Automatic Detector of Abnormal EEG for Preterm Infants

Nisrine Jrad[1(✉)], Daniel Schang[2], Pierre Chauvet[1], Sylvie Nguyen The Tich[3], Bassam Daya[4], and Marc Gibaud[3]

[1] UCO-LARIS-UNAM, 3 place Andre-Leroy, BP 10808, 49008 Angers, France
nisrine.jrad@uco.fr
[2] ESEO Tech-UNAM, 10 Bld Jean Jeanneteau, 49009 Angers Cedex, France
[3] CHU-LARIS-UNAM, 4 rue Larrey, 49000 Angers, France
[4] Institute of Technology, Lebanese University, Saida, Lebanon

Abstract. Many of preterm babies suffer from neural disorders caused by birth complications. Hence, early prediction of neural disorders, in preterm infants, is extremely crucial for neuroprotective intervention. In this scope, the goal of this research was to propose an automatic way to study preterm babies Electroencephalograms (EEG). EEG were preprocessed and a time series of standard deviation was computed. These series were thresholded to detect Inter Burst Intervals (IBI). Features were extracted from bursts and IBI and were then classified as Abnormal or Normal using a Multiple Linear Regression. The method was successfully validated on a corpus of 100 infants with no early indication of brain injury. It was also implemented with a user-friendly interface using Java.

Keywords: Automatic EEG analysis · Inter Burst Interval Detection Feature extraction · Multiple Linear Regression · Preterm infants

1 Introduction

Recent studies reported that 1 million preterm infants, among 15 millions born prematurely per year, were dead [1]. Unfortunately, many of the survived babies suffered from lifetime disabilities like visual and auditory problems, learning difficulties, etc. To avoid these disabilities, it is crucial to diagnose, prognose, and treat preterm born babies as quickly and as accurately as possible [2,3]. Usually, preterm babies receive a special attention provided by neonatal intensive care units. Intensive care units monitor babies brain activities through non-invasive Electroencephalogram (EEG) recordings. In preterm infants, EEG is physiologically constituted by an alternation of bursts of activity and periods of suppression called Inter Burst Interval (IBI) (Fig. 1). The proportion and duration of IBI vary according to the sleep stages (more prolonged in the calm sleep) and according to the term of birth (more prolonged in premature babies).

In everyday clinical practice, the EEG analysis is still done visually which leads to several difficulties. First, physicians accustomed to the analysis of EEG

M. U. Ahmed et al. (Eds.): HealthyIoT 2017, LNICST 225, pp. 82–87, 2018.
https://doi.org/10.1007/978-3-319-76213-5_12

of very preterm infants are rare, causing delays in the interpretation of EEG tracings. Besides, visual analysis are subjective. Furthermore, in small hospitals, the expertise is often not available. Therefore, it is highly crucial to automate the physician's EEG analysis. Several researches tried to automatize bursts detection and the occurrence of seizures of full-term babies. For instance, authors of [4], proposed a method to discriminate between seizure and non-seizure EEG epochs of full-term babies. However, EEG characteristics vary a lot between preterm infants and full-term infants [5]. Few numbers of studies tackled the problem of identifying abnormal EEG of preterm infants. In the scope of automatic EEG analysis for prematurely newborns, we can quote the work presented in [3]. The authors proposed a method for automated burst detection based on *line length*, which is a running sum of the absolute differences between all consecutive samples within a predefined window [6].

Our motivation is to complete these studies by an automatic analysis of preterm EEG so as to detect abnormal brain activities, like an expert would have interpreted EEG. This allows to prioritize EEG that should be urgently analyzed by neurologist. To the best of our knowledge, there was no research addressing this task. Our method consisted on preprocessing data; EEG was filtered, using a band-stop IIR filter and smoothed using a moving average window. After, IBI were detected by thresholding standard deviation of preprocessed EEG. Relevant features were extracted from IBI and bursts and were then classified using a Multiple Linear Regression. Performance measures were evaluated using Areas Under the ROC Curves (AUC, [7,8]). The proposed method was validated on a cohort of 100 preterm babies, with no severe brain injuries.

