Automatic sleep/wake staging of rat polysomnographic recordings using two-step system

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ABSTRACT

This article describes application of an automatic classification system on a database of rat polysomnographic recordings. A two-step automatic system is used to analyze and score the recordings into three stages: wake, NREM sleep and REM sleep. First step of the analysis consists in artifact identification which leads to the selection of artifact-free signals. Then, 30sec epochs are classified according to relevant features extracted from the available artifact-free signals using artificial neural network classifiers. The overall classification accuracy reached by the presented classification system exceeded 95%, when analyzed 53 polysomnographic recordings.

KEYWORDS

decision making, diagnosis, medical applications, pattern recognition, signal processing

1 INTRODUCTION

Polysomnography is a diagnostic method used to analyze sleep. Classification of the polysomnographic recordings into sleep/wake stages is a fundamental part of sleep analysis. Polysomnography consists in simultaneous monitoring of several physiological parameters. For the analysis of animal sleep, electroencephalogram (EEG) and electromyogram (EMG) are typically recorded. In the animal sleep research, rats are frequently used and the recordings are scored into three stages during the analysis. The stages discerned are: wake, NREM (non-rapid-eye-movement) sleep and REM (rapid-eye-movement) sleep.

The aim of the sleep analysis is to classify the polysomnographic recording into succession of predefined sleep/wake stages. For the need of the sleep/wake stage classification, the recording is typically split into equidistant intervals called epochs. Traditional length of an epoch is 20sec or 30sec respectively. In the animal polysomnographic analysis, shorter epochs are frequently used.

The manual classification of polysomnographic recording is performed by an expert and consists in visual analysis and scoring of monitored signals. The stages are distinguished by the expert according to the typical manifestations, activities and powers in the EEG and EMG signals. Traditional
manual classification performed by an expert is also strongly influenced by his/her experience. This fact can lead to high heterogeneity of the classifications.

In order to automate, simplify and unify the sleep classifications, a huge effort to develop automated sleep/wake stagers has been made in the last decades [1], [2], [3], [4]. Three main tasks can be point out in the research activities: implementation of algorithms for artifact identification and minimization, choice of adequate type and structure of an automatic classifier, and extraction of relevant features representing the state of the analyzed object.

This article presents application of a two-step classification system on a set of rat polysomnographic recordings. The automatic system used takes into account presence of possible artifacts and performs automatic classification using features extracted from the available artifact-free signals. The idea of the classification is to use appropriate classifier for each epoch to be classified, depending on the quality of the monitored signals.

The outline of the article is the following. The automatic system for analysis of polysomnographic recordings is presented in the second section. The database of recordings used is presented in the third section. Then, final results are presented and discussed in the section number four. At the end, short conclusions are presented.

2 SYSTEM FOR AUTOMATIC CLASSIFICATION

The process of automatic sleep staging typically consists in succession of several steps – artifact processing, extraction of significant features from epochs of the polysomnographic recordings, and application of the features as inputs to the classifier. In this project, a complex two-step automatic system was used to analyse the polysomnographic recordings. The two-step classification system has been previously evaluated on human polysomnographic recordings [5].

2.1 Two-step System

The two-step automatic system separates artifact identification procedure from the stage of classification. Thus, it can combine the results of artifact identification procedure with adequate automatic classification using relevant features extracted from the available artifact-free signals.

Artifact detection

The first step consists in artifact analysis of the signals and aims to determine if any artifact is present in the epoch to be classified. In our research, polysomnographic recordings consist of EEG and EMG signals.

In order to allow effective identification of short artifacts which are rather common in polysomnographic recordings, the original time resolution has been changed. Detection algorithm dealing with shorter segments can be more precise in localization of the artifacts and also thriftier of the data. Each epoch with original length of 30sec has been split into fifteen 2sec segments. If no artifact is present in a signal or only a small part of a signal in the 30sec epoch (less than four 2sec segments) is artificated, the epoch is marked as “artifact-free” and features can be computed from the parts of the signal which are not confused by artifacts. The
artificed segments of a signal are removed. If too large part of a signal in the epoch is artificed (more than three 2-sec segments), the epoch is marked as “artificed” and is completely removed from the classification. This strategy ensures that only the signals that can be used to classify the current epoch are selected for the second step of the analysis – automatic classification.

