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A two-steps sleep/wake stages classifier taking into account artefacts in the polysomnographic signals

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Abstract: This paper focuses on the development of an automatic system for sleep analysis. The system proposed in this paper combines two phases needed in sleep analysis. In a first step, an artefact detection system selects the polysomnographic signals (EEG, EOG, EMG) that are not corrupted by artefacts. In a second step, relevant features are extracted from the selected signals and classified using a neural network chosen among a bank of four neural networks. The four classifiers differ one from the others by the signals used for the classification. They were learnt using information provided by different combination of signals (EEG, EEG+EOG, EEG+EMG, EEG+EOG+EMG). Thus, the complete system enables the classification to be performed using relevant features computed from artefact-free signals, without losing too many data. The performance reached by the two-steps system is 85% of accuracy, calculated on 47 night sleep recordings.

1. INTRODUCTION

Polysomnography is the basic diagnostic method used to analyze human sleep. Polysomnography consists in simultaneous monitoring of several physiological parameters during a whole night sleep. The standard polysomnographic signals are the electroencephalogram (EEG), the electrooculogram (EOG) and the electromyogram (EMG). A detailed analysis and an exact interpretation of a human whole night sleep enable the diagnosis of a wide spectrum of sleep disorders that are quite common in the human population.

The analysis of polysomnographic recordings is divided into several successive phases. The whole process leads to the recognition of different sleep/wake stages defined in the conventional Rechtschaffen and Kales (R&K) human sleep/wake stage scoring manual (Rechtschaffen and Kales, 1968). In general, six stages are recognized in human sleep. They are: wakefulness, non-rapid eye movement (NREM) sleep stages I, II, III and IV, and REM sleep or paradoxical sleep (PS). NREM stages III and IV represent the slow wave sleep (SWS) which is why they frequently form one united stage. When the polysomnographic recording is finally classified into the sleep/wake stages, it is possible to represent the sleep structure graphically by the means of a hypnogram. A hypnogram is an overall representation of the sleep architecture and presents the chronological distribution of the sleep/wake stages.

The manual classification of polysomnographic recordings consists in analysing successively each 20-sec intervals of the signals recorded. The 20-sec intervals are called epochs. Each epoch is scored into one of the six sleep/wake stages according to some information visually extracted from the traces of the signals monitored within the current epoch. The manual classification is made by a physician. The physician must deal with artefacts or noise that can intermingle with the monitored signals. Artefacts are generated by phenomena which do not have any physiological basis, such as patient's movements. Existence of artefacts in the physiological signals monitored can completely mask some information contained in the signal.

The large expansion of computer technology in the last few decades has also influenced the medical science. A huge effort to fully automatize the whole process of sleep analysis has been made and automated sleep/wake stagers have emerged. An important number of publications characterizing the research in the area of automatic sleep analysis can be found (Robert, *et al.*, 1998). Many of them focus on the choice for an adequate type of classifier, either classical algorithms or artificial intelligence methods such as artificial neural networks. However, few of them take into account the problem of artefacts. Actually, an automatic system should be able to correctly perform the two main steps: features extraction and accurate classification. The presence of artefacts can generate numerical errors in the features extracted which may lead to classification errors.

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The research presented in this paper focuses on the development of a classification system that takes into account the eventual presence of artefacts. An analysis of the quality of the signals is performed before using specific classifiers. The proposed system consists of two processing steps. The first step consists in detecting artefacts in the polysomnographic signals and selecting the signals that can be used for the classification. The second step consists of the classification of input features into sleep/wake stages, using one classifier selected among a bank of different classifiers. The classifiers differ one from the others by the input signals they use. The main idea of this paper is to use a different classifier for each epoch to be classified, depending on the quality of the three polysomnographic signals (EEG, EOG, EMG).

The outline of the paper is the following. The automatic system proposed is presented in the second section. Both the processing levels are presented in detail. The whole polysomnographic database is presented in the third section. Then, final results are presented and discussed at the end of this paper.

