An Intelligent System for Diagnosing Sleep Stages Using Wavelet Coefficients

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Abstract—**Human sleep is divided into two segments, Rapid Eye Movement (REM) sleep and Non-REM (NREM) sleep. NREM sleep is further divided into 4 stages. Sleep staging attempts to identify these stages based on the signals collected in PSG. Significant information can be derived from the EEG signals collected during PSG. Wavelet coefficients are extracted from EEG signals. In order to reduce the amount of data set, the statistical features are calculated from wavelet coefficients. For performing decision making, six ANFIS classifiers and SVM classifier are used to differentiate between REM and Non-REM sleep stages. That is to say, pattern varies under the different sleep stages. Therefore, healthy humans with a regular night's sleep will follow these sleep stages in a particular pattern.**

I. Introduction

Sleep staging, performed in a test called polysomnogram (PSG), is a common and important procedure for the diagnosis of sleep disorders. PSG studies a series of biomedical signals ranging from heart beat, blood oxygen concentration, muscle movements, to brain activity. The most important signal and also the most difficult to analyze is the electroencephalogram (EEG), which shows the brain's activities [1, 2].

Currently, trained technicians manually analyze the relevant biomedical signals to generate a sleep stage classification for every 30 seconds of data, called an epoch. While various algorithms have been implemented to provide additional information on each epoch of data, such as frequency content and peak-to-peak voltage, no algorithm have been commercially used for computerized sleep staging. This automation would drastically reduce the amount of manual tasks, thereby making the process more reliable and cost efficient.

Much research has been dedicated to PSG interpretation. In particular, many studies focus on the analysis of EEG signals. Human analysis follow a set of rules defined in a manual by Rechtschaffen and Kales[3]. These rules define frequency, amplitude, and contextual parameters. Therefore, EEG analysis algorithms must take into consideration both the time and the frequency domain information. One method suggested in research is using a time-frequency representation called spectrogram.

Time frequency representation of EEG has been used in numerous researches as a tool to understand EEG's behavior. Nayak[4]used time-frequency analysis to demonstrate alpha blocking by anesthesia. Van Hese[5] used scalograms to analyze the practicality of using wavelet analysis for sleep staging. Scheuer[6]used spectrograms to demonstrate certain transient activities that can predict epileptic attacks. In a review on spectral analysis of biomedical signals, Muthuswamy[7] indicated wavelet analysis as being one of the most useful utility.

In this study, wavelet coefficients are extracted from each EEG segment, and in order to reduce the feature space, statistical features are extracted from wavelet coefficients. 6 ANFIS classifiers and SVM are used to differentiate different sleep stages.

II. Data Collection

A. Sleeping staging

Human sleep is divided into two segments, Rapid Eye Movement (REM) sleep and Non-REM (NREM) sleep. REM sleep is best characterized by the occurrence of dreams. During REM sleep, the person receives psychological rest and the brain actively reorganizes itself into a better state. NREM sleep provides the person with physiological rest and the brain's activities slow down. NREM sleep is further divided into 4 stages I, II, III, and IV[8]. Therefore, common practice recognizes 5 sleep stages. Healthy humans with a regular night's sleep will follow these sleep stages in a particular pattern. Traditionally, to complete the set of stages, Awake and Movement Time (MT - Movement Time represents the periods of time when the PSG signals are obscured by body movement) are added[9].

Sleep staging attempts to identify these stages based on the signals collected in PSG. Significant information can be derived from the EEG signals collected during PSG[8]. EEG analysis looks primarily at the 6 key features, which are listed along with their characteristics below.

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Table 1: Frequency, amplitude, temporal characteristic of EEG features

feature	frequency	amplitude	temporal
Alpha Activity	8-13 HZ	20-60 µv	Present in awake,stage I and REM
Beta Activity	13+ HZ	2-20 µv	Dominant in awake
Theta Activity	4-8 HZ	50-75 µv	Present in stage I,II,III and IV
Delta Activity	0-4 HZ	75+µv	Present in stage III and IV
Sleep spindels	12-14 HZ		Present in stage II

B. Data

This paper is based on a set of 8 hour sleep study data provided by the PhysioBank (physiologic signal archives for biomedical research). The PhysioBank stores the sleep study data in the European Data Format (EDF). The recordings were obtained from Caucasian males and females (21 - 35 years old) without any medication; they contain horizontal EOG, FpzCz and PzOz EEG, each sampled at 100 Hz. Hypnograms are manually scored according to Rechtschaffen & Kales based on Fpz-Cz / Pz-Oz EEG instead of C4-A1 / C3-A2 EEG [10].

