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Sleep Stage Classification using Wavelet Transform and Neural Network

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Abstract

In this paper we present a new method to do automatic sleep stage classification. The algorithm consists of basically three modules. A wavelet packet transformation (WPT) is applied to 30 seconds long epochs of EEG recordings to provide localized time-frequency information, a feature generator which quantifies the information and reduce the data set size, and an artificial neural network for doing optimal classification. The classification results compared to those of a human expert reached a 70 to 80% of agreement.

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Introduction

Electroencephalogram analysis (EEG) is a very useful technique to investigate the activity of the central nervous system (CNS). It provides information related to the brain activity based on measurements of electrical recordings taken on the scalp of the subjects. Inference and studies about subject's health and effective treatment of some diseases can be carried out analyzing the information obtained from the EEG. Processing of the recorded information mainly concern spectral analysis. Sleep EEG is a very important research branch of medicine, because of the clinical applications.

Sleep scoring by a human expert is a very time-consuming task and normally could require hours to classify a whole night recording (8 hours). Every 30 seconds epochs are classified in different sleep stages, according to the structure of the signal and rules defined by Rechtschaffen and Kales [7].

In the past 20 years different automatic methods have been developed with the purpose of supplying the visual classification. In this last decade several works introduced the use of neural network (NN) as a tool for automated sleep scoring. Most of the systems used spectral information of the signal using Fourier Transformation [1].

The results are different from one system to another. Performance of the NN varied in the range 60-90 % of recognition rates. Rigorous comparisons between the reported systems can hardly be done because they differ in recording conditions and validation procedures.

In a paper published 1994, Jobert et.al [2] illustrated advantages of the wavelet analysis over the Fourier analysis in sleep research. Motivated by the adaptive time-frequency localization property of the Wavelet Transform (WT) and the fact that some structures in sleep recordings have a well defined time-frequency (t-w) pattern we designed a system based on a specific Wavelet Packet Transform (WPT) and a NN structure for the classification task.

Fourier and Wavelet Analysis, Time-Frequency Localization

The Fourier Transform (FT) has been widely used for signal processing. It is a powerful tool to study the frequency content of signals but it has the draw-back that it does not provide any localization in time. To overcome this problem the Windowed Fourier Transform or Short Time Fourier Transform (STFT) was suggested (1),

$$STFT(f(w,s)) = \int g^{*}(t-s) f(t) e^{-iwt} dt \qquad (1)$$

where g is a given time window which can be shifted in time.

Since the same window is used, t-w resolution is fixed over the whole signal, determined by the window's supports in time and frequency domain.

The discrete version of the FT is made on a rectangular grid $m.n \in Z, t_0 > 0, w_0 > 0$, (2),

$$STFT_{m,n}(f) = \int g^{*}(t-nt_0) f(t) e^{-imw_0 t} dt \qquad (2)$$

The window g is supposed to be compactly supported and to fulfill some smoothness properties. If g is Gaussian then the STFT is called Gabor Transform [3].

A more elegant version of time frequency analysis is wavelet analysis [4],[5] where a so-called mother-wavelet $\psi(t)$ is shifted and scaled leading to a constant relative bandwidth. $\psi(t)$ is a localized oscillation with the property :

$$\int_{-\infty}^{\infty} \psi(t)dt = \hat{\psi}(w=0) = 0 \qquad (3)$$

The Wavelet Transform (WT) is then defined analogous to (1)

$$WT(f(a,b)) = \int f(t)\psi_{a,b}(t)dt \qquad (4),$$

where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), a \in R^{+}, b \in R \qquad (5)$$

$\psi_{a,b}(t)$ are called wavelets. They are scaled (stretched and compressed) versions of the mother wavelet $\psi(t)$.

The t-w resolution depends on the scaling parameter a. For smaller a $\psi_{a,b}(t)$ has a narrow time-support and therefore a wider frequency support. When a increases, time support of $\psi_{a,b}(t)$ increases as well and frequency-support becomes narrower. The translation parameter b determines the localization of $\psi_{a,b}(t)$ in time.

