International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:3, No:6, 2009

Automatic Sleep Stage Scoring with Wavelet Packets Based on Single EEG Recording

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***Abstract*—**Sleep stage scoring is the process of classifying the stage of the sleep in which the subject is in. Sleep is classified into two states based on the constellation of physiological parameters. The two states are the non-rapid eye movement (NREM) and the rapid eye movement (REM). The NREM sleep is also classified into four stages (1-4). These states and the state wakefulness are distinguished from each other based on the brain activity. In this work, a classification method for automated sleep stage scoring based on a single EEG recording using wavelet packet decomposition was implemented. Thirty two ploysomnographic recording from the MIT-BIH database were used for training and validation of the proposed method. A single EEG recording was extracted and smoothed using Savitzky-Golay filter. Wavelet packets decomposition up to the fourth level based on 20$^{\mathbf{th}}$ order Daubechies filter was used to extract features from the EEG signal. A features vector of 54 features was formed. It was reduced to a size of 25 using the gain ratio method and fed into a classifier of regression trees. The regression trees were trained using 67% of the records available. The records for training were selected based on cross validation of the records. The remaining of the records was used for testing the classifier. The overall correct rate of the proposed method was found to be around 75%, which is acceptable compared to the techniques in the literature.

***Keywords*—**Features selection, regression trees, sleep stage scoring, wavelet packets.

I. Introduction

THE state of human sleep is divided into two states; The Rapid Eye Movement (REM) sleep and Non REM (NREM) sleep. The REM state is characterized by the occurrence of dreams, while the NREM state is characterized by the brain's activity and the physiological rest of the brain. The NREM stage is also divided into four stages (1-4). Sleep stage scoring is done based on ploysomnographic recordings which includes the following recordings (normally more than one channel for each recording): EEG, EOG, EMG, respiratory; pulse oximetry, and ECG. Sleep scoring is performed according to the recommendations of Rechtschaffen and Kales (R&K) [1]. According to R&K, a sleep score is determined in a time epoch of 20-30 seconds. The recorded ploysomnographic signal has different characteristics of each stage [2]. The stage of wakefulness (W) is characterized by low amplitude and mixed frequency EEG. Alpha waves may also appear and high tonic EMG. The REM stage shows low voltage, mixed frequency EEG, sawtooth wave pattern, low amplitude EMG, and high level EOG signal from both eyes. In stage 1, the EEG signal has the highest amplitude in the range of 2-7 Hz. Alpha waves also exist in this stage in less than half of the epoch and sharp waves may occur. The EMG level is lower than the stage of wakefulness. Stage 2 is characterized by the presence of sleep spindles (12-14 Hz) and K-complexes. Stage 3 is scored when there is a low frequency waves with a frequency less than 2 Hz, also sleep spindles and K-complexes may occur. The deepest sleep stage (stage 4) is similar to stage 3 but with low frequencies (less than 2 Hz) occurring in more than 50% of the epoch. Figure 1 shows the EEG signal for the sleep stages. The sleep scoring procedure is time consuming for experts since they have to do scoring for an entire night recording (8 hours). Since the introduction of R&K scoring procedure, numerous methods were introduced for automatic sleep stage scoring [3, 4, 5]; The reported accuracy was in the range of (60-80%). These methods were based on extracting features from the EEG, EOG, and EMG signals, and use these features in a classification method to identify the sleep stage. Feature extraction is the most important step that affects the accuracy of classification. Several feature extraction methods were used such as band power estimation, time frequency distribution, and the autoregressive parameter model [6, 7, 8].

This work consists of three major steps: features extraction method that generates a features vector from a single EEG signal, features selection method that reduces the size of the features vector, and features classifier that generates the score of the sleep stage. The main contributions of this work were the use of a single EEG signal in identifying the sleep score, the use of features selection method (gain ratio) to reduce the size of the features vector, and the usage of regression trees as a classification method.

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II. Methods

In this study, 32 ploysomnographic recordings from the MIT-BIH database [9], with their associated sleep stage score, were used. EEG signals (electrode Pz-Oz) with a sampling rate of 100Hz were extracted from the ploysomnographic recordings and used for feature extraction. The proposed automated scoring system is shown in Fig. 2. In the pre-processing step, the EEG signal was normalized, smoothed using Savitzky-Golay filter [10], and divided into blocks of 30 seconds according to R&K. The feature extraction was done using the wavelet packet transform (WPT) of the EEG signal, which is a general expansion of the discrete wavelet transform (DWT). WPT has been successfully used in different fields as a feature extraction method [11, 12, 13]. It posses the ability to locate features both in time and frequency domains. In the WPT, the signal is decomposed in an approximation space and details space. The approximation space is done by a scaling function and the details space is done by a mother wavelet transform. Each of the two spaces is decomposed again into approximation subspace and details subspace.