After filtering the signals from 0.5 to 100 HZ, two dataset with 10 hour sleep records are used. Each of this data set contains 1200 epoch which evaluate with an expert. Table 2 shows the number of epoch in two stages. Each set of epochs are stored in Matlab data files.

Table 2: The number of epochs in each stage

Sc4012e0	**Sc4002e0**	**Data set/stage**
176	**255**	**Awake**
92	**59**	**I**
660	**373**	**II**
80	**94**	**III**
16	**203**	**IV**
176	**215**	**REM**
0	**1**	**MT**

III. METHODS

Decision making contains two stages: feature extraction and classification. wavelet coefficients are the extracted features (20 extracted features as ANFIS inputs). The ANFIS classifiers with the backpropagation gradient descent method in combination with the least squares method for differentiating 6 levels of sleep and SVM with RBF kernel for classifying REM and Non-REM levels are used. Six stages of the dataset are used here.

A. Wavelet

The WT is an extension form of classic Fourier transform, except that it works on both time and frequency scales.

The multi-scale characteristic of the WT allows the signal decomposition into a different number of scales, in which each scale represents a special structure of the signal under study. The multiresolution decomposition procedure of a signal $x[n]$ s shown in Fig 1. This is called the Mallat algorithm or Mallat-tree decomposition[11].

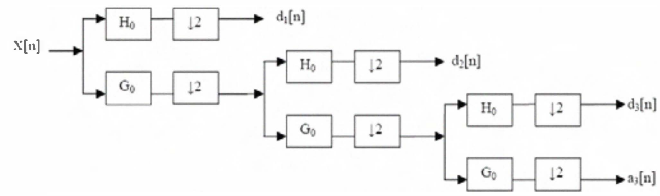

Fig 1. The wavelet decomposition tree[11]

The low pass filter is indicated by G_0 and the high pass filter is indicated by H. At each level, the high pass filter produces detail information; d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n]. With this approach, the time resolution at high frequencies becomes arbitrarily good and the frequency resolution becomes good at low frequencies. [12-14]

B. The SVM classifier

Support Vector Machines (SVM) are basically binary classification algorithms [15]. When the data are linearly separable, SVM computes the hyper plane that maximizes the margin between the training examples and the class boundary. When the data are not linearly separable, the examples are mapped to a high dimensional space where such a separating hyperplane can be found. The mechanism that defines this mapping process is called the kernel function. SVM are powerful classifiers with good performance in the domain of EEG signals[16, 17].

One of the key elements of a SVM classifier concerns the choice of its kernel. In our study, we have chosen to use the RBF kernel. We also experimented with Gaussian, MLP and polynomial kernels. For polynomial kernels, the main difficulty is to determine an appropriate polynomial degree while the results we obtained with the Gaussian kernels are not satisfactory.

C. Adaptive Neuro-Fuzzy System

ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [18, 19]. Such framework makes ANFIS modeling more systematic and less reliant on expert knowledge. ANFIS architecture to implement these two rules is shown in Fig. 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

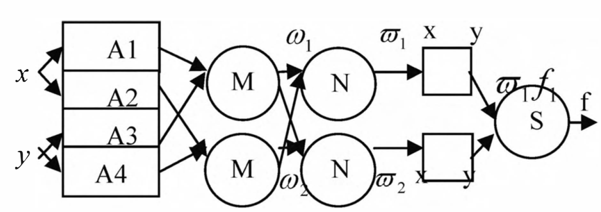

Fig 2. ANFIS architecture

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O^1{}_i = \mu_{A_i}(x) \quad i=1,2 \tag{1}$$
$$O^1{}_i = \mu_{B_{i-2}}(x) \quad i=3,4$$

Where $\mu A_i(x)$ and $\mu B_{i-2}(x)$ can adopt any fuzzy membership function. In the second layer, the nodes are fixed nodes. They are labeled with *M*, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as:

$$o_i^2 = w_i = \mu A_i(x)\mu B_i(y) \tag{2}$$

Which are the so-called firing strengths of the rules. In the third layer, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as

$$o_i^3 = \overline{w}_i = \frac{w_1}{w_1 + w_2} \tag{3}$$

Which are the so-called normalized firing strengths. In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by

$$o_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{4}$$

In the fifth layer, there is only one single fixed node labeled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$o_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{5}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters {*ai, bi, ci* }, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters {*pi, qi, ri* }, pertaining to the first order polynomial. These parameters are so-called consequent parameters [19].

