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Automatic recognition of alertness level by using wavelet transform and artificial neural network☆

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Abstract

We propose a novel method for automatic recognition of alertness level from full spectrum electroencephalogram (EEG) recordings. This procedure uses power spectral density (PSD) of discrete wavelet transform (DWT) of full spectrum EEG as an input to an artificial neural network (ANN) with three discrete outputs: alert, drowsy and sleep. The error back propagation neural network is selected as a classifier to discriminate the alertness level of a subject. EEG signals were obtained from 30 healthy subjects. The group consisted of 14 females and 16 males with ages ranging from 18 to 65 years and a mean age of 33.5 years, and a body mass index (BMI) of $32.4 \pm 7.3\,\mathrm{kg/m^2}$. Alertness level and classification properties of ANN were tested using the data recorded in 12 healthy subjects, whereby the EEG recordings were not used been used to train the ANN. The statistics were used as a measure of potential applicability of the ANN. The accuracy of the ANN was $96 \pm 3\%$ alert, $95 \pm 4\%$ drowsy and $94 \pm 5\%$ sleep. The results suggest that the automatic recognition algorithm is applicable for distinguishing between alert, drowsy and sleep state in recordings that have not been used for the training.

Keywords: Alert; Drowsy; Sleep; Electroencephalogram (EEG); Discrete wavelet transform (DWT); Artificial neural network (ANN); Power spectral density (PSD)

1. Introduction

The aim of this study was to establish a method for processing input data from a full spectrum of (EEG) recordings by the use of an artificial neural network (ANN) that distinguishes between alert and drowsy states in arbitrary subjects by the use of DWT processed EEG signals.

EEG distinguishes between states of vigilance, that is, wakefulness and sleep, and to some extent between the 'levels' of vigilance within a state. The EEG frequency spectrum is subdivided into δ (1–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz) and γ (>30 Hz) frequency ranges. Within NREM sleep, δ power (slow wave power) indicates the intensity of sleep and represents the need for sleep. During wakefulness, α and θ frequencies in the awake state EEG are of particular interest for research on sleepiness. During active wakefulness (with eyes open), α power is usually low unless the subject is severely fatigued. However, in resting conditions (with eyes closed), α power is also high when the subject is fully rested. During the transition from resting conditions, with eyes closed, to sleeping a gradual reduction of α power and a gradual increase in θ power occurs. Reduced α power and increased θ power during resting awake periods, with eyes closed, may thus indicate a high motivation for sleeping. Indeed, it was found that subjective sleepiness during awake periods correlates negatively with α power and positively with θ power in the awake EEG during prolonged wakefulness.

Spontaneous electrical brain activities, that is EEG signals, are dynamic, stochastic, non-linear and non-stationary (Guler et al., 2001; Herrmann et al., 2001; Vuckovic et al., 2002; Peters et al., 1998). The EEG recordings depend on the location of the electrodes, their impedance and the state

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of alertness. In addition, the EEG recordings vary substantially between healthy subjects. Extensive expertise is required to visually interpret the EEG recordings in order to isolate and identify characteristic information from a large amount of data. A computerized analysis of the EEG recordings aims to facilitate the time-consuming and difficult visual inspection and automatically extract characteristic features of brain activity. A computer-assisted EEG classification of drowsiness has been analyzed in several studies (Anderson et al., 1995; Doghramji et al., 1997; Gevins and Smith, 1999; Jung et al., 1997; Khahill and Duchene, 1999; Principe et al., 1989; Tsoi et al., 1994; Wilson and Bracewell, 2000). The classification was based on a spectral analysis of EEG recordings (Doghramji et al., 1997; Jung et al., 1997) and showed that a limited number of electrodes and spectral analysis of characteristic bands could be used as a classifier. More recently, some studies (Jung et al., 1997; Peters et al., 2001) concentrated on detecting the information on drowsiness available from a full EEG spectrum. Principe et al. (1989) designed a finite automaton that was capable of categorizing the sleep into seven different stages. McKeown et al. (1997) used statistical methods for the analysis of EEG signals and detection of vigilance changes. Pradhan et al. (1996) presented preliminary results for the classification of seizure activities by applying an ANN based on learning vector quantization. Kalayci and Ozdamar (1995) showed that an ANN performs better if the input and output data can be processed to capture the characteristic features of the signal (Anderson et al., 1995; Dorffner et al., 1993; Gevins and Smith, 1999; Haselsteiner and Pfurtscheller, 2000; Peters et al., 2001; Principe et al., 1989; Tsoi et al., 1994; Wilson and Bracewell, 2000). The combination of Fourier transform analysis of EEG with ANN in classifying alertness and drowsiness was previously shown to be a suitable algorithm for classifying events from raw EEG signals (Jung et al., 1997), except for specific conscious tasks. De Carli et al. (1999) worked on developing an automatic procedure for arousal detection during sleep. They tested this on a group of subjects, in different pathological conditions by using wavelet transform. The aim of this study was to develop a simple algorithm to discriminate the vigilance states, that is, wakefulness and sleep which could also be applied to real-time.

