

Multichannel Analysis of the Newborn EEG Data

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Abstract: EEG is one of the most important methods of studying the maturation of the child brain. A newborn infant typically sleeps approximately 70 per cent of 24 hour interval. Sleep in infants is significantly different from sleep in adults. This paper addresses the problem of multichannel analysis of newborn EEG signals. The designed technique will be applicable to other similar problem in medicine as well. We apply designed methods for problem of the differentiation between three important neonatal states: quiet sleep, active sleep and wakefulness state. The proportion of these states is a significant indicator for maturity of the newborn brain in clinical practice. In this study we have used data provided by the Institute for Care of Mother and Child in Prague (12 similar aged newborn infants). All recordings have eight EEG channels (these are FP1, FP2, T3, T4, C3, C4, O1, O2), Electrooculogram (EOG), Electromyogram (EMG), Respiratory (PNG) and Electrocardiogram (ECG). Data are scored by an experienced physician to four states (wake, quiet sleep, active sleep, movement artifact). For accurate classification it is necessary to find or calculate most informative features. In our approach we use a method based on power spectral density (PSD) applied to each EEG channel. We also use features derived from EOG, EMG, ECG and PNG signals. The most informative one is the measure of regularity of respiration from PNG signal. We have designed an algorithm for interpretation of these characteristics. This algorithm is based on Markov models. The indispensable part of our work is a comparison of the classifier based on Markov models with various learning algorithms, in particular nearest neighbour, cluster analysis, and induction of decision rules.

I. INTRODUCTION

THE Electroencephalogram (EEG), describing the electric activity of the brain, contains a lot of information about the state of patient health. It has the advantage of being non-invasive and applicable over longer time span (up to 24 hours if necessary). This is an important feature in case we want to follow disorders that are not permanently present but appear incidentally (e.g. epileptic

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seizure) or under certain conditions (various sleep disorders).

The main objective of our work is the design and implementation of appropriate algorithms for neonatal sleep stage classification. During sleep, human brain goes through several psycho-physiological states that are relatively stable. Many nervous centres are inactive, so brain becomes a less complex system and is a suitable object for mathematical modelling. Sleep stages classification is one of the diagnostic tools needed for proper assessment of a number of sleep disorders and other neurological problems [25]. The characterization of the recorded bioelectrical signals is based mainly on the spectral frequency analysis by Fast Fourier Transform (FFT).

In [20] authors described the neuro-fuzzy system for classification of sleep-waking states in healthy infants. They used classifier with a pruning algorithm and achieved accuracy about 70%. In [21] authors compared two methods, heart rate variability and actigraphy, to offer alternative techniques for sleep-wake identification compared to manual sleep scoring. They achieved accuracy 75-80%. Also other publications noted accuracy about 60-80%. Some authors described methods with very high classification accuracy. For example in [22], [26] there are published methods with accuracy more than 95%. But they use the same data for learning and testing. We use data from several newborns for learning, and for testing we use data from another newborn. We utilize hidden information obtained from more biological signals (EEG, ECG, PNG, EMG, EOG) for final classification.

In this study we use data from newborns with a similar gestational age. In [27] there are published results of classification of preterm and term infants from Amplitude-integrated electroencephalography (aEEG).

We have discussed with neurologists the problem of manual scoring accuracy between two or more neurologists, and it is about 70-80%. Therefore it is suitable to show not only final classification but also relevant characteristics from all measured signals.

II. SLEEP STAGES

Sleep is a non-uniform biological state that has been divided into several stages based on polysomnographic measurement (PSG) that includes electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), and oxygen saturation of the blood (SpO₂). It is the most accurate procedure and is considered to be the „gold standard“ in determining sleep states. In addition it is possible to record electrocardiogram (ECG) or respiration (PNG). Polysomnography is usually performed over the

duration of entire night, or at least 6.5 hours, in order to investigate normal and disturbed sleep or vigilance [1].

A newborn infant typically sleeps about 70% of every 24 hours and has two different sleep states that occur in alternating cycles of tens of minutes. These stages have been termed quiet sleep and active sleep, corresponding respectively to NREM sleep and REM sleep in adults. Active sleep is characterized by irregular breathing, saccadic eye movements, small bodily movements and twitches. In contrast to adult REM sleep, peripheral motor pathways are not depressed during active sleep in neonates, making movements possible. During quiet sleep, breathing is regular, and eye and bodily movements are absent. The states have EEG correlates: EEG in quiet sleep shows either continuous high-voltage low-frequency (HVLF) activity or tracé alternant, in which HVLF activity alternates with quiet periods in cycles of few seconds. In active sleep, the EEG is relatively quiet [3].

