UTILIZATION OF TIME-DEPENDENCE IN EEG SIGNAL CLASSIFICATION

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Abstract: Manual evaluation of long-term EEG recordings is very tedious, time consuming, and subjective process. The aims of automated processing are on one side to ease the work of medical doctors and on the other side to make the evaluation more objective. This paper addresses the problem of computer-assisted sleep staging. It describes ongoing research in this area. The proposed solution comprises several consecutive steps, namely EEG signal pre-processing, feature extraction, feature normalization, and application of decision rules. The EEG signal contains contextual information as well. The most important part of it is time-dependence that can be advantageously processed by the Markov models.

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

The main objective of our work is the design and implementation of appropriate algorithms for automated sleep stage classification. During sleep, human brain goes through several psychophysiological 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. The characterization of the recorded bioelectrical signals is based on the spectral frequency analysis by Fast Fourier Transform (FFT).

Our approach to the analysis of human sleep uses a set of pre-defined rules to allocate each 30-s epoch to one of six main sleep stages. Furthermore we use the Markov models for utilization of the contextual information in biological signals.

The correct classification of ill persons is important for proper treatment. We used for our experiment biological records rated by an expert. These records are freely available and downloadable from the webpage [1].

Sleep Stages

Sleep is a non-uniform biological state that has been divided into several stages based on polysomnographic (PSG) measurements that include EEG, EMG, EOG, ECG, temperature, SpO_2 (oxygen saturation of the blood, recorded on the finger), respiration signals, as well as movement or body position. Polysomnography is usually performed over the duration of an entire night, or at least 6.5 hours, in order to investigate normal and disturbed sleep or vigilance [2]. Normal healthy sleep is organized into sequences of stages that typically cycle every 60 – 90 min. The most widely used standard for terminology and scoring of sleep stages is the manual by Rechtschaffen and Kales (RK) [3]. A standard summary method is the hypnogram that graphically represents sleep stages in 20-30 second epochs.

The PSG can be generally divided into epochs of 10, 20, 30, or 60 s, which are then visually classified into one of RK stages by a sleep technologist. The resulting time evolutionary description of sleep in terms of stages, termed hypnogram, is used by physicians for diagnosis.

The Rechtschaffen and Kales manual details a complete process of recording and analysing sleep, which is followed by the vast majority of sleep laboratories, worldwide. The sleep period is divided into epochs (usually of 30 seconds duration) and the „stage of sleep“ in each epoch is identified by application of criteria developed by Rechtschaffen and Kales. On the basis of EEG (plus EOG and EMG), epochs can be scored into sleep stages:

- Stage 1 – shallow/drowsy sleep;
- Stage 2 – light sleep;
- Stage 3 – deepening sleep;
- Stage 4 – deepest sleep;
- Stage REM – dreaming sleep.

Stages 1 to 4 are frequently described as non-REM sleep, and stages 3 and 4 are described as slow wave sleep (SWS). Other scores are Wake (W) and Movement Time (MT).

Since the depth of sleep changes continuously, the artificial demarcation of sleep stages by the RK classification is a simplification. The exact time of change of state is highly subjective and leaves room for interpretation by the physician (scorer) who will score transitional epochs (e.g., Stage 1 and Stage 3) differently on different occasions [4].

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Studies have shown agreement between physicians performing scoring that ranges from 67% to 91% [5], [6], [7], depending on different scoring epoch lengths and number of readers. However it is necessary to remark that most data on interscorer agreement are based on the study of normal subjects.

Processing of sleep recordings requires elaborate training and is time consuming and expensive. No generally accepted standard exists for automatic sleep staging, but computerization can improve efficiency and reduce cost [8], and enhance collaboration between laboratories [9].

Computer Classification of PSG

Visual analysis of recordings is subjective, very tedious, and time consuming therefore it leads researchers to investigate computer classification of PSGs.

Various approaches have been used. Johnson et al. [10] presented a spectral analysis study of the EEG in different stages, which was subsequently used by Larsen and Walter [11] to develop an automated staging technique based on multiple-discriminant analysis. Several investigators presented hybrid techniques that pre-process the data using analogue techniques followed by digital decision-tree like methods. Other methods are based on combination of wave detection and Bayesian approach; on interval histogram; on expert system; on neural network model; on fuzzy clustering.