2. DESCRIPTION OF THE TWO-STEPS SYSTEM

The automatic system of sleep staging must be able to perform different steps – to process artefacts, to extract useful features from each 20 sec epochs for all the three signals recorded (EEG, EOG and EMG) and to use them as inputs to the classifier. In this project, a complex automatic system that integrates these two steps was proposed.

An automatic classifier is a decision system that is fed by a predefined set of features. When an artefact identification procedure is performed on the monitored signals separately from the classification task, it leads inevitably to a loss of data and thus to missing values in the input set of features, which is a problem most classifiers are unable to handle. In this project, a two-steps classification system is proposed as a solution to deal with missing values. The proposed system is able to combine the results of an artefact identification procedure with an adequate automatic classification using relevant features extracted from the available artefact-free signals.

In a first step, the three signals (EEG, EOG and EMG) are checked to determine if any artefact is present in the epoch to be classified. If only a part of the epoch is artefacted, features are calculated using parts of the signal which are not artefacted. If too large part of a signal is artefacted during the epoch, the signal is removed from the classification system. Thus, the signals that can be used to classify the current epoch are selected.

In the second step, these signals are used in the decision system: - the adequate features are extracted and used in a classifier. The decision system is composed of a bank of classifiers: four neural networks using different feature sets as inputs are learned and stored. The proper classifier is selected from the bank of classifiers, using the results of the artefact identification procedure performed on the EEG, EOG and EMG signals. The four neural networks use different inputs, extracted from different combination of signals: EEG only, EEG and EOG, EEG and EMG, EEG and EOG and EMG. When none of the signals are artefacted, the EEG-EOG-EMG classifier is used. If EOG and/or EMG are missing, the corresponding classifier is used. Let us note that EEG is a crucial signal for sleep/wake staging. Thus, if EEG is missing, no classification can be performed.

The structure of the automatic system is shown in figure Fig. 1. Firstly, artefact identification is achieved and the current combination of artefact-free signals is determined. Then, the appropriate neural network classifier is selected from the bank of classifiers, the relevant features are extracted from the epoch and the epoch is scored.

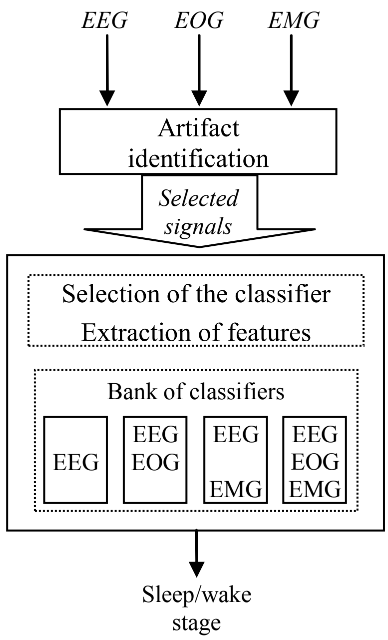

Fig. 1 Scheme of the two-steps classification system

2.1 *Artefact identification strategy*

In this step, artefact detection methods are implemented to detect the parts of the signals which are artefacted. A review of artefact detection techniques can be found in (Anderer, *et al.*, 1999). To reduce the number of data lost, the time resolution of the artefact identification algorithm was reduced from 20 sec to 2 sec. Each original 20-sec epoch was split into succession of ten 2-sec sequences and each 2-sec segment was checked to detect the occurrence of an artefact. A strategy was proposed to decide if the 20-sec epoch polluted by artefacts could be used for classification or not. If more than two 2-sec segments contain any kind of artefacts, then the entire corresponding 20-sec epoch was marked as "artefacted" and thus could not be used in the classification. On the contrary, if the number of artefacted segments is equal or less than two, the corresponding 20-sec epoch was marked as "artefact-free" meaning that it could be used in the subsequent analysis. However, the 2-sec segments contaminated with an artefact were removed from the epoch.

