AUTOMATIC DETECTION OF SLEEP STAGES IN PRETERM NEONATES BY EXPLORING THE TIME STRUCTURE OF THE EEG

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Abstract: The electroencephalogram (EEG) is a sensitive marker of brain maturation and developmental changes in term and preterm newborns. A new method for automatic sleep stages detection in neonatal EEG was developed. The procedure is based on processing of time profiles computed by adaptive segmentation and subsequent classification of extracted signal graphoelements. The time profiles, functions of the class membership in the course of time, reflect the dynamic EEG structure and may be used for indication of changes in the neonatal sleep. The method is sufficiently sensitive to detect the sleep stages even in preterm infants EEG.

Introduction

Neonatal sleep analysis is an important tool in neonatal intensive care units. One of the most important indicators to study the maturation of the child brain is the neonatal electroencephalogram (EEG). Visual analysis of the EEG activity in newborns is a difficult and tedious task; the quantitative method of objective analysis is needed.

The critical evaluation of recent techniques of automated sleep analyses in neonatal neurointensive care units can be found in [1].

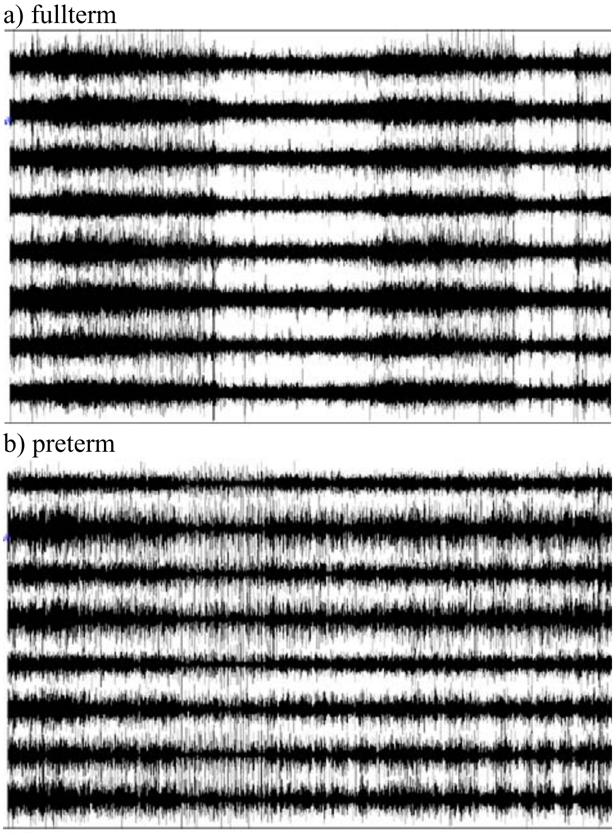
One of the possible approaches to this field is a structural analysis of the EEG segments by hierarchical modeling of the EEG [2] [3]. Jansen et al. [4] used autoregressive spectral estimates for identification and labeling of EEG graphic elements. The pioneering work in the field of adaptive segmentation was done by Bodenstein and Praetorius [5]. Barlow [6] was the first who applied the structural time profiles to the neonatal sleep EEG. The extensive review of methods of analysis of nonstationary EEGs with emphasis on segmentation techniques till 1985 can be found in [7].

We have developed a new method for automatic sleep stages detection in neonatal EEG based on time profiles processing and we have applied it at first to fullterm neonatal EEG [8][9].

The purpose of the present study was to show, that the method is sufficiently sensitive to detect the sleep stages both in the EEG of the preterm and fullterm infants. The method is based on adaptive segmentation, feature extraction and subsequent classification by cluster analysis. The resulting structural time profiles are processed by a novel algorithm to reveal the sleep stages in preterm infant EEG. The signal statistics can be also computed during multichannel signal processing and quantitative features and parameters can be extracted from the classified EEG segments.

If we would be interested only in fullterm EEG sleep stages detection, we could use only the raw EEG signal compressed in the time scale, where the increased voltage during quiet sleep (QS) and decreased voltage during active sleep (AS) manifests itself in the time scale of 1-2 hours (Figure 1a).

a) fullterm



b) preterm

Figure. 1. The comparison of compressed fullterm (a) and preterm (b) neonatal EEG. The time scale is 85 min and 90 min, respectively. The time structure of sleep stages is visible in fullterm EEG, but the increase of ampltude in quiet sleep is not distinct in preterm EEG amplitude.

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However, such voltage amplitude information is usually missing in EEG of preterm infants of postconceptial age (PCA) of 36 weeks and less (Figure 1b), or in abnormal graphs, and we have to use the more sophisticated techniques to reveal the hidden sleep structure from the EEG.

