NEWBORN EEG SEIZURE DETECTION BASED ON INTERSPIKE SPACE DISTRIBUTION IN THE TIME-FREQUENCY DOMAIN

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Abstract This paper presents a new time-frequency based EEG seizure detection method. This method uses the distribution of interspike intervals as a criterion for discriminating between seizure and nonseizure activities. To detect spikes in the EEG, the signal is mapped into the time-frequency domain. The high instantaneous energy of spikes is reflected as a localized energy in time-frequency domain. Histogram of successive spikes intervals is then used as a feature for seizure detection. In the presented technique the EEG data are segmented into 4-second epochs. A *k*-nearest neighbor algorithm is employed to classify the EEG epochs into seizure and nonseizure groups. The performance of the presented technique is evaluated using the EEG data of five neonates. The results indicate that the proposed technique is superior to the other existing methods with 92.4 % good detection rate and 4.9 % false detection rate.

Keywords EEG, Newborn, Seizure, Spike, Time-Frequency, Classification

چکیده این مقاله یک روش جدید مبتنی بر زمان – فرکانس برای تشخیص صرع به کمک الکتروانسفالوگرام ارائه می کند. در این روش از توزیع فواصل بین تغییرات سوزنی شکل در الکتروانسفالوگرام برای تمیز دادن فعالیت های صرعی و غیر صرعی استفاده می شود. برای تشخیص تغییرات سوزنی شکل در الکتروانسفالوگرام ، سیگنال مورد نظر به حوزه زمان – فرکانس انتقال داده می شود. تغییرات سوزنی شکل به علت داشتن انرژی لحظه ای زیاد، در حوزه زمان – فرکانس انرژی متمرکز شده ای از خود نشان می دهند. در این مقاله هیستگرام فواصل بین تغییرات سوزنی شکل بعنوان یک ویژگی برای تشخیص صرع استفاده می شود. در روش پیشنهادی، سیگنال الکتروانسفالوگرام به قطعاتی به طول چهار ثانیه تقسیم می شود. از روش خوشه بندی داده ها برای دسته بندی این قطعات الکتروانسفالوگرام به گروه های صرع و غیر صرع استفاده می شود. عملکرد روش پیشنهادی با استفاده از سیگنال الکتروانسفالوگرام پنج نوزاد ارزیابی می شود. نتایج نشان می دهد که روش پیشنهادی با ارائه ٩٢/٤٪ تشخیص درست و ٤/٩٪ تشخیص خطا در مقایسه با روشهای موجود عملکرد بهتری دارد.

1. INTRODUCTION

Brain abnormalities in newborns are usually first revealed by seizures, which are characterized by a synchronous discharge of a large number of neurons. It has been shown that there is a correlation between the duration of the seizure and the severity of brain damage [1]. Therefore, failure to control seizures may lead to brain damage.

Monitoring brain activity through the electroencephalogram (EEG) is an important tool in the diagnosis of neurological disorders in newborns. The onset of an EEG seizure is identified by transient sharp waves and repetitive rhythmic patterns [2,3]. The detection of these waveforms is complicated due to the fact that the brain of a normal neonate may produce spurious waveforms and sharp spikes which are the result of extra electrical activities associated with the maturing brain [4]. The problem is then to differentiate between the waveforms related to seizure and those related to the normal brain activities.

Currently, there are a number of published methods for detection of seizures in neonates which, for the most part, are based on the assumption that the EEG signals are stationary or at least locally stationary [21,20]. It has been shown that neonate EEG signals are significantly nonstationary and multi-component [17,22]. Since time-frequency (TF) based methods are best suited to analyze these types of signals, the current research used the TF analysis techniques to characterize neonatal EEG seizures.

Frequency domain analysis of EEG data recorded by digital systems with a high sampling rate, for example 256 Hz, can show that EEG activity ranges from almost DC to over 100 Hz [22]. Since seizure signatures may exist in different frequency ranges, from as low as 0.5 Hz [6,13] to higher than 70 Hz [14], some researchers have tried to detect seizure activity using low frequency signatures [20,21,24], while others used high frequency signatures [2,14]. This paper concentrates on the high frequency signatures of the seizure resulting from spiky activities.

