New Approaches for the Adaptive Segmentation of Neonatal EEG Signals

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Abstract. *In this paper we present two new approaches for the segmentation of neonatal EEG signals into pseudostationary segments. The first approach is an adaptation of the sliding halfwindow techniques proposed by Krajca and Agarwal & Gotman. It has similar performance to the existing algorithms and offers a probabilistic approach. The second approach is a new view of combining information of multiple EEG channels into an overall segmentation. Instead of combining the information of the multiple channels before the segmentation, the proposed technique first computes segmentations for each channel separately and then combines them into an overall segmentation via alignment, offering new advantages for the segmentation of neonatal EEG.*

Keywords

Adaptive segmentation, segmentation alignment, newborn, electroencephalography (EEG), algorithm.

1. Introduction

The electroencephalogram or EEG is an easy and safe technique to monitor the brain function. It is measured as the electrical potential between electrodes placed on different points on the scalp of the patient. It is frequently used in the NICU, the intensive care unit of newborns, because of its safety and ability to monitor the healing and maturation process of the brain.

A striking property of the neonatal EEG is the discontinuity of the signal. A main pattern is called the *tracé discontinu* (TD), which consists of periods of high activity (bursts) and periods of low activity (suppressions). As the brain matures, this pattern evolves to a continuous pattern (tracé continu), tracé alternant patterns - these are similar to TD but with less difference between bursts and suppressions - and slow wave sleep patterns. The resulting EEG signal is highly nonstationary, but the burst and suppression segments are considered stationary.

This property makes it difficult to use conventional signal processing techniques to analyse the signal. But with the use of adaptive segmentation, the signal can be split up into pseudo-stationary parts, of which features can be calculated so the signal can be analysed. In section 2, a new method is proposed for the adaptive segmentation, based on existing sliding window techniques.

The EEG measurement usually consists of multiple channels, to include spatial information into the EEG. The segmentation of the total measurement has to be based on the information given in each channel. Section 3 discusses a new approach for combining the information of the different EEG channels to calculate a segmentation for the whole EEG measurement.

Section 4 presents the results of the new approaches described in section 2 and 3. These results are discussed in section 5. In a last section, the conclusions of this work are presented and ideas for future work are given.

2. One-channel Methods

The new technique for the segmentation of the neonatal EEG proposed in this paper is based on a technique described by Krajca et al.[1] and Agarwal & Gotman[2]. These techniques are described in section 2.1. The new technique is proposed in section 2.2.

2.1 Sliding Halfwindow Techniques

The techniques proposed by Krajca et al.[1] and Agarwal & Gotman[2] can be seen as two variants of the same algorithm. The algorithm uses a sliding window to calculate a value for each sample. That value indicates how likely the sample is to be a boundary between two pseudostationary segments. The segmentation is then found as the peaks of this calculated signal.

To calculate the boundary likelihood value of the sample, a window is constructed around the sample. This window is split into two halfwindows, with the given sample on the boundary between the two halfwindows. In each halfwindow, a feature is calculated to represent the characteristics of the window. The boundary likelihood of the sample is then calculated as the difference between the two features.

The only point where the techniques by Krajca and

Agarwal & Gotman differ, is the feature calculated in the halfwindows. Krajca uses the mean amplitude and mean frequency as feature:

$$MAF = \frac{1}{N}\sum_{i=M}^{M+N-1}|x(i)| + \frac{1}{N}\sum_{i=M}^{M+N-1}|x(i)-x(i-1)| \tag{1}$$

M is the current left bound of the window (either $n-N$ or n for the left resp. right window of the current sample n). The first sum is the mean amplitude of the halfwindow, the right sum is an estimate for the mean frequency in the halfwindow. Agarwal and Gotman use a different feature, the Teager energy ([4], [5]). This is the energy based on the nonlinear energy operator or NLEO. The NLEO is calculated as:

$$\Psi(n) = x^2(n) - x(n-1)x(n+1) \tag{2}$$

The teager energy of the halfwindow is calculated as the mean NLEO of the halfwindow.

$$TE = \frac{1}{N}\sum_{i=M}^{M+N-1}\Psi(i) \tag{3}$$

It is an estimate for the instantaneous frequency weighted energy of the signal, as the value for the TE is proportional to the squared amplitude of the signal as well as the squared frequencies.

