Mansoura Engineering Journal

Volume 38 | Issue 3 Article 8

8-9-2020

Automatic Classification of Sleep Stages Using EEG Records.

Mohamed Mowafy
Prof. of Electronics and Communications Engineering Department, Faculty of Engineering, Mansoura University, eng_elmowafy@ymail.com

Marwa Obayya
Electronics and Communications Engineering Department, Faculty of Engineering, Mansoura University., marwa_obayya@yahoo.com

F. Abou-Chadi
Electronics and Communications Engineering Department, Faculty of Engineering, Mansoura University, f-abochadi@ieee.org

Mohamed saad
Head of Dept. Neurology, Faculty of Medicine, Mansoura University

Automatic Classification of Sleep Stages Using EEG Records

التصنيف الآلى لمراحل النوم باستخدام تسجيلات EEG

Mohamed Mowafy [1], Marwa Obayya[1], F.E.Z. Abou-Chadi[1] and Mohamed Saad[2]

[1] Dept., of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University.

Eng_elmowafy@ymail.com; marwa_obayya @yahoo.com; f-abochadi@ieee.org

[2] Head of Dept., Neurology, Faculty of Medicine, Mansoura university.

ملخص البحث:

يستخدم عدد من الإشارات الطبية الحيوية، مثل الرسم الكهربى للمخ، الرسم الكهربى للعضلات، الرسم الكهربى للقلب و إشارات أخرى فى مختبرات النوم لتشخيص وعلاج اضطرابات النوم. الطريقة المعتادة لتصنيف مراحل النوم هو الفحص البصري من قبل الأطباء المتخصصين فى أمراض النوم. وهذا يستغرق وقتا طويلا جدا ومجهودا شاقا. التصنيف الآلى لمراحل النوم يمكن أن يسهل هذه العملية. وفي هذا البحث تم تصميم مصنف آلى باستخدام تقنية الشبكات العصبية الاصطناعية وهى شبكة التغذية الامامية متعددة الطبقات وذلك لتصنيف ست مراحل النوم والتى تشمل كل من: مرحلة اليقظة ، مراحل النوم الخفيف مرحلة ١ ومرحلة ٢، مرحلة النوم العميق مرحلة ٣، مرحلة النوم الاعمق مرحلة ٤ و مرحلة الأحلام وذلك من أربعة وعشرين شخصا تم تسجيل إشارات رسم المخ الكهربى مراحل النوم الستة لكل منهم. تم استخدام طريقة التحليل الطيفى للإشارات وطريقة تحويل الموجات باستخدام تقنية الموجات غير المتصلة وتقنية تحويل حزم الموجات لاستخلاص السمات والخصائص المميزة لهذه الاشارات. أظهرت نتائج التصنيف الآلى أن اعلى نسبة للتصنيف لهذه المراحل الستة من النوم عند استخدام تقنية حزمة الموجات مع استخدام الدالة sym3 حيث كان التصنيف بمتوسط ٨١,٩٤٪. تم دمج البيانات لتحسين دقة نتائج التصنيف باستخدام الدمج فى مستوى استخراج السمه إلى٨٧،٧ %.

Abstract:

Currently in the world there is an alarming number of people who suffer from sleep disorders. A number of biomedical signals, such as EEG, EMG, ECG and EOG are used in sleep labs among others for diagnosis and treatment of sleep related disorders. The usual method for sleep stages classification is visual inspection by a sleep specialist. This is a very time consuming and laborious exercise. Automatic sleep stages classification can facilitate this process. In this work an attempt was made to classify six sleep stages consisting of Awake, Stage1, Stage 2, Stage3, Stage4, and REMS. spectral analysis, Wavelet transform and artificial neural networks were deployed for this purpose. Twenty four recordings of a healthy six stages studied per 30s epochs. The results demonstrated that the performance for automatically discriminated for these six sleep stages from each other when using wavelet packet with sym3 .where the classification was with average 81.94% . Data fusion improves the accuracy of classification results using fusion at the feature extraction level to 87.7%.

