Proceedings of the 2012 IEEE 12th International Conference on Bioinformatics & Bioengineering (BIBE), Larnaca, Cyprus, 11-13 November 2012

EEG-based Automatic Sleep-wake Classification in Humans Using Short and Standard Epoch Lengths

Arnaud Brignol
Département Informatique-ISBS
ESIEE-Paris
Cité Descartes-BP 99
93162 Noisy-Le-Grand, France

Tarik Al-ani
LISV-UVSQ
10-12 Av. de l'Europe
78140 Vélizy and
Département Informatique,
ESIEE-Paris
Cité Descartes-BP 99
93162 Noisy-Le-Grand, France
Email: t.alani@esiee.fr

Xavier Drouot
Service de Physiologie, Hôpital Henri Mondor
APHP, 51 av. de Lattre de Tassigny
94010 Créteil and
EA 4391, Faculté de Médecine
Université Paris Est Créteil
8 av. du Général Sarrail
94010 Créteil, France
Email: xavier.drouot@hmn.aphp.fr

***Abstract*—The alternating among *sleep-wake* stages gives information related to the *sleep* quality and quantity since this alternating pattern is highly affected during *sleep* disorders. The analysis of *sleep* in humans is usually made on periods (*epochs*) of 30-s length according to the original *Rechtschaffen and Kales sleep scoring manual*. In this paper, we propose a new *phase space*-based algorithm (mainly based on *Poincaré plot*) for automatic *classification* of *sleep-wake* states in humans using *EEG* data gathered over relatively short-time periods. The effectiveness of our approach is demonstrated through a series of experiments involving *EEG* data from seven healthy adult female subjects and was tested on *epoch* lengths ranging from 3-s to 30-s. The performance of our *phase space* approach was compared to a 2-dimensional state space approach using spectral power in two selected human-specific frequency bands. These powers were calculated by dividing integrated spectral amplitudes at selected human-specific frequency bands. The comparison demonstrated that the *phase space* approach gives better performance in the case of short as well as standard 30-s epoch lengths.**

Keywords: *sleep-wake*, *phase space-based*, *epoch lengths*, *signal processing*, *spectral power*, *frequency bands*.

I. Introduction

Sleep disorders have become a public health issue in recent years. As an example, increased sleepiness during daytime has been identified as an important cause of accidents in transportation and factory plants [1].

Classification of the *sleep-wake* phases is of particular interest in assessing *sleep* quality and quantity. The study of *sleep* and *wake* in routine is based on *Polysomnography* (*PSG*) which consists of a recording set of multiple bioelectric signals including at least two *EEG*, an *electro-oculogram* (*EOG*) and an *electromyogram* (*EMG*). These analysis are usually made, at night, on periods (*epochs*) of 30-s according to the original *Rechtschaffen and Kales sleep scoring manual*, commonly known as the "*R&K*" rules [2]. Recently, the scoring rules have been updated by the *American Academy of Sleep Medicine Manual for Scoring Sleep and Associated Events* [3]. This manual replaces the original *Rechtschaffen and Kales sleep scoring manual*. According to [3], the *sleep* stages were changed to stage *W* (*wake*), stages N_1-N_3 (*NREM*), and stage *R* (*REM*) from the previously described "*R&K*" stages. In order to study only *sleep-wake* classification, we merge the four *sleep* stages *REM* and *NREM* into a single *sleep* state.

To reveal the alternation of *NREM* and *REM sleep* phases, each *PSG* signal (8 to 24-hour record) is split into equidistant parts called *epochs*. *Epoch* lengths less than or equal to 30-s are generally used. The temporal distribution of *sleep-wake* stages is then obtained through a visual interpretation (manual classification) of each *epoch*. Thanks to this classification known as a *hypnogram*, differences between normal and abnormal sleep patterns are more obvious and analysis becomes simpler.

Sleep diagnosis in routine is based on visual interpretation by Physicians of PSG. Physicians look at the signals and classify successive *epochs* using the standard or the updated "*R&K*" rules.

In behavioural neuroscience research involving *sleep*, there is a need for automated *sleep-wake* classification to correctly identify how the experimental manipulations impact the state of the animal, including humans.