2.2 Probabilistic Approach

The approach proposed in this paper is probabilistic in nature. It uses the same algorithm structure as in section 2.1, but the boundary likelihood of the samples is obtained differently. The boundary likelihood of a sample indicates how likely the sample is to be a boundary between two pseudo-stationary segments of the signal. This likelihood is given by how different the probability distribution of the left halfwindow is from the probability distribution of the right halfwindow. A measure for the difference in probability distributions is the *Kullback-Leibler divergence* ([6]):

$$\mathrm{div}(P,Q) = \sum_i p_i \log_2\left(\frac{p_i}{q_i}\right) \tag{4}$$

The probability distributions calculated here are approximations of the amplitude probability distributions of the signals in the halfwindows. It is obtained via the histogram. For both halfwindows, the intervals I_i of the histogram are calculated. The probability in each halfwindow is then calculated as

$$p_i = \frac{1}{N}\sum_j \delta_{ij} \text{ with } \delta_{ij} = \begin{cases} 1 & \text{als } |x(j)| \in I_i \\ 0 & \text{als } |x(j)| \notin I_i \end{cases} \tag{5}$$

The Kullback-Leibler divergence is now used in the same way the feature difference is used in section 2.1: the segmentation boundaries are detected as the peaks of the calculated divergence signal.

3. Multichannel Methods

The techniques described in the previous section calculate a segmentation based on one EEG signal. But most EEG measurements consist of several channels. To obtain a segmentation for the whole measurement, the information of each channel should somehow be combined into an overall segmentation. The current approach used in signal processing is described in section 3.1. The new approach proposed in this paper is described in section 3.2.

3.1 Averaging Techniques

The current technique to combine the information of multiple EEG channels to segment the whole measurement, is to combine the information prior to being segmented. An easy technique is to average all channels into one signal: for each sample the mean signal value over all channels is calculated. The resulting signal is used as input for the one-channel segmentation algorithms as described in section 2. The most used technique is a variant of this. Instead of averaging the channels directly, the averaging takes place after the features are calculated. Doing so, the features (e.g. MAF or TE) are calculated for each sample in each channel. Then the mean of these values is calculated over all channels. The obtained results are used to calculate the difference between halfwindows, which serves as the boundary likelihood of the sample.

3.2 Segmentation Alignment

The technique proposed here uses another approach. Instead of combining the information of the different channels prior to the segmentation, the segmentations are calculated for each channel separately and combined afterwards. The segmentation of each channel individually is calculated using the one-channel algorithms as described in section 2. The obtained segmentations of each channel are combined by aligning these segmentations and computing the overall segmentation for the EEG measurement.

The alignment of the segmentations is based on an algorithm used in the domain of bioinformatics, where there's a lot of expertise in aligning protein sequences. The algorithm is proposed by Needleman & Wunsch[3]. The success of this algorithm is due to the efficiency and simplicity of *dynamical programming*, which solves an optimization problem by breaking it into subproblems. A necessary condition is that the optimal solution of the whole problem consists of optimal solutions of the subproblems.

The segmentation alignment algorithm breaks the problem of aligning two segmentations into the smallest subproblems: the alignment of two proposed boundaries of the different segmentations. The boundary can be considered as a match, or it can be decided that one segmentation had added the boundary while the other omitted it. The cost function of this algorithm is the distance in time-samples between the two boundaries for the first choice, and a fixed

