An Automatic Sleep-Wake Classifier Using ECG Signals

Hayet Werteni[1] , Slim Yacoub[2] and Noureddine Ellouze[1]
[1]Signal, Image and pattern recognition research unit
Dept. of Genie Electrique, ENIT
BP 37, 1002, TheBelvédère, Tunisia

[2]INSAT, Dépt de Physique et Instrumentation,
BP 37, 1002, The Belvédère, Tunisia

Abstract

Sleep stage influence autonomic nervous system, this influence can be investigated by analysis of ECG signal. This paper presents system aimed to score sleep-wake stages using only the electrocardiogram (ECG) records. The feature extraction stage described in this paper was performed using methods of Heart Rate Variability analysis (HRV) and Detrended fluctuation analysis (DFA). These features are based on QRS detection times. Therefore, this detection was generated automatically for all recordings using a new algorithm based on the detection of singularities through the local maxima in order to construct the RR series. We illustrate the performance of this method using a neural network algorithm called Extreme Learning Machine (ELM). We make a comparative study of our algorithm using two classifiers back propagation neural network (BPNN) and support vector machine (SVM). The proposed method shows significantly better performance than back propagation neural network (BPNN), and almost same result than support vector machine (SVM), it achieves the classification accuracy of 78.33%.

Keywords: *ECG, Heart rate variability, Detrended fluctuation analysis, sleep stages, learning machine.*

1. Introduction

Sleep is a natural part of every individual's life. This state that occurs every 24 hours occupies almost a third of our lives. It is composed of a succession of phases; this succession is very revealing of the quality of the sleep which allows to highlight certain pathologies. For example: apnea patients with respiratory arrest during the night, and narcoleptic patients who are to access daytime sleepiness [1]. Therefore, a good analysis of sleep was presented with a classification of the night stages. For this reason, a Polysomnography (PSG) was done; which is a reference test for quantifying and qualifying sleep disorders. PSG is presented by the recording of several physiological variables during the night's sleep, in order to classify the different phases of sleep. Indeed, these variables present different characteristics according to the stage of considered sleep [1]. Numerous searches exist to classify the stages of sleep to reduce the times of analysis, and to increase the reliability in the results of diagnosis. Most of these searches are based only on the electroencephalogram (EEG) [2, 3, 4]. On the other hand, they exist searches based on the electro-myogram (EMG) and the electro-oculogram (EOG) [5]. During the PSG, other factors intervene to classify the various phases of sleep which are: respiratory effort, air flow entering through nose and mouth, the saturation of oxygen in hemoglobin, the electro-cardiogram (ECG) and effort of the thoracic and abdominal muscles.

ECG recording is one of the simple and efficient technologies in sleep disorders detection. It is governed by autonomous nervous system; this common source is the cause of correlations with breathing [6] and can be source of the correlation with the different sleep stages [7, 8, 9]. Various studies have confirmed that several new methods could possibly recognize sleep apnea and sleep stages from heart rate variability (HRV), since during sleep the HRV presents characteristic oscillations connected to sleep stages [10]. Along with this, some researchers in the literature have proposed many approaches for sleep stages scoring. Reference [11] proposed a cardio respiratory-based sleep staging, where they used ECG, estimated respiratory frequency and respiratory effort signals. Reference [12] presents a comparison between HRV spectral analysis and detrended fluctuation analysis (DFA) applied to sleep ECG. Many other works introduced a new method for change-point detection in time series called progressive detrended fluctuation analysis (PDFA). This method, inspired by the DFA, is used to detect changes in low range times [13]. Recently, [10] present a system that recognizes automatically Wake, REM and NREM during sleep time based only on heart rate fluctuations, and [13] propose a method for sleep–wake stages scoring and sleep efficiency estimation using only a single-lead ECG. This method is based on the extraction, according to three methods; the heart rate variability (HRV), the detrended fluctuation analysis (DFA) and windowed DFA (WDFA). The objective of this study is to assess the performance of

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

two feature extraction methods and three classifiers on sleep-wake stages scoring using ECG signal. The feature extraction was performed using the methods of Heart Rate Variability analysis (HRV), and detrended fluctuation analysis (DFA). These methods were tested on the MIT/BIH Polysomnographic Database (MITBPD) using three classifiers: Extreme Learning Machine (ELM), the back propagation neural network (BPNN), or support vector machine (SVM).

2. Methods

In this study, ECG epochs were classified; in one of two categories "Awake" and "Sleep". The overall classification system is shown in Fig. 1. There are three main stages on this system; the preprocessing was applied on the ECG signal in order to build the RR series, the feature extraction is used by the Heart Rate Variability analysis (HRV) and Detrended fluctuation analysis (DFA) methods. Finally, we adopt a comparative study for Wake/Sleep classification using supervised machine learning techniques such as the: Back-Propagation Neural Network (BPNN), Extreme Learning Machine (ELM) and support vector machine (SVM).

