Inductive Modeling in Newborn Sleep Stage Recognition

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Abstract. *This paper addresses automated classification of newborn sleep electroencephalogram (EEG) using inductive classification methods. Newborn EEG plays an important role in determining the maturity level of neonatal brain. Polysomnography (PSG) recording can be classified into four important behavioral states: quiet sleep, active (non-quiet) sleep, wakefulness and movement artifact. Infant sleep significantly differs from adult sleep; we therefore apply methods designed for the problem of differentiation between the described states. The proportion of these states is a significant indicator of the maturity of the newborn brain in clinical practice. In this study we use data provided by the Institute for the Care of Mother and Child in Prague (12 newborn polysomnografic signal; similar postconceptional age; all data are scored by an experienced neurologist). Automated classification is performed by inductive models evolution through ant-colony approach (ACO-DTree algorithm) and the GAME (Group of Adaptive Models Evolution) inductive models. The results are compared with standard cross validation method. Using inductive modeling methods produced better results with improved generalization skills of the classifier. The purpose of this study is to facilitate the work of neurologist.*

Keywords

Inductive modeling, electroencephalograph, neonatal, sleep stage classification, ant colony optimization, ACO-DTree, GAME.

1 Introduction

Electroencephalogram (EEG) is one of the most important methods of studying maturation degree of neonatal brain. A newborn infant typically sleeps approximately 70 per cent of an 24 hour interval.

In adult sleep, the characterization of recorded bioelectrical signals is mainly performed using spectral frequency analysis. In the case of newborns, different methods have been often used [1], e.g. fractal analysis, dimensional analysis and nonlinear analysis. Active newborn sleep is characterized by irregular breathing, saccadic eye movements, small body 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. These states have EEG correlates: EEG in quiet sleep shows either continuous high-voltage low-frequency (HVLF) activity or trace alternant, where HVLF activity alternates with quiet periods in cycles of few seconds duration. In active sleep, the EEG is relatively quiet [10].

The main aim of our study was to design and develop a combination of feature extraction and classification methods for automatic recognition of behavioral states using polygraphic recording. Such method would speed up and objectify identification of described states and may be used for online classification and can be used as a hint to the neurologist. Till now the identification has been performed manually through visual analysis of the recordings. In our study, first the feature characteristics for individual states were identified and extracted from polygraphic recordings. Then the behavioral states were identified from extracted features using several classification methods. The manual scoring accuracy between two or more neurologists is about 70–80 %.

In [9] 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 our previous study [2] we used Hidden Markov Model combined with EM algorithm [2]. This approach produced satisfactory result (average accuracy 74 %). The results of automatic detection of sleep states were compared with visually determined “sleep profiles”. Statistically significant agreement of both scorings has been found. Some authors described methods with very high classification accuracy. For example in [7], [8] there are published methods with accuracy more than 95%. But they use the same data for learning and testing.

Inductive modeling is an inherent property of many nature systems. For nature has evolved for many centuries, the methods evolved throughout the natural selection process leading to highly robust and efficient concepts. Modeling of such concepts often leads to improved robustness and adaptivity of optimization methods [4]. In this paper we use hybrid classification method which incorporates the evolutionary algorithm together with an ant colony optimization (ACO) [5] approach. The individuals (solutions) in the algorithm are induced using the ACO approach.

Another algorithm we utilize in this study is the GAME [11] method. It proceeds from theory of inductive modeling, and it contains several nature inspired optimization strategies to adjust the structure of the model and its transfer functions.

2 Theoretical Part

2.1 Group of Adaptive Models Evolution (GAME)

The GAME is an inductive model that means it is automatically generated from a data set. It grows from a minimal form during the learning phase, until the optimal complexity is reached. For detailed description of the algorithm see [11].