Although some of the studies show acceptable performance, they are limited to selected populations and none have found acceptance in the clinical setting. Much of this can be attributed to the subjectivity with which the RK classification is adapted for transitional epochs in different laboratories. Additionally, some approaches require threshold and algorithm adjustments for different patient groups.

Agarwal and Gotman [12] use a method based on the segmentation and self-organization technique. In the first phase, the PSG is pre-processed to decompose the record into stationary segments; sleep-related features are then extracted from each segment. In the second phase, the extracted features are processed to generate the hypnogram. The segments are organized into homogeneous clusters based on the features. The reviewer subsequently classifies each cluster of like-patterns into stages, allowing user-defined stages to be incorporated. In short, the following five steps are necessary to perform computer-assisted staging:

- segmentation;
- feature extraction;
- clustering;
- assignment of stages to different clusters of patterns;
- optional smoothing of the hypnogram.

The study [12] shows that the greatest discrepancy occurs in Stage 1. The sensitivity and the specificity are 38.6% and 43.4%, respectively. This is to be expected in the highly transitional Stage 1. Stage 1 also has significant similarities to REM stage and can be considered as one stage away from Stage 1. Moreover, it is accepted that manual scoring of Stage 1 is the most subjective due to its transitional nature.

Proposed Approach

In our study we have used similar procedure as Agarwal and Gotman. The sleep EEG signal classification comprises several steps:

- segmentation,
- feature extraction,
- feature normalization,
- generation of decision rules, and
- generation of Markov models.

Feature Extraction

The feature extraction is the automated recognition of various features on an EEG signals. Power spectral density is the most suitable feature in this case. We use signals from two EEG electrodes (*Fpz-Cz, Pz-Oz)* and EOG signal. At first we resample these signals with the frequency of 128 Hz. It speeds up total computing time. Next we divide signal into 1 second segments. We compute first FFT in each segment and then mean power density in individual frequency bands for each segment. Most important are the following bands: 0.5 - 3Hz (Delta wave), 13 - 15Hz (sleep spindle), 16 - 30Hz (Beta wave) and 0.15-1.2Hz for EOG.

Feature Normalization

The features obtained in this way contain great number of peaks. Since the highest peaks agree with artefacts, we replace them by preceding values. Then we normalize all features. For the execution we have implemented the following method. First we compute the threshold values for every feature (e.g. the mean value multiplied by a constant) and this value is used. Then all values above the threshold are changed to "1" and values below the threshold are changed to "0". Next we divide features into 30 second segments and for every segment compute the percentage representation of value „1" (0 - 100%).

Final features correspond to important trends in EEG signal. This principle of this method is shown in the Figure 1.

Decision Rules

We compute all features of all patients and convert them to the Weka format. Weka [13] is a collection of machine learning algorithms for data mining tasks. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization.

We create from each 30s segment the "instance". It contains the appropriate attributes (frequency features) and appropriate category (sleep stage). For the finding of the rules we use the cross-validation. Cross-validation consists of dividing the data into *m* subsets. In each step, one subset is used as the testing set and the rest of the

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original data is used as the training set. The estimated error rate is the average error rate (expressed in percents of miss-classifications) from these subsets. In this work, leave-one-out cross-validation where *m* equals 10.