Artifact identification procedure has been performed using a specialized PRANA Software. This tool is equipped with a universal automatic artifact detection algorithm which is inspired by the work of Bruner [6]. The algorithm can use either fixed or adaptive thresholds for artifact identification. The algorithm was tuned so as to identify the artifacts most frequently present in the polysomnographic signals, using physiological knowledge. The setting of the algorithms could not been evaluated properly, since the available polysomnographic database did not contain any artifact analysis performed visually by an expert. For the need of the actual research, eight different artifacts were automatically detected, six of them (overflow, electrode detachment, power line artifact, ECG artifact, high-frequency artifact, flat-line) being detected using a priori fixed thresholds and two (low-frequency artifact, muscular activity) using adaptive thresholds. More details about artifact identification strategy can be seen in [5], [7].

Classification
The second step of the whole analysis represents the automatic classification. During the classification, relevant features are extracted from the artifact-free signals and then used in an appropriate automatic classifier. The decision system is generally formed by a bank of different classifiers: one classifier for each combination of monitored signals. Selection of the proper classifier depends on the results of the artifact identification procedure performed on the signals.

Since the polysomnographic recordings, the bank of classifiers contains only two classifiers corresponding to the two possible combinations of signals: EEG only and EEG and EMG. The EEG signal is considered to be indispensable for the automatic sleep/wake stage classification, so if the EEG signal is artificed, the epoch cannot be classified by the system.

Depending on the previous research studies [4], [5], [7], artificial neural networks have been selected as automatic classifiers used in this research. Two architectures of supervised artificial neural networks have been used for the classification: feedforward neural networks and radial basis neural networks.

Feedforward neural networks with three layers represent the first classifier tested in the research. Number of neurons in the first layer is determined by actual number of input features extracted from the epoch to be classified. Neurons in the first layer are equipped with hyperbolic tangent transfer function. The second layer of the network contains 6 neurons equipped with logarithmic sigmoid transfer function. The output layer of the network consists of 3 neurons each corresponding to one sleep/wake stage (wake, NREM sleep, and REM sleep). The transfer function of the neurons in the output layer is a hyperbolic tangent.
Second type of classifiers represents radial basis neural networks with two layers. Spread of radial basis functions in the hidden layer has been set to the value 0.5.

2.1 Features

Selection of the most relevant features has been realized for both the possible combinations of signals (EEG only, and EEG and EMG). The initial pool of all features extracted from the signals contained 22 features. 13 features have been extracted from the EEG signal and 9 features have been extracted from the EMG signal.

Features computed from EEG signal only:
- Five features describe the spectral activity of the EEG signal in traditional frequency bands: δ delta [0.5 ; 4.5] Hz, θ theta [4.5 ; 8.5] Hz, α alpha [8.5 ; 11.5] Hz, σ sigma [11.5 ; 15.5] Hz and β beta [15.5 ; 32.5] Hz. The features have been computed using Welch’s periodogram Fourier transformation computed on 2 sec periods and represent relative powers in the five frequency bands (Prel).

Features computed from EMG signal only:
- The relative power of the EMG in the high frequency band [12.5 ; 32] Hz calculated over the total frequency band [8 ; 32] Hz.

Features computed from EEG and EMG:
- The spectral edge frequency 95 (SEF95) indicates the highest frequency below which 95% of the total signal power is located [8].
- The entropy (entr) of the signal measures the signal variability [9].
- A set of three quantitative parameters defined by Hjorth [10]: activity (act), mobility (mob) and complexity (comp).
- The standard deviation (std) of a random variable.
- The skewness (skew) and the kurtosis (kurt) characterizes the probability distribution function of a signal.

From each polysomnographic recording in the database, all the features presented above have been extracted and then each feature was transformed and normalized in order to reduce possible extreme and outlying values. This transformation strategy has been inspired by previous study focused on automatic scoring of human polysomnographic recordings [7].

Sequential Forward Selection (SFS) strategy has been applied for both the possible combinations of signals (EEG, and EEG+EMG) in order to select the most relevant features. This strategy (SFS) is an iterative method which at each step selects the optimal set of features by increasing the number of features selected.