III. MATERIAL AND METHODS

Data used in this study are provided by the Institute for Care of Mother and Child in Prague (12 infants, normal term gestation, recorded 5-10 days after childbirth, recorder time is about 3 hours for each infant). All recordings have eight EEG channels (these are FP1, FP2, T3, T4, C3, C4, O1, O2), Electrooculogram (EOG), Electromyogram (EMG), Respiratory (PNG) and Electrocardiogram (ECG). Data are scored by an experienced physician to four states (wake, quiet sleep, active sleep, movement artifact). Data are continuous and rather complex. Therefore it is impossible to classify these raw data. In the next subsections we describe feature extraction from individual signal types.

A. EEG FEATURE EXTRACTION

The feature extraction is the automated recognition of various features on an EEG signals. Power spectral density (PSD) is the most suitable feature in this case. Frequency 0.5 to 3Hz is an important feature for sleep staging. It occurs at the quiet stage and is very low at stages of wake and active sleep. It is affected by a pattern known as Tracé alternant (TA). TA pattern [11] is characterized by the occurrence of 3 to 5 second bursts of high amplitude (50 to 100 μ V) slow activity (0.5 to 3.0 Hz), which occur at intervals of 3 to 10 seconds when the background is of relatively low amplitude (10 to 25 μ V). We have been inspired by [15] when designing the frequency features.

Next we recognize quiet sleep from PSD. In Fig. 1 there is shown our simple method for detection of quiet and active sleep. (This method was not suitable for all our data, so we use also method described in section III.F). First we compute the function F_D . It is in detail shown in (1). We set constant t_0 to 10 minutes. We utilize the following found properties: quiet sleep is perceptible mainly on C3 and C4 electrodes and other states on electrodes T3 and T4. Finally we find minima and maxima of this function corresponding

to start and end of the quiet sleep. We use an adaptive algorithm for it. We expect the alternating of maxima and minima. These values are taken over a one-minute window.

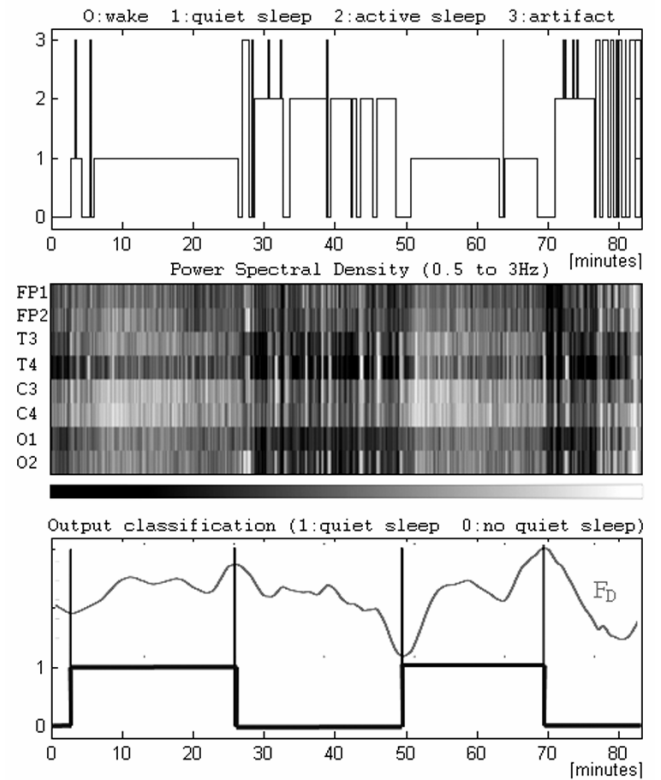


Fig. 1. PSD of all EEG channels (0.5 to 3Hz) and output classification.

$$F_T = \min\{ T3_{mean}(t - t_0, t), T4_{mean}(t - t_0, t) \} \quad (1)$$

$$F_C = \max\{ C3_{mean}(t, t + t_0), C4_{mean}(t, t + t_0) \}$$

$$F_D = F_T - F_C$$

where

$T3_{mean}(t - t_0, t)$ is mean value of PSD taken at T3
from time $(t - t_0)$ to t

