DETECTION OF NEWBORNS' EEG SEIZURE USING TIME-FREQUENCY DIVERGENCE MEASURES

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1. ABSTRACT

In this paper, a time-frequency approach for detecting seizure activities in newborns Electroencephalogram (EEG) data is proposed. In this approach, the discrimination between seizure and non-seizure states is based on the time-frequency distance between the consequent segments in the EEG signal. Three different time-frequency measures and three different reduced time-frequency distributions are used in this study. The proposed method is tested on the EEG data acquired from three neonates with ages ranging from two days to two weeks. The experimental results validate the suitability of the proposed method in automated newborns' seizure detection. The results show an average seizure detection rate of 96% and false alarm rate of 5%.

2. INTRODUCTION

Neurological diseases in newborns are usually first manifested by seizures. Seizure detection in newborns is of crucial importance as seizures can lead to permanent brain damage or even fatality. The widely used method to identify seizures is based on the visual analysis of the EEG data. This is a time-consuming task which requires highly trained professionals. In order to reduce the cost associated with it and also optimize the clinical treatment, reliable automated detection techniques are needed.

The detection methods which use the characteristics of the EEG seizures in time or frequency-domain (e.g. [1, 2]) are based on the assumption that the segments of the EEG signals are quasi-stationary. However, recent works, (e.g. [3]), show that the EEG signals exhibit non-stationary behavior (see Figure 1). For analyzing such signals, time-scale and time-frequency methods have proved the most suitable tools [3, 4, 5]. These methods take into account the non-stationary nature of the EEG signals and use the characteristics of seizure in time and frequency-domain simultaneously.

The seizure detection method which is proposed in this paper is based on the distance between the time-frequency distributions (TFD) of the consequent segments in the EEG signal. It has been shown that the measures of divergence between the TFD of the signals can be used to associate, classify, compress, and restore signals in many applications [6, 7]. Three different time-frequency measures, i.e. Kullback-Leibler, Jensen difference, and Rényi divergence, are used in this study. Also, since the EEG signals are generally multi-component (see Figure 1), to reduce the effect of cross-terms in the TFD of the EEG signals, the so called reduced interference distributions (RIDs) are used. Three of those RIDs, namely spectrogram (SPEC), Choi-Williams distribution (CWD), and modified B distribution (MBD) are used in this paper [8].

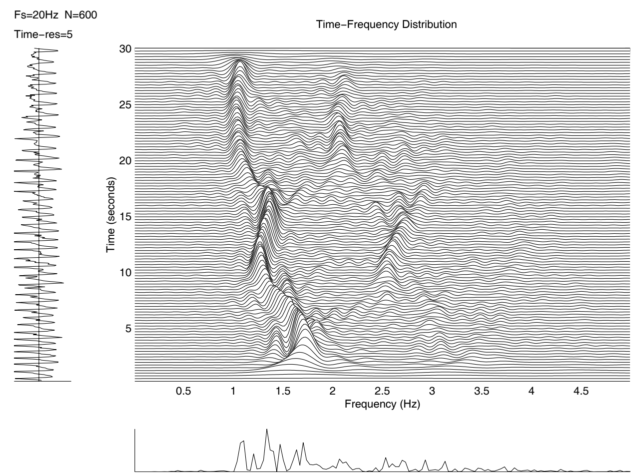

Fig. 1. The MBD of a segment of the EEG signal. It clearly shows that the EEG signal is non-stationary and multi-component.

The structure of the paper is as follows: in section 3, the discrete formula for the RIDs and the time-frequency divergence measures, which are used in this paper, are presented. In section 4, the proposed method for seizure detection based on the time-frequency divergence measures is given. The empirical results obtained by applying the pro-

Time-Frequency Representation	$G(n,m)$
Spectrogram using a rectangular window of odd length P	$\frac{1}{P}$, $\lvert m+n\rvert \leq \frac{P-1}{2}$ 0 otherwise
Choi-Williams (with parameter σ)	$\frac{\sqrt{\sigma/\pi}}{2m} e^{-\sigma n^2/4m^2}$
Modified B distribution (with parameter β)	$k \cosh^{-2\beta}(n)$

Table 1. Discrete-Time kernel function $G(n,m)$ of the RIDs [9].

posed method to the EEG of three newborns are given in section 5. Finally, the paper is concluded in section 6.