3 POLYSOMNOGRAPHIC DATABASE

A large database of conventional animal polysomnographic recordings has been used in this research. The full database contains the 24-hour recordings of a total of 60 adult Sprague-Dawley rats. The recordings included 2 channels per animal, with one EEG
(electroencephalogram) and one EMG (electromyogram) signals, and were performed continuously while the animals were housed in individual cages placed in sound-attenuated chambers at an ambient temperature of 21°C with a 12:12-hour light-dark cycle and unlimited access to food and water. To achieve the recordings, animals were anesthetized, placed in a stereotaxic frame and surgically equipped with electroencephalographic (EEG) and electromyographic (EMG). Two miniature stainless steel screws served as EEG electrodes and were inserted into the animal skull through small trepanation holes drilled at the level of the right central and midsaggital cortex. Two stainless steel wire electrodes were inserted beneath the neck muscles to record the electromyogram (EMG). All electrode wires were soldered to a mini-connector anchored to the skull with acrylic dental cement. A period of one week was allowed for recovery from the surgical procedure. The animals were then acclimated to the recording conditions. To allow the rat to move freely, a light cable and a rotating commuter were used to connect the electrodes and the recording unit. Recordings began 7 to 10 days later, and one day of stable baseline data were obtained for the purpose of this study. The EEG and EMG signals were both collected in a bipolar montage by connecting each pair of electrodes to the positive and negative inputs of the recording unit amplifiers. The signals were digitalized and stored at a sampling frequency of 100 Hz using a quantization range of +/- 500 uV and a 16-bit analog-to-digital converter. Four rats were recorded simultaneously on a 500 Mbytes Flash card using an Embla battery-powered recording unit and the Somnologica acquisition software (Resmed, Saint-Priest, France). A common ground was used for the four animals of each recording batch by connecting the cage hosting the animals directly to the recording equipment.

After data collection, the PSG recordings were scored a first time for sleep/wake stages by one sleep expert using the Somnologica software. Recordings were then converted into EDF recording files, transferred to another computer, and re-scored by an independent expert using the PRANA reviewing and analysis software (PhiTools, Strasbourg, France). The PSG recordings were scored visually by 30sec epochs into 3 sleep/wake stages according to conventional criteria. The sleep-wake states were identified as follows: Wake (desynchronized EEG, low EEG amplitude, high to medium EMG levels); NREM sleep (synchronized EEG with low to high-amplitude synchronized EEG and low EMG levels); and REM sleep (desynchronized EEG with predominant theta rhythm of 6-9 Hz, low to medium EEG amplitude, and very low EMG levels). The experts could also score an epoch as a movement or leave the epoch undefined. These two categories were used only rarely, so they have not been included into the analysis. Seven recordings have been removed from the research because of missing expert classification. So, 53 polysomnographic recordings left for the analysis. The total database contains 153,020 epochs scored by two experts. In order to reduce the uncertainty in the data, only the epochs with relevant classification (Wake, NREM sleep and REM sleep) and concordant visual
scoring of both experts have been included in the study. Thus, out of the 153,020 epochs, 17,749 epochs have been removed. The inter-expert agreement reached about 88%. So, 135,271 epochs has left for the analysis.

Three recordings are characterized by markedly high number of undefined of movement epochs by one of the experts.

4 RESULTS

This part of the article summarizes the results obtained. The results could be split into three sections: artifact identification, creation of classifiers, and evaluation of the two-step system.

4.1 Artifact Identification

Both the analyzed signals, EEG and EMG, have been processed during artifact identification phase separately. Results of the artifact identification performed on the 53 polysomnographic recordings are summarized in Table 1. Out of the 135,271 epochs contained in the final database, 134,625 epochs have EEG signal artifact-free and 77,009 epochs have EMG signal artifact-free. There are only 76,845 epochs with both signals (EEG and EMG) artifact-free. Table 1. also shows distribution of the epochs into the sleep/wake stages.