$\min\{ A, B \}$ is smaller value from number A and B

B. REGULARITY OF RESPIRATION

One of the criteria for determination of the newborn behavioral states is the regularity of respiration. To determine the properties of signals in terms of shape and periodicity the autocorrelation function is often used [17], [18]. One segment of data (in our case 20 seconds of PNG signals) is correlated with its copy, in small steps shifted in time. At the $t=0$ correlation is one, a shift of half a period results in a negative maximum and a shift of a full period shows a positive maximum again. The waterfall plots of the quiet and active sleep states show a clear difference in the magnitude of the second peak (see Fig. 2). The correlation coefficient of this second peak is therefore a good measure for regularity. It is necessary to solve the problem of the second peak position estimation. This value corresponds to the heart beat. We compute appropriate heart beat from respiratory signal over a one minute window. Final feature corresponding to regularity of respiration is shown in Fig. 3.

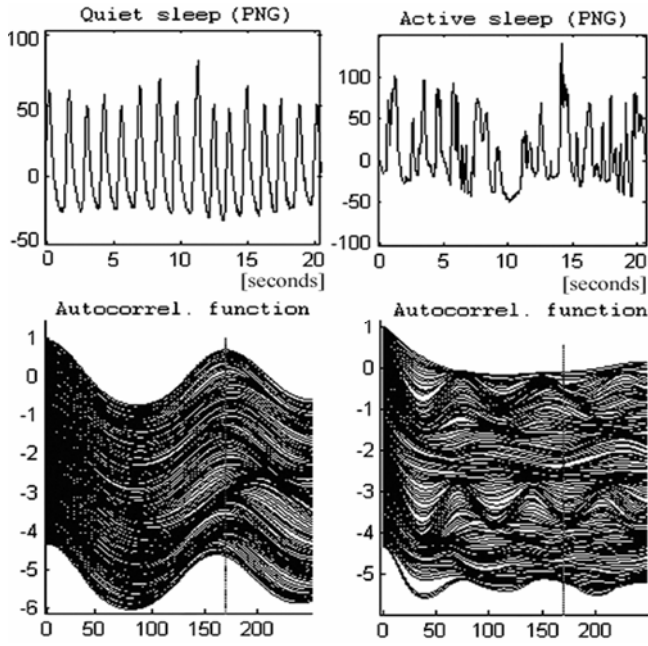


Fig. 2. Waterfall plots of autocorrelation functions computed from the respiration signal.

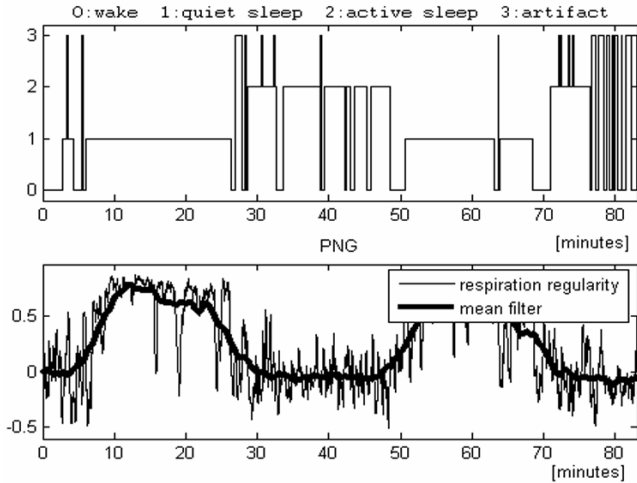


Fig. 3. Final regularity of respiration

C. EYE MOVEMENTS

Eye movements are known to be good measures for stages identification. For our problem, it should only appear in stages wake and active sleep. In the quiet stage there should not be any eye movements.

We detect eye movements using the modified method developed by Varri et. al. [12]. In the original method, the threshold value was set to $10 \mu\text{V}$. In our method the threshold value is calculated for each recording in the following way: 1. Standard deviation of the recording is calculated in 60 second window. 2. The median value of the standard deviations from the whole signal is chosen to the new threshold value. Next the output of the eye movement detection algorithm is converted to 1-2 Hz. The maximum value of eye movements over one second window is chosen as the output. The result is shown in Fig. 4.