The paper is outlined as follows: Sect. 2 describes the database that was collected. Section 3 accounts for the method. Section 4 shows results. Finally a conclusion is drawn.

2 Materials

EEG signals from 100 preterm babies were recorded in the neonatal intensive care unit of neuropediatric department of the University Hospital of Angers in France. This monitoring was part of the usual clinical follow up of premature babies. All babies legal representative gave informed consent for participation in research studies. EEG was recorded, with a sampling rate of 256 Hz, using the Alliance (Nicolet Biomedical) recording system with reduced neonatal montages of 8 to 11 adapted scalp electrodes according to the head size. Electrodes were placed according to the international 10–20 system. No hardware filter was used in the acquisition procedure, except the high-pass filter with 0.1 Hz as a cut-off frequency classically used to remove the offset of the baseline.

A total of 416 EEG recordings of 30 to 45 min durations were performed between January 1, 2003 and December 31 2004. All the 100 infants had less than 35 weeks of gestation. Each infant had between 1 to 7 EEG recordings resulting into the 416 EEG recordings. The 416 EEG were reviewed by a neuropediatrician and classified as normal, abnormal and doubtful. This classification

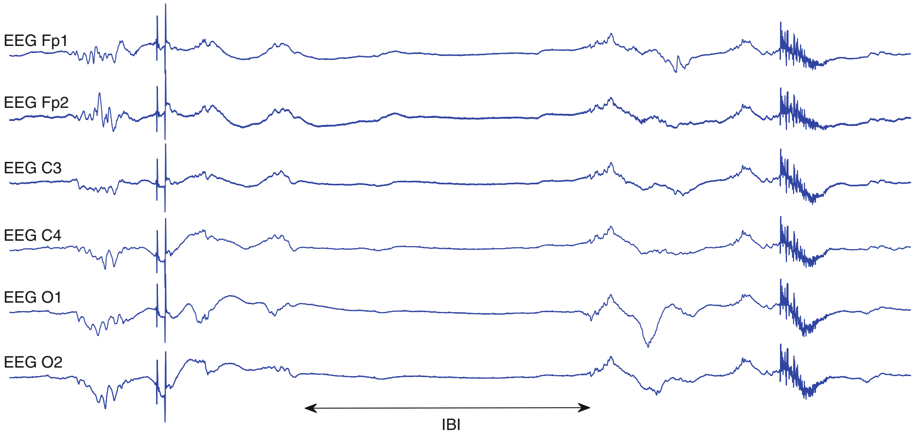

Fig. 1. An IBI example.

has been achieved through a careful visual analysis: EEG was considered as normal if the background activity (in relation to the gestation age) was normal and no abnormal features on the EEG were seen. The abnormal EEG were those who showed excessive discontinuity with maximal IBI duration above 50% of the maximal value (in relation to the gestation age), seizures, positive rolandic sharp waves of more than 2 per minute. 100 EEG recordings were considered as doubtful and were rejected. Finally, for the 316 kept EEG, the visual eye inspection gave 274 normal (88.77%, 31.04 ± 2.13 weeks of gestation) and 42 abnormal (11.23%, 30.01 ± 2.19 weeks of gestation) EEG. An example of abnormal EEG is illustrated in Fig. 1.

3 Methods

3.1 Problem Statement

Let $s(t)$ denote the EEG signal of N samples recorded in a given electrode. This signal essentially contains background activity where abnormal activities (IBI with discontinuity, seizures, rolandic sharp waves, etc.) may appear. The problem, addressed in this paper, consists of detecting the IBI and then classifying EEG into normal or abnormal. Automatic detection of abnormal EEG was done in four steps: preprocessing, IBI detection, feature extraction and EEG classification. In this section, each of these steps was detailed.