The discrete WT is defined taking discrete values of a and b as follows (6):

$$a = a_0^m, b = nb_0 a_0^m, \quad m,n \in Z, a_0 > 1, b_0 > 0$$
$$WT_{m,n}(f) = a_0^{-m/2} \int f(t)\psi(a_0^{-m}t - nbo)dt \qquad (6)$$

The tiling of the t-w plane is very different from the rectangular grid of the STFT. A logarithmic frequency scale is obtained, Fig.1., which allows a better study of short-time high frequency structures. Low frequencies are sampled with large time steps while high frequencies are sampled with small steps.

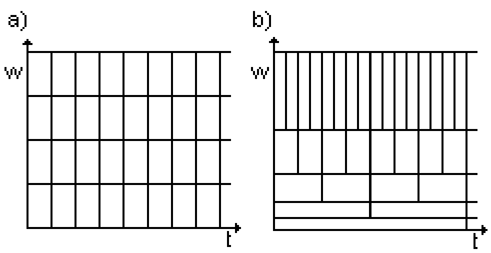

Fig.1. Time -Frequency Tiling a) STFT, b) WT Case a_0=2

In practical applications the values a_0=2, b_0=1 are chosen. This choice naturally connects multiresolution analysis with wavelets [6]. In this case, WT can be seen as generated by a pair of quadrature mirror filter, QMF (h,g), where h is a low pass filter and g a high pass filter. We consider only finite impulse response filter (FIR). h,g are finite sequences related by :

$$g(n) = (-1)^n h(1-n),$$
$$\sum g(n) = 0, \sum h(n) = \sqrt{2} \qquad (7)$$

where h is related to the so-called scaling function ϕ [4] and g to the mother wavelet ψ by :

$$\phi(x) = \sum_n h(n)\sqrt{2}\phi(2x-n)$$
$$\psi(x) = \sum_n g(n)\sqrt{2}\phi(2x-n) \qquad (8)$$

For a discrete signal x of finite length $\{1..2^N\}$, define the following operators H.G:

$$(Hx)_k = \sum_n h(n-2k)x_n$$
$$(Gx)_k = \sum_n g(n-2k)x_n \qquad (9)$$

H, G are convolution-decimation operators. H,G acting on x are convolutions with both filters h,g and a downsampling by two. This transforms the signal x in two subbands of same length ,{Hx}, {Gx}. {Hx} contains the low pass band and {Gx} the high pass band.
Recursive application of H and G on the low pass band defines the WT, as shown in Fig.2.
Each band in the tree spans the whole time extend of x, so time resolution decreases by a factor of 2 in each iteration , but frequency resolution doubles as one goes from the top to the bottom in the WP tree .

Recursive application of the operators H,G on both bands defines the „wavelet packets“. Fig.2
Every non-overlapping complete set of subbands, allows a complete reconstruction of the signal, including those obtained by mixing different levels of the tree. In this huge library of subbands one can choose one distribution of subbands having a good t-w resolution for the particular signal to be analyzed.
The WT is just one special case of the WPT. Fig.2.

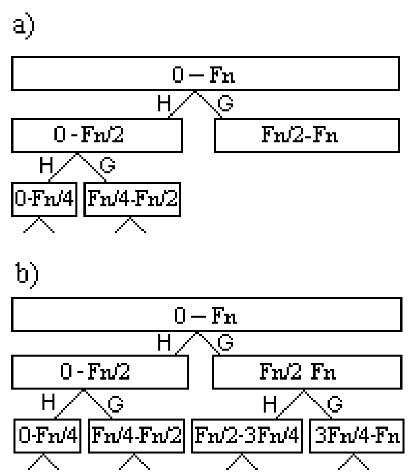

Fig.2. a) Wavelet Tree, b) Wavelet Packet Tree.
The top subband contains the signal x, with Nyquist Frequency Fn.

EEG Sleep, Sleep Stages Structures

In humans, 5 sleep stages and the stage awake are defined [7],[8]. Each sleep stage is characterized by an specific pattern of frequency content. The EEG spectrum is divided in 5 bands for a better study

Delta 0 - 4 Hz
Theta 4 - 8 “
Alpha 8 - 13 “
Beta1 13 - 22 “
Beta2 22 - 35 “

The following sleep stages are defined: Fig.4.