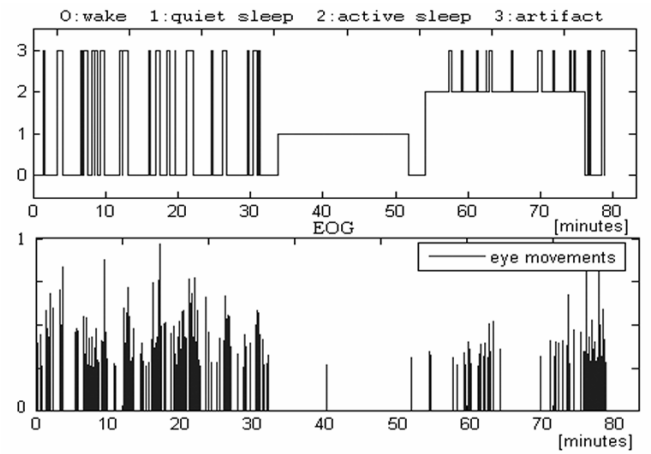


Fig. 4. Detection of eye movements

D. STANDARD DEVIATION OF EMG

One simple feature is sufficient for detection of movement artifacts. It is the standard deviation of signal obtained from muscle activities (chin EMG). Large majority of movement artifacts are present at EMG channel (characterized by the very high amplitude). For further processing it has no sense to classify segments that include movement artifact. We improve the accuracy of artifact detection using combination of mean and max filters (first we use mean filter over a ten second window and as the next step we use maximum value from a one-minute window). The result is shown in Fig. 5. For successive classification it is possible to apply thresholding of output characteristic (threshold computation from combination of mean/median/min/max functions).

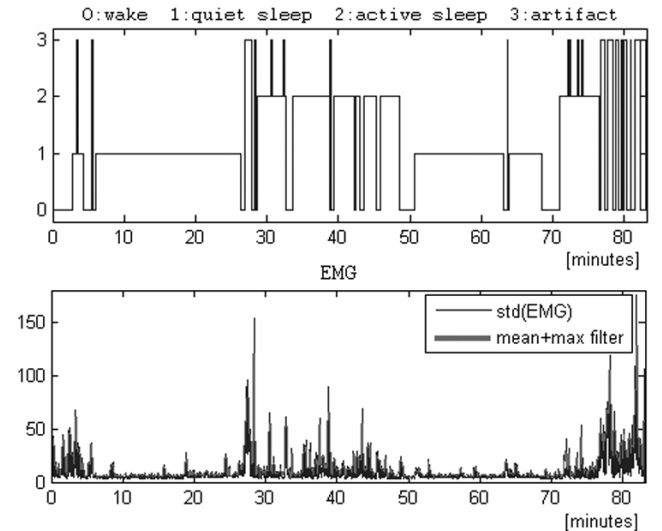


Fig. 5. Standard deviation of EMG signal

E. HEART RATE

The amplitude and the regularity of heart rate is changed during wake and quiet/active sleep. Regularity is good indicator of quiet sleep. In this stage heart rate is low and mainly regular. From the highest amplitude it is possible to

estimate wake stage.

For detection of the heart rate from ECG signal, it is necessary to be able to detect QRS complexes. Various methods can be used for that. One popular algorithm was presented by Pan and Tompkins [6]. In this work, we use a modified version of this algorithm (see Fig. 6). At first we detect the QRS intervals and then we find the R-wave peaks by searching those intervals. Physiologically, the QRS complexes cannot occur closer than 200 ms to each other. If any two R-wave peaks occur faster than this, the later peak is considered an artifact. Finally we compute number of R-waves in 60 second intervals.

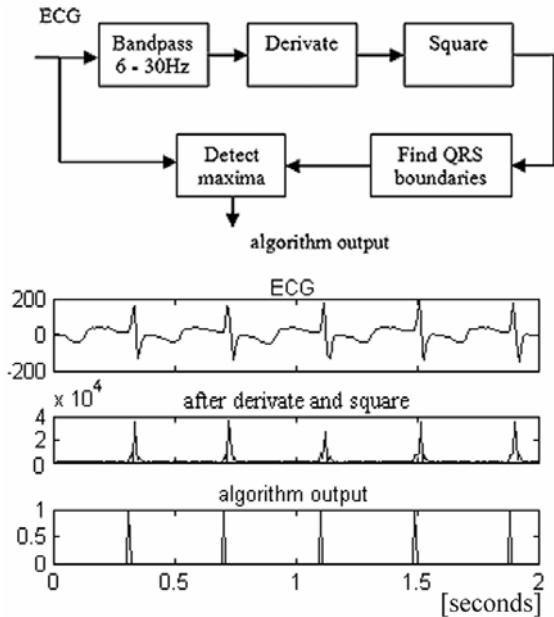


Fig. 6. Algorithm for heart rate detection (on the up) and example of use (on the down)

In Fig. 7 heart rate in beats/minute is shown. For increasing robustness of this method we use mean filter.

