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Automatic Sleep Stage Classification Based on EEG Signals by Using Neural Networks and Wavelet Packet Coefficients

Farideh Ebrahimi, Mohammad Mikaeili, Edson Estrada, Homer Nazeran, Senior Member, IEEE

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 stage classification is visual inspection by a sleep specialist. This is a very time consuming and laborious exercise. Automatic sleep stage classification can facilitate this process.

The definition of sleep stages and the sleep literature show that EEG signals are similar in Stage1 of non-rapid eye movement (NREM) sleep and rapid eye movement (REM) sleep. Therefore, in this work an attempt was made to classify four sleep stages consisting of Awake, Stage1 + REM, Stage 2 and Slow Wave Stage based on the EEG signal alone. Wavelet packet coefficients and artificial neural networks were deployed for this purpose. Seven all night recordings from Physionet database were used in the study. The results demonstrated that these four sleep stages could be automatically discriminated from each other with a specificity of 94.4 ± 4.5%, a of sensitivity 84.2±3.9% and an accuracy of 93.0 ± 4.0%.

I. INTRODUCTION

According to Rechtschaffen and Kales (RK) sleep scoring standard [1], sleep states consist of two general stages: rapid eye movement (REM) and non-rapid eye movement (NREM). NREM is in turn subdivided into four stages: 1, 2, 3, and 4. Stage 1 is a transition stage between wakefulness and sleep. It usually lasts between 1 to 5 minutes. This stage consists of a low-voltage EEG tracing with well-defined alpha and theta activity, occasional vertex spikes, and slow rolling eye movements (SEMs). This stage, on average, represents 4-5% of total sleep and exhibits the absence of sleep spindles, K-complexes, and REM sleep.

Stage 2 is the “baseline” of sleep and it is characterized by the occurrence of sleep spindles and K-complexes and a relatively low-voltage, mixed frequency EEG background. Sleep spindles are episodic bursts of activity in the 12 to 14 Hz range that last for a minimum of 0.5 sec. K-complexes are large waves starting with negative (upward) deflection, followed by a positive (downward) component. The entire k-complexes should last for a minimum of 0.5 sec [2]. Alternatively, high voltage delta waves may comprise up to 20% of Stage 2 epochs. Complete sleep duration may consist of 45-55% of Stage 2. Stage 3 is referred to a period during which at least 20% and not more than 50% of the sleep consists of EEG signals with frequencies of 2 Hz or smaller and amplitudes of more than 75 µV (delta waves). This stage normally appears only in the first one-third of the sleep episode, and usually compromises 4-6% of total sleep time. Stage 4 is quite similar to Stage 3, except that delta waves cover 50% or more of the record. Sleep Stage 4 usually represents 12-15% of the total sleep time. Stages 3 and 4 together are also known as “deep sleep” or slow wave sleep (SWS) and this is the most restorative part of sleep.

REM is the sleep stage in which dreaming occurs and constitutes 20-25% of a normal sleep night. It is well-known by the incidence of rapid eye movements under closed eyelids, motor atonia and low voltage EEG patterns. During REM sleep, the brain activity is reversed from Stage 4 to a pattern similar to Stage 1. Fig.1 shows some typical 10-second epochs of the EEG signal in different sleep stages.

The EEG signal is the most important signal in sleep stage classification but physicians more frequently make use of use other biological signals such as EMG, EOG and ECG in manual sleep stage classification [2]. The EMG tonus decreases severely in REM sleep. Therefore, Stage 1 and REM sleep can be separated by using the EMG signal. The EOG signal is important to detect eye movements in Stage1 and REM sleep.

A careful inspection of the EEG signal can reveal unusual patterns. However, a complete visual inspection of a long-term EEG recording is a time-consuming and difficult task. So, a method to facilitate EEG inspection would be highly desirable. In the past a number of automated sleep stage scoring methods have been proposed based on EEG records, sometimes in combination with the EOG (electrooculogram) and the EMG [3, 4]. EMG and EOG signals have been used as two important switches for discrimination between Awake, Sleep Stage1 and REM sleep. Stage1 and REM have been distinguished from each other by using a single parameter derived from another biosignal (such as EMG) monitored during sleep [5].