Stage awake: Signal with continuity alpha activity.

Stage 1: No presence of alpha activity, low beta and theta activity,

Stage 2: Less than 20 % of delta activity and presence of K-complexes and spindles. K-complexes are low frequency waves near 1.0 Hz, with an amplitude of at least 75 mV. Spindles are well defined waves in the range 11-15 Hz with a time duration of more than 0.5 seconds. There is no criterion about the amplitude of a spindle.

Stage 3: More than 20 % and less than 50 % of delta activity,

Stage 4: More than 50 % of delta activity.

Stage REM: Low amplitude waves with little Theta activity and often sawtooth waves. REM and awake signals might have a similar shape, but REM have little alpha activity.

The classification of EEG sleep is usually made by a visual scorer, which takes 30-s epochs and give a classification according to the rules of Rechtschaffen and Kale [7]. Not every epoch has 100 % properties of an specific stage. The decision is made according to which stage properties are present the most and that is sometimes difficult to be carried out.

In Fig.4. we plotted signals from sleep stages 1,2,4, awake and REM. Stage 3 signals have usually a similar shape as those recorded in sleep stage 4, they only differ in the amplitude delta activity. We plotted the scalogram: absolute value of the Wavelet Packet’s coefficients. Absolute value of each coefficient was color coded, according to the color scale used. Fig.4. Every coefficient is represented by a rectangle of size determined by it’s t-w resolution.

Linear interpolation was made in order to give a continuum color representation and a logarithmic scale representation was used in the frequency axis.

We see that the scalogram clearly shows , specially, in stages 2, 4 and awake the expected t-w characteristics of the pattern. K-complex and sleep spindles are well localized. The continuity alpha activity typical from awake stage is well represented. Even when the coloration coding could not be optimal for representing Beta activity, one can see the little beta activity in the first half of the stage 1 signal. Slow wave phenomena (K-complexes and delta waves) have usually great amplitude and get the most intense color.

On the right column the power spectrum or spectrogram is depicted, calculated with the Fourier Transform. The signals are segments of 16 seconds (2048 Samples).The EEG was sampled at 128 Hz.

In the spectrogram the frequency content of the bands is well represented.

Methods

A WPT of depth 8 (i.e. 8 levels) was designed. Out of the family of generated subbands we selected those containing frequency information of the following 7 bands. Fig.3.

1. 0.4 - 1.55 Hz } K-complexes + Delta
2. 1.55 - 3.2 “ } Delta
3. 3.2 - 8.6 “ } Theta
4. 8.6 - 11.0 “ } Alpha
5. 11.0 - 15.6 “ } Spindle
6. 15.6 - 22.0 “ } Beta1
7. 22.0 - 37.5 “ } Beta2

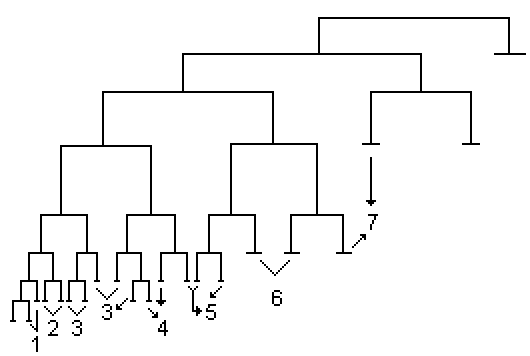

Fig.3 WPT , selected subbands

Time resolution varies according to the band in logarithmic scales according to the branch of the tree, where the coefficients belong to. Small-frequency waves(delta wave, K- complexes) have broader time resolution and high-frequency waves (spindle, alpha waves) have finer time resolution

For every 30 seconds epoch taken from the central EEG electrode C3, we calculated the mean quadratic value (the so-called Energy E) of the WP coefficients for each of the 7 bands. These 7 numbers $E_i, i = 1{:}7$ were used as features for the epoch. Additionally we defined 6 more features based on total energy and the ratio of different energy values:

8.Total Energy of the 7 bands $E8 = \sum_{i=1}^{7} E_i$

9. Ratio (E1 + E2)/E8 Percent Delta Activity
10. " " E4/E8 " " Alpha " "
11. " " (E1 + E5)/E8 " " KK and Spindle
12. " " E4/E3 Ratio Alpha/Theta
13. " " (E1 + E2)/E3 " " Delta/Theta ,

Classification and Results

For the classification task we used a Feed Forward Backpropagation Network with the following structure: 13 neurons in the input layer, each one getting one of the 13 features; 10 neurons in the hidden layer fully connected to the first layer and 6 neurons in the output layer, with a defined target vector of zeros and a one in the position according to an specific sleep stage. The output layer was fully connected to the hidden layer. The goal of the network was to correctly classify the 30 seconds epochs of sleep recording characterized by the 13 parameters.
We used the wavelet db20, from the Daubechies Family of Orthogonal Wavelets, with compact support and highest number of vanishing moments.
Different number of neurons in the hidden layer were tested , varying the number from 6 to 15 hidden neurons, being the optimum of the learning rate by 10 neurons. More than 10 did not bring any improvements in the results.
The data set consisted of 2 EEG, sampled at a frequency of 200 Hz, which provided a total of 1690 30 seconds epochs, distributed as follows: 340 epochs of REM, 350 of awake, 400 of S2, 300 of S1 and 150 of S3 and S4 respectively. Because of the few number of data in stages 3 and 4, we decided to test the performance of the network only on the other 4 stages. 200 samples of every stage were used as training set and the rest to test the performance of the network.
The results are shown in the confusion matrix-table (Tab. 1). The table is organized is as follows: in each row the performance of the network is represented by an specific sleep stage, each column represents the results of the classification. In the case of 'No decision' the net could not classify the epochs. The diagonal of the table represents the number of epochs which were right classified.

The training process showed high dependency on the initial weights distribution in the network. The most used training functions, Gradient descent Backpropagation with and without momentum showed the fastest iteration in the learning process, but the solution always converged to a local minimum, although some random noise was added to the weights. The training function which showed the best performance was the Levenberg-Marquardt (LM). Using this, the iteration process slowed down considerably, but convergence to a minimum was always reached and the cost function converged to zero much faster than with other training functions. All the results presented here were obtained using the LM training function.

Learning set: 800 Epochs

# Epochs	Rem	Awake	S2	S1	No Decision	Total	Agree. %
Rem	**194**	0	0	3	3	200	97
Awake	2	**196**	1	0	1	200	98
S2	0	0	**198**	2	0	200	99
S1	1	1	7	**190**	1	200	95
						800	97.5

Table1. Neural Network performance on the learning set

Testing Set: 590 Epochs

# Epochs	Rem	Awake	S2	S1	No Decision	Total	Agree. %
Rem	**91**	1	0	43	5	140	65
Awake	5	**111**	0	25	9	150	74
S2	1	0	**181**	13	5	200	90.5
S1	16	2	0	**75**	7	100	75
						590	77.6

Table2. Neural Network performance on the test set.

Conclusions

A new method for doing automatic sleep stage classification has been presented and the application on data set tested. As far as we know, only Fourier Transform methods have been used in this problem. As explained, wavelet transform allows an adaptive time frequency resolution, and a method using WT should be able to identify the different time-frequency pattern of the sleep stages. The aim of the report was to show first results of the designed algorithm The net we used learned with a 97.5 % of agreement over the whole learning set. Performance on the whole test set reached a 77.6 % of agreement, which can be considered as an encouraging result. The data used for testing and training the system are in fact small. In further experiments, the system is supposed to be tested in at least 8 EEG recordings, 4 for training and 4 for testing. We expect also to be able to draw out of the EEG signal more detailed information in order to propose the system as an alternative for supplying visual scoring.

