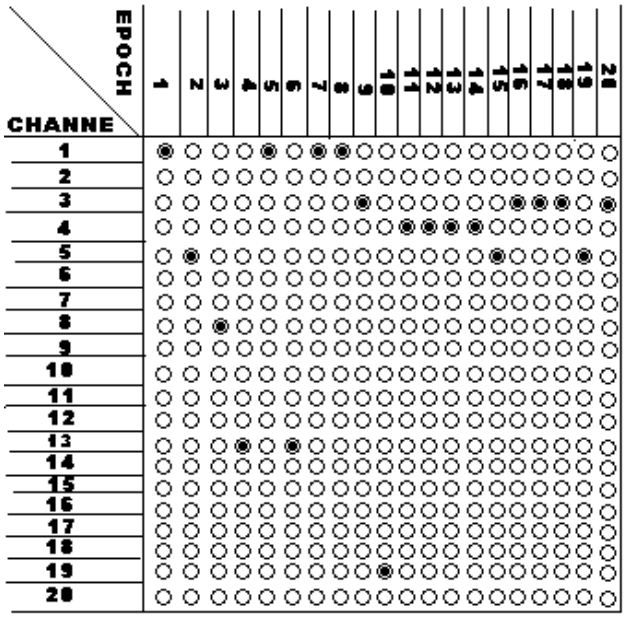

Fig. 4. Seizure tracked on 20–channels EEG signal of a newborn baby

distribution of interspike intervals in the time–frequency domain to discriminate between seizure and nonseizure. The seizure is then tracked by cross–correlation between the encoded signals of both the detected seizure and subsequent EEG epochs. Experimental results using labeled EEG data showed that both processes performed very well.

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