Spikes are nonstationary short-time broadband events with high instantaneous energy. To detect spikes from the EEG signals, the signal is mapped into the TF domain. The high instantaneous energy of spikes is reflected as a localized energy in the TF domain (see Figure 1). The width of the localized energy becomes narrower in higher frequency areas. Consequently, a spike can be seen as a line or ridge at high frequencies in the TF domain. Depending on the signal to noise ratio (SNR), existence of noise in the signal may prevent recognition of true spikes from the noise.

To characterize seizures using spike events in EEG signals, a two-stage seizure detection technique has been developed. In the first stage, the EEG signal is preprocessed to detect spike events. In the second stage, the histogram of successive spike intervals is extracted and used to discriminate between seizure and nonseizure activities. The analysis of histograms of successive spike intervals associated with a number of EEG epochs indicates that histograms of seizure activities can be classified into six different groups dissimilar to the histograms extracted from nonseizure activities.

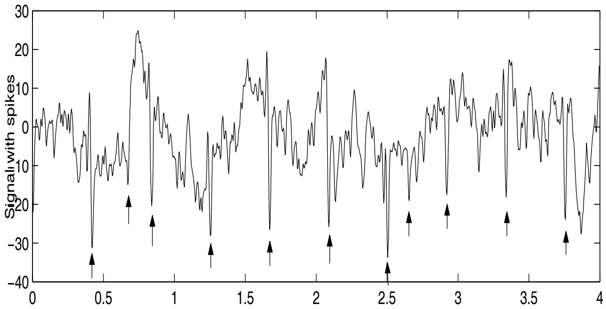
2. SEIZURE DETECTION

In this paper the EEG signals are preprocessed to detect spike events by using a two-stage spike detection technique presented in [10]. The detected spikes are then used in another technique to discriminate between seizure and nonseizure activities. In the spike detection technique, the first stage is an enhancing stage whose goal is to reduce the effect of the noise in the TF domain by using singular value decomposition (SVD)-based method [7]. The second stage is the detection stage. The detection process uses the above-mentioned characteristics of spikes in the TF domain along with the accentuating capacity of the nonlinear energy operator (NEO) [8].

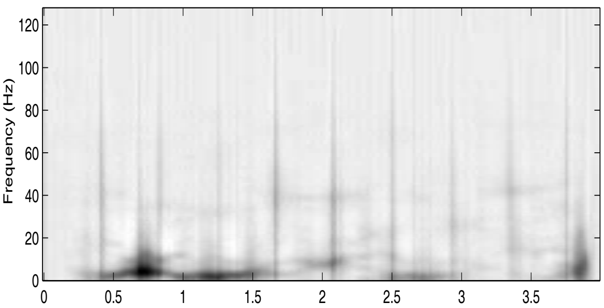
In [14] the authors have shown that during seizure activity there is regularity between the successive spike intervals (SSI). To detect a seizure, histogram of the SSI (HSSI) related to the signal of interest is compared to the reference histogram. In this study, it is shown that the HSSIs of seizures are classified into different groups. A k-nearest neighbor algorithm is used to classify the HSSIs of the EEG epochs into different groups of seizure and nonseizure activities [9].

2.1. Data Acquisition

EEG data acquisition was performed on newborns, whose ages range between two days and two weeks, at the Royal Women's Hospital, Brisbane, Australia. The electrodes were placed on the scalp according to the 10-20 International System of Electrode Placement. The data were recorded on 20 channels using Medelec (Oxford Instruments, UK) software/hardware environment. The signals were low-pass filtered with a cut-off frequency of 70 Hz and then were sampled with the sampling rate of 256 Hz. A 50 Hz notch filter was applied on the signals. The seizure activities on the recordings were visually labeled by a neurologist from the Neurosciences Department at the Royal Children's Hospital, Brisbane, Australia.