Sleep can be analysed by studying only the electroencephalogram (*EEG*) recorded during a night's *sleep*. Spectral composition of *EEG* signals varies according to *sleep* stages, alternating phases of high energy associated to low frequency (*deep sleep*) with periods of low energy associated to high frequency (*wake* and *light sleep*).

When addressing the control of *wake* and *sleep* at the neuronal level, properties of neuronal firing and the resulting structure of *sleep-wake* behavior must be considered on a fine scale [4]. Several researchers proposed to reduce the length of the analysis *epoch* (ranging from 3-s to 30-s) in order to obtain more precise information on the *sleep* of animals including humans. The choice of 3-s *epoch* length as a minimal value of interest in our work is related to the *electroencephalograph arousal* (*EEGA*), defined for healthy subjects, as an abrupt shift in *EEG* frequency, lasting 3-s or more, which may include *theta*, *alpha*, or frequencies greater than 16 Hz but not *spindles* [5]. So, this *epoch* length is the smallest one compatible with

the "R&K" rules of scoring. *Sleep-wake* classification varies widely from laboratory to laboratory as a function of the studied *sleep* parameters.

In animals, traditional *epoch* lengths ranging from 10-s to 30-s have been studied for manual scoring of polysomnographic recording [6] or for automatic analysis and classification of *sleep-wake* in mice and rats based on the standard rules [7], [8].

In humans, different approaches also have been studied via *EEG* recordings based on manual scoring with 4-s *epochs* length [10] and automatic classification with *epochs* lengths ranging from 20-s to 30-s [9], [10], [11], [12].

Automatic sleep analysis and classification have been studied extensively via *PSG* recordings in humans with "R&K" rules and using the standard 30-s *epoch* length, see for example [13], [9], [14]. To the extent of the authors knowledge there is a very limited published work, in the literature, on automatic classification of *sleep-wake* in humans based only on *EEG* and using analysis *epoch* lengths less than 20-s

The aims of this work are threefold: 1) to propose a new automatic *sleep-wake* classification algorithm in humans using *epoch* lengths ranging from 3-s to 30-s. This algorithm is based on phase space analysis (mainly on *Poincaré plot*) generally applied in non-linear and relatively short time series analysis. This direct nonlinear approach permits, in the case of relatively short time periods, to avoid the truncation error and spectral leakage related to side lobes using the traditional *Fast Fourier Transform* [15]; 2) to compare, in the context of automatic human *sleep-wake* classification, the performance of the proposed *phase space*-based approach to *spectral power*-based approach. The last approach is commonly used in sleep community for *EEG*-based *sleep-wake* analysis in animals, e.g. [7], [16] originally applied to mice and rats with *epoch* lengths ranging from 20-s to 30-s. To the extent of the authors knowledge, no published work to compare on automatic classification with short epoch lengths such as 3-s in humans; 3) to study the influence of the chosen *epoch* length on the performance of the automatic classification,

II. Methods

A. Subjects and EEG Records

The whole night of *sleep EEG* records examined in this study were collected by the medical research team at the *Laboratory of Sleep*, *Department of Physiology - Functional Exploration* at *Henri Mondor Hospital* (Créteil-France) using a commercially available recording device (Embla N7000, Embla, Denver, CO, USA, 0.5 - 70Hz). These records (an average of 8 hours) were obtained from seven healthy adult females (25-30 years old). The *EEG* records were acquired at 16-bits, 200 Hz sampling rate. For our *sleep* analysis, we used only the electrode positions C4-O2 to obtain the *EEG* records according to the 10/20 system. These positions have already been used by our research team to validate an automatic sleep analysis software [9]. The *electrooculogram* (*EOG*) was also recorded at the same time. The interest to use only two *EEG* electrode positions and the *EOG* is to make a scoring with a minimum of electrodes so as to not disturb the subject. For each *EEG* record, we used the corresponding *hypnogram*.

In order to reject the artefacts in the *EEG* signals, we developed and applied an algorithm (details will be published soon) for artefact detection and rejection based on the nonlinear *Teager-Kaiser energy operator* (*TKEO*) [17] and *empirical mode decomposition* (*EMD*) [18].

B. Phase space approach

Since, as stated above, spectral analysis is difficult or not practical on short *epochs* such as 3-s, we propose to use a phase space-based approach [19], [20].

