AUTOMATIC DETECTION OF PRETERM NEONATAL EEG BACKGROUND STATES

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ABSTRACT

Background states of an EEG signal describe the distinctive variations in the amplitude of the signal with respect to time. Background state detection in EEG is used to help estimate the brain growth progress in infants. Currently, background detection is mostly done manually, which is highly subjective. This paper proposes a way to automatically detect background states for preterm infants. The distribution of the amplitude vector in a 10-minute window of 2-channel preterm neonatal EEG signal is analysed, and the mean and standard deviations of the amplitudes in log-space are used as features in a linear discriminant analysis based classifier. The results are compared with existing methods of background detection. The algorithm performs well compared with the visual classification. It also shows less sensitivity to local variations the existing algorithm are suffering from.

Index Terms— Biomedical signal analysis, Pattern classification, Electroencephalography, Medical expert systems

1. INTRODUCTION

Electroencephalogram (EEG) is the weak electrical signal registered by putting electrodes on a patient's scalp. The resulting signal is a summation of the electrical signals emitted from neurons in the brain. Although the origin of this phenomenon is not entirely understood, it remains one of the most unintrusive ways to continuously monitor neurological activity. It is therefore particularly suited for vulnerable patients such as preterm infants, where MRI or CT scans are not always a viable option.

In terms of preterm infant monitoring, background state classification is an important aspect of EEG analysis. The backgound state of an EEG signal refers to the general behaviour of the signal. Background states decribe the variations in the amplitude of a signal with repect to time. Figure 1 shows examples of EEG segments which are classified as "continuous" and "discontinuous". The background state is used to estimate the growing progress of the brain, as well as determination of sleep states [1].

The most common ways to determine the background states of a recording are by visually scanning the EEG recording, or by looking at the amplitude-integrated EEG (aEEG) [2, 3], and using the general guidelines shown in figure 2 to determine the background states. Currently the definitions of "continuous" and "discontinuous" EEG are qualitative. Some guidelines have been established to estimate the maximun and minimum points of the aEEG, which are in turn used to determine the background state. However, they are estimates and are largely subjective. The algorithm presented by Navakatikyan et al [4] trys to improve the objectivity of the guidelines by using rEEG [5] and sets a standard to determine the maximum and minimum amplitudes using the rEEG. This gives a more objective way to classify the signal but rEEG, like aEEG, is still very sensitive to local signal variation, and can also be prone to the interference of noise such as muscle artifacts. The algorithm presented in [4] focuses on term infants, who have more developed brains and generally clearer distinctions between continuous and discontinuous signals. This paper presents a system targeted at preterm infants, and analyses and classifies 2-channels EEG signal recorded using the BRM bedside monitoring developed by BrainZ Instruments [6]. The proposed system uses the raw EEG instead of the aEEG or rEEG to determine the EEG background states. The background states of an EEG signal are estimated as being either continuous or discontinuous.

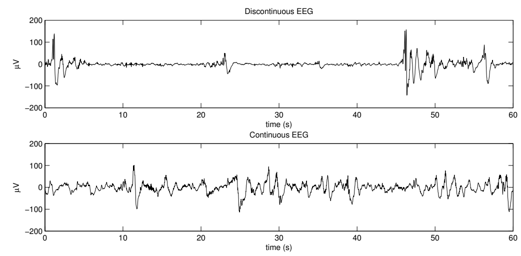

Fig. 1. Examples of 60 seconds of EEG that are classified as discontinuous (top graph) and continuous (bottom graph).

The paper is structured as follows. Section 2 gives an overview of the system. Section 3 looks at the segmentation of the signal to produce pseudo-stationary segments. Section 4 looks at the classification stage of the system. The results are presented and discussed in section 5.

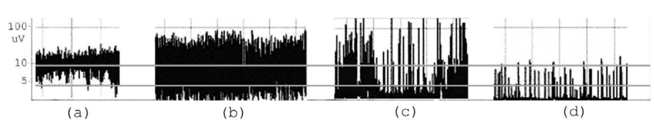

Fig. 2. Guidelines for background state classification by aEEG. The two horizontonal lines indicate $5\mu V$ and $10\mu V$. From left to right: (a) Continuous normal voltage; (b) Discontinuous normal voltage; (c) Burst Suppression; (d) Continuous low voltage. The estimated maximum and minimum of the aEEG is compared with the $5\mu V$ and $10\mu V$ thresholds as classification criteria [3]. Note the conventional semi-log scale (i.e. linear from 0 to 10 μV and in log scale from 10 - 100 μV