The sleep EEG signal is nonstationary and wavelet analysis is very useful for analysis of nonstationary signals. Wavelet transform has been used for sleep staging [6] and alertness level detection [7, 8].
Becq et al. [9] compared the performance of 5 linear and quadratic classifiers, k nearest neighbors, Parzen kernels and neural networks in automatic sleep stage classification. Based on this study they recommend neural networks.

Therefore, here we deployed wavelet transform and artificial neural networks (ANNs) using the EEG signals alone to discriminate between Awake, Stage1 + REM, Stage 2 and Slow Wave sleep.

![Wavelet Coefficients](image)

**Fig.1. 10-second epochs of EEG signal in different sleep stages.**

### A. Data

Sleep data from PhysioBank Database available at [www.physionet.com](http://www.physionet.com) were used for this investigation. EEG signals recorded from seven Caucasian males and females (21-35 years old) without any medication for 24 hours sampled at 100 Hz were selected. Sleep stages were scored according to Rechtschaffen & Kales based on 30-second epochs of Fpz-Cz / Pz-Oz EEG recordings. As the focus of this paper was not on preprocessing of EEG signals for artifact removal, artifact epochs were manually removed to work with clean data. In our previous publications such as [5] we have addressed the issue of preprocessing of EEG signals for feature extraction. The Pz-Oz channel was used in our evaluations. Table I shows the number of 30-second epochs of different sleep stages for each subject. All epochs in this table were artifact-free.

<table>
<thead>
<tr>
<th>SUBJECTS INFORMATION</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wake&amp; Sleep stages</strong></td>
</tr>
<tr>
<td>Subject1</td>
</tr>
<tr>
<td>Subject2</td>
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<tr>
<td>Subject3</td>
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<td>Subject4</td>
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<td>Subject5</td>
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<tr>
<td>Subject6</td>
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<tr>
<td>Subject7</td>
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<tr>
<td>Total 30-second epochs</td>
</tr>
</tbody>
</table>

### B. Wavelet Transform

As time-domain analysis of biosignals such as EEG does not provide frequency details, spectral (frequency-domain) analysis would be very helpful. However, spectral analysis does not show us at what times the frequency changes occur. Moreover, EEG signals are dynamic, sometimes transient (spikes/bursts), mostly nonstationary, and usually corrupted with noise. As such, for their practical analysis, we not only need to know their frequency components but also the times at which they occur. Time-frequency analysis is especially suitable for addressing such issues [10].

In signal processing, we usually need more time accuracy in locating transient waves (high frequency), and for slow waves, we may be more interested in frequency resolution. Such an analysis needs an adaptive time-frequency analysis method. Wavelet transform (WT) is such a tool. For a given signal x(t), in general, wavelet decomposition is given as:

\[
x(t) = \sum_{k=-\infty}^{\infty} c_{N,k} \phi(2^{-N}t - k) + \sum_{j=0}^{\infty} \sum_{k=-\infty}^{\infty} d_{j,k} 2^{-j/2} \psi(2^{-j}t - k)
\]

where \(c_{N,k}\) represents approximation coefficients at level N, while \(d_{j,k}\) represents detail coefficients or wavelet coefficients at level j. \(\phi(t)\) is the wavelet function, while \(\psi(t)\) is a companion function, named scaling function.

If the scaling functions and wavelets form an orthonormal basis, Parseval’s theorem relates the energy of the signal x(t) to the energy in each of the components and their wavelet coefficients. That is one reason why orthonormality is important [11]. Parseval’s theorem for discrete wavelet transform is given by equation (2).

\[
E = \sum_{k=-\infty}^{\infty} c_{N,k}^2 + \sum_{j=0}^{\infty} \sum_{k=-\infty}^{\infty} d_{j,k}^2
\]

### C. Wavelet Packets

In discreet wavelet transform we repeatedly split, filter and decimate the low pass bands. The classical \((a_0=2, b_0=1)\) wavelet system results in a logarithmic frequency resolution. The low frequencies have narrow bandwidths and the high frequencies have wide bandwidths. The wavelet packet system allows a finer and adjustable resolution of frequencies at high frequencies. In wavelet packet transform, we split both the low pass and high pass bands at all stages. It gives a rich structure that allows adaptation to particular signals. The cost of this richer structure is a computational complexity of \(O(N\log(N))\), similar to the FFT, in contrast to the classical wavelet transform which is \(O(N)\) [11].