1) Phase space: The phase space allows to study variations in the signal only with respect to itself. This can be a means to analyse its behavior at different stages of its temporal evolution. [19] showed that from the evolution of dynamic variables of the process, $x(t), t = 1, ..., N$, we can construct a space which is, under certain conditions, topologically equivalent to the original phase space by introducing a time delay T, called *lag*. The aim of our approach is not to construct the phase space but to use the *lag* technique, based on its practical method, called *delay coordinates*. To construct a phase space, one of the most interesting representation, called *Poincaré plot* or *return map* is used where $f(t+T)$ is plotted against $f(t)$, allowing a signal to be analysed in its behaviour in different phases along its evolution in time as shown in Fig. 1. In previous studies, *Poincaré plot* is extensively used for

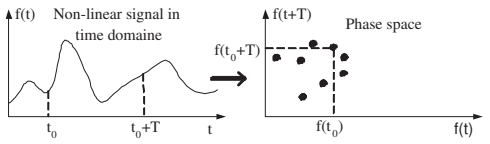

Fig. 1. *Phase space* construction example. A *poincaré* plot is a particular phase space where f(t+T) is plotted against f(t), allowing a signal to be analysed in its behaviour in different phases along its evolution in time.

qualitative visualization of heart rate signals (see for example [21]. *Poincaré plot* is a geometrical representation of a time series in a *phase space*.

Several biological signals such as *EEG, ECG* can have different short and long term correlations on different time scales. When the sampling interval is small, less than the short-time correlation length, then these short-time correlations will be seen [22]. So, in the context of short or long term variability, any instance can influence at least few successive instances [21]. [23] showed that measurement from a series of lagged *Poincaré plot* (multiple lag correlation) can potentially provide more information about the behavior of Poincaré plot than the conventional lag-1 plot measurements. The *Poincaré plot* is a quantitative visual tool which can be applied to the analysis of *EEG* data gathered over relatively short-time periods. In this work, we use it as a quantitative tool for *sleep-wake* automatic classification, which is mainly important for short *epoch* lengths.

2) Linear regression: Let us see how this tool can bring us to classify the stages of *sleep* and *wake*. Consider the *EEG* signal $x(t)$. As we construct the phase space of $x(t+T)$ against $x(t)$, the *scatter plot* varies as a function of the chosen *lag*, T.

To extract the characteristics of the *scatter plot*, we use a linear regression model which seems appropriate given that the data cloud is compact. We are interested more precisely in the slope of the regression (e.g. linear regression Fig. 2).

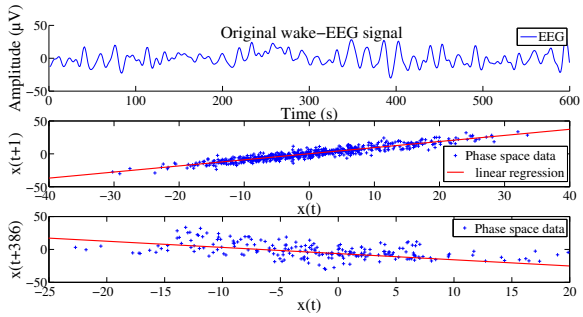

Fig. 2. The *scatter plot* varies as a function of the chosen *lag*. Top: Input EEG signal. Middle: phase space using a *lag* $T = 1$. Bottom: phase space using a *lag* $T = 386$. To extract the characteristics of the scatter plot, we use a linear regression model which seems appropriate given that the data cloud is compact.

We vary the *lag*, T of the phase space between 1 and T_{max} and calculate for each obtained scatter the slope of the line that approximates it. This calculation is repeated for each stage of *sleep* to see if there is a noticeable difference. Fig. 3 shows clearly the presence of a remarkable phenomenon. For the *wake* stage, the evolution of the *slope* (or *trend*), $e(T)$, as a function of *lag* is much like a sine wave, which is much less true for the other stages. Depending on the *sleep* stage, $e(T)$ has a sinusoidal or very little variation. We therefore assume that more $e(T)$ has variations, more likely it is to be a *wake* stage.