Key-Words: - Artificial Neural Networks, Sleep Analysis, Electroencephalogram (EEG) , Data fusion

Accepted September, 30, 2013

1 Introduction

A detailed analysis and an exact interpretation of a human whole night sleep can contribute to the identification or the diagnosis of a wide spectrum of sleep diseases and disorders and can also subsequently give to the physicians some precise instructions on how to treat the patients suffering from sleep disorders [1]. According to the Rechtschaffen & Kales (R&K) manual for normal sleep classification [1], these epochs can be scored as: waking, Non-Rapid Eye Movement (NREM), Rapid Eye Movement (REM), depending on the behaviour of the recorded brain activity (EEG) [2]. EEG is the recording of electrical activity of brain and is the most extensively used signal to study human brain. The waking stage is referred to as relaxed wakefulness, because this is the stage in which the body prepares for sleep. All people fall asleep with tense muscles and their eyes moving erratically. Then, normally, as a person becomes sleepier, the body begins to slow down. Muscles begin to relax, and eye movement slows to a roll [3], and gradually the person moves into NREM sleep. The NREM sleep is further divided into four stages namely, stage 1, stage 2, stage 3, stage 4. Stage 1 sleep or drowsiness, is often described as first in the sequence. The stage is characterized by slow muscle activity and occasional twitching. Stage 1 may last for 5 to 10 minutes [3]. Next NREM sleep stage is Stage 2 and characterized by sudden bursts of brain activity called sleep spindles and high bandwidth peaks which are followed by negative peaks. In this stage the heart rate slows, and body temperature decreases. At this point, the body prepares to enter deep sleep. Stage 3 and Stage 4 are deep sleep stages, with Stage 4 being more intense than stage 3. These stages are known as slow-wave sleep [3]. Stage 3 represents the transition period from light sleep to deep sleep and stage 4 occurs when the person is in deep sleep. In deep sleep, there is no eye movement or muscle activity [3]. Sleep does not progress through these stages in sequence. However, sleep begins with stage 1 and progresses into stages 2, 3 and 4. After stage 4 sleep, stage 3 and stage 2 sleeps are sequentially repeated before entering REM sleep. Once REM sleep is over, the body usually returns to stage2 sleep. Sleep cycle goes through these stages approximately 4 or 5 times throughout the night [3]. The variations in the EEG patterns with respect to the sleep stages are very subtle and therefore, signal processing techniques are needed to extract the features for sleep classification of the different stages. Some of the techniques used for this purpose are spectral analysis [4,5], and wavelet Transform (WT) [6]. It is reported that WT is the most promising technique for feature extraction from the EEG signals for diagnostic classification [7]. WT is preferred for feature extraction owing to its multiresolution property. Moreover, it can deal with the non-stationary, complex and dynamic nature of the EEG signals [8].

In the present work, the main features have been extracted from the EEG signals using both techniques: spectral analysis using the Fast Fourier transform [9], and the discrete wavelet transform (DWT) using the Daubechies and Haar mother wavelets and wavelet packet (WP) using sym3 [10,11]. Dimensionality reduction was performed using principal component analysis (PCA) [12,13] and an artificial neural network classifier was designed where ANNs are able to solve non-linear and complex problems where the classic methods do not provide solutions. and the results are reported. Data fusion at the feature extraction level [14] was used to improve the accuracy of classification results obtained.

2 Sleep Analysis

In the clinical routine, the study of the sleep consists of the acquisition and the recording during one sleep night of a physiological signals set known as polysomnography (PSG). In the present study, the electroencephalogram (EEG) is only considered. EEG signal reflects the cerebral electric activity, it is recorded with electrodes set on the scalp. The site of the electrodes is defined according to the nomenclature of the system 10-20 adopted by the majority of the clinical neurophysiology laboratories [15].

3. Material and Methods

3.1 Data Collection

Twenty-four sleep EEG records were taken from the Cairo Center for Sleep Disorders for normal subjects (twenty males and four females) aged between (35-50) years. EEG signals were recorded bilaterally using the sleep analyzer hybrid microcomputer system (SAHC). Recording was made when the patient was laying down and relaxed in a quiet room with dim light and his head was fixed in a stereotaxic frame connected with ball-shaped silver electrodes with shielded cable for recording. The EEG derivations are C4/A1 or C3/A2 according the standard arrangement of electrodes of 10-20 system refers to the 10% and 20% interelectrode distance was positioned on the human skull over the central and occipital lobes for the right and left sides. The ear or mastoid (A1,A2) were used as recommended references for the electrodes measuring EEG to maximize interelectrode distance and to avoid mixing activity from two different scalp areas. Single-channel EEG signals were recorded without any medication for all subjects and sampled at 100 Hz. For each subject the recording was segmented into six sleep stages of 30 seconds epochs by the physician. Fig.1 illustrates the process of sleep EEG recording. The recorded EEG signals were then stored in computer files for subsequent analysis.

Fig. 1. The Sleep Scoring System.

3.2 Methods

Spectral and wavelet analyses were performed to extract the main features from the sleep EEG signals. These features are then utilized for classification of the different Stages of Sleep EEG signals, Fusion at the feature extraction level are used to improve the accuracy of classification results obtained.