The automatic sleep detection is very desirable for functional brain maturation study in neonates, as discussed in [10], where sleep stages are determined visually. Further on, for objective quantitative analysis of the maturation of the child brain, we need precise signal statistics [11].

Adaptive segmentation can contribute to this purpose by finding the exact instants of burst/interburst events and changes of signal stationarity by dividing the signal into quasi-stationary parts [6].

Both aforementioned tasks i.e. sleep stages detection and quantitative parameters extraction, can be made by structural analysis of the EEG time profiles. The time profiles can serve for the finding the instants of sleep stages changes and the detailed statistical analysis can be done by computing the percentual occurrence of different EEG graphoelements detected by adaptive segmentation and which can be labeled by cluster analysis.

The purpose of this study was to show, how the structural time profiles analysis can provide a unified approach to the all above mentioned tasks. In practical experimental examples we will show, that the method can reveal even the hidden structure of the neonatal sleep EEG, which was not apparent in compressed time scale and therefore is very difficult to detect automatically.

Material

A total of 31 healthy sleeping newborns were recorded in standard conditions for 90-120 minutes. The postconceptial age (PCA) was 32-36 weeks. Also full term neonatal was recorded to be compared with preterm neonatal recordings EEG (20 infants). An experienced physician evaluated the records. The periods of quiet sleep (QS) and active sleep (AS) were marked by flags during visual inspection of the EEG recordings. The polygraphic channels were not used for the automatic analysis.

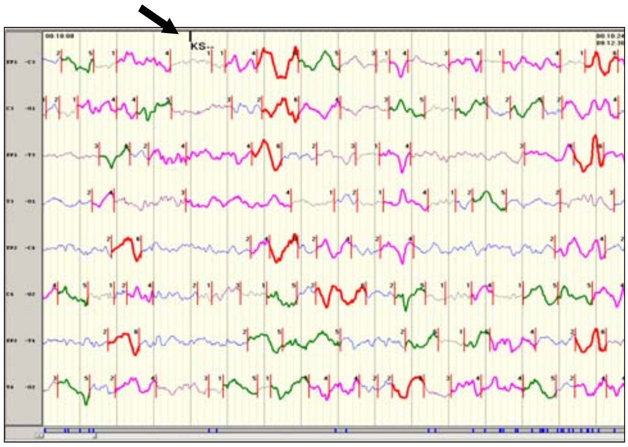
Methods

The procedure is based on processing of time profiles computed by adaptive segmentation and subsequent feature extraction and classification of signal graphoelements

Adaptive segmentation: The used adaptive segmentation method is based on two connected windows that are sliding along the signal. The change of stationarity is indicated by local maxima of their difference measure. The threshold limits the small fluctuations of the measure [12].

This approach makes possible the multichannel adaptive segmentation working independently in all channels simultaneously. The algorithm divides the EEG signal into piece-wise stationary segments of variable length depending on the change of stationarity of the signal. The feature extraction from such relatively homogeneous epochs is more effective than from the fixed epochs. This holds especially true when analyzing highly variable patterns as tracé alternant.

The example of multichannel adaptive segmentation of the signal recorded during quiet and active sleep is shown in Figure 2.



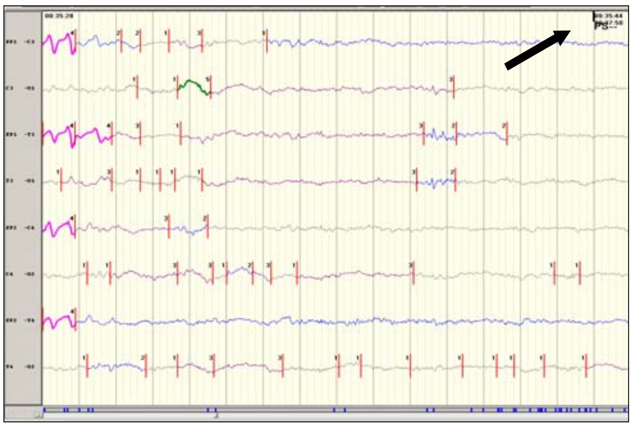


Figure 2. Multichannel adaptive segmentation. Quiet sleep (above), active sleep (below). Numbers indicate the segment labels - the class membership The arrows show the marks made by physician during the visual inspection.

Feature extraction: The EEG segments detected by adaptive segmentation were described by ten features. The most important parameters to distinguish the EEG activity between both sleep states were the amplitude variance, power in the frequency bands delta, theta, and alpha mean frequency first and second derivative of the signal [12]. The features describe frequency and also time characteristics of the EEG graphoelements.