The specialized PRANA software was used to visualize the polysomnographic recordings and to perform a basic analysis of the signals. It is equipped with a universal automatic artefact detection algorithm, inspired by the work of Bruner (Brunner, *et al*., 1996). The algorithm can use either fixed or adaptive thresholds. The algorithm was tuned so as to identify the artefacts most frequently present in the polysomnographic signals, using physiological knowledge. In total, eight different artefacts were detected, six of them being detected using a priori fixed thresholds and two using adaptive thresholds.

Overflow detection. An overflow artefact is detected if the absolute amplitude of the signal calculated during 2-sec segment is greater than a fixed threshold.

Flat-line detection. A flat-line artefact is detected whenever the amplitude of the signal remains below a fixed threshold during a 2-sec segment.

Loss of signal detection. A loss of signal artefact is detected whenever the amplitude of the signal is equal to zero during a given time.

Power line artefact. It corresponds to interferences generated by the power line (50Hz). Such an artefact is detected whenever the amplitude of the band-passed signal (45-64 Hz) is above a fixed threshold.

High-frequency artefact. It is detected whenever the spectral energy in the highest physiological frequency range (higher than 30 Hz) is above a fixed threshold.

ECG artefact. An ECG artefact consists in a sharp peak similar to the original QRS complex of the electrocardiogram. The algorithm computes the ratio of two parameters computed from the first derivation of the signal. The first parameter is the peak-to-peak amplitude of the signal first derivation. Then, the 50^{th} percentile of the signal first derivation is calculated. The ratio is then compared with a fixed threshold. The detector can be also used to detect other sudden and unwanted sharp peaks in the signals.

The last two detectors use an adaptive threshold. The threshold value is updated using the variance of the signal considered, estimated on a moving symmetric 60-sec time window.

Low-frequency artefact. It is detected whenever the maximal amplitude of the filtered signal (0-2 Hz) is above an adaptive threshold.

Muscular activity detection. A muscular activity artefact consists in a burst of (high amplitude) spikes in the signal trace. It is detected whenever the variance of the signal in [5-64] Hz range is higher than an adaptive threshold.

Information about artefacts were not available on the data base used in this study, ie artefacts were not visually marked by an expert. Thus, the tuning and performances of the artefact detectors could not be properly validated. Yet, it is obvious that the setting of the threshold values affects both the sensitivity and the specificity of the artefact detectors.

2.2 *Presentation of the classification system – bank of classifiers*

Four neural networks form the bank of classifiers used by the decision system. In the concrete, feedforward neural networks with three layers were implemented as automatic classifiers. The number of neurons in the first layer is defined by the number of input features extracted from the epoch to be processed. The transfer function of the neurons in this layer is a hyperbolic tangent function. 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. The inputs of the classifiers are features extracted from EEG only (classifier 1), from EEG+EOG (classifier 2), from EEG+EMG (classifier 3), and from EEG+EOG+EMG (classifier 4). The most relevant features corresponding to each combination of signals were selected using an automatic feature selection method. Once the features were selected, the neural networks were trained using a small sub-set of the data base presented in section 3 (about 0.8% of the whole data base), and stored for further classification.

The list of features that were proposed to be selected by the automatic method is presented below. They can be classified in two groups:

a first group containing the features that represent information from the frequency domain, computed by the means of Fourier transformation.

- A set of five features are used to describe the spectral activity of EEG 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 were calculated using Whelsh's periodogram Fourier transformation, on 2 sec periods. Relative powers, *Prel*, were computed in the five frequency bands by dividing the absolute powers in each frequency by the sum of powers in the [0.5 ; 32.5] Hz frequency band.

- 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.

- The spectral edge frequency 95 (*SEF95*) indicates the highest frequency below which 95% of the total signal power is located. The spectral edge frequency function used in this paper is described in (Rampil, *et al*., 1980). It was calculated on the three signals (EEG, EMG, EOG).

a second group containing features computed in the time domain, all of them calculated on EEG, EOG and EMG.

- The entropy (*entr*) of the signal measures the signal variability, from the distribution of its amplitude values. The algorithm used in this project was published in (Moddemeijer, 1989).

- A set of three quantitative parameters defined by (Hjorth, 1970) : activity (*act*), mobility (*mob*) and complexity (*comp*).