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely {*ai, bi, ci* } and {*pi, qi, ri* }, to make the ANFIS output match the training data. When the premise parameters *ai* , *bi* , and *ci* of the membership function are fixed, the output of the ANFIS model can be written as

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 \tag{6}$$

Substituting Eq. (11) into Eq. (14) yields

$$f = \varpi_1 f_1 + \varpi_2 f_2 \tag{7}$$

Substituting the fuzzy if-then rules into Eq. (16), it becomes

$$f = \overline{w}_1(p_1 x + q_1 y + r_1) + \overline{w}_2(p_2 x + q_2 y + r_2) \tag{8}$$

After rearrangement, the output can be expressed as

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \tag{9}$$

This is a linear combination of the modifiable consequent parameters p1, q1, r1, p2, q2, and r2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [18-20].

IV. RESULTS

One of the most important notices in analyzing signals using WT is appropriate wavelet and the number of decomposition levels. According to signal dominant frequency Component, the number of decomposition levels is considered. The levels are chosen based on the different frequencies of EEG signal required for classification[14].

In this study, EEG 4 decomposition levels are considered. Thus, the EEG signals were decomposed into the details $D1$–$D4$ and one approximation, $A4$.
In order to find the best wavelet, different types of those are tested. B-Spline is suitable for detecting EEG changes. Therefore in this study, the wavelet coefficients are computed using B-Spline. MATLAB software package is used for computing wavelet coefficients.
Using computed wavelet coefficients shows a good representation of the signal Time and frequency energy distribution. Therefore, the computed wavelet coefficients of EEG signals are used as the feature vectors. The EEG signal considered to be stationary using a rectangular window. Wavelet coefficients are computed for each EEG segment. These Computations for each segment and each subject, led to a large feature space. In order to reduce the feature space dimensionality, statistical methods are used over the wavelet coefficients of the each subject[11].
In order to cover the special characteristic of EEG signal, following statistical features are used.

(1) Maximum of the wavelet coefficients in each subband.
(2) Minimum of the wavelet coefficients in each subband.
(3) Mean of the wavelet coefficients in each subband.
(4) Standard deviation of the wavelet coefficients in each subband.

The six ANFIS classifiers were trained with the backpropagation gradient descent method in combination with the least squares method when 24 features (dimension of the extracted feature vectors) representing the EEG signals were used as inputs. To improve classification accuracy, the SVM classifier was trained using the outputs of the six ANFIS classifiers as input data
The EEG signals have different subbands with special information. Separating and sorting the EEG structure is one purpose of wavelet analysis.
Each sleep stage of the EEG signals with 4 statistical features (24 features) was used as the 6 ANFIS classifiers inputs.
Confusion matrix is used to display the classification results (Table 3). In a confusion matrix, each cell contains the raw number of exemplars classified for the corresponding combination of desired and actual network outputs.
In this study 10 times cross validation is used and the data set is separated into two sets with 75% and 25% parts. The training dataset with 75% of the total data is used to train the ANFIS model, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for classification of the classes of EEG signals.

Table 3. Confusion matrix

	Awake	I	II	III	IV	REM
Awake	250	5	0	0	0	0
I	7	51	1	0	0	0
II	0	0	369	3	1	0
III	0	0	6	88	0	0
IV	0	0	0	0	198	5
REM	0	0	0	0	9	206

According to the confusion matrix, seven EEG segments from awake stage were classified incorrectly by the ANFIS model as segments from stage I. Five segments from stage I were classified as segments from awake stage. one segments from stage II was classified as segments from stage I. three segment from stage III were classified as a segment from stage II. One segment from stage IV was classified as segments from stage II and nine segments from REM stage. Five segments from REM stage were classified as segments from IV stage.
As mentioned before, human's sleep is divided into two segments, Rapid Eye Movement (REM) sleep and Non-REM (NREM) sleep. To differentiate between REM and NREM stages, SVM with RBF kernel is used. To classify REM and Non-REM stages, the 6 ANFIS outputs are used as SVM inputs and the SVM output shows the accuracy rate.
The classification rate between REM and Non-REM is 98%. using SVM.

V. CONCLUSION

Wavelet coefficients differentiate Awake and REM states based on the sleep staging manual's feature mixed frequency. Wavelet coefficients are shown to be the best in terms of performance dealing with Awake from REM differentiation, with 98% which is much better than reported in [21]. Also, ANFIS has a good performance in differentiating 6 sleep stages from adjacent stages.

In our study, statistical features improved classification rate and reducing the computational load as a necessary component. Summarily, through the feature space constructed by WT, different stages of EEG signals can be recognized from each other expressly. That is to say, pattern varies under the different sleep stages. Therefore healthy humans with a regular night's sleep will follow these sleep stages in a particular pattern.

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