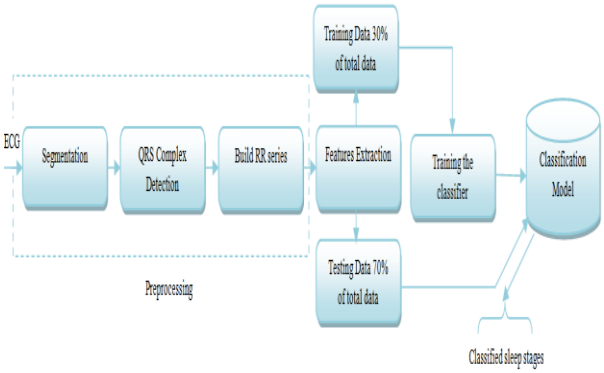

Fig. 1 Block diagram of the adopted algorithm

2.1 Database

The approach presented in this paper is tested using ECG registrations from the MIT-BIH polysomnographic (MITBP) database. This database is a collection of recordings of multiple physiologic signals during sleep with sampling rate 250Hz. The database contains over 80 hours' worth of four-, six-, and seven-channel polysomnographic recordings, each with specifically an ECG signal annotated beat-by-beat. The 16 patients (16 males aged 32 to 56) in this database suffer from a condition known as sleep apnea in which they are repeatedly awoken during the night due to their breathing being interrupted [14]. The data files contain the header file, the QRS annotations file and the sleep stages file. The header file is a text file containing the information related to the record such as, the types of the signals, calibration constants, the length of recordings, and the anthropometric data of the subject. The QRS annotations give the time occurrence of each QRS complex, whereas sleep stages file contains the class label of each epoch, i.e., wake, REM sleep, stages 1, 2, 3 or 4 of the NREM sleep, epoch with MT (movement time) annotation was not included in this work.

2.2 Preprocessing

Extraction of characteristic parameters requires ECG segmentation, the entire ECG is divided in 30s long epochs. Indeed, the sleep annotations provided by the MIT/BIH Polysomnographic Database are given in that time length. Then, In our previous work [15] we developed a new algorithm for R wave's locations using the multiscale wavelet analysis that is based on Mallat's and Hwang's approach for singularity detection via local maxima of the wavelet coefficients signals. The principle of this algorithm can be depicted as in Fig. 2.

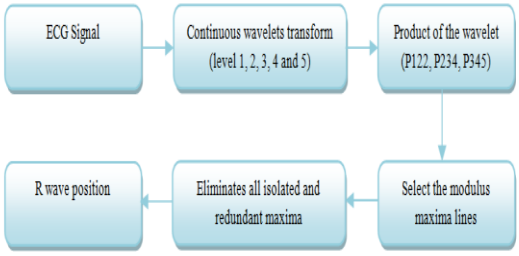

Fig. 2.Algorithm of QRS complex detection

Once the detection of the R wave was made, the heart rate variability is defined as the variation of the interval of time separating two waves R consecutive of the electrocardiogram (ECG). Fig. 3 shows the detection result using product of the wavelet coefficients, and the series RR determined after detection of the waves R.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

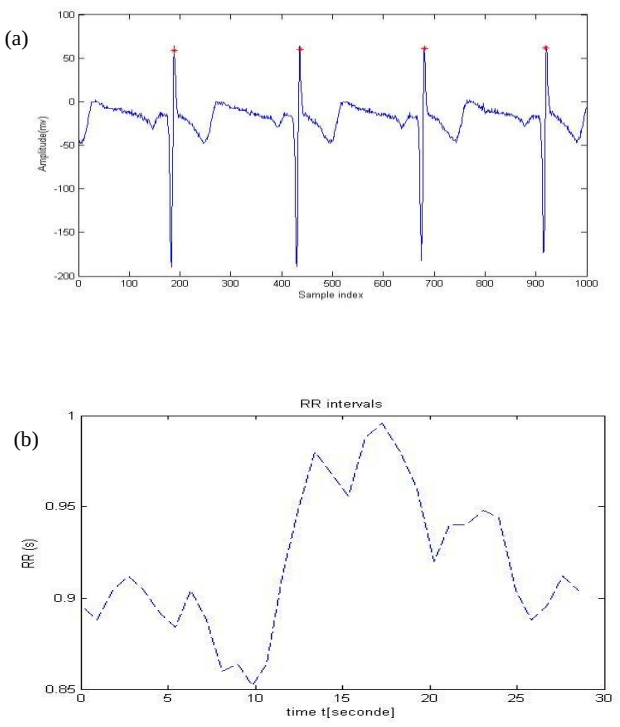

Fig. 3 (a) Detection result using product of the wavelet coefficients, (b) RR interval

2.3 Features extraction

Sleep stage influences autonomic nervous system. This influence can be investigated using features based on the analysis of signal ECG more precisely based on the analysis of the RR interval. In this paper, 12 features are used for sleep stages scoring. This sleep stages are scored according to epoch times of 30 s length. Then, for every epoch time of 30-second length, the features are extracted using two methods; the Heart Rate Variability analysis and the detrended fluctuation analysis.

2.3.1 Heart Rate Variability (HRV)

The HRV is a method used to interpret the oscillation in the interval between consecutive heart beats and oscillations in consecutive instantaneous heart rates. Heart rate variability covers large number of methods but not all of them are suitable for analyzing short intervals of records in which we try to detect sleep stages. Two main domains, spectral and time-domain, are used in heart rate variability analysis. In our tests, seven spectral and three time-domains HRV measures are used.

