NEWBORN EEG SEIZURE PATTERN CHARACTERISATION USING TIME-FREQUENCY ANALYSIS

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ABSTRACT

Previous techniques for seizure detection in newborn are inefficient. The main reason for their relative poor performance resides in their assumption of stationarity of the EEG. To remedy this problem, we use time-frequency distributions (TFD) to analyse and characterise the newborn EEG seizure patterns as a first step toward a time-frequency (TF) based seizure detection and classification scheme. This paper presents the results of the analysis of these time-frequency patterns for two abnormal newborn EEGs. We demonstrate that the newborn EEG seizures are well described by a class of mono- and multi-component linear FM signals. This result is novel and contradicts the simplistic assumptions routinely made in the field.

1. INTRODUCTION

Neonatal seizures occur in approximately one out of every 200 newborn babies and are usually the first signs of neurological abnormalities. They can lead to permanent brain damage or even fatalities if not detected at the early stages [7]. Three major approaches have been used to detect seizures in newborns [2]. All three techniques are based on the assumption that the EEG signals are stationary or at least locally stationary. However, a closer examination of these signals shows that EEG signals often exhibit significant non-stationarities and may also be multi-component ([2], [7], [8]). To take these characteristics into account, we propose a time-frequency domain approach. A prerequisite is the selection of an appropriate time-frequency distribution (TFD) that is capable of handling multi-component signals. Once a suitable TFD is chosen, a calibration process is undertaken. This involves initially reproducing the seizure detection criteria and characteristics used previously in spectral [5] and Autocorrelation [6] methods and map them in a joint time-frequency domain. Features in the TF domain indicating seizure are then identified. After the calibration process, we analyse and characterise the different EEG seizure patterns using the time-frequency patterns in full.

1.1 EEG Seizures in Newborns

A seizure is defined to occur when there is an excessive synchronous discharge of neurons within the central nervous system. Its manifestation in the EEG, known as electrographic seizure, consists of paroxysmal events which are trains of rhythmic repetitive sharp waves that emerge more or less abruptly and have a distinct beginning and end. They may start with low voltages that increase usually as the discharge progress and often contain subharmonics. These discharge patterns can be divided into four categories: focal spike and sharp waves (> 2Hz), local low frequency discharges (around 1Hz), focal rhythmic discharge (0.5–15Hz), and multifocal [7]. These types of discharges were found to correlate best with clinical seizures [5].

1.2 Data Acquisition

Electrical signals produced in the brain are monitored in a non-invasive manner by measuring variations in potential on the scalp. Due to the size of most newborn babies' heads, only five channels of EEG have been recorded in each session using the 10-20 International System of Electrode Placement. The EEG data has been recorded using a sampling frequency of 256 Hz. For artefact detection, three auxiliary signals representing electro-oculogram (EOG), electrocardiogram (ECG), and respiration are also recorded. EEG signals containing seizures used in our study has been collected at the Royal Women's Hospital in Brisbane, Australia. They were obtained from two different newborn babies that have been clinically identified to have seizures. The gestational ages of the babies were 35 weeks and 40 weeks and 3 days. The recording lasted 137 minutes and 23 minutes respectively.

1.3 Selection of a Time-Frequency Distribution

To develop seizure detection and classification methods in the time-frequency domain, it is necessary to select a suitable TFD to represent EEG data. Since neonatal EEG signals are non-stationary and occasionally multi-component, a desirable time-frequency distribution should have a good spectral resolution and reduced cross-terms. In [2], the performance and characteristics of several distributions were compared to find an optimal representation of real neonatal EEG data in the time-frequency domain. We found that the B-distribution with smoothing parameter (σ) equals to 0.01 is the most suitable representation for the EEG signals in the time-frequency domain. Hence, the EEG signals in this paper are represented in time frequency using the B-distribution with a smoothing parameter of 0.01, a window length of 127 samples, and a time resolution of 5 samples.