A. Spectral analysis

To perform the spectral analysis, each epoch was broken into 30 segments (segment = 100 samples). It is noticeable that, choosing longer segments would show the signal nonstationarity, where the spectrum is not meaningful. Furthermore, short-lasting and paroxysmal activities are taken into account with longer intervals. The segmented signals were tapered down using a Hamming window truncation error [16]. The power spectrum was calculated for each record of different sleep stages using the fast Fourier Transform (FFT) algorithm [9]. Moreover, the following sleep-related features were then calculated for each segment and averaged over the same staging epoch and then averaged for the 24 patients as follows [17].

1- Detection of some indicators for the waves with particular frequencies (Table1).

2- The relative spectral power (RSP) of the four brain activity bands; (Delta,Theta, Alpha, and Beta), were calculated as the ratio of the band spectral power (BSP) of each individual component to the total power of the record (TSP).

$$RSP = \frac{BSP}{TSP}, i \in \{Delta, Theta, Alpha, Beta\} \quad (1)$$

Table 1: Main EEG indicators.

Rhythm	Beta	Alpha	Theta	Delta
Frequency	14-25 Hz	8-13 Hz	4-7 Hz	Below 3.5 Hz
Amplitude	25μv	50μv	100-150μv	250-300μv

Therefore, each sleep EEG segment is represented by the four values of the RSP to which a label representing the sleep stage was assigned.

B. Wavelet Coefficients

Both discrete wavelet transform (DWT) and wavelet packet (WP) were used for feature extraction from the EEG signals [8]. A 10-level DWT using "db2", "db3", "Haar" and third level wavelet packet using "sym3" were applied to decompose segments of sleep EEG signals into specific wavelet-band components.

C. Dimentionality Reduction

There are two main reasons to keep the dimensionality of pattern representation (i.e., the number of features) as small as possible: measurement cost and classification accuracy. A limited yet salient feature set simplifies both the pattern representation and the classifier that are built on the selected representation. Consequently the resulting classifier will be faster and will use less memory. Moreover, a small number of features can alleviate the curse

of dimensionality when the number of training samples is limited [12]. So each feature set was subjected to dimensionality reduction using two methods alternatively:

1-Karhunen-Loeve (K-L) transform, also called Principal component analysis (PCA) [12,13,18].

The Karhunen – Loeve (K – L) transform finds the representation of the input vector in terms of the eigenvectors of their covariance matrix. It has excellent energy compaction property, therefore it is frequently used in statistical pattern recognition [12].

Given an ensemble of M real valued vectors, xk ∈ Rn , $1 \le k \le M$, their covariance Rx matrix is calculated as :

$$R_x = \frac{1}{M}\sum_{k=1}^{M}(x^k - \hat{x})(x^k - \hat{x})^T \qquad (2)$$

Where,

$$\hat{x} = \frac{1}{M}\sum_{K=1}^{M} x^K \qquad (3)$$

The unit eigenvectors of Rx are the orthogonal basis for K-L transform and are obtained by solving the following equation:

$$Rx\,\psi = \psi\,\Lambda \qquad (4)$$

where, Λ is a diagonal matrix having the eigenvalues of Rx and ψ is the modal matrix having eigenvectors of Rx for its columns, ordered in decreasing eigenvalues. After determining ψ, the K – L transform of any vector can found as

$$v = \psi^T x \qquad (5)$$

Reducing ψ to ψm by eliminating the last (n – m) eigenvectors results in an m – dimensional subspace spanned by the remaining m eigenvectors in ψm . These eigenvectors are called the principal components and the subspace spanned by them is called the principal subspace. It results in dimensionality reduction if ψm is used instead of ψ in Equation (5). If the mth eigenvalue is considerably small when compared to the first eigenvalues, the vector transformed to the principal subspace carry approximately the same information as the original vector even though the dimensionality is reduced.

2- WT feature vector of the average energy content of the coefficients energy[19].

The average energy content of the coefficients for the DWT at each of the 10 resolution using db2 ,db3 and haar , where the approximation coefficients was computed as [19]:

$$v_i^{dwt} = \frac{1}{n_i}\sum_{j=1}^{ni} w_{i,j}^2 \quad i = 1,2,\ldots, l \qquad (6)$$

where i = number of element of a feature vector, n1 = 2l-2, n2 = 2l-1, n3 = 2l-2, … nl = 20 is the number of samples in an individual subband, w2i,j is the jth coefficient of the ith subband [19]. There were a total 10 subbands from which features were extracted. For the wavelet packet, eight subbands were calculated and the average energy content for each subband at the third level resolution was computed using equation (2) and the WP feature vector. The number of representing features of each segment of record when using db2 and db3 was 10 coefficients, and Haar was 10 coefficients, and when using sym3 was 8 coefficients. For using the principal component

analysis (PCA), the representation of the input vector in terms of the eigenvectors of their covariance matrix . at each resolution in the wavelet coefficients, the number of representing features of each segment of record when using db2 and db3 become 7 coefficients, Haar become 7 coefficients and sym3 become 7 coefficients .