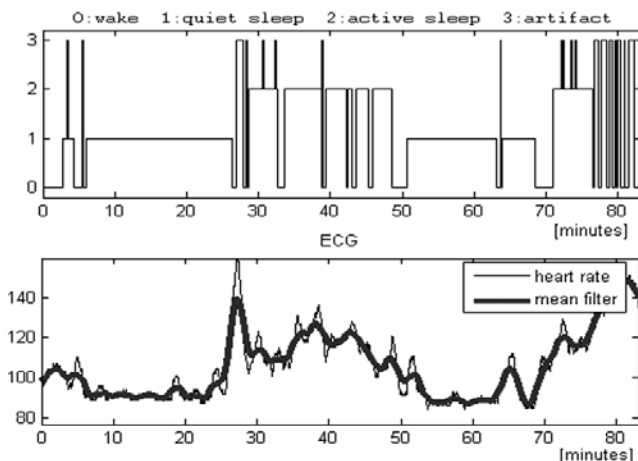


Fig. 7. Final heart rate feature in beats/minute

F. PCA, CLASSIFIER COMPARISON

In Fig. 8 the block diagram for classifier comparison is

shown. We apply principal component analysis [13], [14] for all 12 described features - 8 from EEG (PSD 0.5 – 3Hz for 8 EEG channels) and 4 from PNG/ECG/EOG/EMG. We use PCA for data compression (reducing the number of dimensions, without significant loss of information). In this way we obtain 3 final features (these contain about 93% of information compared to original features). Before PCA we do not use normalized features, we only center them (applying the subtraction of the mean value). After PCA we use for classification Hidden Markov models, nearest neighbour, cluster analysis and decision rules. The training data set for model learning is created in the same way (the feature extraction and PCA). We consider manual scoring provided by a neurologist as correct classification class.

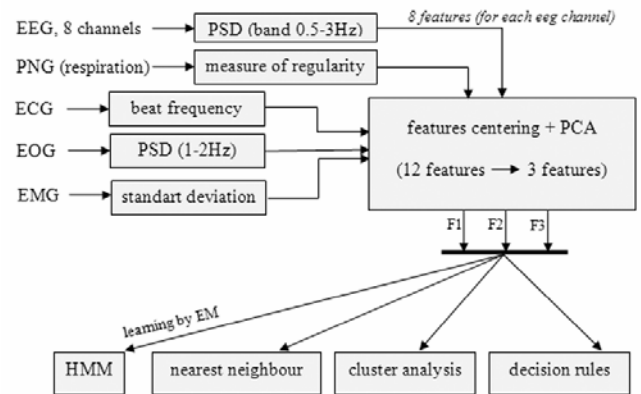


Fig. 8. Block diagram of the method used for classification

G. HIDDEN MARKOV MODELS

In the process of the classical pattern recognition we classify each segment on the basis of the features obtained from this segment. Hidden Markov models (HMMs) are widely used for this problem [23]. HMMs are a special class of stochastic processes that uniquely determine the future behaviour of the process by its present state. We use the EM algorithm for finding the maximum-likelihood estimate of the parameters of HMMs given a set of observed feature vectors. This algorithm is also known as the Baum-Welch algorithm [9]. The Baum-Welch algorithm starts from an initial model and iteratively improves it until convergence is reached (in our case it is sufficient to use 10 interactions). Since the Baum-Welch algorithm searches for a locally optimal HMM with respect to the likelihood function, the choice of an initial model is crucial [24]. We compute this initial model from the training data set.

We have designed a HMM structure and we have used the probabilities for description of all relations. In our case, HMMs allow to describe relations between features and hidden states (all sleep stages) and mutual relations between individual hidden states (see Fig. 9). We use four hidden states - active sleep, quiet sleep, wake stage and movement stage. The introduced method is very useful for our problem. Likewise if there exist segments about which we have no

information, HMMs allow classify these segments by using known state-transition probabilities.