(a)



(b)

Figure 1. Four seconds of a newborn EEG signal containing spike events: (a) time domain, (b) TF domain. The arrows depict the position of spikes. As can be seen time domain spikes are represented as lines or ridges in the TF domain.

Artefact free EEG of the five newborns, selected by the neurologist, have been used in this research.

2.2. Preprocessing

The aim of the preprocessing stage is to detect spikes in the EEG signal. Nonstationary behavior of spikes makes the TF distribution (TFD) a preferable tool for spike detection [10]. Hence, the TFD-based technique presented in [15] is used for detecting spikes. In this technique, the signal is first mapped into the TF domain. The multicomponent behavior of the EEG signal creates cross-terms in the TFD. To reduce the cross-terms, a TFD with a reduced interference distribution (RID) capability is needed [11].

A number of RIDs exist in the literature. In this study, the Choi-Williams distribution (CWD) has been adopted. This distribution outperforms other distributions in representing spiky signals [10].

To attenuate the effects of noise on the time-frequency representation (TFR) of the signal, the SVD-based technique proposed in [7] is used. This technique is based on low-pass filtering the singular vectors associated with the matrix representing the TFD of the signal under analysis. In [7] the authors have shown that reconstructing the TFD of the signal using filtered singular vectors significantly reduces the noise effect without altering the basic structure of the TF patterns of the signal.

At higher frequencies in the TF domain, spikes are represented with more localized energy than at lower frequencies and, hence have less interference from the background. Consequently, using high frequencies of the TFD is more suitable for spike detection (see Figure 2).

To localize the spike events, two frequency slices of the enhanced TFR are used [2]. If both of the frequency slices, at the same position, have a spike signature, the related time domain signal is judged to contain a spike at that position.

The nonlinear energy operator (NEO) can be applied to the frequency slices to amplify the spike signatures. For a discrete signal x(n), the NEO is defined as

$$\psi[x(n)] = x^2(n) - x(n+1)x(n-1),$$

where ψ tracks the energy of the signal. The instantaneous nature of the NEO makes it a suitable tool for the detection of transients.

The existence of local peaks higher than a threshold value at the output of the NEO represents the spike events in the related time series signal [10]. In [8] the authors have shown that the Barlett window can be used to smooth the output of the NEO to better localize the local maxima.

The preprocessing stage encodes the EEG signals into zeros and ones, where ones represent the position of the detected spikes in the original signal. For a given signal, x(n), the preprocessing stage is expressed as:

$$x_e(n) = \begin{cases} 1, \text{if a spike was detected at n in } x(n) \text{ for } n = 1,\dots,N \\ 0, \text{otherwise} \end{cases}$$

where N and $x_e(n)$ represent the length of the signal and the encoded signal, respectively.