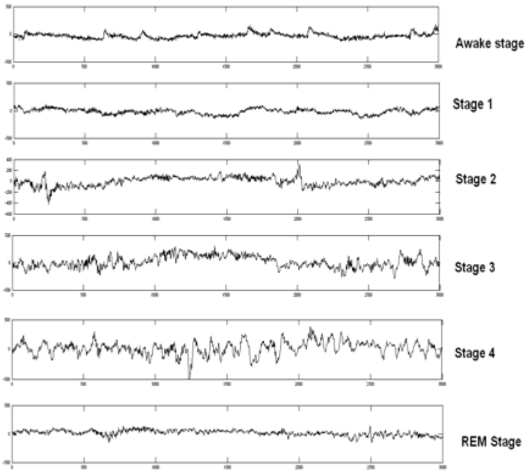

Fig. 1 EEG signal for different sleep stages

In this work, the EEG signal was decomposed up to four levels as shown in Fig. 3. Different subspaces at different levels were selected for features extraction based on the properties of the EEG signal and the characteristics of each sleep stage. Features were calculated in each of the selected subspaces using the statistical parameters: mean, standard deviation, power, kurtosis, maximum, and minimum. The extracted statistical parameters were combined to form the features vector of 54 parameters. The features vector was reduced in size using the information gain ratio method [14]. The gain ratio method uses the information (entropy) gain of each feature. If f is the set of all features and Ex the set of all training data, the information gain for a feature $a \in f$ is defined as follows:

$$IG = H(Ex) - \sum_{v \in values(a)} \frac{\left|\{x \in Ex \mid value(x,a) = v\}\right|}{|Ex|} H(\left|\{x \in Ex \mid value(x,a) = v\}\right|) \quad (1)$$

Where *value(x,a)* defines the value of a specific x for feature a, and H specifies the entropy, which for a random variable X with possible values $\{x_1, x_2, \ldots, x_n\}$ is given by:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \quad (2)$$

Where p denotes the probability mass function of X.

The gain ratio (GR) is defined as:

$$GR(X) = \frac{IG}{-\sum_{i=1}^{n} \log p(x_i)} \quad (3)$$

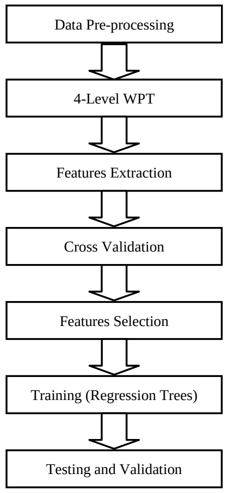

Fig. 2 The EEG automated sleep stage scoring process

Only features with high gain ratio were selected. The selected features were split into a training set and test set using a 10 fold cross validation method. The cross validation method was used to avoid the problem of over fitting that may occur during the classification procedure [15]. The classifier used in this work was based on the regression trees for predicting categorical variables [16]. Regression trees classify data based on logical conditions and produce fast, accurate, and simple results compared to other methods like neural networks and discriminate analysis. The regression tree is built using the binary recursive partitioning process, which is an iterative process of splitting the features data into partitions, and further splitting it up on each of the branches. Initially all features (training set) are together in one lot. The algorithm then breaks the data using every possible binary split on every field. The method chooses the split that partitions the data into two parts such that it minimizes the variance (mean square error) defined as follows:

$$\sigma^2(T) = E[(Y - E[Y/T])^2] \quad (4)$$

Where T is the split or node and Y is the predicted sleep score. The splitting continues to the new branches until reaching a pre-defined minimum node size and tree has its full structure. Usually the tree suffers from over-fitting, so pruning was performed to avoid this problem [8].