### D. Selection of Wavelet and Number of Levels

A wavelet packet tree (WPT) of depth 7 (7 levels) was designed for this purpose. Daubechies order 2 (db2) wavelet transform was applied to 30-second epochs of EEG signal.
The frequency ranges of the EEG signal were broken down into Delta (below 3.5 Hz), Theta (4-7 Hz), Alpha (8-13 Hz), and Beta (14-30 Hz) bands [12]. In the sleep EEG, because of presence of sleep spindles, there is another frequency band, that is, spindle frequency band. Out of the family of subbands, those containing frequency information of the following 6 bands were manually selected (Fig. 2).

![Wavelet Packet Transform (WPT) and selected subbands.](image)

**Fig. 2.** WPT and selected subbands.

1. **{0.39 - 3.13 Hz}, Delta, Wavelet coefficient = [C36, C30, C31, C32] = S1**
2. **{3.13 - 8.46 Hz}, Theta, Wavelet coefficient = [C33, C34, C22, C23, C35] = S2**
3. **{8.46 - 10.93 Hz}, Alpha, Wavelet coefficient = [C36, C25] = S3**
4. **{10.93 - 15.63 Hz}, Spindle, Wavelet coefficient = [C26, C27, C28] = S4**
5. **{15.63 - 21.88 Hz}, Beta1, Wavelet coefficient = [C16, C17] = S5**
6. **{21.88 - 37.50 Hz}, Beta2, Wavelet coefficient = [C15, C3] = S6**

**E. Feature Extraction**

The following statistical features were used to represent the time–frequency distribution of the EEG signals:

1. Mean quadratic value or Energy ($E_1, E_2, ..., E_6$) of wavelet packet (WP) coefficients for each of the 6 bands,
2. Total Energy ($E_T$),
3. Ratio of different Energy values ($E_{08}, E_{06}, E_{10}$),
4. Mean of the absolute values of the coefficients in each sub-band, and
5. Standard deviation of the coefficients in each sub-band.

Total Energy ($E_T$) is the sum of energy in the above-mentioned 6 frequency bands. $E_0$ is the ratio of energy in the Alpha band and the combined power in Delta and Theta bands, $E_9$ is the ratio of energy in the Delta band and the combined power in Alpha and Theta bands and $E_{10}$ is the ratio of energy in Theta band and the combined power in Delta and Alpha bands. These feature vectors, calculated for the frequency bands 1-6, were used for classification of the EEG signals.

**F. Classification (Artificial Neural Networks)**

Becq et al. [9] compared the performance of 5 linear and quadratic classifiers, $k$-nearest neighbors, Parzen kernels and neural networks in automatic sleep stage classification. Based on this study they recommend neural networks. Therefore, we used a tree-layer feed forward perceptron ANN (artificial neural network) with 12 inputs, one hidden layer (with 8 neurons for best results) and one output layer (with 4 nodes) as our classifier. Standard backpropagation algorithm converged to local minimums. Therefore, we used the error backpropagation training algorithm with momentum and adaptive learning rate (traindx). During learning, momentum helps the ANN to avoid stabilization in local minima of the error surface, which would prevent the network from finding the desired lowest error solution for the matrix of the weights connecting the neurons. Training time was reduced by using an adaptive learning rate, which attempted to keep the learning step size as large as possible, while keeping learning stable. There were 4 neurons in the output layer for discrimination between sleep stages Awake, Stage1+REM, Stage2 and SWS. The neurons of the hidden and output layers had an asymmetric sigmoid function. In the classification stage, the aim was to assign the input patterns to one of the several classes, usually represented by outputs restricted to the range from 0 to 1, so that they represented the probability of class membership. MATLAB was used as the programming language.

**III. RESULTS**

The features were extracted from 30-second segments of Pz-Oz channel EEG signal. All epochs in Table I were used. Segment features used for clustering were a mixture of different scales. Before clustering, it was therefore necessary that all the features be scaled such that the weighting of any feature does not play a more important role than any other. Each feature was normalized with respect to a value such that 75% of features were smaller than it. Following feature extraction and normalization, we used a MLP artificial neural network with momentum and adaptive learning rate to classify these features. The results are summarized in Tables II and III.