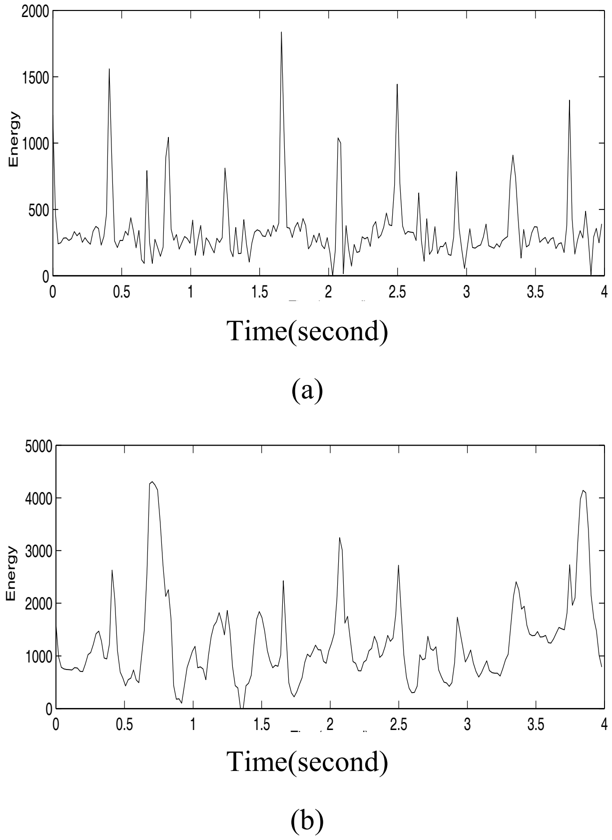


Figure 2. Frequency Slices extracted from the TFD in Figure 1 (a) at 70 Hz, (b) at 15 Hz.

2.3. Seizure Signatures A number of neurons firing synchronously create a signal with sharp waves [1]. Monitoring of the EEG reveals many spikes together with low frequency activity. There are however, some differences between the spike patterns related to the background and those which occur during the seizure activity. Analyzing intervals between successive spikes in the TF domain allows one to distinguish the nature of the spike firing patterns [14]. One way to characterize the variation of the SSI is by constructing a histogram of those intervals. The distribution of the intervals between successive values of ones in x_e, the encoded EEG signal, is computed and assigned to x_d. Then, the histogram of x_d is constructed:

$$H=\eta(x_d, b),$$

where η is the histogram function that places the elements of x_d into bins of width b indicating the number of sample spaces between successive spikes. Figure 3 represents two different EEG epochs containing seizure and nonseizure activities. The data have been sampled at 256 Hz. The positions of spikes in the signals detected by the TF-based spike detection technique are shown on subsequent figures by the pointing pins.

Figure 4 shows the HSSIs (H) related to the epochs shown in Figure 3 with b = 5. Note that the resolution setting of the TF analysis affects the value of b. Resolution of the TFD used to analyze Figure 3 was set to 5, hence, the b was set to 5. The first ten bins of the histograms are represented in the figure. It can be seen that there is a significant difference between the HSSI of seizure and nonseizure activities. During seizure activity, as the bin number increases the HSSI increases to a maximum value and then decreases gradually to

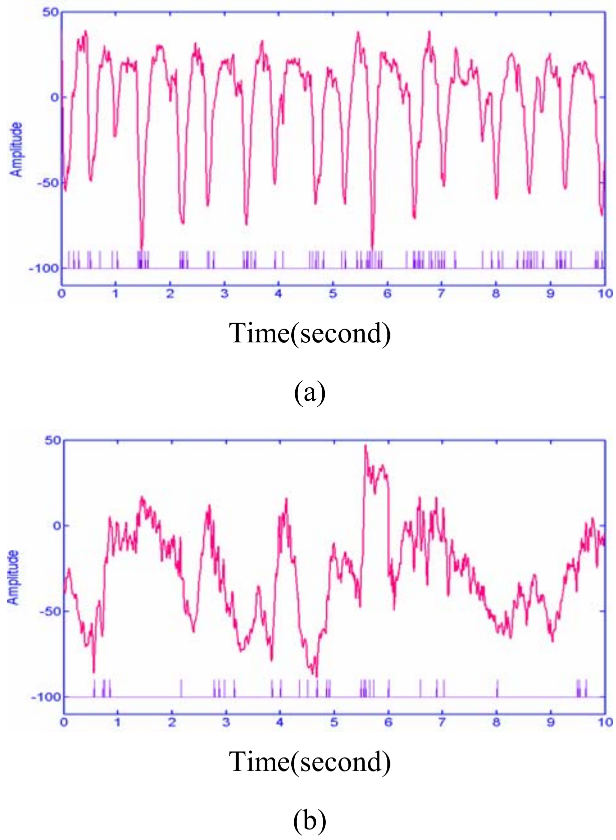


Figure 3. Newborn EEG signals. The pointing pins at the bottom of the signals represent the position of spikes detected by the TF-based spike detection technique. (a) Seizure activity, (b) Nonseizure activity.