Temporal Analysis of HRV

The temporal analysis defines several measures of the heart rate variability by using statistical methods or geometrical methods. Generally, the geometrical methods require a large number of samples. That is why they are difficult to interpret for the detection of sleep stages [9]. Indeed, the sleep stages are scored according to epoch times of 30 s length. For this reason, only the following statistical indices were chosen for the detection of sleep phases [16]:

- **RRmean:** Mean of *RR* interval length $\left(\overline{RR}\right)$
- **SDNN:** The standard deviation of *RR* intervals. The *SDNN* reflects the overall variation within the RR interval series. This is defined as:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(RR_j - \overline{RR}\right)^2} \quad (1)$$

Where RR_j denotes the value of $j'th$ *RR* interval, and N is the total number of successive intervals.

- **RMSSD:** The root mean square of successive differences. This measure shows the instantaneous variability seen as a reflection of the parasympathetic component [16].

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N-1}\left(RR_{j+1} - RR_j\right)^2} \quad (2)$$

Spectral Analysis of HRV

The spectral parameters are important parameters in the classification of sleep stages. Indeed, the HRV spectral represent the markers of the autonomous nervous system. Before the extraction of the frequency measures, a preprocessing was carried out on the RR interval based on the fact that the spectral analysis cannot be affected only on regularly sampled signals [17]. This preprocessing is presented by resampling the data at a frequency of 1 Hz using an interpolation method developed by Berger et al [18]. The resampling process was made to get regular RR series. Thus, the frequency measures were extracted from the power spectral density of the RR series by the Autoregressive Model (AR). The AR has fine properties to deal with non-stationary time series [10]. For this reason, the RR series is modeled by the autoregressive model (AR) which is presented as follows:

$$\hat{x} = \sum_{i=1}^{p} ap(i)x\left(n-i\right) + e\left(n\right) \quad (3)$$

Where p is the filter order, $x\left(n\right)$ is the sample n of *RR* intervals, $\left(a_i\right)_{i=1\ldots p}$ are the coefficients of the model, $\hat{x}$ denotes the prediction output. $e\left(n\right)$ is the prediction error, it presents the randomness of a white noise signal which has variance σ^2.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

The estimation of coefficient of the AR model was determined by the Levinson-Durbin algorithm of order 13. The selection of this order can be verified by "arfit toolbox" [19]. This selection is a compromise, because the proper order may vary. This is caused by short interval length and by the natural diversity in heart rates [9].

The coefficients $(a_i)_{i=1...p}$ are used to estimate the power spectral density $P_{ar}(f)$ of the RR intervals, according to the following expression:

$$P_{ar}(f) = \frac{\sigma^2}{\left|1 - \sum_{i=1}^{p} ap(i) e^{-j2\pi fi}\right|^2} \quad (4)$$

From the spectrum of RR series presented for each sleep stage, we selected the following characteristics to classify sleep stages:

- **TOTPWR:** Total spectral power of all RR intervals up to 0.04 Hz.
- **VLF:** Total spectral power of all RR intervals between 0.003 and 0.04Hz.
- **LF:** Total spectral power of all RR intervals between 0.04 and 0.15Hz. It is considered a reflection of sympathetic activity.
- **HF:** Total spectral power of all RR intervals between 0.15 and 0.4 Hz, and reflecting parasympathetic activity.
- **LF/HF:** Ratio of low to high frequency power. It illustrates the predominance of sympathetic activity on parasympathetic activity.

These spectral parameters are very significant for the separation of the sleep stages. Indeed, HF is considered to reflect the parasympathetic activity whereas, LF reflects sympathetic activity according to some researchers or both parasympathetic and sympathetic activity. Therefore, the LF/HF ratio can be used as an index of sympathetic to parasympathetic balanced [10].

2.3.2 Detrended Fluctuation Analysis (DFA)

In this paper we present the DFA method for quantifying the correlation property in non-stationary time series. First, the RR interval time series is integrated [20]:

$$y[k] = \sum_{i=1}^{k} \left[RR(i) - \overline{RR} \right] \quad (5)$$

$$k = 1, ..., N$$

Where $\overline{RR}$ is the average RR .Then, the integrated series $y[k]$ is divided into segments of equal length n. Within each segment, a least squares line is fitted into the data. Let $y_n[k]$ denote these regression lines. Next the integrated series $y[k]$ is detrended by subtracting the local trend within each segment and the root-mean-square fluctuation of this integrated and detrended time series is calculated by [20]:

$$F[n] = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left(y[k] - y_n[k] \right)^2} \quad (6)$$

$F[n]$ Characterizes the fluctuations of the indefinite integral of the series $RR[i]$, Corrected by her trend. $F[n]$ is computed for all time-scales n. Typically, $F[n]$ increases with n, the "box-size". If $\log(F)$ increases linearly with $\log(n)$, then the slope of the line relating $F[n]$ and n in a log-log scale gives the scaling exponent, which can be used to discriminate between sleep stages [12]. The DFA needs a longer analyzed interval due to the logarithmic dependence of scaling exponent α. This scaling exponent is computed for several boxel size ranges n, but in our case the size of the analyzed interval of 30 seconds does not permits fitting of the second independent scaling exponent, therefore 2 overlapping exponents were chosen[9]. The basic boxel size was set to 6 to remove degradation of scaling coefficient caused by detrending at small number of samples [9]. This effect is stronger for higher order of DFA. DFA of higher orders can be used to eliminate on the noise and to refine the results obtained from DFA-1. The DFA of higher orders has ability to eliminate effects of trends of lower orders [9]. The DFA measures consist of:

- α_{fast-1} : is computed from the basic boxel size n = 6 to boxel size n = 16, DFA order is 1.
- $\alpha_{total-1}$: scaling coefficient computed from basic boxel size n = 6 to boxel size of the total number of samples in the analyzed interval, DFA order is 1.
- α_{fast-2} **:** is computed from the basic boxel size n = 6 to boxel size n = 16, DFA order is 2.
- $\alpha_{total-2}$ **:** scaling coefficient computed from basic boxel size n = 6 to boxel size of the total number of samples in the analyzed interval, DFA order is 2.