3) Classification criteria: We now seek a way to characterise how $e(T)$ has a sinusoidal form. Finally, we calculate the integral of the energy $E(T)$ of $e(T)$, or *energy classification function* (*ECF*)

$$ECF = \sum_{T=1}^{T_{max}} E(T), \qquad (1)$$

where T_{max} may be chosen experimentally. A priori study (see Fig. 3) allows to choose a typical value of T_{max}. Our study from all the *EEG* records showed that a value of $T_{max} = 100$ is sufficient to ensure a good estimation of the trend.

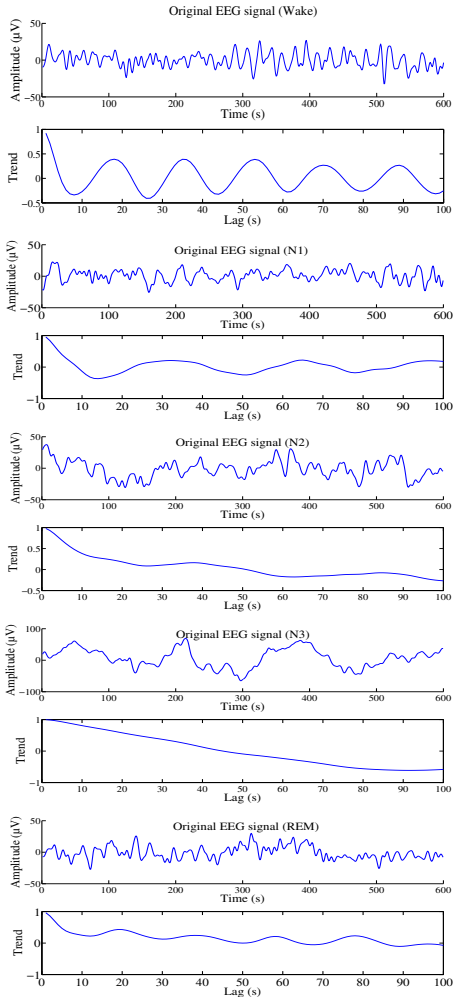

Fig. 3. Evolution of the *slope* (or *trend*), $e(T)$, as a function of the *lag*, T, in *wake*, N_1, N_2, N_3 and *REM* stages respectively. For the *wake* stage, the evolution is much like a sine wave, which is much less true for the other stages. The experiments were realised on *epochs* of 3-s. A typical maximum *lag* value, $T_{max} = 100$, may be chosen to ensure a good estimation of the trend.

Table I shows three examples of *ECF* obtained for the five *sleep* stages. We note that the highest values of *ECF* correspond to the *wake* stage. To estimate a threshold value to classify *sleep-wake* states, we conducted an estimation study on all our *EEG* records (see Table I as an example of three records). In all cases, the highest values of *ECF* in the *wake* stage are always at least 30% more than the values of *ECF* in the other sleep stages. We average the *ECF* values for *wake* and mean values for N_1, N_2, N_3 and *REM*. We then take the median value between these two means: let this value be 0.66. As we study sleep disorders, we want to know as precisely as possible when the subject is awake: we prefer to limit false positives (false awakening) compared to false negatives (false sleep). Therefore, a value of *Thr* equals to 0.50 guarantees a good discrimination.

TABLE I
THREE EXAMPLES OF *ECF* OBTAINED FOR THE FIVE *sleep* STAGES USING THREE *EEG* RECORDS. IN ALL CASES, THE HIGHEST VALUES OF *ECF* IN THE *wake* STAGE ARE ALWAYS AT LEAST 30% MORE THAN THE VALUES OF *ECF* IN THE OTHER SLEEP STAGES.

Stage	ECF_1	ECF_2	ECF_3
Wake	**0.88**	**0.82**	**1.66**
$\mathbf{N_1}$	0.31	0.29	0.14
$\mathbf{N_2}$	0.26	0.337	0.17
$\mathbf{N_3}$	0.16	0.07	0.08
REM	0.30	0.31	0.14

Algorithm 1 summarises the steps to classify the given *epochs* in two stages: *wake* and *sleep* according to the value of the obtained integral.

Algorithm 1 Classification of the *sleep-wake*.