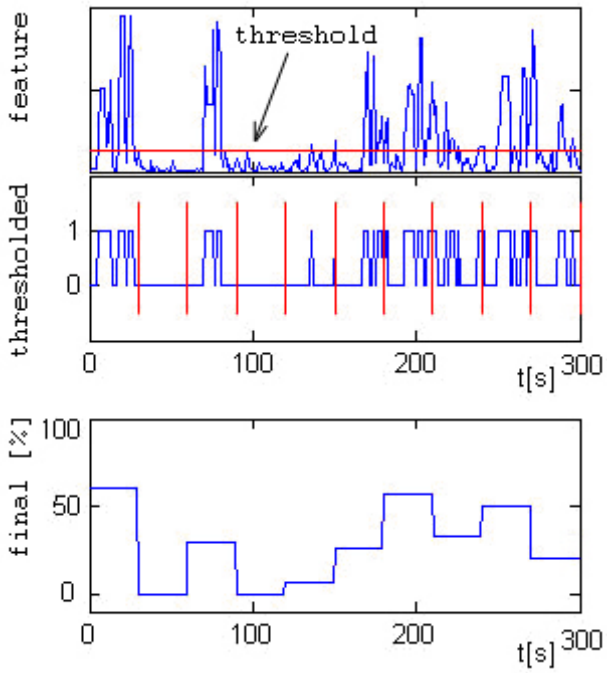

Figure 1: Feature normalization

WEKA contains an implementation of the Apriori algorithm for learning association rules. Apriori algorithm can compute all rules that have a given minimum support and exceed a given confidence value. Figure 2 shows the most significant found rules.

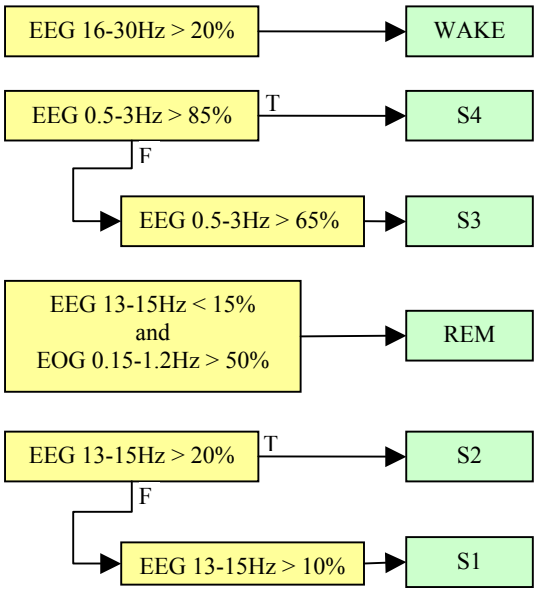

Figure 2: Decision rules

These simple rules correspond with the known characteristics of the EEG. For example in the deep sleep there dominate very low frequencies (delta waves) and in the Wake stage beta waves.

Utilization of Time-Dependence - Markov Models

We create the matrix of state probabilities by using all aforesaid rules. If in the same segment there are more true rules, we modify matrix of the state probability (see Figure 3). Next we use the pre-computed matrix of transition probabilities. It can be computed from all available hypnograms obtained by the expert. This matrix means a probability of the transition from one stage of sleep to the other stage. The zeros mean an impossible transition. Markov model [14] allows find the likeliest final chain from these two probability matrixes. We use for this calculation the Viterbi algorithm [14], which finds the optimal solution. This algorithm is reasonably fast.

In the process of the classical pattern recognition we classify each segment on the basis of the features obtained from this segment. If we know probabilities of the transitions between sleep states we can use this information by using Markov model. Markov processes are a special class of stochastic processes that uniquely determine the future behaviour of the process by its present state. This means that the distributions of events (rates of occurrences) are independent on the history of the system. Furthermore, the transition rates are independent on the time at which the system arrived at the present state. Thus, the basic assumption of a Markov process is that the behaviour of the system in each state is memoryless. The transition from the current state of the system is determined only by the present state and not by the previous state or the time at which it reached the present state. Markov models are widely used to model sequential processes, and have achieved many practical successes in many areas.

In our case, Markov models allow to describe relations between features and inner states (sleep stages) and mutual relations between individual inner states. We have had to design a Markov model structure and we have used the probabilities for description of all relations.

The introduced method is very useful for our problem. If there exist segments about which we have no information (all decision rules are false), Markov model allows classify these segments by using previous segments and transition probabilities. We replace all values in the states probabilities for these segments by the identical probabilities.

Results

Figure 4 shows two hypnograms. At the top is the hypnogram rated by the expert and at the bottom is the hypnogram obtained by our method.