After the feature extraction step, each epoch of 30 s length will be represented in our database by 12 characteristics that we associate a label representing the stages of sleep.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

2.4. The Classifiers

Recently, extensive studies have been carried out on sleep stages classification algorithms using neural network. To improve practicality, many studies have focused on learning speed and the accuracy of neural networks [21]. However, algorithms based on neural networks still have some problems concerning practical application, such as slow learning speeds and unstable performance [21]. In this paper, the classification is performed using a recent neural network algorithm: the Extreme Learning Machine (ELM), which is able to overcome the difficulties of a neural network through a fast learning speed and high performance [21]. We make a comparative study of ELM algorithm, in terms of accuracy and learning time, using two classifiers back propagation neural network (BPNN) and support vector machine (SVM).

2.4.1 Extreme Learning Machine

The ELM is known to achieve good performance in complex problems as well as reduce the computation time compared with other machine learning algorithms [22]. The ELM was proposed for Single Hidden layer Feedforward Neural Networks (SLFNs).The information on this kind of neural network propagates directly from the input to output neurons through the hidden neurons. The architecture of this network organized in an input layer consisting of units representing the number of the extracted characteristic of the RR series, an output layer consisting on units representing the number of class. The connections in this architecture are established between neurons belong to successive layers and not between neurons in the same layer. The ELM with a single hidden layer can be summarized as follows [23]:

Given a training set $\phi = \{(x_i, t_i) / x_i \in R^n, t_i \in R^m, i = 1, ..., N\}$ where x_i is a training sample and t_i is the corresponding target value, the activation function $g(x)$ and the number of hidden neurons $\tilde{N}$, perform the following steps.

- Step1: Assign arbitrary input weight w_{ij} and bias b_i.
- Step2 : Calculate the output matrix at the hidden layer

$$H = g(w.x + b) \tag{7}$$

- Step 3 : Calculate the output weight β

$$\beta = H^{\dagger}T \tag{8}$$

$H^{\dagger}$ is the Moore-Penrose generalized inverse of the matrix H.

2.4.2 Back Propagation Neural Network

BPNN is a learning algorithm for the multi-layer neural network. In this method, the error output of the network will be propagated back to the hidden layers where the name back propagation. The criterion function of the BPNN is expressed as Equation (9):

$$j(w) = \frac{1}{2}\sum_{k=1}^{N}(t_K - z_k)^2 \tag{9}$$

Where $\mathbf{w}$, $\mathbf{t_k}$, and $\mathbf{z}$ are the weight vector, the target vector, and the output vector, respectively. BPNN is the representative gradient descent method for searching the weight vectors w, which are initialized with arbitrary value at the beginning, and then are adjusted according to the most rapid decrease of $J(w)$.

$$\Delta w = -\eta \frac{\partial J}{\partial w} \tag{10}$$

BPNN takes a long time to learn and has the risk of falling into a local minimum, because it solves the equation (10) iteratively until $J(w)$ reaches the minimum [21].

2.4.3 Support Vector Machine

Support Vector Machine (SVM) is a supervised learning method used for classification and regression. The SVMs extends the applicability of linear classifier to non-linear separable data by using the kernel method [24]. Non-linear SVM is considered to solve a conditional optimization problem as Equation (11):

$$\max W(\alpha) = \Sigma_{i=0}^{m}\alpha_i - \frac{1}{2}\Sigma_{i,j=1}^{m} y_i y_j \alpha_i \alpha_j K(x_i, x_j), i = 1, ..., m. \tag{11}$$

Under the following constraints:

$$\sum_{i=1}^{m} \alpha_i y_i = 0, 0 \le \alpha_i \le C \tag{12}$$

Where $K(A, B)$ is a kernel function of A and B, α_i are called Lagrange multipliers. C is a regularization parameter which is used to determine the tradeoff between margin maximization and training error minimization [25]. y has 1 or -1 as target value. Thus, when using SVM there are two parameters to be decided, $K(A, B)$ and C. In this paper, we used a radial basis function kernel, like Equation (13), which is adopted for all the experiments.

$$K(A, B) = \exp\left[-\left\|x - x'\right\|^2 / 2\gamma^2\right] \tag{13}$$

For the implementation of this method, it is necessary to proceed iteratively, by creating a couple of values γ and C. In this work, we use the following couples γ, C [26]:

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

$$C = \left[2^{(-5)}, 2^{(-4)}, ..., 2^{(15)} \right] \quad \text{and}$$
$$\gamma = \left[2^{(-15)}, 2^{(-14)}, ..., 2^{(3)} \right]$$