3. TIME-FREQUENCY DIVERGENCE MEASURES

The general formula for a quadratic TFD of a given analytic signal $z(t)$ associated with the real signal $x(t)$[1] is given by [8, p. 48]

$$\rho_z(t,f) = \underset{\tau \to f}{\mathcal{F}}\{G(t,\tau) \underset{t}{*} \left(z(u+\frac{\tau}{2})z^*(u-\frac{\tau}{2})\right)\} \quad (1)$$

where $G(t,\tau)$ is the kernel of the TFD in time-lag domain and $\mathcal{F}\{\ \}$, and $\underset{t}{*}$ stand for the Fourier transform and convolution in time, respectively. If $\rho_z(t,f)$ in (1) is discretized over time and frequency, we obtain [9]

$$\rho_z(n,k) = 2 \underset{m \to k}{\mathrm{DFT}}\{G(n,m) \underset{n}{*} (z(n+m)z^*(n-m))\} \ . \quad (2)$$

Since neonatal EEG signals are multi-component, TFDs which reduce the effects of cross-terms while giving a good resolution are needed. These TFDs are known in the literature as RIDs. Three well-known RIDs which are used in this paper are: the SPEC, CWD and MBD. Table 1 lists $G(n,m)$ for those RIDs. The parameters σ and β in the CWD and MBD, respectively, control the reduction of the cross-terms versus the resolution of the TFD.

In [6], three different divergence measures, namely Kullback-Leibler, Jensen difference, and Rényi divergence have been adapted to the TFDs. The Kullback-Leibler measure is defined as

$$D_{KL}(\rho_1,\rho_2) = K(\rho_1,\rho_2) + K(\rho_2,\rho_1) \quad (3)$$

[1]The analytic signal $z(t)$ associated with the real signal $s(t)$, is defined as

$$z(t) = s(t) + j\mathcal{H}\{s(t)\}$$

where $\mathcal{H}\{\ \}$ represents the Hilbert transform.

where $\rho_i(n,k),\ i=1,2$ is the TFD of the signal $z_i(n)$ and

$$K(\rho_1,\rho_2) = \sum_n \sum_k \rho_1(n,k) \log_2 \frac{\rho_1(n,k)}{\rho_2(n,k)} \ . \quad (4)$$

The second divergence measure is based on the Jensen difference and is given by

$$D_{J_\alpha}(\rho_1,\rho_2) = H_\alpha(\frac{\rho_1+\rho_2}{2}) - \frac{H_\alpha(\rho_1)+H_\alpha(\rho_2)}{2} \quad (5)$$

where

$$H_\alpha(\rho_i) = \frac{1}{1-\alpha} \log_2 \sum_n \sum_k \rho_i^\alpha(n,k), \ \ i=1,2 \quad (6)$$

is the α^{th} order Rényi entropy, with $\alpha > 0,\ \alpha \neq 1$.

Another measure has been derived based on the Rényi's generalized entropy and is given by

$$D_{R_\alpha}(\rho_1,\rho_2) = R(\rho_1,\rho_2) + R(\rho_2,\rho_1) \quad (7)$$

where

$$R(\rho_1,\rho_2) = \frac{1}{1-\alpha} \log_2 \sum_n \sum_k \rho_1^\alpha(n,k)\ \rho_2^{1-\alpha}(n,k) \ . \quad (8)$$

The seizure detection algorithm which is proposed in the next section is based on the above time-frequency divergence measures.

4. PROPOSED METHOD

The proposed seizure detection method can be summarized as follows:

1. **Segmentation :** The EEG signal is first segmented using a rectangular window of length 6 seconds. The sequences $s_i(n),\ n = 1,2,...,N-1$ are obtained where $N = 6 * f_s$ with f_s being the sampling frequency of the EEG data.