3.2 Preprocessing

For each electrode, raw EEG signal $s(t)$ was band-stop filtered at 50 Hz with a notch second order Butterworth IIR filter, so as to obtain a filtered signal

$s_{BP}(t)$ where the 50 Hz power supply frequency was removed. Then, $s_{BP}(t)$ was smoothed by computing the moving average over a window of width ω_1:

$$s_{MA}[n] = \frac{1}{\omega_1} \sum_{k=n-\omega_1/2}^{n+\omega_1/2} s_{BP}[k], n = 1, \ldots, N \quad (1)$$

3.3 IBI Detection

To detect IBI, standard deviation of signal $s_{MA}(t)$ was computed and thresholded like in [9]. Indeed, standard deviation was computed on sliding windows of size ω_2 with an overlap of ω_3 samples ($\omega_3 < \omega_2$) as following:

$$\nu^2[n] = \frac{1}{\omega_2 - 1} \sum_{k=n\omega_3}^{n\omega_3+\omega_2-1} s_{MA}^2[k] - \frac{1}{\omega_2(\omega_2 - 1)} (\sum_{k=n\omega_3}^{n\omega_3+\omega_2-1} s_{MA}[k])^2, n = 1, \ldots, N \quad (2)$$

Successive standard deviation series with values below a threshold V_T (in μV) and longer than 1 s in duration were detected and delineated by an onset and an offset boundary limit markers. Consecutive detections less than 0.5 s apart were grouped together and considered as the same IBI. Finally, only IBI present across all EEG electrodes and longer than 1 s were kept.

3.4 Feature Extraction

For each EEG electrode, a vector of 13 features was extracted as following:

1. Number of IBI: nb_IBI,
2. Total duration of IBI, defined as the sum of all IBI durations: tot_IBI (*seconds*),
3. Percentage of IBI in the EEG: $P\_IBI(\%) = \frac{tot\_IBI}{EEG\_duration}$,
4. Duration of the longest IBI: Max_IBI (*seconds*),
5. The maximum of IBI percentage in the EEG, $P\_Max\_IBI(\%) = \frac{Max\_IBI}{EEG\_duration}$,
6. The mean duration of IBI, defined as the sum of the IBI durations divided by the number of IBI: $Mean\_IBI$ (*seconds*),
7. Number of bursts: nb_B,
8. Total duration of the bursts calculated as the sum of all bursts durations, tot_B (*seconds*),
9. Percentage of bursts in the EEG, $P\_B(\%) = \frac{tot\_B}{EEG\_duration}$,
10. The duration of the longest burst: Max_B (*seconds*),
11. The maximum of bursts percentage in the EEG: $P\_Max\_B(\%) = \frac{Max\_B}{EEGduration}$,
12. The mean duration of the bursts calculated as the sum of the bursts durations divided by the number of bursts, $Mean\_B$ (*seconds*),
13. The gestational age of the newborn at the time of the EEG examination: Age_EEG in *weeks*.

3.5 Multiple Linear Regression

Extracted features formed a set of vectors $x_m \in \mathbb{R}^d, m = 1, \ldots, M$ with M the total number of EEG electrodes and $d = 13$ the number of extracted features. The entire data set was written as $\{(x_1, y_1), \ldots, (x_m, y_m), \ldots, (x_M, y_M)\}$ with class labels $y_m \in \{+1, -1\}$ for Abnormal and Normal EEG respectively. Learning a Multiple Regression classifier consisted on finding a function f:

$$\begin{aligned} f : \mathbb{R}^d &\longrightarrow \mathbb{R} \\ x &\longmapsto f(x) = \sum_{i=1}^{d} w_i x_i + b \end{aligned} \tag{3}$$

with $w \in \mathbb{R}^d$ is the slope and $b \in \mathbb{R}$ is the intercept of the function f. The predicted class is then given by the sign of f. Hence, we have to compute $\alpha = \begin{bmatrix} w \\ b \end{bmatrix} \in \mathbb{R}^{d+1}$ minimizing the quadratic error:

$$\min_{\alpha \in \mathbb{R}^{d+1}} \|\epsilon\|^2 = \min_{\alpha \in \mathbb{R}^{d+1}} \|y - \mathbf{X}\alpha\|^2 \tag{4}$$

with $y = \begin{bmatrix} y_1 \\ \vdots \\ y_m \\ \vdots \\ y_M \end{bmatrix}$ and $\mathbf{X} = \begin{bmatrix} x_{1,1} & x_{1,2} & \ldots x_{1,d} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ x_{m,1} & x_{m,2} & \ldots x_{m,d} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & \ldots x_{M,d} & 1 \end{bmatrix}$. The solution was given by $\hat{\alpha} = \left(\mathbf{X}^T \mathbf{X}\right)^{-1} \mathbf{X}^T y$.