This paper is organised as follows. Section 2 presents the calibration of the proposed method using current techniques. In section 4, we describe the different time-frequency EEG patterns. We end the paper by some conclusions.

2. CALIBRATION OF T-F METHOD

2.1 From Time to Time-Frequency

In [6] a time-domain method was based on the assumption that the essential characteristic in newborn seizure EEG is periodicity. The amount of periodicity in the autocorrelation of short epochs of EEG data is scored and used in a rule based algorithm to perform classification. In this technique, an epoch consisting of 30 seconds of data is divided into 5 windows (see figure 1). Depending on the autocorrelation function of each window, up to four moment centres are calculated for each window in an epoch. The windows are then scored whereby more evenly spaced primary periods are allocated larger scores.

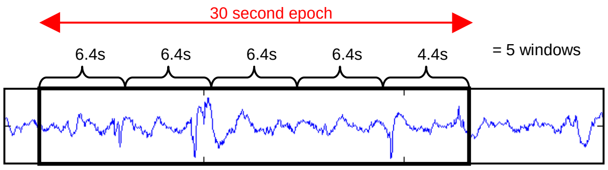

Figure 1 Epoch and window definitions used by [6]

After closely analysing the scoring system to find the definite constraints defining seizure from non-seizure, we concluded that: a single window is considered as a seizure positive if the following criteria are met: 1) at least four periods exist within the positive half of the Autocorrelation function, 2) the differences between the ratios of each moment centre to the first and the nearest integer are less than 0.150, and 3) the total score obtained by summing all moment centre scores is greater than or equal to 12 (maximum 15).

Mapping those time domain features to the time-frequency domain, we were able to characterise the EEG seizure signal. In time-frequency domain, an EEG signal within a given window is considered seizure if a continuous spectral peak exists within the window and meets the following criteria: 1) all frequencies within the spectral line are greater than 0.625 Hz within 6.4-second windows or greater than 0.909 Hz within 4.4-second windows and 2) the length of continuous dominant spectral peak within the window is greater than 3 seconds.

Extraction of the seizure criteria listed above in the TF domain has been successfully calibrated for the Autocorrelation method. Peak detection techniques have been employed to simplify the extraction process, resulting in a detection array illustrating positions and lengths of continuous spectral lines within each epoch as shown in figure 2. In this figure, filtered epoch is obtained by processing the original epoch using image processing tools. The TF arrays in this figure are divided into four distinct 6.4-second windows and one 4.4-second window as defined by [6]. Window scores attained for these epochs are displayed at the end of each window division. This makes for an easy comparison between the TF information contained within each window, and the corresponding allocated score.

2.2 From Frequency to Time-Frequency

The method proposed by [5] is based on spectral analysis and is used to detect periodic discharges. The aim of this method is to determine if a dominant peak exists in the power spectral density (PSD). The feature space used to classify an epoch as seizure ensures that the dominant peak of the spectrum is significant compared to the background spectrum. A background epoch is defined as a 20-second segment of EEG finishing 60 seconds before the start of the current 10-second epoch (see figure 3).

The frequency spectrum of each 10-second epoch is calculated and the following features are extracted: 1) the frequency of the dominant spectral peak, 2) the width of the dominant spectral peak, and the ratio of the power in the dominant spectral peak to that of the background spectrum in the same frequency band.