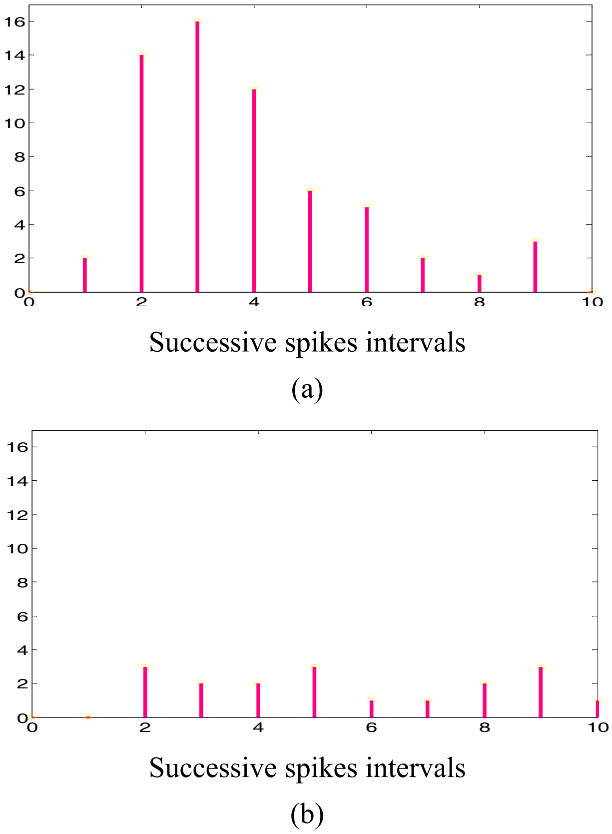


Figure 4. Histogram of the SSI for the signal represented in Figure 3: (a) seizure activity, (b) nonseizure activity.

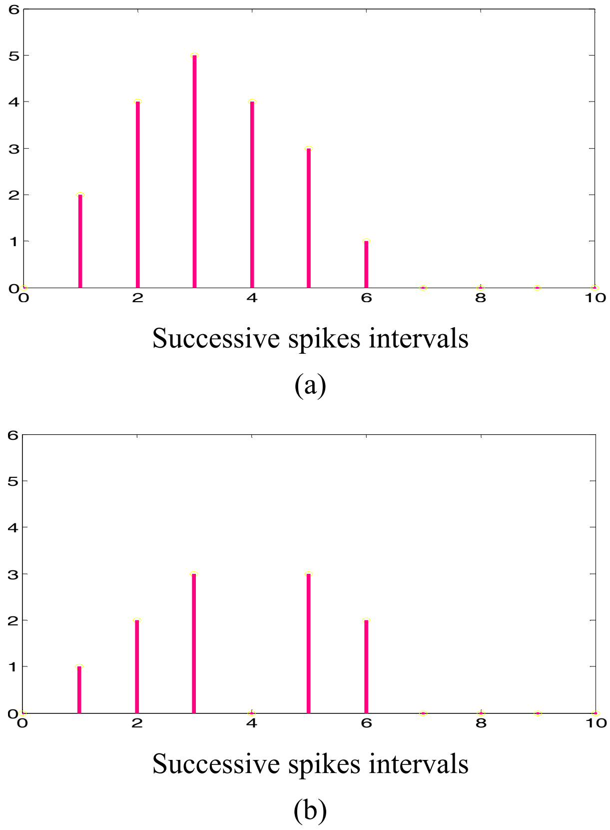


Figure 5. Histogram of successive spike intervals of seizure activity represented in Figure 3(a): (a) the first four seconds (b) the first two seconds.

zero. In addition, the total value of the bins for the HSSI related to seizure activity is higher than the one related to nonseizure activity.

