Automatic Classification of Sleep/Wake Stages Using Two-Step System

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Abstract. This paper presents application of an automatic classification system on 53 animal polysomnographic recordings. A two-step automatic system is used to score the recordings into three traditional stages: wake, NREM sleep and REM sleep. In the first step of the analysis, monitored signals are analyzed using artifact identification strategy and artifact-free signals are selected. Then, 30sec epochs are classified according to relevant features extracted from available signals using artificial neural networks. 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 represents a diagnostic method used to analyze sleep and sleep disorders. Classification of the polysomnographic recordings into sleep/wake stages is a fundamental part of sleep research. The method consists in simultaneous monitoring of several physiological parameters. For the analysis of animal sleep, electroencephalogram (EEG) and electromyogram (EMG) are typically used. In the animal sleep research, rats are frequently used.

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 – epochs. Traditional epoch length is 20sec or 30sec, but in the animal sleep/wake stage analysis, shorter epochs are also frequently used.

The manual classification of polysomnographic recording is performed by an expert and consists in visual analysis of monitored signals and assignment of appropriate sleep/wake stage to the epochs. In the case of rat sleep analysis, the classification is done into one of three stages: Wake, NREM (non-rapid-eye-movement) sleep and REM (rapid-eye-movement) sleep. The stages are distinguished by the expert according to the typical manifestations, activities and powers in the

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EEG and EMG signals. Traditional manual classification performed by an expert is also strongly influenced by his/her experience, which can in the consequence 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]. In general, the research is mainly focused on three main tasks in automated sleep analysis: choice of adequate type and structure of an automatic classifier, implementation of algorithms for artifact identification and minimization, and extraction of relevant features representing the epochs of the polysomnographic signals.

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

The outline of the paper is the following. The automatic system proposed is presented in the second section. The whole polysomnographic database is presented in the third section. Then, final results are presented and discussed in the section number four. At the end of the paper, short conclusions are presented.

2 System for Automatic Classification

The process of automatic sleep staging typically consists in several successive 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 process the polysomnographic recordings. The two-step classification system has been already presented and evaluated on human polysomnographic recordings [5]. In the next part of the paper, principle of the two-step classification system will be described briefly.

2.1 Description of the Two-Step System

The two-step automatic system performs artifact identification procedure separately from the classification. Thus, it can combine the results of an artifact identification procedure with an 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 to be tested (EEG and EMG in this research). The aim is to determine if any artifact is present in the epoch to be classified. In order to allow effective identification of short artifacts which are rather common in polysomnographic recordings, the original time resolution has been changed from 30sec epoch to 2sec segments. In the concrete, each 30sec epoch has been split into succession of fifteen 2sec segments. Detection algorithm dealing with shorter segments can be more precise in localization of the artifacts and also thriftier of the data. If no artifact is present in a signal or only a small part of a signal in the

30sec epoch is artifacted (less than four 2sec segments), the epoch is marked as "artifact-free" and features are computed from the parts of the signal which are not artifacted. The artifacted segments of a signal are removed from the processing. If too large part of a signal in the epoch is artifacted (more than three 2-sec segments), the epoch is marked as "artifacted" 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.

Artifact identification procedure has been performed using a specialized PRANA Software which is equipped with a universal automatic artifact detection algorithm, inspired by the work of Bruner [6]. The algorithm can use either fixed or adaptive thresholds for identification. The algorithm was tuned so as to identify the artifacts most frequently present in the polysomnographic signals, using physiological knowledge. 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. Since the polysomnographic database did not contain artifact analysis performed visually by an expert, the tuning and performances of the artifact detectors have not been properly validated. For more details about artifact identification strategy used in the analysis see [5], [7].

Classification

The second step of the analysis represents the automatic classification. The signals selected in the previous step as artifact-free are used in the decision system: the relevant features are extracted and used in an appropriate automatic classifier. The decision system is formed by a bank of different classifiers: one classifier for each combination of monitored signals. Then, the proper classifier is selected from the bank of classifiers, using the results of the artifact identification procedure performed on the signals. In the actual research, 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 artifacted, the epoch cannot be classified by the system.