- The 75th percentile (*prctile75*) defines the value below which 75% of the random variable values are located.
- The standard deviation (*std*) of a random variable.
- The skewness (*skew*) and the kurtosis (*kurt*) characterizes the probability distribution function of a signal.

On the whole, a set of 33 features was used to characterize each epoch. Before the set of features were used for classification, each feature was transformed and normalized in order to reduce the extreme and outlying values, using the transformation strategy described in (Zoubek, *et al.*, 2007).

The selection of the relevant features using SFS (Sequential Forward Selection) was achieved for each of the four classifiers, using features corresponding to the signals used by the classifier. The same strategy as in (Zoubek, *et al.*, 2007) was used both to prepare the data sub-set and to perform the entire feature selection. Only epochs where all signals (EEG, EOG, and EMG) were marked as artefact-free were used to prepare the data sub-set. Epochs were selected from the data-base presented in section 3. The initial set of available features depends on the physiological signals used by each neural network. The different combinations of signals for which optimal features selection was achieved are: EEG, EEG + EOG, EEG + EMG, and EEG + EOG + EMG. The optimal feature sets selected by SFS are presented below.

EEG. The set of relevant features contains four features extracted from EEG: $Prel\beta$, $entr_{EEG}$, $Prel\sigma$ and $Prel\alpha$. The accuracy obtained on the validation sub-set is 74.5%.

EEG + EOG. The relevant feature set contains $Prel\beta$, $mobility_{EOG}$, $Prel\alpha$, $entr_{EEG}$, $Prel\sigma$, $kurt_{EOG}$ and $Prel\theta$. The accuracy obtained on the validation sub-set is 80.7%.

EEG + EMG. The set of relevant features contains $Prel\beta$, $mobility_{EMG}$, $Prel\alpha$, $Prel\sigma$, $entr_{EEG}$, $entr_{EMG}$ and $Prel\theta$. The accuracy obtained on the validation sub-set is 79.8%.

EEG + EOG + EMG. The feature set contains $Prel\beta$, $mobility_{EMG}$, $Prel\alpha$, $Prel\sigma$, $entr_{EOG}$, $entr_{EEG}$ $kurt_{EOG}$. The accuracy obtained on the validation sub-set is 82.5%.

The detailed analysis of the sets of relevant features shows one interesting remark. The four optimal features extracted from the EEG signal ($Prel\beta$, $entr_{EEG}$, $Prel\sigma$ and $Prel\alpha$) were also selected in the other combinations of signals. This is similar to the manual scoring performed by the physician. During a manual scoring, the physician analyzes at first the EEG trace, more specifically the EEG frequency content, and then, if his decision is not clear, focuses on EOG and/or EMG traces.

3. POLYSOMNOGRAPHIC DATABASE

3.1 Presentation of the polysomnographic database

The full database used in this study contains 47 night-time polysomnographic recordings obtained from 41 healthy adult subjects (19–47 years old, 39 males and 2 females). Recordings were made continuously during the night (8 hours between 22:00h and 06:00h). Each polysomnographic recording contains seven traces of physiological signals. The recorded channels are: four EEG channels (C3-A2, P3-A2, C4-A1 and P4-A1), one transversal electrooculogram (EOG), one chin electromyogram (EMG) and one electrocardiogram (ECG). The analog signals were digitized with a sampling frequency f_s=128 Hz. The data and the precise protocol of the investigation are described in the paper (Chapotot, *et al.* 2003). Only C3-A2 EEG channel, EOG and EMG signals were analyzed in this work.

Each recording was separately visually scored by two independent physicians. Each 20-sec epoch was visually scored into one of five sleep/wake stages (wakefulness, NREM I, NREM II, SWS, Paradoxical sleep) according to the criteria defined in R&K manual. When the signals in the epoch were confused, the whole epoch was labelled as “undefined”. Only the epoch scored in the same epoch by both experts were used in this study. This strategy was proposed in order to reduce the uncertainty in the data. Thus, the total database of 77,649 epochs was reduced. 10,263 epochs were excluded. It represents about 13% of the total database. So, the final database contains 67,386 epochs. The numbers of epochs scored in each sleep stage for the final database are presented in Table 1.