<table>
<thead>
<tr>
<th></th>
<th>Final database</th>
<th>EEG Artifact-free</th>
<th>EMG Artifact-free</th>
<th>EEG+EMG Artifact-free</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>135,271</td>
<td>134,625</td>
<td>77,009</td>
<td>76,845</td>
</tr>
<tr>
<td>Wake</td>
<td>61,379</td>
<td>60,904</td>
<td>33,368</td>
<td>33,263</td>
</tr>
<tr>
<td>NREM</td>
<td>62,600</td>
<td>62,498</td>
<td>36,780</td>
<td>36,732</td>
</tr>
<tr>
<td>REM</td>
<td>11,292</td>
<td>11,223</td>
<td>6,861</td>
<td>6,850</td>
</tr>
</tbody>
</table>

It is evident, that automatic classification strongly depends on the quality and relevancy of the input data – features. To ensure the quality of the data used during phase of learning the classifiers, only the recordings containing at least 80% of artifact-free epochs (EEG+EMG) have been used. Out of the 53 polysomnographic recordings, only 23 recordings have met this quality criterion. These recordings form reduced database which is characterized in Table 2.

<table>
<thead>
<tr>
<th>Reduced database</th>
<th>EEG Artifact-free</th>
<th>EMG Artifact-free</th>
<th>EEG+EMG Artifact-free</th>
</tr>
</thead>
<tbody>
<tr>
<td>61,979</td>
<td>61,837</td>
<td>60,008</td>
<td>59,897</td>
</tr>
</tbody>
</table>

4.2 Learning of Classifiers

An automatic classifier represents a decision system that makes its decision on the basis of a predefined set of features. In the actual research, two decision systems based on artificial neural networks theory have been evaluated. The decision systems are based either on feedforward neural network classifiers, or on radial basis neural network classifiers.

As could be seen in Table 1, distribution of the epochs in the sleep/wake stages is not the same for every stage. This fact corresponds to the general sleep structure. In order to avoid errors and bias in the classification results that could be caused by the difference in representation of the individual stages, a small test database containing 6,000 epochs in which all analyzed stages (Wake, NREM and
REM) are represented by about the same number of epochs has been created out of the epochs with EEG and EMG identified as artifact-free. These epochs have been selected randomly from the reduced database presented in Table 2. The test database has been then split into ten test subsets \( S = \{S_1, S_2, \ldots, S_{10}\} \), each subset \( S_k \) containing 600 epochs, evenly distributed in the stages analyzed (see Table 3).

<table>
<thead>
<tr>
<th></th>
<th>Wake</th>
<th>NREM</th>
<th>REM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test</td>
<td>2,050</td>
<td>2,050</td>
<td>1,900</td>
</tr>
<tr>
<td>database</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test</td>
<td>205</td>
<td>205</td>
<td>190</td>
</tr>
<tr>
<td>subset</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The test subsets have been then used to select the relevant feature sets and to learn the automatic neural network classifiers. Feature selection (Sequential Forward Selection – SFS) has been performed for both possible combinations of signals (EEG, and EEG+EMG) and for both types of neural networks tested in the research.

The idea of feature selection is as follows: a circular permutation is performed on the 10 test subsets \( S_k \) at each step of the feature selection. Automatic classifier is trained on one subset \( S_k \) and validated on the dataset \( S_{\bar{k}} \) containing data from the other 9 subsets \( S_{\bar{k}} \), \( S_{\bar{k}} \in S_{\bar{k}} \) with \( \bar{k} = S - S_k \). The classifier is trained 10 times and each time an accuracy function indicating percentage of correctly classified epochs from the set \( S_{\bar{k}} \) is calculated. Then, the criterion \( J \) used to select the features is computed as a mean value over the 10 \( \text{Acc}(k, \bar{k}) \) values.

As presented in the section 2, there are 22 features extracted from the polysomnographic recordings formed by the EEG signal and EMG signal. The initial set of features for the feature selection process depends on the available physiological signals used. The features selection was performed for both combinations of signals: EEG, and EEG + EMG. The initial pool of features contained 13 features when only EEG has been available and 22 features when EEG + EMG have been available. The optimal feature sets selected by SFS are presented below. For each feature selection is indicated also the value of criterion \( J \) computed on the test subsets.