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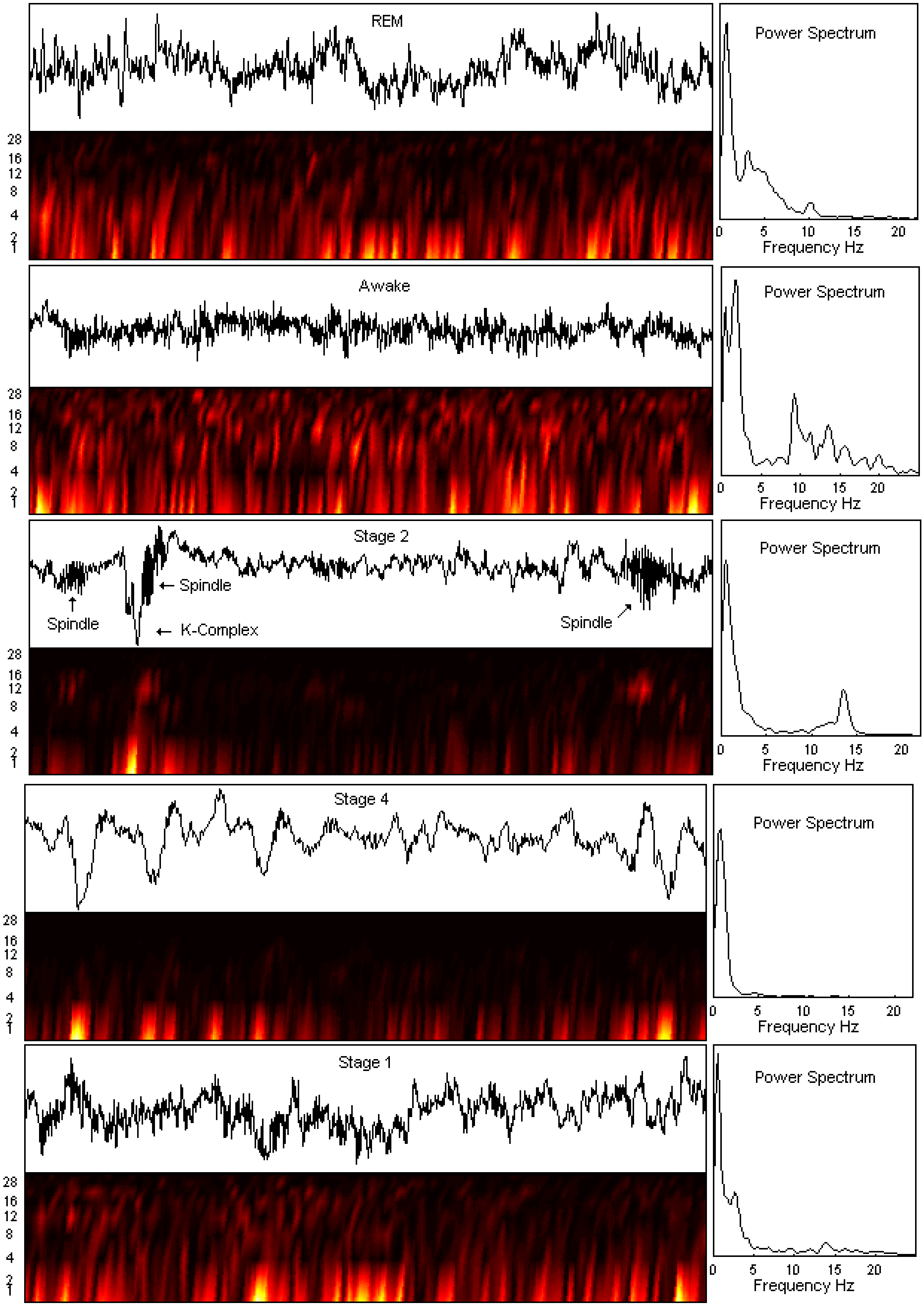
Fig. 4 (Next page) Left Column: Signals, 16 seconds epochs from sleep stages 1,2,4, awake and Rem, and corresponding scalogram. Horizontal axis in both graphs is time, vertical axis in the scalogram is frequency in Hz.

Right Column: Spectrograms: Power Spectrum from the STFT

Color Scale, Minimum Maximum


REM
Power Spectrum
Frequency Hz
Awake
Power Spectrum
Frequency Hz
Stage 2
Spindle
Spindle
K-Complex
Spindle
Power Spectrum
Frequency Hz
Stage 4
Power Spectrum
Frequency Hz
Stage 1
Power Spectrum
Frequency Hz