Table 1. Description of the polysomnographic database.

	wake	NREM I	NREM II	SWS	REM
Final database	*5,376*	*1,989*	*33,100*	*11,498*	*15,414*

4. RESULTS

This section presents the results obtained during this project. The results can be split into two main groups. Firstly, the results of the artefact identification strategy are shortly presented. Then, the performance of the whole system is evaluated on the whole database of polysomnographic recordings. The performance of the proposed classification system is then compared with a single neural network using all three signals, where the artefacts are not analyzed.

4.1 Results obtained by the artefact detectors

Artefact identification techniques were applied on the EEG, EOG and EMG signals. The results obtained are summarized in the Table 2. The lines show the percentage of 20-sec epochs marked as artefacted in different sleep/wake stages. Each line characterizes one signal. During the automatic classification using the two-steps system, these epochs were automatically removed by the system.

A detailed analysis of the results showed that a high number of artefacts are present during the wake stage (about 50% of wake time), most of them are overflow and high-frequency artefacts. In the case of the EMG, overflow occurs rather frequently during all stages which is the reason why EMG is the most artefacted signal in the available recordings. It seems that the high number of overflow artefacts is caused by insufficient settings of the monitoring and/or recording devices. Four out of the 47 recordings are extremely artefacted. The EEG signal of one of them is continuously contaminated by high-frequency artefacts. This recording was excluded from the final test, where the automatic classifiers were evaluated on the whole night recordings.

Table 2 Summary of artefact identification performed on the physiologic signals

%	wake	NREM I	NREM II	SWS	PS
EEG artefacted	*53.6*	*4.8*	*3.0*	*1.8*	*3.3*
EOG artefacted	*51.5*	*15.7*	*6.2*	*1.4*	*18.3*
EMG artefacted	*44.2*	*18.3*	*14.0*	*12.0*	*15.3*

4.2 Test of the two-steps system on the data-base

Before the results are shown, it is important to mention that the epochs where the EEG signal is artefacted or the epochs where all three signals are artefacted cannot be processed by the method. These epochs are excluded from the classification and the conclusion provided by the system is "not classified". Table 3 shows the number of epochs processed by the specific classifiers contained in the proposed bank of classifiers. The recordings form a set of 66,164 epochs with consensual scoring of two physicians. Out of this set, 3,765 epochs (5.7%) were excluded because of artefacts. So, 62,399 20-sec epochs were finally scored by the scoring system proposed.

Table 3 Percentage of epochs processed by the classifiers

EEG	EEG EOG	EEG EMG	EEG EOG EMG	excluded
2.3	*11.7*	*6.8*	*73.5*	*5.7*

The results of the automatic classification are presented using the accuracy parameter *Acc* (percentage of correctly classified epochs) as well as the confusion matrix. The columns of this matrix represent the stages classified 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 both experts and *j* by the classifier, expressed as a percentage of the examples classified as *i* by the experts. The overall classification accuracy is 85.6% which is above the performances of existing classification systems. The detailed analysis of the results is presented in the Table 4, which shows the confusion matrix.

Table 4 Confusion matrix of the two-steps classification system

%		classifier				
		wake	NREM I	NREM II	SWS	PS
expert	wake	76.4	14.8	4.0	1.1	3.7
	NREM I	7.9	64.6	7.2	0.6	19.7
	NREM II	1.7	4.6	87.2	4.7	1.8
	SWS	0.1	0	5.2	94.7	0
	PS	2.1	16.0	1.7	0.4	79.8

The system proposed was compared to a single neural network that does not perform artefact identification and processing. It means that the classifier has been learned from sub-set of data which were not cleared from artefacted epochs. The overall classification accuracy of such a classifier obtained on the whole data base is 83.2%. The confusion matrix is presented in Table 5.