**Feedforward neural networks.**
- EEG. Relevant set of features: \( \text{entrEEG}, \text{Prel}\delta, \text{Prel}\theta, \text{skewEEG} \) and \( \text{compEEG} \). \( J = 95.78\% \).
- EEG + EMG. Relevant set of features: \( \text{entrEEG}, \text{Prel}\delta, \text{entrEMG} \) and \( \text{Prel}\theta \). \( J = 96.67\% \).

**Radial basis neural networks.**
- EEG. Relevant set of features: \( \text{entrEEG}, \text{Prel}\delta, \text{Prel}\theta, \text{skewEEG} \) and \( \text{compEEG} \). \( J = 95.82\% \).
- EEG + EMG. Relevant set of features: \( \text{entrEEG}, \text{Prel}\delta, \text{entrEMG} \) and \( \text{Prel}\theta \). \( J = 96.74\% \).

The results shows, that for both types of neural networks have been selected the same sets of features. Another interesting result is that the EEG signal represents the key and indispensable information for sleep staging which corresponds to our presumption. However, application of relevant information extracted from both EEG and EMG signals can typically lead to
higher classification accuracy achieved with smaller number of parameters compared to classification based only on EEG features.

For the final implementation of the two-step classification system, only one of the ten neural network classifiers trained has been selected for each combination of monitored physiological signals and for each type of neural network. In the concrete, the neural network classifier characterized with the highest classification accuracy computed on the corresponding dataset has been chosen and stored in the bank of classifiers (EEG only, and EEG+EMG). This selection ensures that only 600 epochs were used to train the classifiers forming the classification system. Then, the proposed system is ready to be used to analyze and score the 53 polysomnographic recordings contained in the available database.

4.3 Evaluation of the Two-step System

As presented above, the original database contains 53 recordings visually scored on 30sec epochs (Table 1). As could be seen, due to presence of artifacts, only 76,845 epochs out of the total set of 135,271 epochs have EEG signal and EMG signal artifact-free. Traditional classification system requiring presence of both the signals would be able to process only about 57% of the database, which strongly limits application of such automatic classification systems.

The two-step structure combined with a bank of classifiers is able to classify also epochs, in which EMG signal is not available due to artifacts. Such a system can score almost all the epochs from the original database (99.5% of the epochs).

Analysis of the 53 polysomnographic recordings performed by the two-step automatic system is summarized in Table 4. For both types of neural networks (feedforward and radial basis), the global classification accuracy achieved by the two-step system exceeds 95% (column Totally classified in Table 4). During the classification process, both classifiers have been used – EEG only, and EEG+EMG. 57,780 epochs have been scored by the classifier using only EEG features (classification accuracy 93.55% for feedforward neural network and 94.34% for radial basis neural network). All the remaining epochs, 76,845 epochs, have been scored by classifier combining features from EEG and EMG signals (classification accuracy 96.65% for feedforward neural network and 96.45% for radial basis neural network).

Classification accuracy achieved for the traditional classifier which corresponds to the combination EEG+EMG (last column of the Table 4) is only about 1% higher than the accuracy achieved for the two-step system. The main difference between traditional classifier and the proposed two-step system with bank of classifiers is thus number of epochs actually scored. This criterion proves advantage of the proposed system. As could be seen, the proposed structure using bank of classifiers allows classifying of 134,625 epochs out of the total sum of 135,271 epochs contained in the database analyzed. On the contrary, the traditional automatic classifier requiring both EEG and EMG could classify only 76,845 epochs which represents about 57% of the database.
Table 4. Results of classification using system based of bank of classifiers.

<table>
<thead>
<tr>
<th></th>
<th>Totally classified</th>
<th>EEG only classifier</th>
<th>EEG+EMG classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of epochs scored</td>
<td>134,625</td>
<td>57,780</td>
<td>76,845</td>
</tr>
<tr>
<td>Classification accuracy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(feedforward)</td>
<td>95.32%</td>
<td>93.55%</td>
<td>96.65%</td>
</tr>
<tr>
<td>Classification accuracy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(radial basis)</td>
<td>95.55%</td>
<td>94.34%</td>
<td>96.45%</td>
</tr>
</tbody>
</table>

More detail information about the automatic classification can be shown using confusion matrix presenting accuracy of the automatic classification for individual stages. The columns of the confusion matrix represent the stages determined by the automatic classifier and the rows represent the stages determined by the experts. Each case \((i,j)\) corresponds to the number of examples classified as \(i\) by the experts and \(j\) by the classifier, expressed as a percentage of the examples classified as \(i\) by the experts.