D. Anova test

The p-value can be obtained using analysis of variance between groups (ANOVA) test [20, 21] , where when the factor was significant ($p \prec 0.05$) the significance of the differences between sleep stages was further checked. ANOVA uses variances to decide whether the means are different. This test uses the variation (variance) within the groups and translates into variation (i.e. differences) between the groups, taking into account how many subjects there are in the groups. If the observed differences are high, then it is considered to be statistically significant. Tables (2-6) show the results of Anova test. For the spectral analysis features, the Anova test shows that all features show significant difference for the sleep stages at 5% level of significance. For DWT features, when using db2, db3, Haar functions, it has been found that only 5 features show significant differences, while the other features are not significant. For Wavelet packet using sym3 function, the Anova test shows that all features are highly significant.

E. An Artificial Neural Network Classifier

A three-layer feed forward perceptron ANN (artificial neural network) was used, an input layer varied by varying the feature vectors, one hidden layer of about 10-20 neurons for different feature vectors and output layer with 3 neurons corresponding to the six sleep stages. The back-propagation algorithm was utilized for training procedure using MATLAB 7.10 Toolbox.. Weights were initially set to small random values. The learning rate was changed for each feature vector. It ranged from 0.3 to 0.5. The trained and test data sizes are each 50% of the total data. 36 records (12 for wake stage, 12 for stage1, 12 for stage2, 12 for stage3, 12 for stage4, 12 for stage REM) were used for training and the other 36 records were used for testing phase.

F.data fusion

Fusion at the feature extraction level [14] was used to improve the accuracy of classification results obtained, where feature extracted using multiple techniques are concatenated. It combines feature vectors at the representation level to provide higher dimensional data points. A new feed forward neural network was designed, it has three layers: an input layer 72 neurons, a hidden layer 17 neurons, and output layer 3 neurons corresponding to six sleep stages. Table 8 shows the results of data fusion.

4. Results

The features were extracted from 30-second segments SAHC channel EEG signal. All the results are presented as mean±S.D. with "p"-

values. The results of these were subjected to ANOVA test with more than 95% confidence interval giving excellent 'p'-values for spectral analysis features as in table2, wavelet packet features as in table 3, and 5 features of DWT features when using db2,db3 and haar functions as in table4,5,6. Following feature extraction and normalization, a feed forward MLP artificial neural network with momentum and adaptive learning rate was used to classify these features. The results are summarized in Tabl.7. For fusion at feature extraction level, a result of ANN gives an average classification rate of 87.7%.

5. Conclusion

In this research, we attempted to discriminate Awake stage, Stage1, Stage2, Stage3, Stage4 and REM stage by using a single channel EEG signals. spectral analysis, DWT, and Wavelet packet transform were applied to 30-second segments of SAHC channel EEG signals. Feature vectors were calculated. These feature vectors were then classified by using a feed-forward MLP artificial neural network with back-propagation algorithm with one hidden layer and trainrp training algorithm was used where output error was used to update weight till reach minimum error. By varying the number of neurons in the hidden layer, it was observed that The best performance was achieved when using 10 neurons in the hidden layer with the feature of spectral analysis, and about 10-20 with feature for DWT and wavelet packet transform. More than these numbers of neurons did not produce any improvements in the outcome. The results shown in Table7. Training and testing sets in each run were chosen separately by the 50% of the data . The results indicate that the percentage of correct classification varies according to the used technique for analysis, and the sleep stage wanted to be classified. The highest average classification rate reached 81.9% when using Sym3 for wavelet packet transform. The best classification results were obtained when using wavelet packet transform with function sym3. For fusion at feature extraction level, the average classification rate improved and reached to 87.7% where this show that the developed system gave better results than previous work that reported in [4] when using using ANN and spectral analysis with Fast Fourier Transform (FFT) for Automatic classification of Sleep Stages, where the result gives a 76% rate of agreement for the 6 stages. Further work: Another choice of parameters and/or the addition of other parameters resulting from another modeling techniques like the detection of the graphical-elements and the integration of the other physiological signals may be able to improve the obtained results.