Classification: The EEG segments characterized by the above features were classified into several classes by cluster analysis (k-means algorithm [13]). The example of classification into 12 classes is shown in Figure 3. Only the classes 1 and 11 are shown.

The most typical representative segments can be extracted form the clusters, as the objects closest to the centre of gravity of the class (Figure 4). In the figure are shown the three representative EEG segments for each class for one channel and also the signal statistics – the percentual occurrence of the segments of relevant class in the relation to the total signal duration of this particular EEG channel.

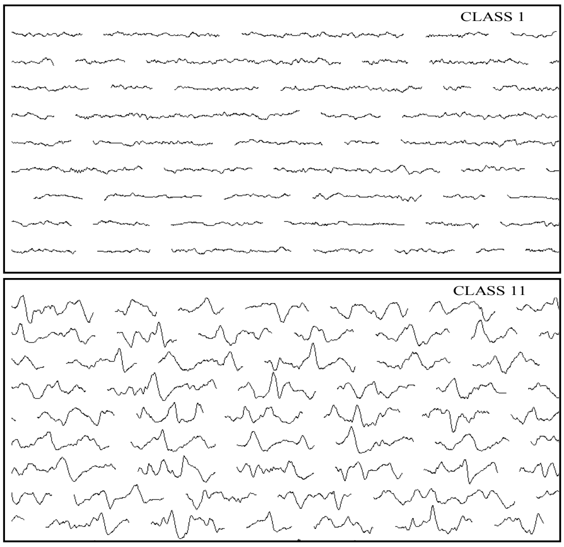


Figure 3. Clustering of EEG segments.

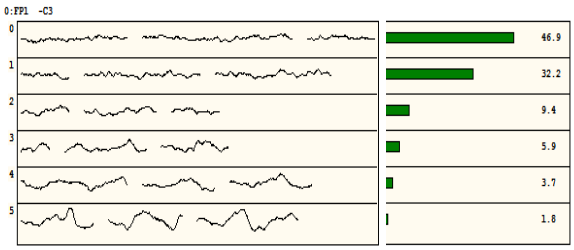


Figure 4. The signal statistics. The example of three representative segments of each class of the channel Fp1-C3 and their percentual occurrence (histogram). Classification into 6 classes.

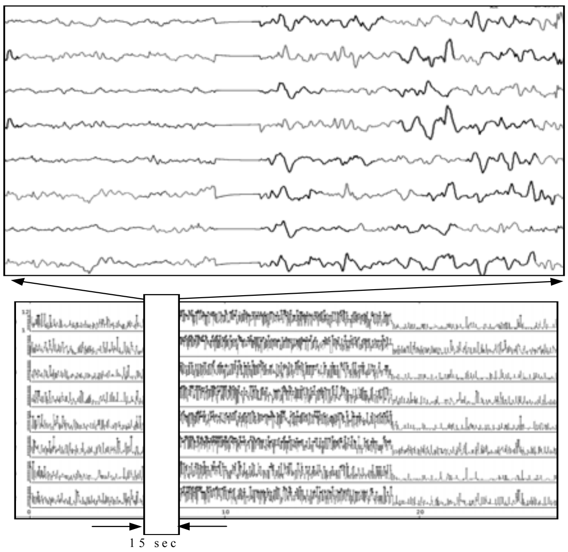


Figure 5. Multichannel time profile (30 minutes of the signal) and one page of corresponding EEG record (15 sec) at the cursor position. The transition from the wake period (left) to the quiet sleep (right).

Multichannel time profiles: The time profiles are the functions of the class membership in the course of time, they reflect the dynamic EEG structure during sleep (Figure 5) and can be used for sleep state change detection.

Algorithm: The processing of time profiles consists of the following steps (see Figure 6.):

1) Multichannel time profiles were created by adaptive segmentation and cluster analysis.
2) The class membership in time profiles was averaged to obtain a single detection curve from all channels. Running mean of averaged class membership was computed by 111 point moving average (MA) filter.
3) Class membership was subtracted from the running mean and squared.
4) Resulting curve was twice smoothed with the help of 151 point moving average filter.
5) The threshold for the change of sleep stage detection was computed as an average of the final curve.