Inputs: *EEG* signal; Maximum epoch number N_{max}; Maximum *lag* value, T_{max}, e.g. T_{max}=100; Threshold, *Thr*, on the *ECF*, e.g. *Thr*=0.50.
Artefact removing
for $n = 1$ to N_{max} **do**
  for $T = 1$ to T_{max} **do**
    Construct a phase space *P(T)*: $x(t + T)$ against $x(t))$
    Apply a linear regression on *P(T)*: $y = sx + b$
    Calculate and stock the current slop s: $e(T) = s$
  end for
  Calculate the energy $E(t)$ of $e(T)$
  Calculate *ECF* using Eq. (1)
  If $ECF \geq Thr$ then the state is *wake*
  else the state is *sleep*
end for

C. Spectral power approach

Studies on *sleep-wake* in rats and mice [7], [16] have shown that different *sleep-wake* stages may be successfully identified (with epoch lengths of 10- 30Hz) using two spectral power ratios.

[16] used a state space and identified two spectral amplitude ratios calculated by dividing integrated spectral amplitudes at selected frequency bands in *EEG*. They demonstrated that these ratios can separate the different stages of *sleep* in mice. [7] used an approach similar to that of [16] to study the *sleep* stages (*Wake*, *NREM*, *REM*) in mice.

The direct application of these ratios to automatically classify *sleep-wake* cycles in human case gave us unsatisfactorily results even for 30-s *epoch* length. Unlike the case in rat and mice, the *sleep-wake* are not linearly (and even nonlinearly) separable in the range of 3-s to 30-s *epoch* lengths. This is consistent with the conclusions given by [24]: "As *delta* activity (0.5- 4.5 Hz) increased from light to deep *slow-wave* sleep, the number of epochs per scoring epoch with high *sigma* activity (11- 16 Hz) as well as power densities in the rest of the spectrum (5- 20 Hz) including *sigma* frequencies also increased. This is in parallel with other rat studies but contrasts findings in humans, where *EEG sigma* activity is reported to decrease as sleep deepens. During the 8-h recording period, *delta* activity decreased whereas sigma activity increased."

Therefore, we defined human-specific frequency bands with *epoch* lengths of 3-s, 15-s and 30-s. We calculated in similar way to that of [16] using these frequency bands. We obtained the spectral powers corresponding to these frequency bands. The selected frequency bands are: $b_1 = \{0.5 - 7\}\ Hz$, and $b_2 = \{8 - 50\}\ Hz$, where b_1 includes the frequency bands delta and theta, while b_2 includes alpha and beta bands. In the *sleep* state, b_1 is large and b_2 is small. The opposite produces during *wake*.

In order to make an optimal classification of *sleep-wake* with the *spectral power approach*, we applied the *support vector machines* (*SVMs*) classification method based on the Gaussian *Radial Basis Function* (*RBF*) [30], [31], [32], $K(x, y) = \exp(\frac{||x-y||^2}{\sigma^2})$, with a scaling factor, σ, of 1 was selected as it gives the most accurate results to evaluate how long it allows optimal separation between *wake* and *sleep epochs*.

D. Statistical evaluation method

To evaluate our automatic classification approaches of *sleep-wake*, we use the *Receiver operating characteristics* (*ROC*) [25]. Consider a classification system that aims to rank *epochs* of *sleep* into two classes: *wake* and *sleep*.

a) Confusion matrix: We choose the following classical criteria for assessing the performance quality of classification: 1) *True positive* (*TP*): *epochs* of *wake* correctly classified as *wake*; 2) *False positive* (*FP*): *epochs* of *sleep* classified as *wake* instead of *sleep*; 3) *True negativ*e (*TN*): *epochs* of *sleep* correctly classified as *sleep*; 4) *False negative* (*FN*): *epochs* of *wake* classified as *sleep* instead of *wake*

We can represent all these variables in the form of a *confusion matrix*, Table II:

TABLE II
CONFUSION MATRIX.