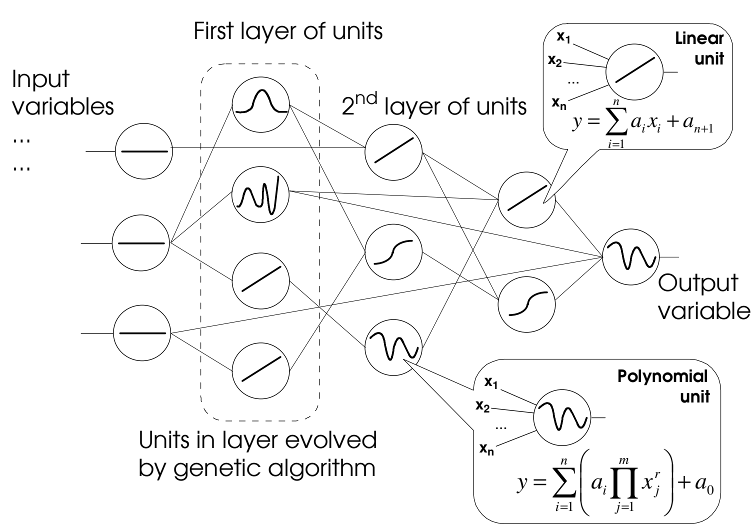

Fig. 3.1. Model generated by the GAME method

More detailed description of the GAME method in the full version of the article.

2.2 ACO_DTree method

As described in [4], nature inspired methods can be successfully used in data mining process. The method used (ACO-DTree) [6] uses an evolutionary approach combined with ant colony optimization approach: *Evolutionary methods* work on the population basis, where the individuals (candidate solutions) are evolved in Darwinian style. *Ant colony optimization* is based on the real ant colony behavior in nature: ants deposit a chemical substance (pheromone) through time. The pheromone concentrates in areas frequently visited by the ants, leading to the discovery of the shortest path. In addition, as the pheromone evaporates, the ants are able to cope with dynamically changing environment.

The ACO-DTree method works with a population of classifier trees (a decision-tree like structure): a hierarchical binary structure of nodes where each node divides data set into two parts using a single if-rule (e. g. `if` (feature[i] < value) `then` pass_data_left `else` pass_data_right). The population is continuously evaluated, new individuals are continuously added and worst solutions removed. Only the best individuals can contribute in pheromone laying process (in compliance with [5]). New individuals are inductively created using the pheromone matrix, preferring important features (features selected by the best individuals).

2.2.1 Decision Tree Construction

By a classification tree we mean hereby a tree-like structure composed of similar nodes. Each node can have left and right sub node. Each node is represented by a decision rule with two parameters (feature index $j \in \langle 0;n \rangle$ and decision value $decisionValue \in Supp(f_j)$) which can be described in the following way for an item $s_i \in S$:

```
t1  if (si.feature(j) < decVal)
t2    classifyToLeftBranch
t3  else
t4    classifyToRightBranch
```

The same applies to the root node. By level in the tree we mean the distance from the given node to the root node. Tree height is a maximum level in the tree. Depending on the classification tree, the data are divided into subgroups which should have similar properties (minimization of intra-cluster distance) and the classes should be different (maximization of inter-cluster distance). This process is known as data clustering.

2.2.2 Decision Tree Evaluation

Each tree can be assigned a real number $e \in \mathbf{R}$ which can be called fitness function. Such number represents the classification efficiency of the tree. In the method this number is determined by the ratio of incorrectly classified data to the total data in the class (in this paper it is called *error ratio*). The goal of our method is to obtain tree with the lowest error ratio on the dataset. For method evaluation, the training data set is used. The testing dataset is used to evaluate the tree on the unknown data (data which have never been presented to the tree). If the classification of the testing data is not known, cluster validation techniques can be used.

2.3 Feature extraction

All recordings used in this work contain eight EEG channels (these are FP1, FP2, T3, T4, C3, C4, O1, O2), Electrooculogram (EOG), Electromyogram (EMG), Respiratory channel (PNG) and Electrocardiogram (ECG). All the data have been annotated by an expert into four classes (wake, quiet sleep, active sleep, movement artifact). For accurate classification it is necessary to determine and/or calculate the 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.

The following methods, which have been used for feature extraction, are in detail described in [2]:

2.3.1 EEG signal
First, we focused on computing features derived from the EEG signal. We computed Power spectral density (PSD) for common frequency ranges (delta, theta, alpha, beta, and gamma).

