Detection of Rhythmic Discharges in Newborn EEG Signals

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Abstract— **This paper presents a scalp electroencephalogram (EEG) rhythmic pattern detection scheme based on neural networks. Rhythmic discharges detection is applicable to the majority of seizures seen in newborns, and is listed as detecting 90% of all the seizures. In this approach some features based on various methods are extracted and compared by a modified multilayer neural network in order to find rhythmic discharges. Statistical performance comparison with seizure detection schemes of Gotman *et al.* and Liu *et al.* is performed.**

I. Introduction

SEIZURE in the newborn is a phenomenon occurring in approximately 0.5% of all live births. The causes of seizure are many and various, with 90% of all cases being attributed to biochemical imbalances within the CNS, intracranial hemorrhage, intracranial infection, developmental (structural) defects, and passive drug addiction and withdrawal [1]. Controversy exists as to whether seizures damage the brain. Although the healthy immature brain does not appear to incur injury from prolonged seizures, in an immature brain that has suffered some injuries, seizures can cause brain damage or death Because the duration of the potential therapeutic window, for the use of neural rescue agents, is about 2–6 hours [2], automatic detection of predefined patterns have started to be investigated. The detection of seizure is usually made on the basis of clinical signs, together with accompanying electroencephalogram (EEG) correlates. In the newborn, clinical signs are not always as obvious as those for the adult, where seizure is often accompanied by uncontrollable, repetitive, or jerky movement of the body or body parts, or the tonic flexion of muscles. The less obvious clinical signs in the newborn, termed subtle seizures, may include sustained eye opening with ocular fixation, repetitive blinking or fluttering of eyelids, drooling, sucking, or other slight facial manifestations or body movements. Unless a constant and careful watch is kept over the infant, these clinical signs are easily missed, and the seizure goes undetected. Because of this fact, the EEG plays an important role in the detection of seizure in the newborn.

To the best of our knowledge, three efficient methods have been developed and thoroughly assessed for computer-aided detection of seizures in newborn and infant scalp EEG signals. The first method is based on the computation of a running autocorrelation function and was proposed by Liu *et al.* [3] (LIU). The second method, proposed by Gotman *et al.* [4] (GOTMAN), is based on the analysis of running periodograms. The third method has been carried out by modeling and complexity analysis [5]. Analysis of this work has shown that the variety of the characteristics related to seizure events makes it difficult for these approaches to perform reliable newborn seizure detection [6].

EEGs from newborns and infants have distinct patterns and also vary from day to day, displays nonstationarity during a single recording [7] and various artifacts. These signal characteristics may impinge on the performances of computer-based detection. This fact motivates the assessment of published methods and finding a robust method to overcome the effects of mentioned variations.

Rhythmic discharges are the most majority variation of seizures seen in newborns and is listed as 90% of all the seizures in newborns. Indeed, the rhythmic discharges detection is the only method which has been designed for newborn EEG analysis, thus in this work a method for detection of the rhythmic discharges is proposed.

Using various methods, a number of features are extracted and some of them are selected with mahalanobis distance and then detection of Rhythmic patterns is accomplished by a modified multilayer neural network.
This paper is organized as follows:

II. Data Acquisition

All EEG data was collected from newborn babies with seizures in the neonatal intensive care units of *Imam Khomeini* Hospital in Tehran, Iran. Written consent was obtained from the parents of each baby who was studied and this study had full ethical approval from the Ethics Committees of hospital. An instrument for EEG monitor was used to record 12 channels of EEG using the 10-20 system of electrode placement modified for neonates (F_4-C_4, C_4-P_4, P_4-O_2, F_3-C_3, C_3-P_3, P_3-O_1, T_4-C_4, C_4-C_z, C_z-C_3, C_3-T_3, T_4-O_2, T_3-O_1). The sampling frequency was set to 250 Hz.

Ag–AgCl electrodes which were stuck by tape were flushed with conductive gel and then attached to the skin of the infant [8]. Four babies were showing signs of clinical and electrical seizures. These four recordings were visually segmented (extraction of the seizure epochs) by a neurologist from the Neurosciences Department at the Imam Khomeini's Hospital. All digitized EEG data was then converted to the text (*.txt) file format.

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III. THE PROPOSED METHOD

The proposed system for newborn seizure detection consists of three main parts: feature extraction stage, feature selection stage with using Mahalanobis distance and comparison selected features stage with using a modified neural network which is illustrated in Fig 1.

To find rhythmic discharges, first, the signal is segmented with using a sliding window of 100 points (0.4 second). The window proceeds by 75% overlap with previous window. In each window, some features are extracted and for consequent windows, these extracted features are compared with a neural network. If they are similar to each other, it means that the windows are similar and a rhythmic pattern is now occurring. Various features are used, however to prevent the complexity of neural network, some of these features are selected by means of mahalanobis distance.

In the following sections each stage of the proposed algorithm will be described in details.