3. Experimental Results

The performance of the proposed algorithm was evaluated by all records of the MITBP database. We used 2 classes of sleep stage as shown in Table 1, where: Wake (W) is a period when no sleep stages can be classified. Sleep (S) period includes sleep stage 1 or 2 or 3 or 4 or REM sleeps. The classification of sleep-wake stages was performed with two scenarios: subject- specific system and subject-independent system. A subject specific classification is trained by selecting epochs from 1/3 of the night's sleep, remaining 2/3 of the night's sleep was used to test the system [11]. A subject-independent classification was constructed using training epochs drawn from all subjects. For this reason, we construct the training set by 1/3 of the database and 2/3 for testing. The classification is performed with ELM, BPNN and SVM. The performance of these classifiers is compared on all records of the MITBP database. For ELM classifier the number of input neurons is fixed to 12, which the corresponding number of features extracted. The output is set at the number of classes that is equal to 2 to classify 'W /S'. The number of hidden neurons is the adjustable parameter affecting performance. The activation function chosen is the sigmoid function. BPNN is a learning algorithm for the multi-layer neural network, this performance are based on: the learning rate, the momentum, the number of training iterations and hidden neurons, and the number of hidden layers used. In this paper, the BPNN are part of these parameters: the number of hidden layer is equal to that in the ELM case as 1, and the learning rate of 0.01, the momentum constant of 0.4, iteration number 400, and the number of hidden neurons is the adjustable parameter. For the SVM, we used the LibSVM toolbox [29]. Thus using SVM, there are these parameters to be determined: the kernel parameter, γ and the constant of regularization C . In this paper, we use the following couples C , γ [21]:

$$C = \left[2^{(-5)}, 2^{(-4)}, ..., 2^{(15)} \right] \quad \text{and}$$
$$\gamma = \left[2^{(-15)}, 2^{(-14)}, ..., 2^{(3)} \right]$$

The performance of these three classifiers is compared in terms of accuracy, and learning time [21]. The classification rate is based on the percentage of correct recognition rate classes' sleep, it is calculated as follows:

Classification rate = (number of feature vectors correctly classified / total number of attributes tested)*100.

Table 2 shows a Comparison of network complexity of ELM, BPNN and SVM. For BPNN and ELM, the numbers of hidden nodes are gradually increased by an interval of 5[21]. For the SVM classifier, it is necessary to proceed iteratively by creating a couple of values γ and C. Tables 3, 4 and 5 show the classification rate by two methods, the heart rate variability (HRV) and the detrended fluctuation analysis (DFA), also shows the classification rate by combining these two methods. The comparison of the learning time of three classifiers for all subjects in MITBP database is shown in Fig. 4. Table 6, we present the total classification rate and the total learning times with subject-independent system.

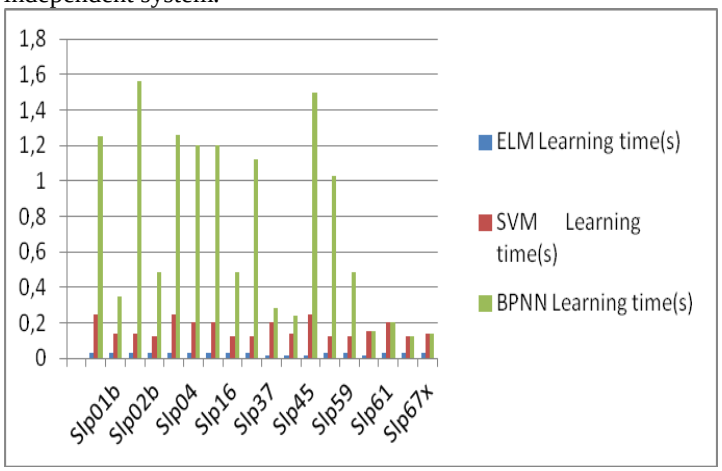

Fig.4.Comparison of learning time of BPNN, SVM and ELM

Table 1: Training and Testing data in records of the MITBPD

Record	Total	Training Data		Testing Data	
		Wake	Sleep	Wake	Sleep
Slp01a	236	3	75	4	154
Slp01b	355	109	9	68	169
Slp02a	349	8	61	42	238
Slp02b	242	4	72	96	70
Slp03	701	29	204	104	364
Slp04	667	32	190	99	346
Slp14	685	25	203	274	183
Slp16	690	100	130	205	255
Slp32	625	117	91	262	155
Slp37	688	60	168	13	447
Slp41	765	69	135	147	414

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

Record	Total	Training Data		Testing Data	
		Wake	Sleep	Wake	Sleep
Slp45	749	2	239	5	503
Slp48	750	93	157	120	380
Slp59	457	58	94	81	224
Slp60	680	102	128	175	275
Slp61	716	71	166	49	430
Slp66	434	41	104	130	159
Slp67x	153	35	16	37	65
Total	9942	958	2242	1911	4831