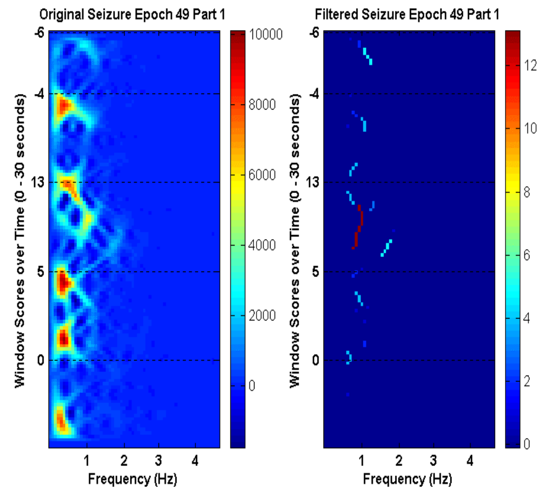

Figure 2 Calibration by the Autocorrelation method

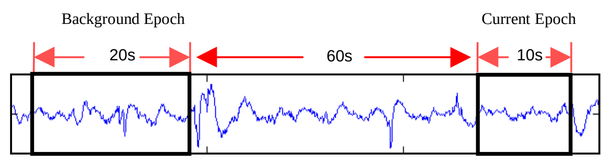

Figure 3 Epoch and window definitions used by [5]

The 10-second epoch of data is considered seizure positive if any of the following criteria are met:

	Dominant Frequency	*Half-Maximum Bandwidth*	*Power Ratio*
1.	0.5 – 1.5 Hz	≤ 0.6 Hz	3 – 4
2.	1.5 – 10 Hz	≤ 0.6 Hz	2 – 4
3.	1.5 – 10 Hz	≤ 1 Hz	4 – 80

As it can be easily be seen, mapping the frequency domain seizure criteria to time-frequency is straightforward. Using similar image processing tools to the ones mentioned above, we were able to successfully calibrate the extraction of seizure criteria in the TF domain for the spectral method. The results of this calibration are illustrated in figure 4. Data is presented by highlighting the position of the dominant frequency with a colour indicating the width and the power ratio of the spectral peak. Boxed sections of the array indicate regions detected as containing seizure by the spectral method. This has been included to aid visual recognition of any predominant features that may stand out in the processed time-frequency array of seizure epochs.

The successful mapping of the Autocorrelation and spectral features of the EEG seizures to time-frequency domain indicates that both the Autocorrelation and the spectral methods can be easily extended to a time-frequency method.

3. TIME-FREQUENCY EEG PATTERNS

Having calibrated the TF approach for seizure detection with the Autocorrelation and spectral methods, it is now desired to fully explore the patterns and features which characterise seizure in the full TF domain.

3.1 EEG Seizure Pattern Analysis

The time-frequency analysis of EEG data shows that that the seizure patterns are characterised by either a linear FM law or a piece-wise linear FM. These observations correlate well with the clinical information related to the different patterns found in EEG [7]. Representative time-frequency representations (TFR) of each of the subclasses are described below.

3.2 Linear FM (LFM) Patterns

We observe that EEG seizures can be approximated to a high degree of accuracy by linear FM signals. These observed patterns can be classified into the following classes:

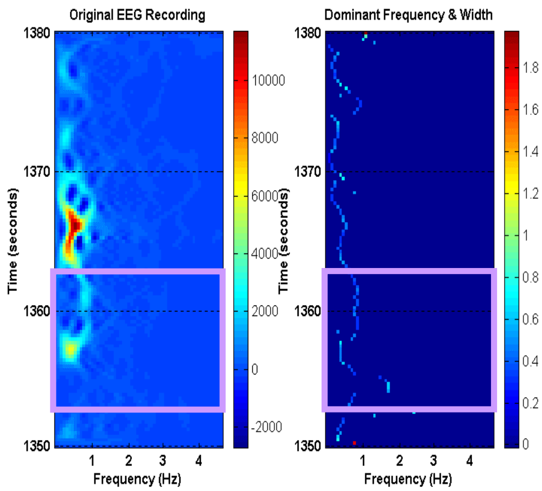

Figure 4 Calibration by the spectral method

Class A: LFM with a Quasi-Constant Frequency

Figure 5 shows a seizure that has a linear FM behaviour with an almost constant frequency. The amplitude of the time-frequency seizure pattern increases at the onset and decreases toward the end. These observations accord with the seizure definition found in the literature [7]. We can easily see the dominant peak and the repetitive pattern of the spikes and sharp waves characterising the newborn seizures. A major advantage of the time-frequency representation is that we can easily distinguish the seizure from other phenomena such as burst activities (see for example, figure 9). These low-frequency burst activities can be easily removed from the EEG signal using a time-frequency filter. Another phenomenon is the existence of sub-harmonics in a number of time-frequency representations of EEG seizure (see for example, figures 6, 8, and 9) as reported in [7].