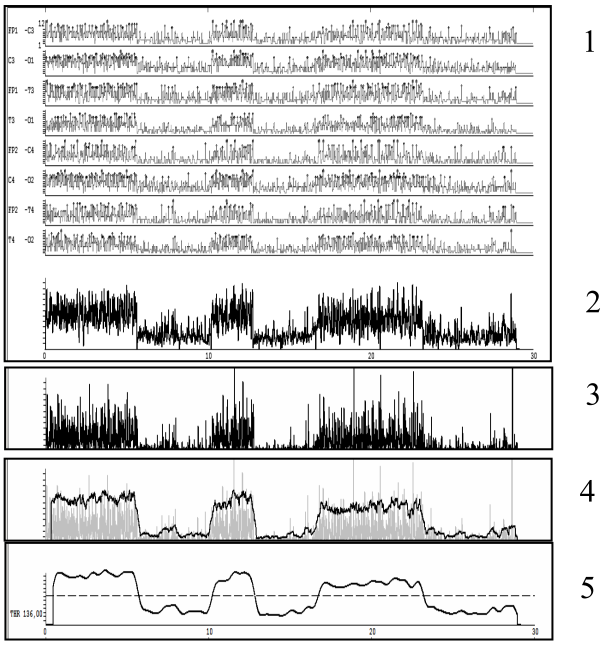


Figure 6. The schematic diagram of the time profiles processing. The numbers correspond to the steps above.

The lengths of MA filters were found experimentally. The sleep stage change is signaled by threshold crossing. This process is illustrated in Fig. 6.

Results

The following pictures show the results of application of the described methods to neonatal EEG records. In all figures, above is the compressed raw EEG signal; below are the time profiles, under them are the curves corresponding to the steps 1-5 from Figure 6. At the bottom is the final detection curve. The visual evaluation of the physician is also showed QS, AS-quiet, active sleep, AW-awake.

Figure 7a shows the processing of the fullterm EEG record (the same signal as in Figure 1a. The Figure 7b. shows the processing of the signal from Figure 1b.

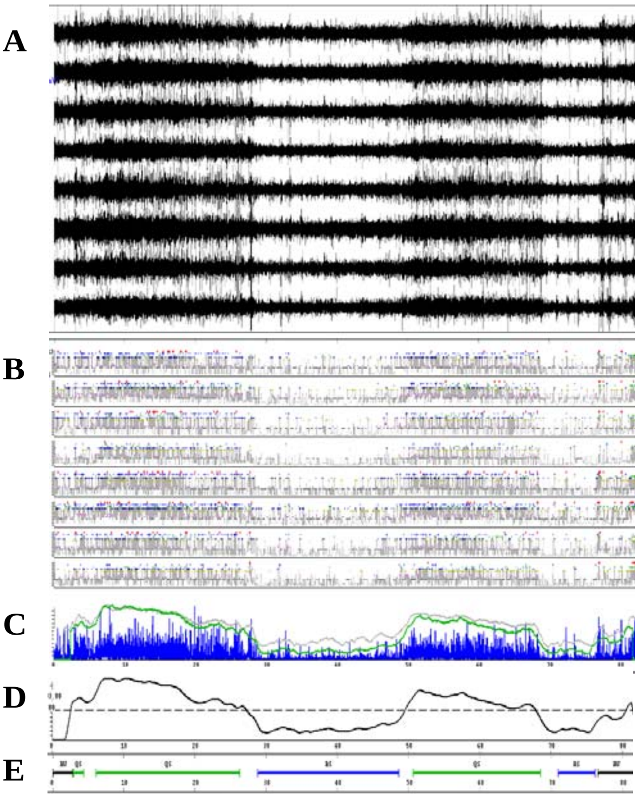


Figure 7a. Full term EEG record (the signal from the Fig.1a). A-original raw EEG. B-structural time profiles. C-curves and parameters resulting from steps 1-5 of the time profile processing (Figure 5). D-resulting detection curve and the threshold. E-visual evaluation of the physician.

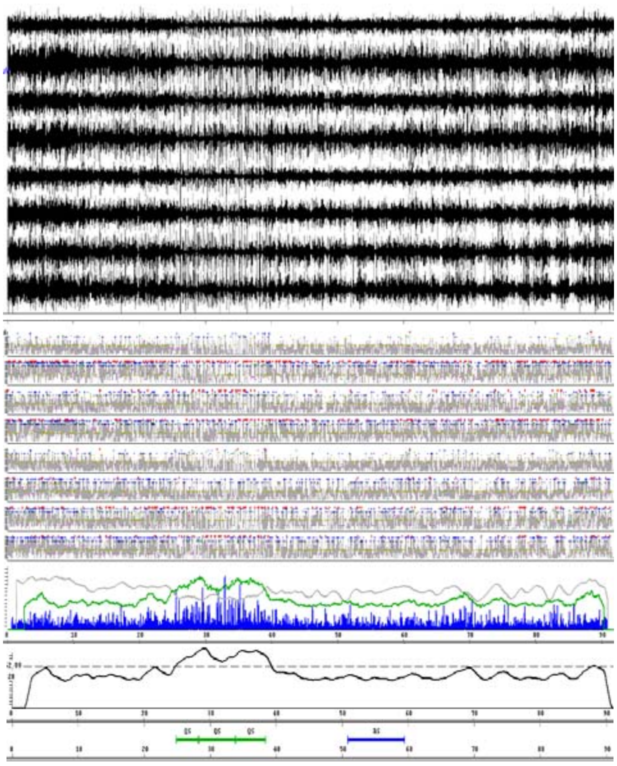


Figure 7b. Preterm EEG record (the signal from 1b).