Table 2: Network Complexity of BPNN, SVM and ELM with the best accuracy

Record	BPNN	SVM	ELM
	# nodes	(C, γ)	# nodes
Slp01a	5	$(2^{(-5)}, 2^{(-1)})$	50
Slp01b	5	$(2^{(-3)}, 2^{(-6)})$	50
Slp02a	10	$(2^{(-5)}, 2^{(-12)})$	100
Slp02b	15	$(2^{(-4)}, 2^{(-13)})$	150
Slp03	5	$(2^{(-5)}, 2^{(-4)})$	50
Slp04	20	$(2^{(-5)}, 2^{(2)})$	200
Slp14	15	$(2^{(-5)}, 2^{(-1)})$	150
Slp 16	15	$(2^{(-4)}, 2^{(-6)})$	150
Slp32	20	$(2^{(-3)}, 2^{(-1)})$	200
Slp37	30	$(2^{(-3)}, 2^{(-10)})$	50
Slp41	35	$(2^{(-5)}, 2^{(2)})$	50
Slp45	20	$(2^{(-5)}, 2^{(-1)})$	50
Slp48	10	$(2^{(-5)}, 2^{(2)})$	50
Slp59	15	$(2^{(-3)}, 2^{(-10)})$	150
Slp60	15	$(2^{(-5)}, 2^{(-4)})$	150
Slp61	5	$(2^{(-3)}, 2^{(-10)})$	100
Slp66	20	$(2^{(-5)}, 2^{(-4)})$	200
Slp67x	15	$(2^{(-5)}, 2^{(-1)})$	150

Table 3: Results using ELM Algorithm for Subject-Specific System

Record	Classification Rate (%)		
	HRV	DFA	HRV+DFA
Slp01a	97.84	95.47	97.08
Slp01b	62.48	59.16	64.67
Slp02a	86.44	79.77	88.77
Slp02b	79.59	76.87	81.99
Slp03	82.19	80.56	84.66
Slp04	77.28	76.03	78.75
Slp14	57.55	57.48	60.92
Slp 16	60.04	58.55	61.13
Slp32	81.24	78.3	83.55
Slp37	83.66	79.77	84.33
Slp41	70.12	67.16	71.88
Slp45	95.02	90.34	97.45
Slp48	80.33	77.45	82.82
Slp59	64.76	60.22	68.22
Slp60	79.33	76.88	80.01
Slp61	81.12	79.02	84.36
Slp66	73.2	70.55	76.14
Slp67x	61.12	59.11	63.23
Average	76.29	73.48	**78.33**

Table 4: Results using BPNN Algorithm for Subject-Specific System

Record	Classification Rate (%)		
	HRV	DFA	HRV+DFA
Slp01a	95.43	94.44	96.89
Slp01b	53.88	50.56	59.33
Slp02a	83.55	79.12	85.99
Slp02b	77.88	75.88	79.99
Slp03	80.98	78.55	82.16
Slp04	82.22	80.66	84.88
Slp14	51.56	49.76	60.09
Slp 16	58.88	56.57	60.44
Slp32	80.56	79.13	82.77
Slp37	81.11	78.17	83.34
Slp41	66.01	63.45	68.87
Slp45	94.98	90.46	95.99
Slp48	78.44	77.99	79.88
Slp59	64.66	60.45	65.99
Slp60	74.88	70.65	79.55
Slp61	76.88	73.09	79.87
Slp66	73.12	70.17	77.33
Slp67x	53.73	50.19	58.23
Average	73.81	71.07	**76.74**

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

Table 5: Results using SVM Algorithm for Subject-Specific System

Record	Classification Rate (%)		
	HRV	DFA	HRV+DFA
Slp01a	94.66	91.01	96.15
Slp01b	55.43	49.67	60.66
Slp02a	86.29	81.22	88.99
Slp02b	78.44	70.19	80.11
Slp03	81.33	80.03	83.55
Slp04	76.11	72.34	77.59
Slp14	58.66	56.23	61.96
Slp 16	68.13	67.88	70.82
Slp32	79.66	78.15	81.29
Slp37	82.47	80.11	84.66
Slp41	66.73	65.7	69.44
Slp45	95.33	93.55	97.55
Slp48	79.42	78.22	80.82
Slp59	67.55	65.99	69.66
Slp60	78.99	71.44	80.84
Slp61	81.55	80.42	82.77
Slp66	78.02	77.97	79.29
Slp67x	59.88	57.68	60.01
Average	76.03	73.21	**78.12**

Table 6: Results using ELM, BPNN and SVM algorithm for subject-independent system

	Classification rate (%)			Learning time(s)
	HRV	DFA	HRV+DFA	
ELM	68.19	66.33	70.78	0.1334
BPNN	65.99	60.75	68.74	1.8845
SVM	68.22	65.88	70.15	0.6056

4. Discussion

Sleep stages classification using RR series derived from the ECG signal was developed. A set of features were extracted from RR series according two methods i.e., HRV and DFA. We estimated the performance of these features using three different learning techniques, i.e., ELM, BPNN and SVM. This operation had two goals. First, find the best method of features, extracted from the ECG signal, for sleep–wake stages classification. Second, establish the best methods of classification. The methods used in this paper showed good results as it is presented in Tables 3, 4 and 5. These results indicate that the capability to differentiate sleep/wake by the HRV features perform better than DFA features.

