Usage of Hidden Markov Models for automatic sleep stages classification

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Introduction

Brain activity level is determined by wake-sleep cycle. Sleep is organized as a sequence of several stages. Their cyclic organization proves the existence of the special regulatory system. This work is devoted to development of the algorithm for automatic sleep stages determination and following study of brain bioelectric activity during healthy sleep.

The most popular and widely used system for sleep classification was developed by Rechtschaffen and Kales (R&K) in 1968 [7]. The system allowed to standardize the criteria for sleep stages discrimination and thus provided the possibility to compare results of experiments from different laboratories and hospitals. According to that method, the whole EEG record is firstly divided on segments lasting 20-30 seconds and then for each segment main amplitude and spectrum parameters for standard EEG rhythms are calculated. By analyzing those values a human expert, e.g. somnologist, makes a decision about membership of analyzed segment to particular sleep stage.

Obviously, it is very hard and time consuming to use that method for analysis of whole night sleep recording which sometimes lasts as long as 8-10 hours. In spite of tremendous number of research in the field of automatic sleep stage classification [3, 5, and 8], still manual sleep staging systems are more popular than automatic ones.

For objective sleep studying we have used the polysomnography method which comprised on electroencephalography (EEG), electrooculography (EOG) and electromyography (EMG) registration. Then amplitude and frequency features were calculated and fed to neural net classifier based on Hidden Markov Models (HMM) [1]. That allowed us to identify sleep stages and phases and to build their sequence known as a hypnogram.

The results of that classification were validated by comparison with classification made by human expert who had utilized R&K rules. We have demonstrated that HMM can be used for sleep staging based only on 2 bipolar EEG channels (Fpz-Cz and Pz-Oz) with the quality sufficient for usage in real diagnostic process.

Sleep structure

Two different phases are discriminated during a sleep – slow wave sleep (SWS) and fast sleep (FS) [1]. In turn, slow wave sleep phase is divided on several stages. Each stage has different EEG picture and reflects difference in sleep depth:

Stage I, or drowsy stage, is characterized by gradual replacement of 8-12 Hz alpha-rhythm with low frequency oscillations like 4-7 Hz low amplitude theta-rhythm and some delta activity as well as low voltage high frequency beta activity. EEG can be described as a flat desynchronized signal with polymorphic low voltage components. Usually that stage lasts from 1 to 7 minutes. Slow waves appear mostly at the stage end. Their amplitude is below 75 µV.

Stage II is characterized by appearance of sleep spindles. Spindles duration is 0.5-3 seconds and amplitude is around 50 µV. Also in that stage K-complexes appear. They look as biphasic potentials frequently followed by sleep spindles. Their amplitude is maximal at vertex...
and duration is not less than 0.5 seconds. These complexes emerge spontaneously or as a response on sensory stimuli.

*Stage III* is characterized by increasing the delta activity with amplitude higher than 75 µV. This activity occupies from 20 to 50% of all segment duration.

*Stage IV* is defined then amplitude of delta waves exceeds 75 µV and the waves occupy more than 50% of the segment duration.

*Fast sleep phase* is characterized by abrupt decrease of EEG amplitude with appearance of specific saw-tooth like signals, low voltage fast activity and rare alpha activity. Fast eye movement can be recorded by EOG channels and overall muscle tonus is decreased as registered by EMG channel. This phase is also referred as Rapid Eye Movement (REM) phase or paradoxical sleep.

In natural conditions a sleep starts by slow wave phase ranging from shallow sleep stage 1 to deepest stages 3 or 4 and then is replaced suddenly by fast sleep phase. That forms a single sleep cycle which lasts 90-120 minutes. During a whole night 4-5 such cycles can be observed for healthy persons. The duration of fast sleep is minimal at the sleep onset but gradually increases toward morning. In contrary, the duration of deep sleep (stages 3 and 4) is maximal at the 2nd and 3rd sleep cycle and diminishes toward the sleep end.