		True class	
		Wake	*Sleep*
Predicted class	*Wake*	*TP*	*FP*
	Sleep	*FN*	*TN*

Using the confusion matrix, we may calculate, among several common metrics: 1) *Accuracy* $(Acc) = \frac{TP+TN}{P+N}$, is the proportion of true results (both true positives and true negatives) in the population. It describes the quality and usefulness of a test; 2) *True positive rate* (*TPR*) (or *Sensitivity* (*Sen*)) = $\frac{TP}{P}$, measures the proportion of actual positives which are correctly identified as such; 3) *False positive rate* (*FPR*)= 1 - *Sensitivity* = $\frac{FP}{N}$. 4) *Specificity* (*Spe*) = $\frac{TN}{N}$, measures the proportion of negatives which are correctly identified.

where $P = TP + FN$ and $N = FP + TN$, are the total positive instances (sum of the first column of the confusion matrix) and the total negative instances (sum of the second column of the confusion matrix) respectively given by the experiment.

b) ROC graph and area under an ROC curve: Based on these criteria, we use the *ROC graph* to assess the quality of the two *sleep-wake* automatic classifiers and *area under*

an ROC curve (*AUC*) to compare the performances of these classifiers on the same *sleep-wake* classification problem. In the case of normalised units, the *AUC* is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (assuming positive ranks higher than negative). It can be shown that the *ROC* curve is closely related to the Mann-Whitney-Wilcoxon test statistic [26], [27], [28]. The *AUC* is related to the *Gini coefficient* (G_1), $G_1 = 2AUC - 1$, where $G_1 = \sum_{k=1}^{n}(X_k - X_{k-1})((Y_k - Y_{k-1})$. In this way, it is possible to calculate the *AUC* by using an average of a number of trapezoidal approximations.

The *AUC* is commonly interpreted by the traditional academic point system: Excellent (0.90 - 1), Good (0.80 - 0.90), Worthless (0.70 - 0.80), Poor (0.60 - 0.70) and Fail (0.50 - 0.60) (see e.g., [29]). In our work, *AUC* is used to compare our proposed *phase space* approach to the *spectral power* approach.

III. Results

A. EEG Data

The statistical results given in this section were based on a sufficient number of *EEG-epoch*s that we used in our experiment from each subject as shown in Table III.

TABLE III
NUMBER OF *EEG-epochs* FOR EACH SUBJECT AS A FUNCTION OF THE SELECTED *epoch* LENGTH.

Subject	3-s *epoch* length	15-s *epoch* length	30-s *epoch* length
1	9203	1840	920
2	9853	1970	985
3	10133	2026	1013
4	9896	1978	988
5	10413	2082	1041
6	9880	1976	988
7	9783	1956	978

B. Performance comparison

We performed a comparative study between the two proposed approaches *phase space* and *spectral power* using 3-s, 15-s and 30-s *epoch* lengths respectively. Figure 4 shows on the same *ROC graph* the classification performance obtained by these two approaches. We calculated the mean of the areas under the *ROC curve* (see section II-D) in the three *epoch* lengths to evaluate the performance of each approach. Figure 4 and Table IV indicate that phase space approach is the best to classify the *sleep-wake*. The comparative study shows that the *phase space* approach is effective on short *epoch* lengths as well as on standard *epoch* lengths such as 30-s. Hence, it is more efficient than the spectral analysis approach if we study the *sleep EEG* with epoch lengths shorter than 30-s. The accuracy and reliability of our algorithm approaches that of human scorers.

IV. Discussion

In this study we proposed a new *phase space*-based approach to automatically classify *sleep-wake* cycles in humans using only two *EEG* electrode positions for four reasons: 1)