A. Feature Extraction

Attempts to use neural networks with raw EEG data as the input will not be capable of generalization across a wide patient database, because the input representation is amplitude-dependent and hence patient-dependent. Furthermore, dimension of raw data is usually very high (number of samples in the chosen time interval). To learn a nonlinear function mapping, a neural network must have input vectors with low dimension. Hence a feature extraction stage is required to reduce the dimension of the input space and this reduction enables the network to learn the function mapping simply, therefore the learning of the details of the training data is not required.

Previous attempts at newborn seizure detection are described in [6] which details the methods of extraction of measures of the main frequency, bandwidth, power and rhythmicity from the EEG to classify it as seizure or non-seizure. Not only was it shown that these measures, or features, generally change during seizure, but also they only give analysis from one aspect, through the Fourier spectrum. Therefore, in this section features from various areas of digital signal processing and their relative performances are described.

1) Modeling: There have been numerous approaches to model the EEG signal in an attempt to detect changes and therefore seizures. Here, the EEG is windowed and the first half of the data is used to train a 10_{th} order Autoregressive (AR) model with using the least squares approach. Then this fitted model on the second half of the data is examined. In seizure EEG, the trained model should be able to approximate the test data well because seizure EEG has consistent characteristics. In non-seizure EEG, the EEG is pseudo-random and hence the model trained on the first half of the data will most probably not be able to approximate the test data.

2) Wavelet Analysis: Wavelet transform is a multi-resolution analysis tool which can reveal the characteristics of the signal in joint time-frequency domain. It is quite suitable for processing of non-stationary signal and has been successfully applied to the analysis of EEG [9] and other biological signals [10]. Discrete wavelet transform (DWT) is widely used because it demands relatively less computation compared to continuous wavelet transform (CWT).

With this analysis, the frequency spectrum can be split up into frequency sub-bands and time resolution can be kept. Here, 8 sub-bands are taken and the power of each sub-band is calculated and considered as a feature.

3) Time-frequency domain: Time-frequency distribution localizes a signal in both time and frequency domains. It provides simultaneous time resolution and inversely proportional frequency resolution. For example, an epileptic signal has component in both time and frequency, but the conventional time and frequency representations present only one aspect of signal. There are a large number of possible time-frequency distributions; however we will focus only on two of them which are most often used: matching pursuit and the smoothed-pseudo Wigner-Ville.

The matching pursuit is an iterative algorithm which decomposes a signal into a linear expansion of waveforms selected from a redundant and complete dictionary. Mallat and Zhang in [11] used TF shifted and scaled Gaussian atoms as basic dictionary elements to decompose a given signal and in this study, these atoms is used for analyzing the EEG signal.

Krishnan and Rangayyan [12] used an optimized matching pursuit method to refine the Wiegner-Vill distribution and reject its unwanted cross-terms. Considering that the resulted distribution was $M(t,f)$, they extracted four sub-signals from each signal and called them: Energy Parameter, Energy Spread Parameter, Frequency Parameter and Frequency Spread Parameter. These signals are mathematically presented in equations (1) to (4) and the calculation of their *means* and *variances* leads to eight features to be used in the classifier.

$$EP(t) = \frac{\sum_{f=0}^{f_M} M(t,f)}{f_M} \tag{1}$$

$$ESP(T) = \left(\frac{\sum M(t,f) - EP(t)^2}{f_M} \right)^{1/2} \tag{2}$$

$$FP(t) = \frac{\sum_{f=0}^{f_M} fM(t,w)}{\sum_{f=0}^{f_M} M(t,f)} \tag{3}$$

$$FSP = \left(\frac{\sum_{f=0}^{f_M} [f - FP(t)]^2 M(t,f)}{\sum_{f=0}^{f_m} M(t,f)} \right)^{1/2} \tag{4}$$

In these formulas f_M, stands for the maximum frequency in the analysis.

In this research, these two distributions (matching pursuit and smoothed-pseudo Wigner-Ville) are used for detection of neonate seizure rather than what proposed in [12]. These two conventional distributions were used as $M(t, f)$ in the above formula.

B. Feature Selection

Increasing the dimension of data will impinge the performance of classification and to decrease the dimension of data and therefore solve this problem, several feature selection methods have been proposed and developed.

To select proper features, we should seek features which show similarity when they are extracted form similar data. One criterion for measuring similarity is Euclidean distance. But, the most significant drawback of the Euclidean distance is that it does not consider the distributions of the input data.

The Mahalanobis distance is defined as a distance between two *N* dimensional points scaled by the statistical variation in each component of the point. For example, if $\vec{x}$ and $\vec{y}$ are two points from the same distribution which has covariance matrix C, then the Mahalanobis distance is given by:

$$((\vec{x}-\vec{y})^T C^{-1}(\vec{x}-\vec{y}))^{1/2} \tag{5}$$

The Mahalanobis distance is the same as the Euclidean distance if the covariance matrix is the identity matrix.

On labeled similar and dissimilar pairs of segmented signals, the Mahalanobis distance is computed for each pair of features that are extracted from the labeled segmented signals. Features which have the minimum mean distance in overall pairs are selected. Finally, the variance of the EP, ESP, FP and FSP calculated from the matching pursuit are yielded as the best features.