Table 5 Confusion matrix of the simple classifier without artefact identification

%		classifier				
		wake	NREM I	NREM II	SWS	PS
expert	wake	81.0	14.0	1.9	1.8	1.3
	NREM I	5.7	67.6	8.6	0.3	17.8
	NREM II	1.3	5.0	87.0	4.8	1.9
	SWS	0.7	0	5.1	94.0	0.2
	PS	1.5	25.3	2.4	0.5	70. 3

5. DISCUSSION

About 25% epochs (17,541 epochs) of the whole test database contain at least one signal artefacted. However, only 20% (3,765 epochs) of these 25% epochs (i.e. 5.7% of the data base) cannot be used for classification because of artefacts (either EEG is artefacted or all signals are artefacted) and are excluded. The rest of the epochs can be successfully scored on the basis of the features extracted from the artefact-free signals. As can be seen in Table 3, most of them have only one signal artefacted. This means that the strategy proposed in this paper enables the classification of 13,776 epochs (20% of the data-base) that would be rejected by a system detecting artefacts and using only one classifier. The classification accuracy computed for these 13,776 epochs is 81.2%. This value alone is high enough to conclude on the interest of the method presented here. The classification of sleep epochs using an incomplete set of signals to overcome the presence of artefacts is worth the effort.

The two-steps system was compared to a single classifier that does not perform any artefact processing strategy. The two-steps automatic system performs slightly better than the single classifier, with 2.2% increase in overall accuracy, calculated on the whole night polysomnographic recordings.

Both systems are able to correctly classify stage II and SWS with more than 85% accuracy for these stages. These stages are traditionally easy to classify. The lowest classification accuracy was obtained with stage NREM I for both systems, which is confused with PS. This is a result that was already observed in (Zoubek *et al.,* 2007). This is due to the fact that spectral EEG information is about the same in the two stages. Indeed, NREM stage I has been called "Skipped REM" by several authors who observed high frequency EEG activity during this transitional stage.

Although the two-steps system, combining the artefact identification and a bank of classifiers, did not bring very significant improvement in the global classification accuracy, a detailed analysis of the confusion matrixes shows an obvious improvement of about 10% in the classification of the PS stage. Although this improvement is partially compensated with a slight increase of about 1.5% of the NREM I stages confused with REM stages, the two-steps system is capable to better distinguish between NREM I and PS stages. The improvement is obviously due to the elimination of artefacted segments since as seen in Table 2, a high portion of artefacted epochs in EOG and EMG are present in these two stages.

The slight decrease observed in the classification of wake could be explained by the fact that about half of the wake epochs are detected with high amplitude artefacts. It seems that the single classifier, learnt on artefacted data, misinterpreted the high amplitude artefacts as a true high-amplitude signal, which is typical of the wake stage and facilitated the classification in this stage.

CONCLUSION

This paper presents a two-steps decision system for the automatic scoring of sleep/wake stages. The automatic system consists of two main blocks. In the first block, artefact-free signals are selected for each epoch to be classified. Then, feature sets are extracted from the artefact-free signals and classified using an adequate classifier.

Various artefacts or noise can intermingle with the physiological signals and can confuse the information characterizing human sleep activity. So, careful artefact processing is an important task to be performed in sleep analysis. To be able to discover hidden knowledge and/or physiological mechanisms characterizing the behaviour of a person during a sleep, only the artefact-free signals and epochs should be analyzed. In total, eight different artefact types are identified in this project. During tests on a large database, the highest number of artefacts was detected in the EMG signal. The high-amplitude muscle activity often leads to the overflow of the monitoring and/or recording device, which may be due to a wrong setting of the acquisition system.

The system proposed consists of a bank of classifier. This structure was selected so as to enable the analysis of epochs containing missing values caused by the presence of artefacts in some of the signals. The results showed that, when an automatic classifier that requires a complete set of features to be computed from all three signals is used, about 20% of the epochs cannot be scored because of artefacts.

Some improvement in the automatic classification could be obtained by optimizing the artefact detection algorithms. It could lead to a more accurate identification of artefacts and in consequence to the extraction of more precise and more reliable information (features) from the signals.

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