Table 2: Significance for the spectral features of sleep EEG signals

Features	Sleep Stage						P-Value
	Stage wake	Stage1	Stage2	Stage3	Stage4	Stage REM	
	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	
Delta	0.10±0.04	0.23±0.09	0.26±0.09	0.39±0.12	0.49±0.14	0.20±0.09	2.62E-22
Theta	0.19±0.07	0.35±0.06	0.33±0.06	0.31±0.07	0.29±0.08	0.26±0.05	2.94E-13
Alpha	0.49±0.09	0.28±0.08	0.21±0.06	0.17±0.07	0.14±0.05	0.34±0.07	9.6916E-15
Beta	0.22±0.05	0.15±0.05	0.21±0.06	0.13±0.05	0.09±0.04	0.20±0.09	5.48E-11

Table 3: Significance for all wavelet decomposition coefficients using db2

Wavelet Discrete coefficients	Sleep Stages						p-Value
	Stage Wake	Stage1	Stage2	Stage 3	Stage 4	REM Stage	
	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	
1	18.03±9.8	19.57±11.13	19.67±12.64	18.56±10.52	28.25±14.10	21.23±12.5	0.486
2	9.11±1.57	8.94±1.38	9.27±1.05	10.37±1.60	11.08±1.51	9.52±1.74	2.79E-06
3	8.00±1.70	8.12±1.22	8.45±1.06	9.62±1.60	10.45±1.56	8.57±1.83	6.60E-08
4	6.25±1.53	6.78±1.88	7.42±1.15	8.71±1.70	9.74±1.65	7.33±1.83	2.34E-13
5	5.07±1.52	5.37±1.18	6.36±1.24	7.57±1.71	8.70±1.76	5.89±1.64	5.98E-15
6	3.81±1.33	4.22±1.43	4.88±1.40	5.80±1.59	6.70±1.92	4.22±1.76	1.77E-09
7	2.83±1.50	2.90±1.46	3.42±1.25	3.78±1.69	4.26±2.09	2.87±1.49	0.0485

Table 4 : Significance for all wavelet decomposition coefficients using db3

Wavelet Discrete coefficients	Sleep Stages						P-Value
	Stage Wake	Stage1	Stage2	Stage 3	Stage 4	REM Stage	
	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	
1	15.48±6.63	15.51±7.23	15.49±9.51	14.33±6.26	20.65±8.53	16.39±8.5	1.093E-06
2	9.03±1.62	8.78±1.41	8.95±1.08	10.16±1.49	11.01±1.55	9.21±1.84	2.583E-08
3	7.84±1.87	7.77±1.47	8.08±1.12	9.43±1.51	10.38±1.59	8.26±1.973	2.239E-13
4	6.19±1.59	6.50±1.31	7.09±1.21	8.57±1.63	9.63±1.66	7.15±1.80	1.935E-13
5	4.84±1.46	5.11±1.25	5.79±1.43	7.14±1.75	8.36±1.85	5.44±1.75	5.498E-08
6	3.37±1.31	3.64±1.43	4.24±1.35	5.10±1.68	5.93±2.06	3.67±1.47	0.1185
7	2.02±1.24	2.10±1.35	2.35±1.2891	2.68±1.475	2.86±1.64	1.97±1.06	0.0943

Table 5: Significance for all wavelet decomposition coefficients using Haar.

Wavelet Discrete coefficients	Sleep Stages						P-Value
	Stage Wake	Stage1	Stage2	Stage 3	Stage 4	REM Stage	
	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	Mean ± SD	
1	9.13±1.52	9.06±1.31	9.22±1.11	0.347±1.44	1.05±1.53	9.56±1.83	5.85E-06
2	7.95±1.40	7.10±1.16	8.33±1.09	9.70±1.37	0.3029±1.60	8.43±1.68	1.90E-09
3	6.16±1.35	6.73±1.20	7.25±1.10	8.78±1.41	9.48±1.65	7.08±1.68	1.16E-14
4	4.72±1.27	5.32±1.26	5.10±1.14	7.40±1.49	8.15±1.70	5.50±1.49	8.57E-16
5	3.35±1.29	3.67±1.41	4.18±1.22	5.34±1.53	5.70±1.75	3.65±1.3303	5.35E-09
6	2.01±1.31	2.28±1.54	2.44±1.25	3.02±1.68	2.89±1.37	2.09±1.09	0.0598
7	1.42±1.12	1.60±1.33	1.53±1.11	1.43±1.02	1.58±0.84	1.42±0.80	0.978