The principle of the automatic classification is the following: at first, relevant features are extracted from the polysomnographic signals recorded during an epoch using signal processing techniques and form so called feature vector. This first step transforms the raw signals into a set of characteristics describing the signals shape during one epoch. In a second step, the feature vector is used as an input for a automatic classifier.

Artificial neural networks have been selected as automatic classifiers used in this research. This selection is based on previous research studies [4], [5], [7]. In the concrete, two different architectures of supervised artificial neural networks have been used:

- feedforward neural networks with three layers. For the first layer, number of neurons is defined by actual number of input features extracted from the epoch to be processed. Hyperbolic tangent transfer function is used for the neurons of first layer. The second layer of the network contains 6 neurons; the transfer function is a logarithmic sigmoid function. The output layer of the network consists of 5 neurons each corresponding to one sleep/wake stage; the transfer function of each neuron is a hyperbolic tangent.

- radial basis neural networks with two layers. Spread of radial basis functions in the hidden layer has been set to value 0.5.

2.2 Features

For both the possible combinations of signals (EEG only, and EEG and EMG) have been selected the most relevant features out of a set of 22 features extracted from the polysomnographic recordings. 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

- A set of five features is used to describe the spectral activity of 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. Welch's periodogram Fourier transformation computed on 2 sec periods has been used The features represent relative powers, *Prel*, in the five frequency bands.

Features Computed from EMG Signal Only

- The relative power of EMG in the high frequency band [12.5 ; 32] Hz was calculated. The total frequency band was defined as [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, from the distribution of its amplitude values [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.

All the features have been extracted from the polysomnographic recordings contained in the database. For each recording, each feature was transformed and normalized in order to reduce the extreme and outlying values. This transformation strategy has been inspired by [7].

To select the most relevant features, Sequential Forward Selection (SFS) strategy has been applied for both the possible combinations of signals (EEG, and EEG+EMG). Sequential Forward Selection is an iterative method which at each step selects the optimal set of features by increasing the number of features selected so as to maximize the classification criterion (function of the percentage of epochs correctly classified by a classifier).

3 Data

3.1 Database of Polysomnographic Recordings

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

The results achieved can be split into three main parts: artifact identification, creation of classifiers, and evaluation of the two-step system.

4.1 Artifact Identification

Artifact processing strategy has been characterized in the second section. Both the analyzed signals, EEG and EMG, have been processed separately. Results of 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. Only 76,845 epochs have both signals (EEG and EMG) artifact-free.

Table 1. Description of the polysomnographic database summarizing artifact identification

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

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

Table 2. Description of the reduced database used for learning of classifiers

Reduced database	EEG Artifact-free	EMG Artifact-free	EEG+EMG Artifact-free	EEG+EMG Artifact-free Wake	EEG+EMG Artifact-free NREM	EEG+EMG Artifact-free REM
61,979	61,837	60,008	59,897	26,484	28,171	5,242

4.2 Creation 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 - feedforward neural networks and radial basis neural networks.

As could be seen in Table 1 and Table 2, distribution of the epochs in the sleep/wake stages analyzed is not the same for every stage which corresponds to the general sleep structure. In order to avoid errors in the classification results that could be caused by the difference in classes representation, 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 detected as artifact-free. The epochs have been selected randomly from the reduced database. The test database has been then split into ten test subsets S = {S1, S2,..., S10}, each subset Sk containing 600 epochs, evenly distributed in the stages (see Table 3).

Table 3. Description of the test database – stages represented by about the same number of epochs

	Wake	NREM	REM
Test database	2,050	2,050	1,900
Test subset	205	205	190

The test subsets have been then used for feature selection and process of learning of automatic 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 used.

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

As presented in the second section, 22 features have been extracted from the polysomnographic recordings. The initial set of features for the feature selection process depends on the available physiological signals used. The features selection was achieved for two combinations of signals: EEG, and EEG + EMG. The initial pool of features contained 13 features when only EEG has been available, and 22 features for EEG + EMG combination of signals. 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: *entrEEG*, $Prel\delta$, $Prel\theta$, *skewEEG* and *compEEG*. $J = 95.78\%$.
- EEG + EMG. Relevant set of features: *entrEEG*, $Prel\delta$, *entrEMG* and $Prel\theta$. $J = 96.67\%$.