However, we should remember that the best classification results are obtained when combining the two methods. In this paper, we used the same HRV features used by other research, But for the DFA features we all extracted from a window of 30 s length, we did not work on windows superior in 30secondes. Reference [12] Show that the sleep stages scoring using parameters derived from the DFA is better than it is using spectral parameters of the HRV. Actually, [12] compare temporal HRV combined by DFA with the spectral HRV, which explain their results. On the other hand, we introduced in this paper a comparison between three classifiers, i.e., ELM, BPNN and SVM. We conclude that the performance of the ELM algorithm showed the best performance, the rate of classification with SVM was slightly lower, but the BPNN algorithm were low compared to our proposed algorithm. This is in conformity with results of [21]. ELM algorithm also has advantages in terms of learning time as it is presented in Figure 4. The learning time of the ELM algorithm was shorter of BPNN and SVM based algorithm. We also conclude, in terms of complexity, that ELM needs more hidden nodes than BP [30].
These approaches are tested on classification of two types of data; the subject-specific and the subject independent. The performance of the classifier on the subject independent task was poor, compared to specific classification, this is logical since similarities exist in records of the same person. Subject-independant scheme gives less good results because of big differences between persons' data. This is confirmed by [11]. Table 6 shows that the classification rate for subject-independent system is better by combining the two types of features.
In addition, the results showed that excellent classification efficiency was obtained for some records: slp01a, slp02a, slp37, and slp45. The results are quite good for some records: Slp02b, Slp03, Slp32, Slp48, Slp60, and Slp61. Finally, the results show moderately low performance for records: Slp01b, Slp04, Slp14, Slp16, Slp41, Slp59, Slp66, and Slp67x. This is confirmed by [13].

5. Conclusions

In this work, we studied the feasibility of sleep-wake classification using only the electrocardiogram signal. The features extraction is realized using HRV and DFA methods. We made a comparison between the linear (HRV) and nonlinear (DFA) features. We evaluated the performance of these features using three different

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

classifiers: ELM, BPNN and SVM. The results show that good results can be obtained to classify Wake-Sleep stages by combining these two features (DFA+HRV). We conclude that the ECG signal contains information related to Wake-Sleep stages, but we try in other works to separate the various stages in the sleep class (stage 1, stage 2, stage 3 and stage 4). This result can be improved if we use other signals as EEG signal or if the number of features is increased.

References

[1] D. Stéphanie, "Classification automatique en stades du sommeil : extraction de caractéristiques et comparaison des principaux classificateurs", Thèse Académie universitaire Wallonie-Bruxelles, 2007.

[2] N.Schaltenbrand, R.Lengelle, M. Toussaint, R.Luthringer, G. Carelli, A. Jacqmin, E. Lainey, A. Muzet, and JP.Macher, "Sleep stage scoring using the neural network model: comparison between visual and automatic analysis in normal subjects and patients Sleep", 1996,19(1):26 – 35.

[3] D.W. Barnett, A. Laposky, C. Thomas , and M. Anch, "Neural network scoring of rat sleep stages", In Proceedings of the 21st Annual International Conference of the IEEE Eng Med Bio Soc, 1999, volume 1, page 389, Atlanta, GA, USA.

[4] G.Agustina, E.Correa, H.Laciar, P.Máximo, E. Valentinuzzi, ,"An Automatic Sleep-Stage Classifier Using Electroencephalographic Signals", International Journal of Medical Sciences and Technology, Volume 1, 2008, Issue 1, Page(s): 13-21.

[5] K.Šušmáková, A. Krakovská," Discrimination ability of individual measures used in sleep stages classification",Artif. Intell.Med., Vol. 44, No. 3, 2008, pp. 261–277.

[6] R.Sven, F. Heinrich, S.Becker, B.Havlin, W. Jan, P.Thomas ,"Breathing during REM and NONREM sleep: correlated versus uncorrelated behaviour",Physica A, 2003, 319:447–457.

[7] W.Jan, TP .Kantelhard, P. Jorg-Hermann, B. Armin, H.Schlomo, and V.Karlheinz," Correlated and uncorrelated regions in heartrate fluctuations during sleep", Physical Review Letters, 85(17):3736–3739,2000.

[8] HF.Becker, JH.Peter, A. Bunde, P. Thomas, W. Kantelhard ,"Detrended fluctuation analysis and spectral analysis of heart rate variability for sleep stage and sleep apnea identification", Computers in Cardiology, 30:307–310,2003.

[9] TR.Al-ani, and D. Kazbunda ,"Automatic sleep scoring based only on electrocardiogram records", ISBN 978-3-901608-32-2,2007, Proc. EUROSIM.

[10] MO.Mendez, Matteucci, M., Cerutti, S., Aletti, F., A.M. Bianchi (2009).Sleep Staging Classification Based on HRV: Time-Variant Analysis. 31st Annual International Conference of the IEEE EMBS Minneapolis, Minnesota, USA, September 2-6.

[11] Redmond, S. J., and Heneghan, C. (2006). Cardiorespiratory-based sleep staging in subjects with obstructive sleep apnea. IEEE Transactions on Biomedical Engineering, 53(3), 485–496.

[12] Penzel , T., kantelhardt, J.W. Grote, L., Peter, JH., and Bunde, A. (2003) Comparison of detrended fluctuation analysis and spectral analysis for heart rate variability in sleep and sleep apnea. IEEE Trans on Biomedical Engineering, 50(10),pp.1143–1151.

[13] Adnane, M., ZJiang, a., Z.Yan. (2012) Sleep–wake stages classification and sleep efficiency estimation using single-leadelectrocardiogram. Expert Systems with Applications 39 1401–1413.