Stages Wake, REM and S4 are recognized relatively precisely. The stage S3 is very similar to the stage S4. The problem is also with the stage S1, which is between Wake stage and stage S2. The results show the problem of

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exact classification of transition states, which is closely linked with subjective rating of the expert because the expert rating has been used for training of the system.

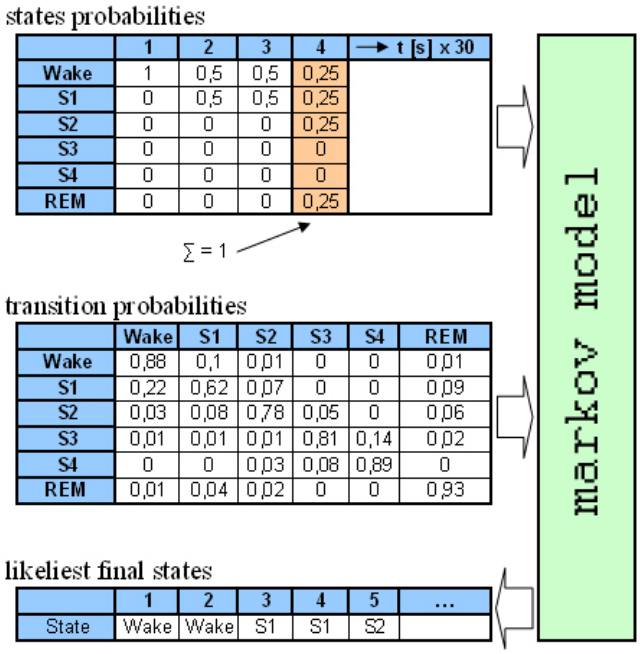

Figure 3: Markov model

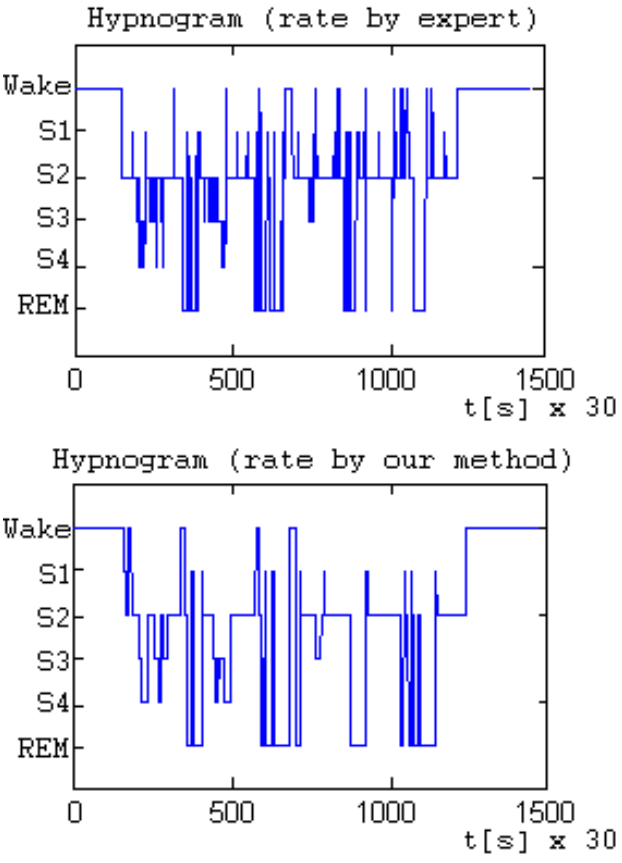

Figure 4: Final solution

Conclusion

Sleep problems belong to the most common serious neurological disorders. Reliable and robust detection of these disorders would improve the quality of life of many people. The implemented methods allow automatic classification of EEG signals. The approach has been tested on real sleep EEG recording for which the classification has been known. Final classification accuracy has been approximately 80% (not considering errors in the transitional stage S1). The designed technique will be also applicable to similar problems in other areas of medicine.

The classification could be improved by using a cluster analysis or methods of pre-processing (filtering EEG signal and removing artefacts). We also plan to test new features, detect k-complex waves and use EMG.

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