2.3. Segmentation of EEG Signals In the detection process of the TF technique, individual channels of EEG data are segmented into 4-second epochs. The duration of seizures varies widely [12]. In addition, there is no consistency between neurologists about the minimum duration of seizure. Some require that a seizure last for at least 10 seconds; others require a minimum duration of 20 seconds and still others do not specify time limits for EEG seizure [16]. However, the results of this research show that the HSSIs for any duration of seizures are mostly similar. Figure 5 shows the HSSIs of the first four and two seconds of the seizure activity represented in Figure 3(a). As it can be seen these HSSIs are similar to the HSSI represented in Figure 4(a).

The results also show that by increasing the length of epochs the good detection rate as well as the false detection rate is increased. However, by choosing 4-second EEG epochs the best detection rates are achieved.

2.4. Decision Making It is shown that from a signal processing point of view there are different patterns of seizure activities [12,17]. An EEG epoch is considered to have a seizure activity if the related HSSI is similar to the HSSI of a class of seizure activity. To find the similarity, a one dimensional Jensen function is used to measure the similarity of two histograms [18].

Given two vectors S and R, representing the HSSIs of the EEG epoch under analysis and that of the reference respectively, the Jensen function, ζ, is defined as:

$$\zeta(S,R)=\frac{1}{2}\sum_{i=1}^{K}\{s'_i\log_2 s'_i + r'_i\log_2 r'_i - (s'_i+r'_i)\log_2((s'_i+r'_i)/2)\}$$

Where

$$S=[s_1\ s_2\ ...s_k\ ],\ \ R=[r_1\ r_2\ ...\ r_k\ ]$$

$$s'_i = s_i / M_S\ \ ,\ r'_i = r_i / M_R \quad \text{For}\quad i=1:k$$

$$M_S=\sum_{i=1}^{K}s_i,\ \ M_R=\sum_{i=1}^{K}r_i,$$

The values of the Jensen function are constrained between 0 and 1. If vectors S and R are exactly the same, the value of the Jensen function will be equal to zero. Therefore, the smaller the value of the Jensen function, the more likely the epoch associated with the histogram S is extracted from an EEG which exhibits a seizure. In the present work, an EEG epoch is considered as a seizure if the corresponding Jensen function is smaller than 0.1. The selected threshold value was the best trade-off between the good detection and false detection rates in EEG epochs of the database.

2.5. Forming Seizures Class Set To classify a set of HSSIs, $H = \{H_1, H_2, \ldots, H_n\}$, into different classes, $C = \{C_1,C_2,\ldots,C_m\}$ the *k*-nearest neighbor algorithm is used as follows:

$$C_1 = H_1\quad ,\quad C = \{C_1\}$$

$$R=\varphi(H_i ,C)|_{i=2:n}$$

where φ is a function that compares H_i with different classes in C using the Jensen function to find the nearest one, and C_i is a vector holding the average values of H_i related to the class represented by C_i. The output of the function is a vector including the distance and the class number, the winner class or the class with the shortest distance. Hence, R = [gd] is a vector of two elements where g and d represent the class number and the distance, respectively.

For a given H_i, in the classification process, if d is less than a predefined threshold value, H_i is considered to be in the winner class. Otherwise H_i makes a new class by itself. This process is continued to classify all the members in the database.

To validate the class set, the classification process is repeated. In the next trial of classification, the class set from the last trial is used as the initial state. In the new trial of the classification, the number of classes may change. If H_i is not close enough to any of the existing classes, it creates a new class. If a class could not obtain any member, it would be removed from the class set. The validation process is continued until the class set has no more changes.

To form the seizure class set, the EEG data of 11 newborns who were admitted at the Royal Children's Hospital in Brisbane, Australia were used. Firstly, a database was made of 4-second epochs associated with seizure activity. The database includes 5000 seizures. The HSSIs extracted from the database have been classified into six different classes, without supervision, using the *k*-nearest neighbor technique. Figure 6 shows the HSSI of the class set. The majority of seizures from the database join either Class 1 or Class 2. Rates of different classes in classifying seizures from the database are shown in Table 1. These investigations show that HSSIs extracted from the EEG seizures of a baby may be similar to any of the six HSSI class sets. However, the rate of HSSI patterns may not bet the same in different babies.