2.3.2 PNG signal
One of the criteria for determining newborn behavioral states is regularity of respiration. We have used use the autocorrelation function in this case.

2.3.3 EOG signal
We detected eye movements using the modified method developed by Värri et al. [3]. This approach is based on applying a weighted FIR-median-hybrid (FIR-MH) filter.

2.3.4 ECG
For detecting the heart rate we used modified version of Pan and Tompkins algorithm.

2.3.5 EMG
In newborns, there is a major problem with movement artifacts. A large majority of these artifacts is present in the EMG channel. It was sufficient to use the standard deviation feature for this signal.

3 Experiments
Numerous tests have been performed; only the most promising ones are mentioned. In all experiments we used recordings of eight newborns. Significant results have been obtained in the task of automated artifact removal and distinguishing active sleep from the non-active one. This paper concentrates on distinguishing all the four classes. The data (approximately 42 000 data vectors) have been randomly assigned into 10 cross-validation folds. The resulting classification accuracy is averaged from the performance of methods tested on all folds. The goal of the classifiers was to separate different classes of the PSG recording correctly (and minimize the classification error). In ACO-DTree method, the maximum tree level has been set to 9.

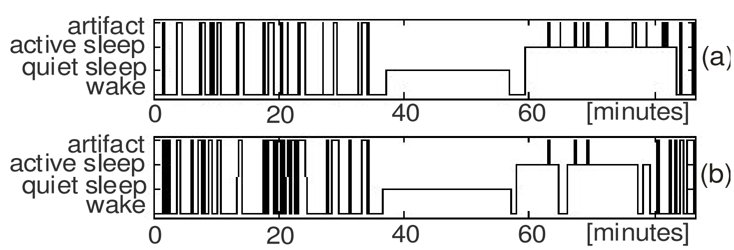

Fig. 1. Final classification. (a) manual evaluation by an expert, (b) final classification

4 Results

The ACO-DTree method has been compared with RandomTree method from widely used WEKA data mining software (http://www.cs.waikato.ac.nz/ml/weka) and the GAME inductive models. The results are summarized in Table 1. The tree depth of the RandomTree method was unlimited.

4.1 GAME Results

We have experimented with the configuration of the GAME engine. The best configuration for this problem seems to be standard setting. It means that heterogeneous units are enabled, optimized by Quasi Newton, a niching genetic algorithm optimizes units for 30 epochs in each layer.

Table 1: Classification results of the GAME engine in percent on individual folds (10-fold cross-validation technique has been used).

Configuration of GAME	Fold 0	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	**Average**
Quick	70.18	72.39	70.89	72.08	73.2	70.13	72.01	72.32	68.65	72.92	**71.477**
Standard	73.44	75.08	74.7	75.27	73.08	72.27	74.94	74.16	71.85	71.92	**73.671**

4.2 Final evaluation of inductive methods

All methods were tested on identical data folds.

Table 2: Comparison of methods: classification results obtained by 10-fold cross-validation technique. Methods were evaluated on identical folds.

Test	**ACO-Dtree**	**GAME**	**RandomTree**
Classify all classes	68.832%	73.671%	66.179%

5 Conclusion

Sleep in infants is significantly different from sleep in adults (both sleep architecture and continuity).

The methods for automated classification of adult sleep EEG cannot be applied to neonatal EEG, due to fundamental differences in sleep architecture, continuity and EEG patterns.

This paper presented methods that can help to classify the newborn PSG. The most important part of the work was identification of the most informative features in all PSG signals and their successive extraction. The applicability of these features was verified. They were utilized for classification and we reached very good results. Note that in the case of RandomTree classifier, no limit on the tree depth has been used (in the case of ACO-DTree method, the limit has been set to 9). All the inductive methods show promising results, inducting the models using the training data.

Both the ACO-DTree and GAME method also (as a side effect) produces feature rating (based on the pheromone amount), which can be further used for feature selection. The accuracy of results obtained is comparable with manual classification accuracy and the characteristics can be used as a hint to neurologists for neonatal sleep stages evaluation.

The ACO-DTree method has also gained good results when classifying noise contained in the EEG recording.

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