III. RESULTS

Wavelet packets decomposition up to the fourth level based on 20th Daubechies mother wavelet was used to extract features from the EEG signal. The 54 parameters features vector was reduced to 20 features using the gain ratio technique implemented in WEKA software. Different patient records were used in the classification procedure with the total number of epochs being in the range of 700-2830 epochs for different patients. The Features data were divided into two sets using 10 fold cross validation, the training set (67%) and the test set (33%). The regression trees were used to classify each epoch of the data. The results of classification were compared with the recorded manual scoring procedure by experts. The performance of the algorithm was evaluated by computing the percentages of sensitivity (SE), specificity (SP), and accuracy of classification (AC). The equations, respectively, are as follows:

$$SE = \frac{TP}{TP + FN} \text{ x } 100 \quad (5)$$

$$SP = \frac{TN}{TN + FP} \text{ x } 100 \quad (6)$$

$$AC = \frac{TN + TP}{TN + TP + FP + FN} \text{ x } 100 \quad (7)$$

Where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives. For all test data (subjects), the accuracy of the classification method (the agreement between manual scoring and automated scoring) was around 75%, while the accuracy of each sleep stage was in the range of (46-90) %. Tables I and II show the confusion matrix for both training set and testing set, respectively, for an EEG signal sampled at 100 Hz. The EEG signal has a total number of 936 of 30 seconds epochs distributed as follows: 66 of awake, 75 of stage 1, 353 of stage 2, 126 of stage 3, 157 of stage 4, and 159 of REM stage. The result in Table II shows that there is a poor performance of the classification of stage 1; nine out of 29 test stages were classified as awake stages. This is mainly due to the similarities between stage 1 and stage awake. The sensitivity of the algorithm for the training data set was found to be 61% and the specificity 99%.

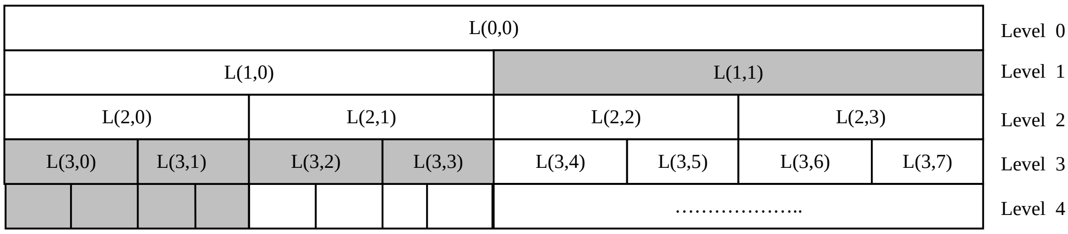

Fig. 3 Wavelet packets decomposition. Shaded subspaces were used for features extraction

TABLE I
REGRESSION TREES CLASSIFICATION ON THE LEARNING SET

# Stage	Awake	Stage 1	Stage 2	Stage 3	Stage 4	REM	Accuracy %
Awake	34	2	0	1	0	1	83
Stage 1	3	45	2	2	0	2	85
Stage 2	2	1	214	6	1	1	94
Stage 3	0	0	6	77	0	0	87
Stage 4	0	0	1	3	106	0	99
REM	2	5	6	0	0	101	96
							93

TABLE II
REGRESSION TREES PERFORMANCE ON THE VALIDATING SET

# Stage	Awake	Stage 1	Stage 2	Stage 3	Stage 4	REM	Accuracy %
Awake	13	9	2	0	1	0	93
Stage 1	1	12	2	0	1	7	46
Stage 2	0	5	93	11	0	6	76
Stage 3	0	0	14	19	6	0	58
Stage 4	0	0	2	3	49	0	86
REM	0	3	10	0	0	43	77
							74

IV. Discussion and Conclusion

A new approach for automated sleep stage scoring based on a single EEG channel was implemented. Wavelet packets have shown to be a powerful tool for feature extraction. The dimension reduction of the features vector was implemented. This step is important as it eliminates any redundant features and improves the accuracy of the classification method. The use of regression trees has shown to be accurate, simple, and fast compared to the traditional Neural Networks method. The accuracy of classifying some stages was found to be less than others. This was mainly due to the low number of these stages in the training data. Furthermore, the recorded signals were shown to an expert and there was a discrepancy between the score reported by the expert and the associated score with the data which may be another source of error. In this work, EEG (Pz-Oz) was the only information we used for extracting features. Further improvement can be introduced to this method by including the EMG and EOG in the classification procedure for REM and Awake stages. This can be implemented in two steps; First the data can be classified into two groups; awake and REM group, and stages (1-4) as a second group. The second step is classifying each of the two groups.

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