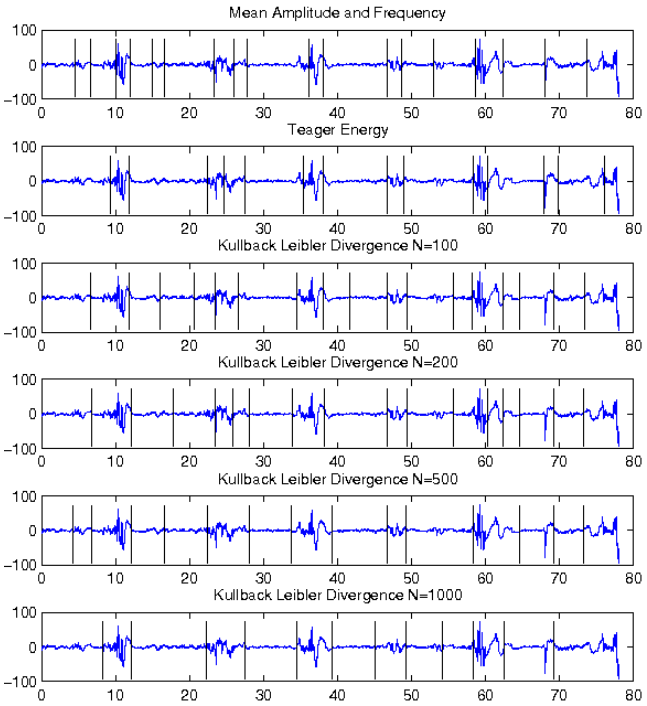


Fig. 1: Segmentations obtained using different algorithms

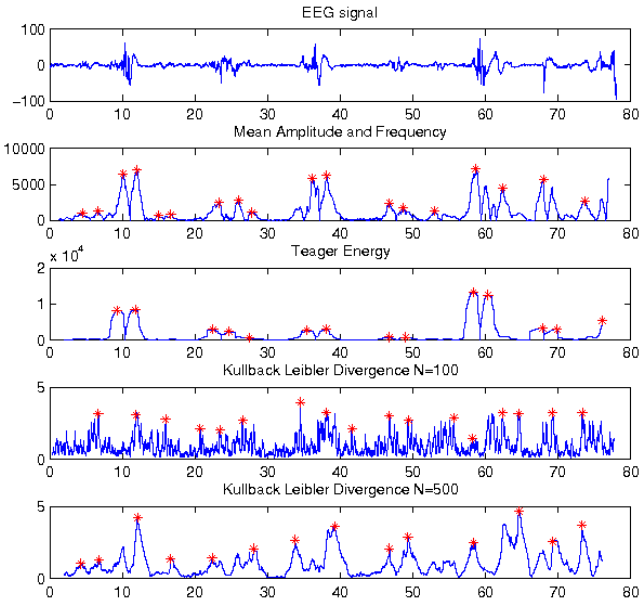


Fig. 2: Boundary likelihoods obtained using different algorithms. The detected boundaries (peaks) are plotted as stars.

penalty cost for the second choice. The algorithm searches a path through the segmentations which has the lowest cost: the matching boundaries will lie close to each other and there will be as few omissions and additions as possible.

4. Results

The presented segmentation algorithms are tested on neonatal EEG data. The obtained segmentations were evaluated through visual inspection. An example of the segmentation obtained with different algorithms is shown in figure 1. Figure 2 compares the boundary likelihoods obtained using the different algorithms. Figure 3 shows an example of the alignment of two segmentations. The segmentation boundaries are plotted as vertical lines, the horizontal axis is in seconds. The segmentation is done on a EEG-signal with a tracé discontinu pattern. The bursts and suppressions are clearly visible for a human reader. The calculated segmentations should be able to detect the burst and suppression segments.

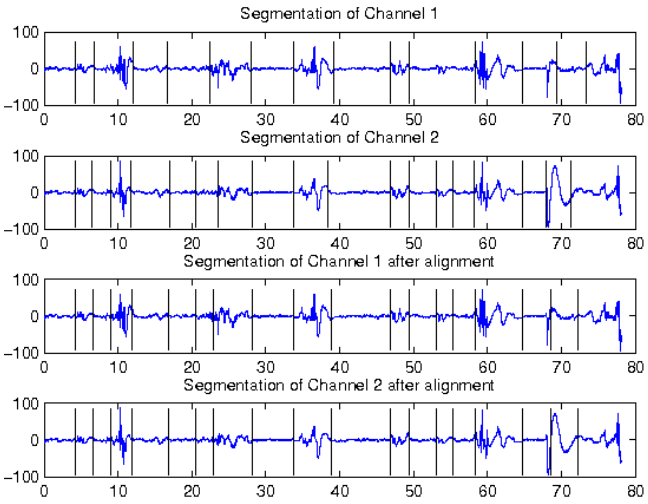


Fig. 3: Example of the alignment of two segmentations

5. Discussion

The results of the proposed new techniques are promising. The calculated segmentations clearly divide the signal into pseudostationary parts. The technique has about the same performance as the techniques described by Krajca[1] and Agarwal & Gotman[2]. A remark about this performance is that it is highly subjective. The resulting segmenta-

tions are visually checked with the signal. There is no objective measure to calculate the performance. This is because the segmentation is not a problem on its own, but rather a first step toward the analysis of EEG signals. To have an objective measure, one has to look at what is needed for the whole application. The segmentations should be used for the next step in the application and the performance should be calculated after that step.

The window length is a parameter of the algorithm that influences the resulting segmentations. As the window length is larger, the KL-divergence signal will be smoother, as can be seen in figure 2, because of the lowpass filtering effect of the window. Smaller peaks will be smoothed away, so the algorithm will detect less boundaries. The window length can thus be used as a parameter to choose the granularity of the segmentation, as can be seen in figure 1.

The results of the alignment algorithm are encouraging. The algorithm is able to find matching boundaries and detect omissions and additions. The obtained segmentation is more robust against time delays between channels, as it segments each channel separately. This is usefull because sometimes phenomena spread through the brain and acquire a time delay between the different EEG channels. The alignment algorithm is well adapted to this process as it is inherently present in the algorithm.

6. Conclusion

The proposed segmentation technique offers an alternative for the existing segmentation algorithms. It offers a new probabilistic adaptation of the segmentation algorithm described by Krajca et al[1] and Agarwal & Gotman[2]. Future work can be done by incorporating frequency information into the calculation of the probability distribution. For now, the used probability distribution is the probability distribution of the amplitude.

The segmentation alignment algorithm clears the way for a new approach for combining multichannel information into an overall segmentation. Instead of combining the information of the multiple channels before the segmentation, the proposed technique first computes segmentations for each channel separately and then combines them into an overall segmentation via alignment. This method has the advantage that is robust against small delays between channels. Future work can be done by aligning multiple segmentations at the same time, whereas now segmentations are aligned pairwise. This would improve the robustness of the algorithm.

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