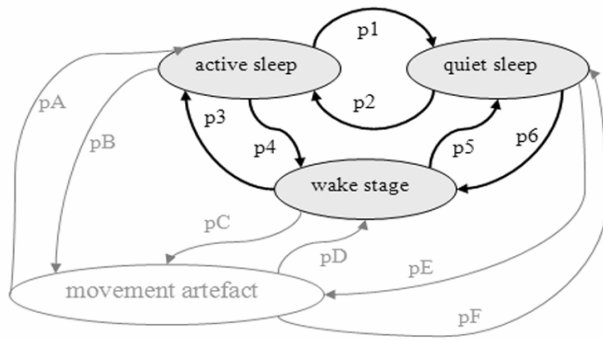


Fig. 9. Hidden states structure, p1-p6 and pA-pF are transition probabilities

H. NEAREST NEIGHBOUR, CLUSTER ANALYSIS, DECISION RULES

We compare results from HMMs with others classifier. Final accuracies are described in section IV. First we have used a method based on the nearest neighbour classifier. This very simply model depends on the quality of the training set. It is possible to achieve good results on the known data (the training data set corresponds to the testing data set), but it has no ability of generalization. This classifier does not work correctly on the unknown data.

Next we have tested cluster analysis. In the output feature space we have tried to find significant four clusters. The found centres of these clusters are classified using the nearest neighbour classifier to individual neonatal states. This analysis is not extremely accurate, but it separates some states (active sleep and movement stage).

The classifier based on decision rules has not only been good classifier, but it has also described important trends in data. For the decision rule classifier we do not use features after PCA processing but those original 12 features. The accuracy and the ability of generalization has influenced number of used rules (optimal number has been 10-15 different rules, great number of rules means high accuracy but low ability of generalization). We use Weka software [19] for finding the rules.

IV. RESULTS

In this section we summarize the results of our research. [Table I] shows all recognized dependencies. Similar results are described in [16]. All neonatal states have been recognized by combination of EEG, EMG, EOG, PNG and ECG features. The accuracy of classification is in detail shown in [Table II] and [Table III].

V. CONCLUSION

Sleep in infants is significantly different from sleep in adults (both sleep architecture and continuity). In this paper methods for classification of the newborn EEG have been

TABLE I.
STATE-RELATED POLYGRAPHIC CHANGES

Physiological Measure	AWAKE / SLEEP STATE		
	Awake	Active Sleep	Quiet Sleep
Electromyogram	higher	higher	lower
Respiration	irregular	irregular	regular
Body movements	much	little	none
Eye movements	random + blink	REM	none
Heart rate	higher, irregular	irregular	lower, regular

TABLE II.
FINAL ACCURACY OF CLASSIFICATION 1

	active sleep	quiet sleep	wake stage	movement stage	mean
HMM + EM	84%	89%	82%	72%	82%
nearest neighbour	79%	80%	74%	69%	76%
cluster analysis	65%	71%	62%	68%	67%
decision rules	72%	78%	64%	74%	72%

We have used all data from 12 newborns and cross-validation (10 group). For HMMs we use the training set only for learning of an initial model. For cluster analysis we use the training set only for classification of final clusters (by the nearest neighbour method).

TABLE III.
FINAL ACCURACY OF CLASSIFICATION 2

	active sleep	quiet sleep	wake stage	movement stage	mean
HMM + EM	71%	74%	73%	63%	70%
nearest neighbour	59%	56%	59%	61%	59%
cluster analysis	62%	66%	58%	59%	61%
decision rules	63%	71%	63%	61%	65%

We have used data from 11 newborns for learning and data from remaining one newborn for testing. This procedure has been repeated for all newborns and computed mean value. For HMMs we use the training set only for learning of an initial model. For cluster analysis we use the training set only for classification of final clusters (by the nearest neighbour method).

presented. The approach has been tested on real sleep EEG recording for which the classification has been known. The aim of these methods is to ease the work of medical doctors. During automated classification we have problem with clear separation of stages of wake and active sleep. Now we try to find hidden information enabling this separation. We are developing methods for rapid eye movements detection from EOG signals and try to detect specific graphoelements in EEG signals.

Computer-assisted methods can extend our abilities to examine physiologic relationships between cerebral and non-cerebral measures, and explore associations with representative outcome variables.

In our further research we will develop methods for quantification that can help in evaluation of newborns brain maturity. These methods can be used for on-line analysis of premature newborns. Nowadays this analysis is made only in off-line mode (measuring of appropriate signals and manual scoring by a physician afterwards).

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