**Method**

For automatic sleep stage classification we have used signals from two EEG channels. Records were cut on 30 seconds segments. To extract and evaluate delta, theta, alpha and beta rhythms each segment was windowed by Hamming window and then filtered in correspondent frequency range by FFT-based band pass filter.

After filtration rhythm indexes and amplitudes were calculated. The amplitude was calculated as a difference between adjacent maximum and minimum. To define rhythm index we set a threshold. If amplitude of some signal portion exceeds the threshold, then that part was considered as containing the rhythm and its duration was added to index calculation. Additionally, we set upper threshold to eliminate movement artifact from calculations.

Alpha rhythm characteristics were defined from signal registered on Pz-Oz bipolar lead. To calculate features of other rhythms we have used Fpz-Cz bipolar lead.

Classification was made by utilizing HMM [6]. HMM represents a finite state machine which changes its state at a discrete time. Transitions between states are random with some fixed probabilities [4].

Calculated set of EEG features was used for initialization and training of HMM. Baum-Welch algorithm was employed for training. Following cluster analysis reveals the groups of similar elements, number of groups was set equal to number of stages to be identified. Cluster centers were stored in the model and used later to label observations.

Trained model was used for further classification by utilizing Viterbi algorithm which inputs a set of signal characteristics for all EEG segments. Resulting sequence of state changes is considered as a sequence of sleep stages.

As a last step, we have filtered obtained stages sequence by median filter to eliminate short-term transients. Such transients are related to non stationary EEG portions which have features from two different sleep stages. Value averaging for 2-3 minutes helps to clean up the graphics and to reveal better the sleep structure. Based on this post-filtration the hypnogram finally was plot.

**Results**

The algorithm was tested on 15 records containing several EEG channels, as well as EOG and EMG data. All records were scored by human expert according to R&K system [9]. To verify our algorithm the output of automatic evaluation was compared with expert scoring.
Upper portion of the figure 1 depicts the hypnogram built on the basis of HMM automatic classification. The picture lower part shows the hypnogram built by somnologist. Correlation between these two graphics is equal 0.7924.

![Result of classification by HMM’s method](image1)

![Result of classification by R&K’s method](image2)

**Figure 1 Result of sleep stage classification without filtering**

Both hypnograms expose some noisy behavior. To clean them up median filters with various length were applied. The effective filter order was determined experimentally and varied for different records.
After filtration the correlation coefficient increased up to 0.8461. Classification results after filtering are shown in picture 2. Results for all records are summarized in table 1.

### Table 1 Compare two classification methods: R&K and HMM (the table presents normalize coefficient of coincidence in every sleep stage)

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Maximum coincidence between human and machine scoring is seen for stage 4 of deep sleep and equals 92%. REM stage is also matched with high accuracy (86% cases). The lowest
classification precision was found for stage 1 and equaled 5%. In most cases this stage is
classified either as stage 2 (48%) or REM sleep (47%).

Thus our algorithm can identify with high precision all key sleep stages such as REM,
wakefulness and deep sleep. Further discrimination of slow wave stages is done with lower
precision which is related to similarity between rhythm parameters for those stages [2].

Summary

The most important feature of our approach is that classification algorithm is trained
without supervision. As a result, we don’t need to create training set and can easily apply this
method to different EEG records. Parameter calculation is performed individually for every
subject. In contrast to traditional human scoring additional EOG and EMG channels are not
required.

Automatic sleep analysis is more faster than manual scoring. Machine processing of 8
hours record takes less than 1 minute but it might take several hours for expert to evaluate the
same record. Automatic analysis is objective because classification results are not tied with any
subjective experience of human expert.

This system can be used in hospitals for sleep disturbance diagnosis as well as for
fundamental sleep research.

Future work is related with the usage of additional polysomnograph channels to improve
the diagnosis in clinics and with the development of portable Holter-EEG device which will
allow to record sleep in natural environment outside research laboratory or hospitals.

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