Radial Basis Neural Networks

- EEG. Relevant set of features: *entrEEG*, $Prel\delta$, $Prel\theta$, *skewEEG* and *compEEG*. $J = 95.82\%$.
- EEG + EMG. Relevant set of features: *entrEEG*, $Prel\delta$, *entrEMG* and $Prel\theta$. $J = 96.74\%$.

As could be seen, the same feature sets have been selected by both neural network types used in the research Results of the selection process correspond to the presumption that the EEG signal represents the indispensable information for sleep staging. However, automatic classification using relevant information extracted from both EEG and EMG signals can typically lead to higher classification accuracy achieved with smaller number of parameters.

When the relevant features have been selected, a two-step classification system can be implemented. 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 $\bar{S}_k$ 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. The proposed system is then ready to be used to analyze and score the whole night polysomnographic recordings contained in the database.

4.3 Evaluation on PSG Recordings

As presented above, the original database contains 53 recordings visually scored on 30sec epochs. The database is characterized in Table 1. As could be seen, due to the artifacts, only 76,845 epochs out of the total set of 135,271 epochs have EEG and EMG signal artifact-free. Thus, traditional classification system requiring presence of both the signals would be able to process only about 57% of the database. This fact strongly limits application of such traditional 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, the global classification accuracy achieved by the two-step system is over 95% (column Totally classified). During the classification process, both classifiers have been used – EEG only, and EEG+EMG. 57,780 epochs have been scored by classifier using only EEG features, with classification accuracy 93.55%. All the remaining epochs (76,845 epochs) have been scored by classifier combining features from EEG and EMG signals with classification accuracy 96.65%.

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 two-step system with bank of classifiers is thus in the 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

	Totally classified	EEG only classifier	EEG+EMG classifier
Number of epochs scored	134,625	57,780	76,845
Classification accuracy (feedforward)	95.32%	93.55%	96.65%
Classification accuracy (radial basis)	95.55%	94.34%	96.45%

To provide more detail information about the automatic classification, confusion matrix presenting classification of individual stages has been also prepared. 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 5. Confusion matrix summarizing classification of the whole database – feedforward neural networks

		automatic classifier		
		Wake	NREM	REM
expert	Wake	93.20	4.51	2.29
	NREM	2.07	97.22	0.71
	REM	2.76	1.04	96.20

Table 6. Confusion matrix summarizing classification of the whole database – radial basis neural networks

		automatic classifier		
		Wake	NREM	REM
expert	Wake	93.56	4. 12	2.32
	NREM	1.88	97.25	0.87
	REM	2.74	0. 47	96.79

As could be seen in Table 5 and Table 6, classification accuracies reached for all the stages determined significantly exceeded 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 exceeded 93%. This indicates that the individual stages have been well discerned by the features determined during feature selection process.

5 Conclusions

This paper presents performance of a two-step classification system on a database of animal polysomnographic recordings. The presented decision system performs identification of possible artifacts separately from the classification process. Moreover, since each of the monitored signals is analyzed for the presence of artifacts independently to the other signals, parameters characterizing only the manifestations referred to the sleep 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 is implemented in order to ensure quality and relevance of the analyzed signals and extracted features. Careful artifact identification can play crucial role in the whole process of automatic sleep staging. If no artifact identification is performed, or 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. 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 value achieved. In the actual project, eight typical artifact types have been identified. As a result of the artifact identification performed on the polysomnographic database, EMG signal has been much more confused by artifacts than the EEG signal. This fact confirms the need to handle possible missing attributes in the case of traditional automatic classifiers.

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. The results show, that large amount of data may be not classified because of missing values using a traditional automatic classifier.

To improve performance of the system, effort should be specially paid on two crucial activities. Optimization of artifact identification algorithms is necessary to prepare segments of signals containing only the information related to the sleep manifestations. It is evident that presence of artifacts can mask the original activity of the body. Nevertheless, the artifact identification algorithms should also avoid false positive detections which could lead to loss of available data to be successfully scored. 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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