As the numbers of clean epochs, especially in the awake state, were small we deployed the bootstrap technique [13] to be able to maximize the use of available dataset (and consequently the derived features) for training and testing the ANN. The bootstrap technique is a standard method in data mining. It involves choosing random samples with replacement from a dataset and treating each sample the same way. Sampling with replacement means that every sample point is returned to the dataset after sampling.

So a particular data point from the original dataset could appear multiple times in a given bootstrap sample. The number of elements in each bootstrap sample equals the number of elements in the original dataset.
Bootstrap samples were used to derive the feature vectors and these were in turn used for neural network training. The neural network performance was then tested on the feature vectors of each class that were not used in the training stage.

IV. DISCUSSION AND CONCLUSIONS

In this research, we attempted to discriminate Awake, Stage1+REM, Stage2 and SWS stages by using a single channel EEG signals. Wavelet packet transform was applied to 30-second segments of Pz-Oz channel EEG signals. Feature vectors were calculated from wavelet packet coefficients. These feature vectors were then classified by using a MLP artificial neural network with one hidden layer and traindx training algorithm. By varying the number of neurons in the hidden layer, it was observed that with increasing the number of neurons the mean of accuracy increases and standard deviation decreases. The best performance was achieved when using 8 neurons in the hidden layer. More than 8 neurons did not produce any improvements in the outcome. With partial variation in the numbers of neurons, the mean accuracy did not vary a lot but standard deviation increased. The results shown in Table II and III were achieved for the MLP neural networks with 8 neurons in its hidden layer and in 50 runs. Training and testing sets in each run were chosen separately by the Bootstrap technique as outlined above. When we used the trainlm (Levenberg-Marquardt backpropagation) and traindx (Gradient descent with momentum and adaptive learning rate backpropagation) training functions to train the ANN, we achieved good performance but the difference between the training and testing results was more when using trainlm compared to traindx. It was observed that our approach could separate the 4 sleep stages with very good outcomes.

The results indicate that our method could discriminate between Awake, Stage1+REM sleep, Stage2 and SWS with a specificity of 94.4±4.5%, a sensitivity of 84.2±3.9% and an accuracy of 93.0±4.0%.

As there is a fair bit of disagreement between sleep specialists in manual sleep scoring, the design and realization of a robust and reliable automatic sleep stage classification system based on quantitative features of sleep data could prove very helpful.

As the feature vectors E1-E6 are nonlinear functions of E1-E6, in our future work we intend to remove these features from our feature set and observe the performance of ANN classifier. In this study we used bipolar EEG recordings. However, our approach is applicable to monopolar EEG recordings in the future. Deployment of other EEG channels as well as a neuro-fuzzy classifier could also offer further enhancement in performance.

REFERENCES


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<th>Specificity</th>
<th>Sensitivity</th>
<th>Accuracy</th>
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<tbody>
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<td>85.4±2.8</td>
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<td>Stage1+REM</td>
<td>94.5±0.78</td>
<td>87.2±2.3</td>
<td>97.3±0.66</td>
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<td>Stage2</td>
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<tr>
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<td>94.4±4.5</td>
<td>84.2±3.9</td>
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<td>88.6±0.7</td>
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<tr>
<td>Stage2</td>
<td>87.6±2.0</td>
<td>84.0±2.7</td>
<td>94.6±0.4</td>
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<tr>
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<td>93.0±4.0</td>
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TABLE II

MLP CLASSIFICATION RESULTS - TRAINING SET IN 50 RUNS (THE NUMBER OF HIDDEN NEURONS = 8)

<table>
<thead>
<tr>
<th>Wake&amp; Sleep Stages</th>
<th>Specificity</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Total stages</th>
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</thead>
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<tr>
<td>SWS</td>
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<td>93.0±4.0</td>
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</tr>
</tbody>
</table>

TABLE III

MLP CLASSIFICATION RESULTS - TESTING SET IN 50 RUNS (THE NUMBER OF HIDDEN NEURONS = 8)