[14] Goldberger, A., Amaral, L., Glass, L. M. Hausdorff, M.,. Ivanov, P.CH., Mark, R.G., J.E. SMietus, G.B .Moody , C-K.Peng , and H.E. Stanley(2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation, Vol. 101, No. 23, pp. 215–220.

[15] Werteni, H., Yacoub, S., and Ellouze ,N.(2012) Multiscale products for the detection of an electrocardiogramme R wave :MIT-BIH polysomnographic. 6th International Conference: Sciences of Electronic Technologies of Information and Telecommunications, 2012

[16] VIOLA, A.,(2004). La Variabilité Cardiaque au Cours des Cycles de Sommeil chez l'Homme. Thèse, l'Université de STRASBOURG .

[17] M.Sami, M.Isa,Ito Wasito and Aniti Mur. Kernel Dimensionality Reduction on Sleep Stage Classification using ECG Signal. IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 4, No 2, July 2011.

[18] Berger, RD., Akselrod, S.,and Gordon, D. (1986).An efficient algorithm for spectral analysis of the heart rate variability. IEEE Trans Biomed Eng., vol.33, pp. 220-222.

[19] Schneider, T. and Neumaier, A. Algorithm. arfit—a matlab package for the estimation of parameters and eigenmodes of multivariate autoregressive models. ACM Transactions on Mathematical Software, vol.27,pp.58–65.

[20] Absil, P.A. (1998). Analyse non linéaire de signaux cardiologiques en vue d'applications cliniques. Travail de fin d'´études, Université é de Liège.

[21] H. Guang-Bin , Z. Qin-Yu , and S. Chee-Kheong (2006).Extreme learning machine: Theory and applications. Neurocomputing 70,pp. 489–501.

[22] Jinkwon, K., Hang, S., Kwangsoo, S., and Myoungho, L. (2009). Robust algorithm for arrhythmia classification in ECG using extreme learning machine. BioMedical Engineering OnLine 8--31 doi, 10.1186/1475-925X-8-31.

[23] Kwak, C., andWook Kwon, O., (2008) . Cardiac Disorder Classification Based on Extreme Learning Machine.World Academy of Science, Engineering and Technology 48 .

[24] Vapnik, V., & Chapelle, O. (2000). Bounds on error expectation for support vector machines. Neural Computation, 12, 2013–2036.

[25] Wang, J.-C., Lee, H.-P.,Wang, J.-F., & Lin, C.-B. (2008). Robust environmental sound recognition for home automation. IEEE Transactions on Automation Science and Engineering, 5, 25–31.

[26] Sameh , S., and Lachiri, Z.(2012) Multiclass support vector machines for environmental sounds classification in visual domain based on log-Gabor filters. Springer International Journal of Speech Technology ,ISSN 1381-2416.

[27] SKuncheva, L. I. (2004). Combining pattern classifiers methods and algorithms. New York: Wiley. ISBN 0-471-21078-1.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

[28] Hsu, C.-W., Chang, C.-C., & Lin, C.-J. (2009). A practical guide to support vector classification. Department of Computer Science and Information Engineering National Taiwan University, Taipei, Taiwan. Available: www.csie.ntu.edu.tw/~cjlin/.
[29] http://www.csie.ntu.edu.tw/~cjlin/libsvm/,2013
[30] Wang, D., Huang, G.-B., (2005) Protein sequence classification using extreme learning machine, in: Proceedings of International Joint Conference on Neural Networks, Montreal, Canada. s

H.Werteni received the master degree In electrical engineering (Signal processing & automatic) from the National School of Engineer of Tunis (ENIT-Tunisia). Actually, He is a PhD candidate in laboratory "LSTS" of the same university. His doctoral study focused on the sleep stages classification using ECG and EEG.

S.Yacoub is an associate professor at the Institut National des Sciences Appliques et de technologies de Tunis. He Graduated from the Ecole Nationale dIngenieur de Tunis and earned his MSc degree from the Institut National Polytechnique de Grenoble France (LEG) and his PhD from the University Joseph Fourier de Grenoble France(UJFG). His research interests are in signal processing in electromyography.

N. Ellouze received a Ph.D. degree in 1977 from l'Institut National Polytechnique at Paul Sabatier University (Toulouse-France), and Electronic Engineer Diploma from ENSEEIHT in 1968 at the same University.
In 1978, Dr. Ellouze joined the Department of Electrical Engineering at the National School of Engineer of Tunis (ENIT–Tunisia), as assistant professor in statistic, electronic, signal processing and computer architecture. In 1990, he became Professor in signal processing; digital signal processing and stochastic process. He has also served as director of electrical department at ENIT from 1978 to 1983. General manager and President of the Research Institute on Informatics and Telecommunication IRSIT from 1987-1990, and President of the Institut in 1990-1994. He is now Director of Signal Processing Research Laboratory LSTS at ENIT, and is in charge of Control and Signal Processing Master degree at ENIT.
Pr Ellouze is IEEE fellow since 1987, he directed multiple Masters and Thesis and published over 200 scientific papers both in journals and proceedings. He is chief editor of the scientific journal Annales Maghrébines de l'Ingénieur. His research interest include neural networks and fuzzy classification, pattern recognition, signal processing and image processing applied in biomedical, multimedia, and man machine communication.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.