In the Figure 7b it is shown, that the proposed method can detect the sleep stages despite the fact, that they are not apparent in the compressed raw EEG signal.

Other examples of analysis of the pre term EEG recording are presented in Figures 8, 9.

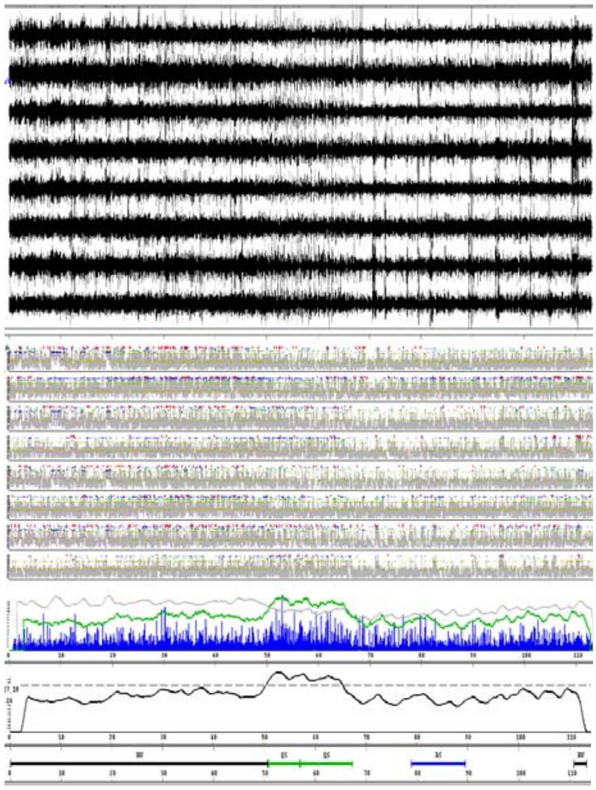


Figure 8. Preterm EEG record.

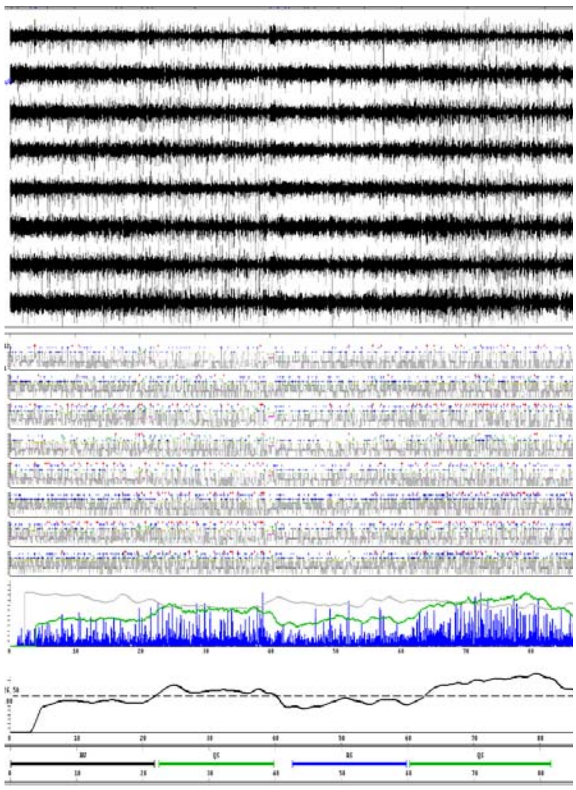


Figure 9. Preterm EEG record.

Discussion

The examples demonstrate that the new method can successfully detect the changes of the sleep state from quiet sleep to the active sleep and vice versa even in the cases of pre term neonates, where the structure of the signal is not as evident, as in the cases of full term neonatal EEG recordings.

The optimal class number during clustering was determined by extreme values of the pseudo-F statistics [12] computed for the clustering into 2 till 25 classes. The most frequent class number was between 12 and 16.

The method describes the electroencephalogram of neonates with sufficient accuracy. The quantitative parameters reflect the difference of EEG activity of quiet and active sleep.

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