2. **Normalization :** In order to have the TFD behaves like a probability density function, one need to normalize it properly. Therefore, each EEG segment $s_i(n)$ is normalized such that the energy of the segment is equal to 1. This ensures that the TFD is normalized, i.e:
$$\sum_n \sum_k \rho_i(n,k) = 1$$

3. **Time-Frequency distance measurement :** Using the RIDs explained in section 3, the time-frequency representation of each normalized segment, $\rho_i(n,k)$, is calculated. Then, the time-frequency distance between $\rho_i(n,k)$ and the time-frequency of the EEG background (non-seizure) $\rho_B(n,k)$ is measured using the divergence measures presented in section 3.

4. **Thresholding :** The measured distance is then compared with a threshold. If the distance between $\rho_i(n,k)$ and $\rho_B(n,k)$ is more than the threshold, the segment i of the EEG data is labeled as a seizure event, otherwise it is a non-seizure.

5. EXPERIMENTAL RESULTS

5.1. Data Acquisition

The neonatal EEG signals used in this study were recorded under clinical conditions, by means of the MEDELC system, at the Royal Children's Hospital in Brisbane, Australia. Each recording contained 20 EEG channels, according to the modified international $10-20$ system. The data were recorded in digital form, at a $f_s = 256$ Hz sampling rate and a sensitivity of 100 μV. The EEG signals were passed through a band-pass filter with cut-off frequencies of $0.5-70$ Hz. An expert opinion about the presence of seizure activities in different channels of the recorded EEG signals of three neonates, with ages ranging from two days to two weeks, was obtained. The labeled seizure activities and EEG backgrounds were used to create a test database.

5.2. Results and Discussion

The seizure detection algorithm explained in section 4 was applied to the test database. In this experiment, the SPEC, CWD, and MBD were used. The control parameters of the CWD and MBD were chosen to be $\sigma = 10$ and $\beta = 0.01$, respectively. The reference TFD, $\rho_B(n,k)$, and the threshold was obtained using the first ten segments of the EEG recordings of each of the three neonates which represent the EEG background. The time-frequency distance between $\rho_B(n,k)$ and $\rho_i(n,k)$ was measured using (3)-(8). For illustration, the result of applying the three distance measures to the MBD of the EEG signal of one of the neonates is shown in Figure 2. Seizure activities are clearly distinguishable from non-seizures (the background) by their higher distance.

Two criteria; namely seizure detection rate (SDR) and false alarm rate (FAR), were used to evaluate the performance of the proposed method. The SDR shows the ability of the detection method to successfully classify seizure activities as seizures, and FAR gives the rate of non-seizure segments which is falsely labeled as seizure activities.

The overall results of applying the three divergence measures to the TFDs are summarized in Tables $2-4$. It has been shown that the Jensen measure performs best when α is close to 1 and the Rényi measure does not show a significant change to α [6]. Therefore, in our experiments, the parameter α in (5) and (7) was chosen equal to 0.9.

From the given results we observe that the detection method based on the Kullback-Leibler measure outperforms