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2. SYSTEM OVERVIEW

The proposed method of background classification involves using the amplitude distributions of EEG signals in 10-minute windows to determine whether the signal is continuous or discontinuous in nature. Because of the non-stationary nature of EEG signals, the recording is first segmented into pseudo-stationary segments. The averages of the absolute voltage of the segments are recorded over the 10-minute windows. The distributions of these readings can be described by the log-normal distribution. The estimated means and standard deviations of the distributions are used as features in a classifier to classify the 10-minute window as continuous or discontinuous. The 10-minute windows have a 90% overlap for proper resolution.

3. SIGNAL SEGMENTATION

To describe the amplitude variations and distribution of an EEG recording (which defines the continuity of the recording), the EEG signal was first divided into pseudo-stationary segments. This was done so that one value could be extracted from each segment to accurately represent the amplitude for the duration of the segment. Earlier evaluation showed that generalized likelihood ratio (GLR) is suited for the task of segmenting neonatal EEG [7].

GRL is a method for segmentation of time series signals proposed by Appel and Brandt [8, 9].The idea of GLR is to analyse the predictive error of the signal using an autoregressive model, and assign segment boundaries at the point of the signal where, if no segment boundary is present, a higher predictive error is obtained. The segmentation criteria, $d(n)$, is defined in (1), where n is the start of the test window, L is the length of the test window, and $e(n)$ is the predictive error at time n.

$$
\begin{aligned}
d(n) \quad = \quad & (n+L)\ln\left(\frac{\sum_{k=1}^{n+L} e(k)^2}{n+L}\right) - \\
& [(n-1)\ln\left(\frac{\sum_{k=1}^{n-1} e(k)^2}{n-1}\right) + \\
& L\ln\left(\frac{\sum_{k=n}^{n+L} e(k)^2}{L}\right)]
\end{aligned} \tag{1}
$$

A segment boundary is assigned at n if $d(n)$ exceed a predefined threshold. Once a segment boundary is detected, the algorithm repeats starting at $n+1$. Figure 3 shows a typical segmentation result.

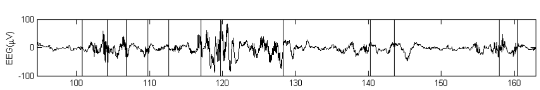

Fig. 3. Example of segmentation for 30 seconds of EEG signal using the GLR algorithm.

After the signal has been segmented, the mean absolute voltage of each segment is calculated. This value is used to represent the amplitude of the signal for the duration of the segment. In order to take into account the length of the segment (which is not a constant), instead of storing the amplitude readings in a vector which contains one value for each segment, the value is repeated for each sample of the signal, such that the resulting vector has the same length as the EEG signal data. This amplitude vector is then used for the classfication stage.

4. PATTERN CLASSIFICATION

Because the continuity of the signal is defined as the variation in amplitude, the window used for the classification process needs to take into account a long enough period of data for such classification to be valid. A 10-minute sliding window is used for this system as a compromise between resolution and the amount of information taken into account. The amplitude value vector as described in section 3 is used for the classification stage. 10 minutes of the amplitude vector are processed and classified to produce one value that indicates the continuity of the EEG signal during the time window. The sliding window moves 1 minute for each iteration to give one value for every minutes of the EEG signal (except for the first and last 5 minutes).

4.1. Feature Extraction

Figure 4 shows a histogram of the values in the amplitude vector for one 10-minute window. The distribution can be modelled using a log-normal distribution, where the log value of the data is assumed to follow the normal distribution. The estimated mean and standard deviation of the data in log space are calculated as follows:

$$\hat{\mu} = \frac{\sum_{i=1}^{N} \log \mathbf{x}_i}{N} \tag{2}$$

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{N} (\log \mathbf{x}_i - \hat{\mu})^2}{N}} \tag{3}$$

Where $\mathbf{x}$ is the windowed amplitude vector, N is the number of values in $\mathbf{x}$, and $\hat{\mu}$ and $\hat{\sigma}$ are the estimated mean and standard deviation of $\mathbf{x}$ in the log space. The latter two values are used to classify the 10 minute window to determine the continuity of the signal. The mean and and standard deviation of the distribution are used since the background states of EEG are defined by the variations of the signal, and the parameters of the distribution would be best to describe this variation.