<table>
<thead>
<tr>
<th></th>
<th>automatic classifier</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wake</td>
<td>NREM</td>
<td>REM</td>
<td></td>
</tr>
<tr>
<td>expert</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wake</td>
<td>93.20</td>
<td>4.51</td>
<td>2.29</td>
<td></td>
</tr>
<tr>
<td>NREM</td>
<td>2.07</td>
<td>97.22</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>REM</td>
<td>2.76</td>
<td>1.04</td>
<td>96.20</td>
<td></td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th></th>
<th>automatic classifier</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Wake</td>
<td>NREM</td>
<td>REM</td>
<td></td>
</tr>
<tr>
<td>expert</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wake</td>
<td>93.56</td>
<td>4.12</td>
<td>2.32</td>
<td></td>
</tr>
<tr>
<td>NREM</td>
<td>1.88</td>
<td>97.25</td>
<td>0.87</td>
<td></td>
</tr>
</tbody>
</table>

As could be seen in Table 5 and Table 6, classification accuracies reached for all stages (Wake, NREM and REM) significantly exceeds 90%. The highest classification accuracy has been achieved for NREM sleep (over 97%) and REM sleep (over 96%). Accuracy achieved for stage Wake is slightly lower and exceeds 93%. This indicates that the individual stages have been well discerned by the features determined during feature selection process.

5 CONCLUSIONS

This article presents performance of a two-step classification system on a database of 53 animal polysomnographic recordings. The presented decision system performs identification of possible artifacts and classification process in two separate steps. During artifact identification, each of the monitored signals is analyzed for presence of artifacts independently to the other signals. Artifact identification phase ensures that features characterizing only the manifestations referred to the actual state of the animal are extracted from the available artifact-free signals and then used during automatic classification. For the phase of classification, structure based on a bank of classifiers differing in origin of their input features (EEG only, or EEG+EMG) is used.

Phase of artifact identification ensures quality and relevance of the analyzed signals and in the consequence ensures relevance of the features extracted from the monitored signals contained in the polysomnographic recordings. It is
evident that careful artifact identification plays crucial role in the whole process of automatic sleep staging. If no artifact identification is performed, or if artifact identification is of insufficient quality, automatic classification based on the features extracted from the analyzed signal does not reflects the physiological mechanisms of sleeping animal. Such automatic classification is not beneficial, regardless the classification accuracy reached. In such case, relevant information and knowledge cannot be mined from the data, even thought the global classification accuracy can be sometimes higher when artifacts are not processed and removed from the recordings. In the phase of research and system development, the knowledge gained and problem understanding should outweigh the pure classification accuracy achieved. In this research, eight typical artifacts have been identified and processed. In general, it could be said that, EMG signal has been much more confused by artifacts than the EEG signal.

The approach based on application of a bank of classifiers is used to allow classification of epochs characterized by incomplete set of recordings after the artifact identification phase which leads to incomplete feature set at the input of a traditional automatic classifier. The results show, that large amount of data may not be classified because of missing values using a traditional automatic classifier. This fact would negatively impact applicability of such automatic classification systems.

To improve performance of the system, effort should be specially paid on two crucial activities – artifact identification, and process of feature extraction and selection. Optimization of artifact identification algorithms is necessary to prepare segments of signals that contain only the information related to the sleep/wake manifestations. It is evident that presence of artifacts can mask the original activity of the body. The artifact identification algorithms should also avoid false positive detections. False detections can lead to inadequate loss of valuable data. The second critical point corresponds to extraction and selection of relevant features used during classification. Features representing information important for the automatic classification must be extracted from the artifact-free signals in order to simulate expert decision as well as to propose automatic classification system independent to the measuring system.

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6 REFERENCES