Class B: Short LFM with a Quasi-Constant Frequency

Figure 7 shows a pattern that differs from class A in terms of its duration. A disagreement exists between researchers about what constitutes a seizure. The duration of rhythmic discharges is highly variable, from as short as 1 second to as long as 30 minutes [8]. In order to consider an EEG discharge as a seizure, some researchers require that it must last at least 10 seconds ([3], [5]), others require a minimum of 20 seconds, while a third group does not specify a time limit [8]. For this reason, we classified these “controversial seizures” in a separate category.

Class C: LFM Patterns with a Decreasing Frequency

Figure 8 from this class differs from those above by the fact that its frequency decreases with time. This frequency decreasing behaviour is widely accepted as a characteristic of the seizure [4]. From the time-frequency behaviour of the seizure, we can deduce the precise non-stationary character of the seizure. Classical detection methods based on the stationarity assumption will most likely miss these patterns.

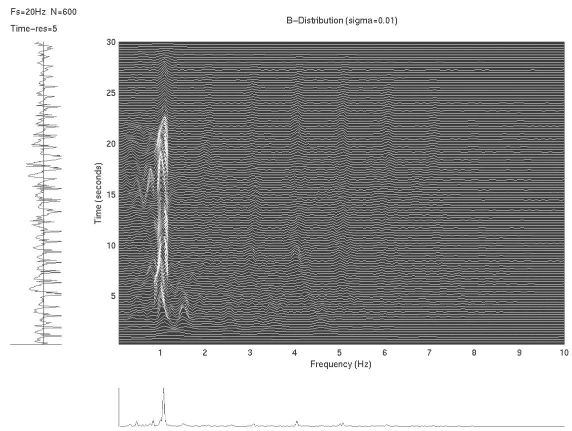

Figure 5 TFR of a constant frequency LFM EEG seizure

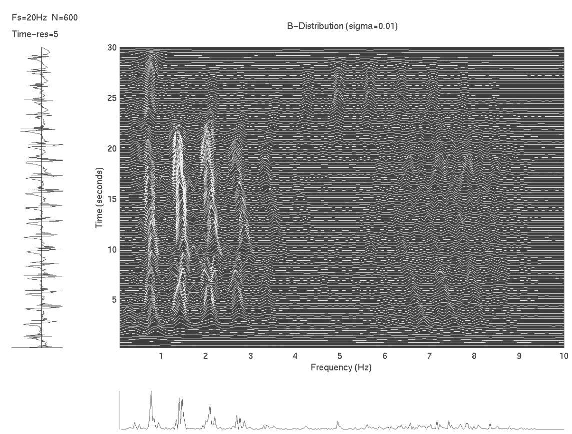

Figure 6 TFR of an EEG seizure with sub-harmonics

Class D: LFM with an Increasing Frequency

The time-frequency pattern shown in figure 9 behaves as a linear FM with monotonically increasing frequency. The increasing frequency of the discharge with time was also reported as being a characteristic of the newborn EEG seizure [8]. This type of patterns, however, seems to appear rather rarely as compared with the other Linear FM types. An odd behaviour of this pattern is that what may appear to be a sub-harmonic is actually morphologically different from the fundamental at least in its magnitude change over time.