3. PERFORMANCE ASSESSMENT

In order to assess the performance of the above technique in detecting EEG seizure, the EEG data collected from another five newborn babies whose ages range between two days to two weeks were used. The seizure and nonseizure areas on the EEG data were labeled by a neurologist at the Royal Children's Hospital in Brisbane, Australia.

The performance of the proposed seizure detection method is then compared with three other published methods, namely: Autocorrelation [19], Spectrum [20] and Singular Spectrum Analysis [21] (SSA). The Autocorrelation method performs analysis in the time domain and is based on the

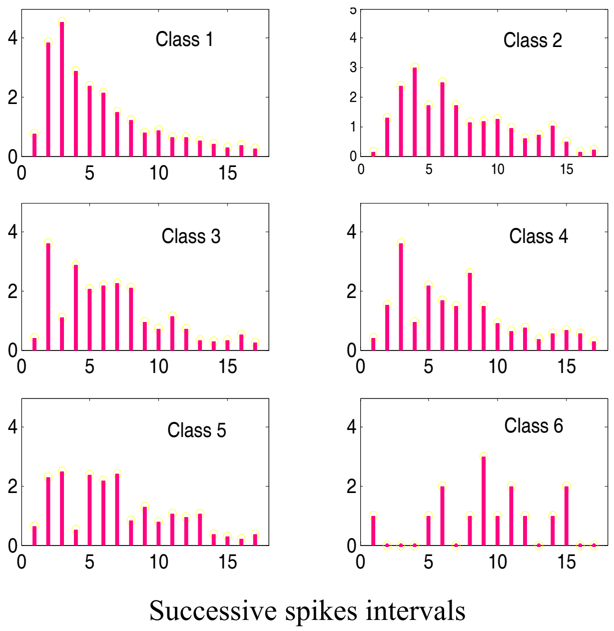


Figure 6. Histogram of the SSI related to different classes of the EEG signal.

TABLE 1. Prevalence of Six Classes of Seizure in Newborn EEGs.

Class set	Rate
Class 1	49 %
Class 2	21 %
Class 3	13 %
Class 4	12 %
Class 5	3 %
Class 6	2 %

autocorrelation function of short epochs of EEG data. The Spectrum technique is based on spectral analysis and is used to detect periodic discharges. The SSA technique employs singular spectrum analysis and information theoretic-based selection of the signal subspace.

The performance assessment of the proposed method was accomplished by applying its algorithm to all the EEG channels of each newborn. The EEG epoch is considered to contain a seizure in a given time interval if the algorithm detects a seizure in one or more channels on that specific interval. The performance results are summarized in Table 2. In this table, the good detection rate (GDR) and false detection rate (FDR) are defined as:

$$\mathrm{GDR} = 100 \times \frac{\mathrm{GD}}{\mathrm{R}}\%, \quad \mathrm{FDR} = 100 \times \frac{\mathrm{FD}}{\mathrm{GD}+\mathrm{FD}}\%$$

where GD and FD are the total number of good and false detections, respectively, and R represents the total number of seizures recognized by the neurologist. A good detection occurs if the detected EEG epoch matches the epoch labeled as a seizure by the neurologist.

4. DISCUSSION

The performance results represented in Table 2 show that except for Baby 3, the TF-based technique has better GDR than the other methods. The reason for the low GDR associated with Baby 3 using the TF-based technique has been recognized. One epoch of the data that was labeled as a seizure by the neurologist and detected by the different techniques, except the TF-based technique, is shown in Figure 7. The figure shows the existence of a low frequency activity as well as high frequency activity (spikes) in the signal. As mentioned before, the repetitiveness in the low frequency activity of the signal is a signature of the seizure. Since the Autocorrelation, Spectrum and SSA techniques are low frequency-based methods, they have succeeded in detecting the seizures.