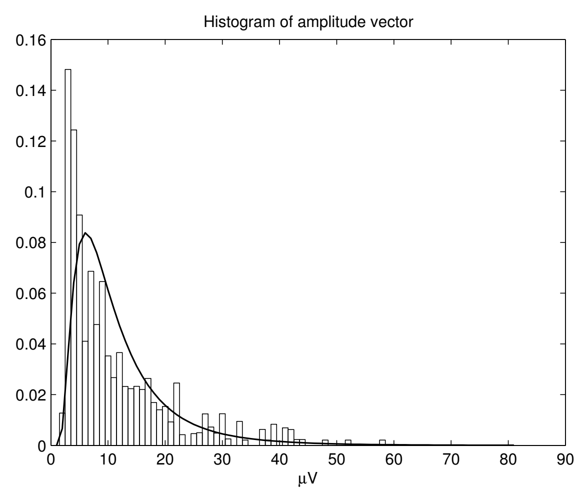

Fig. 4. Histogram showing the distribution of the amplitude vector. The curve represents the fitted log-normal distribution.

4.2. Linear Discriminant Analysis

Segments of EEG, 10 minutes in length, and with known continuity categories (continuous or discontinuous), are used as training data. Features are extracted from the training set as described in section 4.1, and a classifier based on linear discriminant analysis is developed. Figure 5 shows the distribution of the features in the training set. LDA looks at the data points in the two classes to determine a

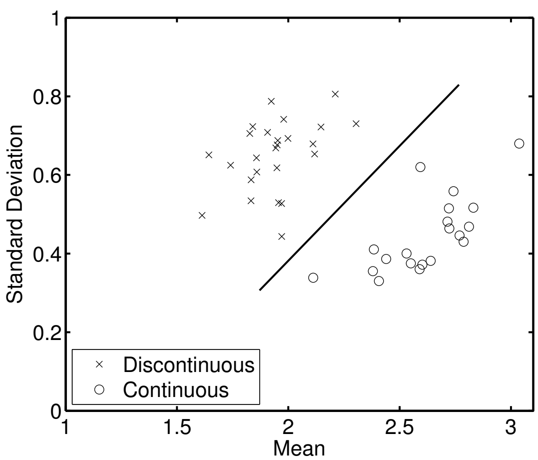

Fig. 5. Distribution of the $\hat{\mu}$ and $\hat{\sigma}$ in the training set.

linear mapping that increases the between-class variance and minimises the within-class variance [10]. Where the within class variance is defined as:

$$S_w = \sum_{j=1}^{C} p_j \times (cov_j) \tag{4}$$

where C is the number of classes, cov_j is the covariance of class j, and p_j is the priori probability of class j. The between-class variance is defined as:

$$S_b = \sum_{j=1}^{C} (\mu_j - \mu) \times (\mu_j - \mu)^T \tag{5}$$

where μ is the global mean and μ_j is mean of the class j. The projection matrix is defined as the eigenvectors of $S_w^{-1} \times S_b$. The transformation is optimised to ensure the ratio $det|S_b|/det|S_w|$ is maximised. The transformed data is then used for classfication purposes, using the Euclidean distance between the testing point and the center of the data in each class of the testing data set.

Both crisp and soft classifications were performed for comparative purposes. The soft classification version was adjusted in such a way that the training data gave a probablity of 1 in the class which the sample was labelled with.

5. TESTING AND RESULTS

5.1. Training and Testing Data

From a database of preterm EEG recordings, 10 minute segments of EEG were selected after exmaining the aEEG and raw EEG data to ensure the segments were good representations of continuous or discontinuous signals. 25 segments were selected for each state as the training data.

From the same database, 60 recordings, approximately 2 hours in length, were selected. Selections were based on the quality of the recording, and signals without seizures or significant mechanical artifacts were selected as testing signals.

5.2. Testing procedure

The EEG recordings from the testing data set were processed using the algorithm described in this paper, and the results were visually compared with the aEEG and an exisiting algorithm for term infant background detection. The first and last 5 minutes of each recording were not classified. No attempt was made to reject artifacts of any nature. Both the crisp and soft classifications were graphed against the background state detected using algorithm described in [4] and the aEEG signal, the latter being an established way for clinicians to determine the background continuity.

5.3. Results and Discussion

Figure 6 shows the proposed and the rEEG [4] classfication results.