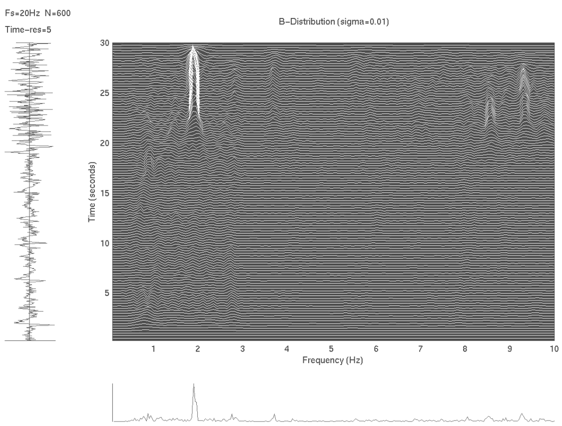

Figure 7 TFR of a short duration LFM EEG "seizure"

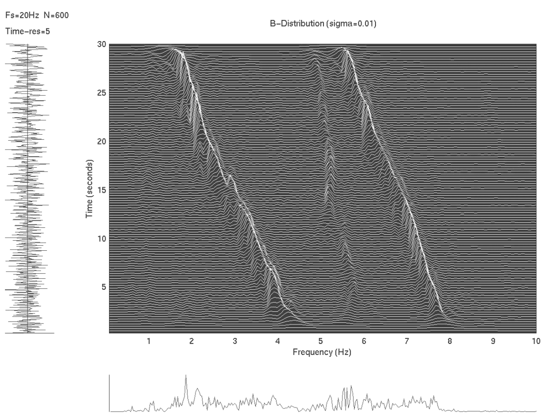

Figure 8 TFR of a decreasing frequency LFM EEG seizure

3.3 Piece-Wise LFM Patterns

The pattern of this class is shown in figure 10. It can be approximated by piece-wise linear FM. Similar patterns were observed in adult seizures originating from the mesial temporal lobe [4]. Here also we can clearly see the first sub-harmonic of the seizure signal.

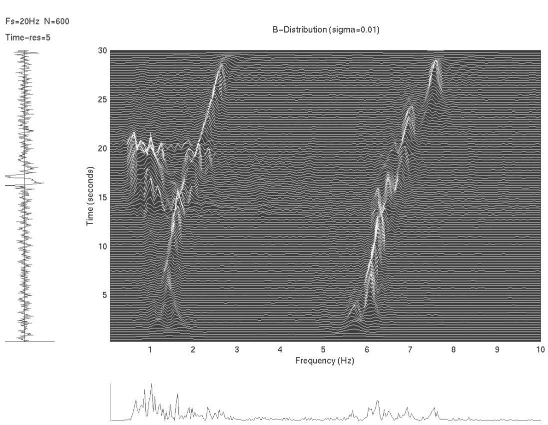

Figure 9 TFR of an increasing frequency LFM EEG seizure

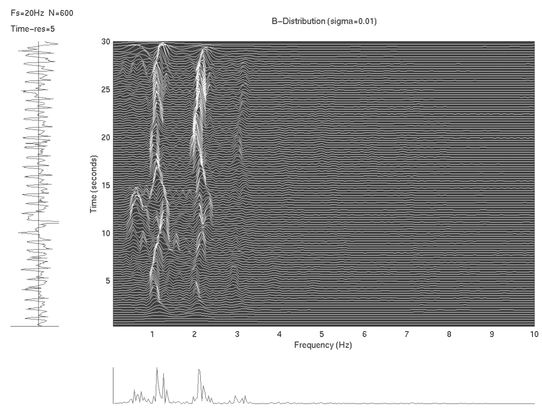

Figure 10 TFR of a piece-wise LFM EEG seizure

4. CONCLUSIONS

This paper describes the initial patterns obtained by a time-frequency analysis of EEG seizure signals corresponding to 2 sick babies. We have specifically confirmed the assumption in [2] that seizures in newborn can be easily characterised by a linear FM or at the extreme a piece-wise linear FMs. These results are encouraging and further analysis on other data sets will be undertaken to refine and extend these findings. The characterisation of non-stationary EEG signals in the time-frequency domain is the first step towards a global method of seizure detection and classification using time-frequency signal processing [1].

5. REFERENCES

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