4 Results and Discussion

Experiments on EEG data set, described in Sect. 2, were conducted to evaluate performance of the proposed method. Performance were quantitatively analyzed using the Receiver Operating Characteristic (ROC) curves [7]. The ROC curve is a parametric plot representing sensitivity as a function of specificity for different thresholds. Area Under the ROC curve, AUC, was computed for a handy representation of results [7]. The whole data set was resampled, using a 5-cross validation, into training and testing sets on a per class basis.

Mean comparison statistical tests of Abnormal versus Normal features revealed that these distributions have different means with p-values under 0.01. Experimental results showed that Multiple Linear Regression estimated on temporal features can detect accurately abnormal EEG. The optimal threshold V_T was of 23 µV. Detection of an abnormal preterm infant EEG reached a sensitivity of $85.83\% \pm 15.97$ and a specificity of $74.14\% \pm 15.97$ with an AUC of $80.00\% \pm 0.08$. Thus, if the automatic detection considered that an EEG is abnormal, it must be interpreted primarily by the doctor to undergo more medical examinations such as an MRI (Magnetic Resonance Imaging) scanner, an expensive test that can not be done routinely. Moreover, due to the high sensitivity, an EEG classified as normal does not need to be interpreted urgently by the neurologist.

It is worthy to note that performance were achieved on a set of 416 EEG after rejecting 100 doubtful EEG. It will be interesting to learn a classifier that automatically labels these suspicious as doubtful. The correlation of our results with the outcome at 2 years was not done because infants who were clinically diagnosed as pathological and treated had a chance of recovering. Finally, the proposed method was implemented, using java, in a user-friendly interface designed to inspect detection results and test different parameters, if needed.

5 Conclusion

This study presented a software for automatic detection of abnormal Electroencephalograms (EEG) of preterm infants. The method consisted on detecting Inter Burst Intervals, extracting features from EEG and classifying them into normal or abnormal EEG. Experimental results illustrated the efficiency of the proposed method in terms of sensitivity and specificity. These findings are very promising and encourage further researches that may enhance detection of abnormal EEG.

References

1. Howson, C., Kinney, M., McDougall, J.L.L.: Born too soon: preterm birth matters. Reprod. Health **10**(1). https://doi.org/10.1186/1742-4755-10-S1-S1
2. Deburchgraeve, W., Cherian, P., Vos, M.D., Swarte, R., Blok, J., Visser, G., Govaert, P., Huffel, S.V.: Automated neonatal seizure detection mimicking a human observer reading EEG. Clin. Neurophysiol. **119**(11), 2447–2454 (2008)
3. Koolen, N., Jansen, K., Vervisch, J., Matic, V., Vos, M.D., Naulaers, G., Huffel, S.V.: Line length as a robust method to detect high-activity envents: automated burst detection in premature EEG recordings. Clin. Neurophysiol. **125**(10), 1985–1994 (2014)
4. Temko, A., Thomas, E., Marnane, W., Lightbody, G., Boylan, G.: EEG-based neonatal seizure detection with support vector machines. Clin. Neurophysiol. **122**(3), 464–473 (2010)
5. Joseph, J., Lesevre, N., Dreyfus-Brisac, C.: Spatio-temporal organization of EEG in premature infants and full-term new-borns. Electroencephalogr. Clin. Neurophysiol. **40**(2), 153–168 (1976)
6. Esteller, R., Echauz, J., Tcheng, T., Litt, B., Pless, B.: Line length: an efficient feature for seizure onset detection. In: Proceedings of the 23rd IEEE EMBS International Conference (2001)
7. Hanley, J., McNeil, B.: The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology **143**, 29–36 (1982)
8. Fawcett, T.: An introduction to ROC analysis. Pattern Recogn. Lett. Spec. Issue ROC Anal. **27**, 861–874 (2006)
9. Chauvet, P., Tich, S.N.T., Schang, D., Clement, A.: Evaluation of automatic feature detection algorithms in EEG: application to interburst intervals. Comput. Biol. Med. **54**, 61–71 (2014)