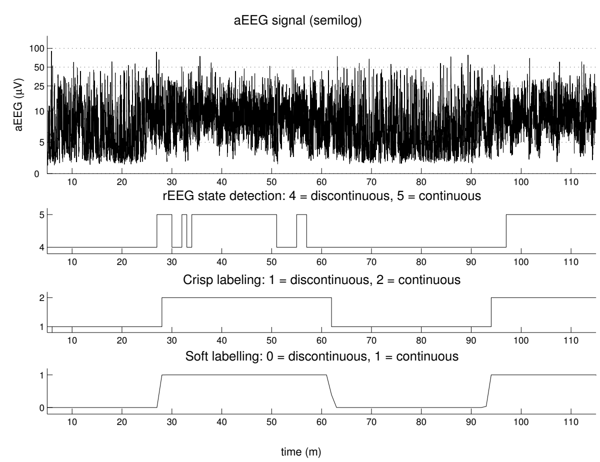

Fig. 6. Classification results as compared with rEEG based algorithm.

Because the system does not rely on aEEG, which is very sensitive to artifacts such as muscle noise, the background states as classified by the system are a lot more stable than the existing solution. The 10-minute window used for the feature extraction stage ensures the features extracted from the window (i.e. $\hat{\mu}$ and $\hat{\sigma}$) take into account a long enough period of the EEG to determine the background state. This means the resulting classification system gives states that are more stable and less prone to noise interference and less sensitive to local variation of the signal, as shown in figure 6. The fact that the proposed classifier was trained using preterm data also increases the accuracy to make it better suited for preterm infants.

One problem with the background state detection is the fact that the changes between one state and another do not occur instantly but rather, from the aEEG graph, gradually change from one state to another. Using the soft classification, each window is classified with a probability of belonging to the two classes. The soft label can be easily converted to crisp labelling, while giving more infomation about the background state of the EEG. The soft labelling can also assist future work in EEG analysis by defining the area of signal where no state changes occur.

Currently the system only distinguishes between continuous and discontinuous signals. Future work will include extending the classification system to includemore states such as burst suppression, continuous low voltage, and flat-lining. A score of continuity can also be developed to improve the soft-labelling.

6. CONCLUSIONS

A technique for background state detection was developed for preterm infant 2-channel EEG signal. The technique uses the distribution of the mean average amplitude of pseudo-stationary segments to determine the background state. Both crisp and soft labelling can be used, to compensate for the gradual change of background states. The proposed classifier performs well when compared with aEEG and is more robust against local signal variations.

Tests using actual preterm infant 2-channel EEG recordings show that this method of classification helps eliminating the problems seen in classifiers that use aEEG, which is sensitive to noise such as muscle artifacts and local variations. Further work is planned to include more background states and improve the soft labelling ability of the algorithm.

7. REFERENCES

[1] B.J. Fisch, *Fisch and Spehlmann's EEG primer*, Elsevier Science Publishers B.V., Amsterdam, 3 edition, 1999.

[2] P.F. Prior and D.E. Maynard, *Monitoring Cerebral Function: Long-Term Monitoring of EEG and Evoked Potentials*, Elsevier Science Publishers B.V., Amsterdam, 1986.

[3] L. Hellström-Westas, L.S. de Vries, and Rosén I., *An Atlas of Amplitude-Intergrated EEGs in the Newborn*, The Parthenon Publishing Group, New York, 2003.

[4] M.A. Navakatikyan, Barks J.D.E., G. Greisen, A. Mathur, and M.C. Toet, "Automatic background classification of the amplitude-integrated EEG in infants," *Acta Pædiatrica*, vol. 96, pp. 144, 2007.

[5] M.A. Navakatikyan, "New compressed representation of EEG for the monitoring of brain function," *Acta Pædiatrica*, vol. 96, pp. 144, 2007.

[6] "BrainZ BRM2 brain monitor: a bedside continuous EEG and cerebral function monitor," 2005, [Online] Available: http://www.brainzinstruments.com/index.asp [30 June 2005].

[7] L. Wong and W. Abdulla, "Time-frequency evaluation of segmentation methods for neonatal EEG signals," in *Proceedings of the 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2006, pp. 1303 – 1306.

[8] U. Appel and A.V. Brandt, "Adaptive sequential segmentation of piecewise stationary time series," *Information Sciences*, vol. 29, pp. 27 – 56, 1983.

[9] R.M. Rangayyan, *Biomedical signal analysis : a case-study approach*, IEEE Press, New York, 2002.

[10] A.M. Martínez and A.C. Kak, "PCA versus LDA," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, pp. 228 – 233, 2001.