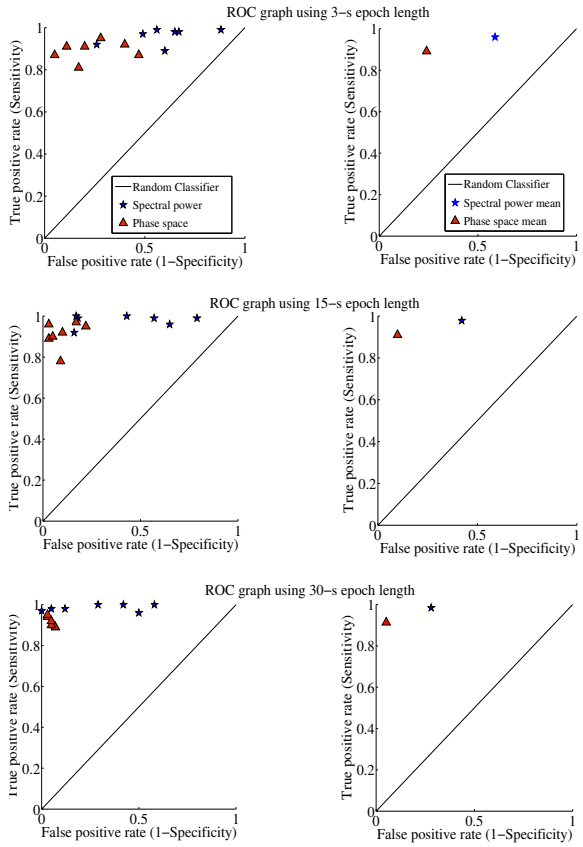

Fig. 4. *ROC graph* (left column) and the mean *ROC graph* (right column) of the seven healthy subjects using 3-s, 15-s and 30-s *epoch* length respectively. The point (0, 1) represents perfect classification. The *phase space* approach do better than the spectral power approach on short epoch lengths.

TABLE IV
CLASSIFICATION OF *sleep-wake* CYCLES: EVALUATION OF EACH APPROACH WITH THE MEAN OF THE *AUC* FOR THE SEVEN HEALTHY SUBJECTS USING 3-S, 15-S AND 30-S *epoch* LENGTHS RESPECTIVELY. THE *phase space* APPROACH DO BETTER THAN THE SPECTRAL POWER APPROACH ON SHORT EPOCH LENGTHS.

Approach	*Epoch*	*AUC*	Evaluation
Spectral power	3s	0.69	Poor
	15s	0.74	Worthless
	30s	0.87	Good
Phase space	3s	0.83	Good
	15s	0.90	Good
	30s	0.93	Excellent

Scoring with a minimum of electrodes is less intrusive for the patient during the recording. Therefore, the records are more faithful to the natural cycles of sleep-wake. 2) Reduction of the recording protocol in its human and economic aspects. 3) The poor quality of the *EMG* in the general case led us to use only the *EEG*. 4) In this study we are concerned only with the automatic classification of *sleep-wake* cycles and not in the classification of each sleep stage. The complexity of the algorithm may be estimated as a function of the maximum *epochs* to be analysed, N_{max}, and the chosen maximum *lag* value, T_{max}: $O(N_{max} \times T_{max})$.

In our tests, with Processor Intel Pentium SU4100 (1.3 GHz,

800 MHz FSB), 3 GB RAM and Windows 7 (64-bit) OS, the execution times of the algorithm (implemented in Matlab) are approximately 5 min (using a *EEG* signal with 1000 *epochs*, 600 samples/*epoch*), 7 min (using a *EEG* signal with 2000 *epochs*, 3000 samples/*epoch*) and 25min (using the same *EEG* signal with 10000 *epochs*, 6000 samples/*epoch*) for 30-s, 15-s and 3-s respectively.

The variation of the *lag*, T_{max}, should be large enough to be able to highlight the possible periodicity of the *trend* (see Fig. 3) and describe how it is sinusoidal. In Fig. 3, we see that the period is apparent for $T_{max} \geq 50$. As a precaution, we choose the double of this value, i.e. $T_{max} = 100$.

The *ECF* of the energy $E(T)$ of the trend $e(T)$ is more important during the *wake* stages. We choose the threshold value, Thr, so as to clearly separate *ECF* of *wake* and *ECF* of *sleep*. We have $ECF(wake) \geq Thr \geq ECF(REM)$, where $ECF(REM) \approx ECF(N_1) > ECF(N_2) > ECF(N_3)$. We found that $ECF(REM)$ and $ECF(N_1)$ usually reach approximately values of 0.30. $ECF(wake)$ reaches approximately a value of 0.80. We choose $Thr = 0.50$ which seems as a reasonable choice.

Some advantages of the proposed *phase space*-based algorithm may be: 1) Studying the evolution of the signal with respect to itself does not require a model or prior knowledge of the analysed signal. 2) Robustness with respect to the selected *epoch* lengths (3-s, 15-s and 30-s). This means that the algorithm characterises well the signal dynamics.

We may mention two minor drawbacks of this algorithm: 1) The performances depend on the empirical choice of T_{max} and Thr. 2) In this study, we limited ourselves to the channel C4-O2. Other channels should be explored simultaneously to obtain more information and to improve the results.

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