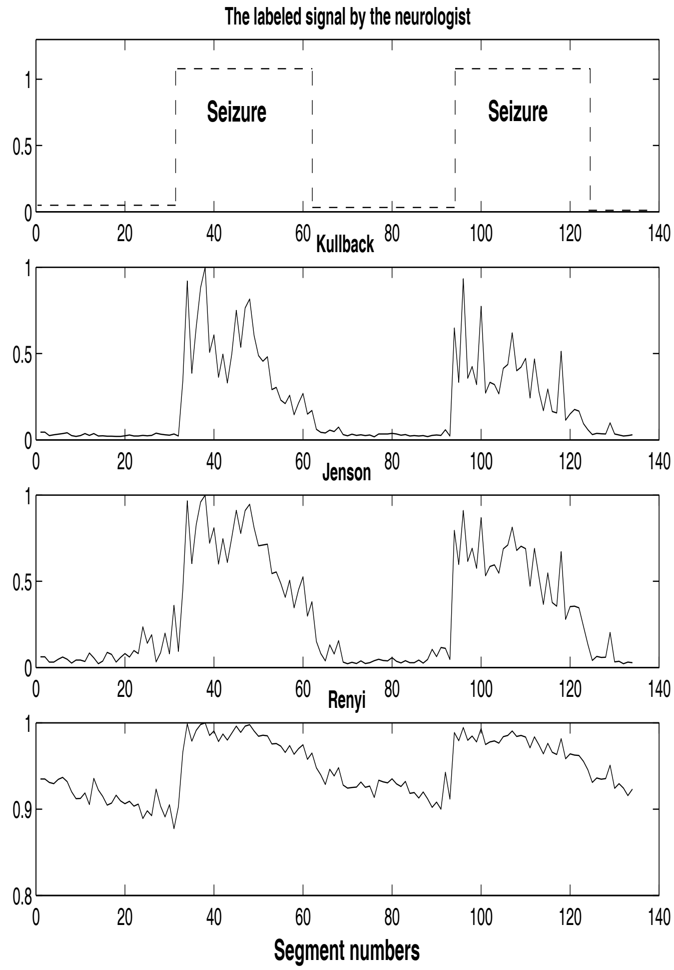

Fig. 2. The divergence measures have been applied to the MBD of the baby's EEG signal and compared to the labeled signal. From top to bottom: the labeled EEG signal, the normalized Kullback-Leibler, Jenson, and Rényi distance between $\rho_i(n,k)$ and $\rho_B(n,k)$.

Kullback-Leibler measure						
TFD	**SPEC**		**CWD** ($\sigma = 10$)		**MBD** ($\beta = 0.01$)	
	SDR	FAR	SDR	FAR	SDR	FAR
Baby1	93.67	3.33	97.5	1.7	100	1.66
Baby2	94.91	0	98.3	0	98.30	0
Baby3	92.92	12	90.90	12	91.91	12
Average %	93.83	5.11	95.56	4.56	96.73	4.55

Table 2. The results of applying the Kullback-Leibler measure to different reduced interference TFD of the segments of the EEG signals in the test database.

Jenson measure($\alpha = 0.9$)						
TFD	**SPEC**		**CWD** ($\sigma = 10$)		**MBD** ($\beta = 0.01$)	
	SDR	FAR	SDR	FAR	SDR	FAR
Baby1	97.46	1.66	100	0	100	0
Baby2	89.83	9.52	98.3	11.90	98.3	16.66
Baby3	89.89	0	90.9	8	91.91	8
Average %	92.39	3.7	96.4	6.63	96.73	8.22

Table 3. The results of applying the Jenson measure to different reduced interference TFD of the segments of the EEG signals in the test database.

Rényi measure($\alpha = 0.9$)						
TFD	**SPEC**		**CWD** ($\sigma = 10$)		**MBD** ($\beta = 0.01$)	
	SDR	FAR	SDR	FAR	SDR	FAR
Baby1	87.21	0	96.2	0	94.93	0
Baby2	88.13	0	88.13	0	88.13	0
Baby3	90.9	0	87.87	8	87.87	8
Average %	88.74	0	90.73	2.66	90.31	2.66

Table 4. The results of applying Rényi measure to different reduced interference TFD of the segments of the EEG signals in the test database.

the other methods, followed by the Jensen measure. The Rényi measure shows a poor performance, compared to the others. However, the algorithm can still detect the seizure activities with a lower FAR.

6. CONCLUSION

In this paper, we proposed the use of the time-frequency divergence measures in conjunction with the reduced interference TFDs to detect seizure activities in newborns' EEGs. The proposed method was applied to the EEG of three newborns. The experimental results showed that the Kullback-Leibler measure in conjunction with the MBD has superior performance and obtains maximum SDR of 96% and minimum FAR of 5%.

7. ACKNOWLEDGMENT

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