C. Neural Network

This is perhaps the most popular network architecture in today's use, due originally to Rumelhart and McClelland (1986) discussed at length in most neural network textbooks (e.g., [13]). Each unit performs a biased weighted sum of its inputs and passes this activation level through a transfer function to produce its output and these units are arranged in a layered feed-forward topology. The network thus has a simple interpretation as a form of input-output model, with the weights and thresholds as (biases) the free parameters of the model.

We modified the multilayer neural network in order to compare two sets of inputs (P_i, P_j) and to check whether they are similar or not. The architecture of this supervised network is described in Figure 1. Each set of input in the first layer is weighted separately and after passing through a sigmoid function they are combined linearly. As it can be seen in the Figure 1, the activation function of the last layer is a rectangle function:

$$u(x)=\begin{cases}1 & abs(x)<.5\\ 0 & else\end{cases} \tag{6}$$

This is a time supported function which prevents the complexity of the network where the input EEG data have enormous patterns. Also using this function as long as the correct neuron is known, neither the information on the exact output values nor a specific cost function criterion will be needed. Moreover, only the misclassified patterns in each sweep can incur the actual update. Thus, the frequency of actual updating will decrease significantly as the network converges closer to the final solution.

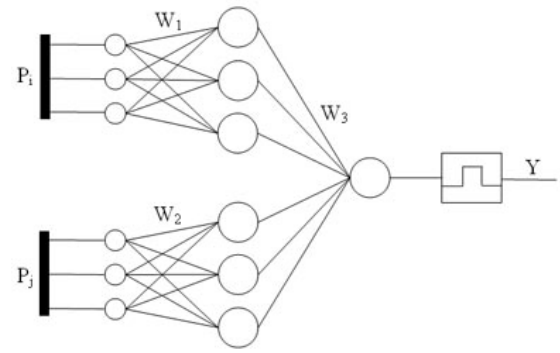

Figure 1. The structure of the multilayer network for detection of similarity between two inputs.

In the last stage of the detection procedure, we set a flag one (1) if the network finds the similar segmented signals and otherwise zero (0). We finally stack the flags into a vector and apply a median filter of order three in order to remove isolated flags one (1).

IV. OTHER METHODS

Several automated neonatal seizure detection methods have been described in the literature. In this study, two well-documented algorithms were chosen which are based on detection of rhythmic discharges. These methods analyze the EEG from a traditional frequency point of view.

The technique proposed by Liu et al. [3] searches for periodic, rhythmic data, such as which occur in seizure EEG. The autocorrelation function is used to provide the measure of rhythmicity. Autocorrelation, the cross-correlation of a signal with a delayed version of itself, is useful for finding repeating patterns in a signal, such as for determining the presence of a periodic signal in noise.

The Gotman detection method [4] is based on the information available in the frequency spectrum of the newborn EEG, obtained with using the Fast Fourier Transform (FFT). A rhythmic signal, such as typical newborn seizure EEG, consists of a large and distinct peak at the main seizure frequency, perhaps accompanied by one or two other main frequencies, and with little power elsewhere in the spectrum. The Gotman method relies on these differences in frequency domain characteristics for classification of the EEG.

Method by Celka *et al*. [5] also is a known method for detection of newborn seizure. But this method is based on using the complexity of signal rather than finding discharges.

Evaluation of these method can be seen in reference [6] in which the difficulties involved in detecting seizures in neonates and the lack of a reliable detection scheme for clinical use are demonstrated

V. Results and Discussion

Seizure detection was performed on the entire recorded channels because the spatial location of the seizure is *a priori* unknown. As it is mentioned, the data was windowed with a rectangle window of .4 seconds with overlap of 75 percent. Features were extracted from the EEG from the areas discussed in previous sections and passed to the described neural network. The most rhythmic and arrhythmic patterns of the first 2 hours EEG of each patient was used to train the neural network with using the gradient descent training algorithm. All the signals are used to test proposed algorithm.

Table I shows the result of the three detection schemes on newborns and infants EEG seizure signals. The Sensitivity is defined as the percentage of seizure epochs which were classified correctly and the specificity as the percentage of non-seizure results which were classified correctly.

Table I. Performance results of the methods

	Liu Method	Gotman Method	Proposed Method
sensitivity	38.3%	46.5%	72.4%
specificity	76.4%	57.7%	93.2%

As it is illustrated in Table I, the results of the proposed method are better than those of previous attempts at neonatal seizure detection.

The maim advantage of our method is: it uses very short (0.4 second) segment of the data in compare to the other methods (10 seconds), so it can detect seizure sooner and more accurately. Moreover it uses a supervised classifier that can adopt itself to various situations.

VI. Conclusion

A novel neonatal seizure detection (finding rhythmic discharges) system is proposed in this paper. After extracting feature from various areas of digital signal processing, the features with using matching pursuit were selected. They were passed through a modified multilayer neural network for detection of similarities between them. Statistical performance comparison with seizure detection schemes of Gotman et al. and Liu et al. also was performed.

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