To analyze the behavior of spikes in the signal using the TF-based method, positions of the detected spikes are shown by the pointed pins at the bottom of the figure. Detection of a few spikes in the signal shows that most of the spike-like patterns are due to noise. The histogram of interspike intervals is shown in Figure 8. The first ten bins are shown in the histogram. It is clear that the histogram is not similar to any histogram related to the different classes of seizure activity (see Figure 6).

The failure in detecting the seizure signal represented in Figure 7 is due to the fact that the

TABLE 2. Performance Results on Five Newborn EEG Data.

Patients	Autocorrelation		Spectral		SSA		HSSI	
	GDR	FDR	GDR	FDR	GDR	FDR	GDR	FDR
Baby1	50 %	11 %	44%	14%	50 %	19 %	95%	10%
Baby2	32%	7.5%	47%	0	97%	2%	100%	2.5%
Baby3	95%	37%	85%	36%	99%	35%	70%	12%
Baby4	31%	0	0	0	91%	0	97%	0
Baby5	67 %	1 %	78 %	1 %	98 %	1 %	100%	0
Average	55%	11.3%	59.6%	12.7%	87%	11.4%	92.4%	4.9%

seizure appeared to have a low frequency signature. In other words, the high frequency signature of the seizure is absent.

For the first baby in Table 2 the TF technique has a remarkably better GDR than the other techniques with the lowest FDR. This could be due to the existence of seizures with a mostly high frequency signature or to the nonstationary behavior of the seizure. It can be conclude from Table 2 that the TF-based method has better performance than the three other techniques in terms of both GDR and FDR.

It should be noted that the superior performance of the proposed technique over the existing methods is based on a sample of five newborn EEGs. The data sample needs to be increased to improve the confidence of the results for automatic EEG seizure detection.

5. CONCLUSION

This paper presents a new approach for automatic seizure detection in newborn EEG signals, based on the distribution of interspike intervals. The technique is composed of two stages. In the first stage, the EEG signal is preprocessed to detect spike events. In the next stage, the histogram of successive spike intervals is extracted to discriminate between seizure and nonseizure activities. Results obtained with five newborn EEG data show that the time-frequency based technique outperforms the three other existing methods. However, more data set is needed to convince of the superiority of the proposed technique in detecting newborn EEG seizures.

6. ACKNOWLEDGMENTS

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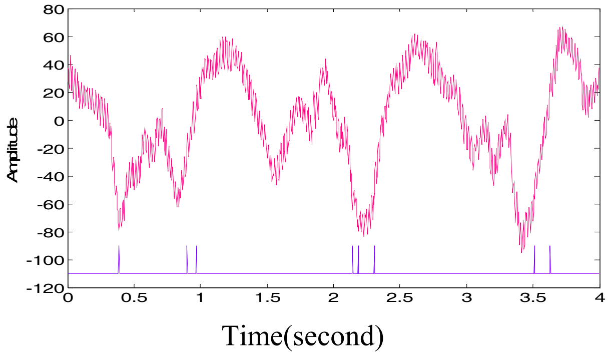

Figure 7. Four seconds of the third baby's EEG signal in Table 2.

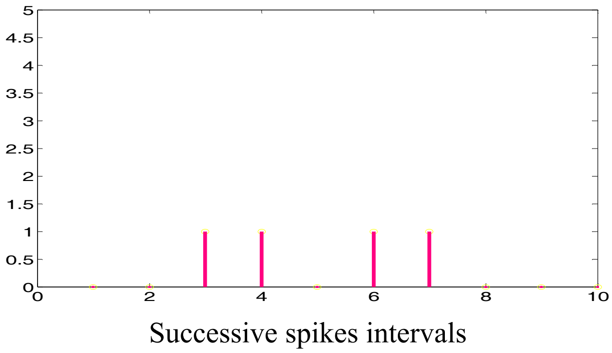

Figure 8. Histogram of interspike intervals extracted from the EEG signal shown in Figure 7.

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