The following reasons were the basis for improving the methods of automatic detection of changes from alert to drowsy, and vice versa states: (1) clinical pre-processing of long-term recordings of wakefulness in order to select sequences of alert and drowsy states for further human inspection (Shimada et al., 2000); (2) online experiments, where timing of a stimuli for cognitive evoked potential are needed; (3) software for interactive learning (Akay et al., 1998); and (4) warning systems for detecting the drowsiness in operator rooms. The specific design requirement was applicability of the algorithm to short sequences of EEG recordings, hence plausible use in real-time. The second requirement was to develop a simple algorithm that would work on recordings that were not been used for the training of the same or arbitrary subject.

2. Materials and methods

2.1. Subjects

In this study, EEG signals were obtained from 30 subjects. The group consisted of 14 females and 16 males with ages ranging from 18 to 65 years and a mean age of 33.5 years, and a body mass index (BMI) of $32.4 \pm 7.3\,\mathrm{kg/m^2}$. Subjects with normal intelligence and without mental disorders were included in this study after passing the neurological screening. All recordings were performed in accordance with medically ethical standards. The subjects were not sleep-deprived. They had no deviations from their usual circadian cycle, and they took no medicine and alcohol. Two neurologists with extended experience of interpreting EEGs, evaluated and rated the recordings used for this study. Each of them inspected the EEG recordings, and then agreed which EEG sequences clearly indicated alert, drowsy or sleepy states of the subject.

2.2. EEG data acquisition and representation

The EEG data used in this study was taken from Medical Faculty, Sleep Laboratory Department of Psychic Health and Diseases. Silver-plated electrodes were used for the recordings, and a C3-A2 standard settlement was applied to the subject of the experiment, according to the 10–20 international electrode placement system. Measurements were taken by using Grass Model-78 Polysomnography. The recordings were band pass filtered between 0.3 and 70 Hz. The EEG recordings were digitized with 12-bit resolution, at a sampling rate of 150 Hz per channel (PCI MIO-16-E+ type) and a personnel computer as shown in Fig. 1 (Guler et al., 2001). Eight channels of the instrument can be used at the same time. Each channel can be gained distinctly and has at most 1000 Hz sampling rate. Data is taken into the computer memory quickly by using this card which is connected to the PCI data bus of the computer.

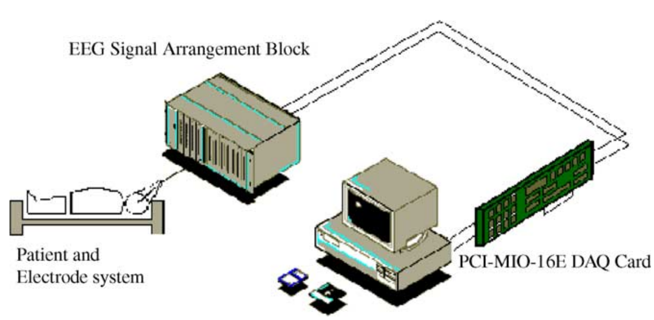

Fig. 1. Scheme of the EEG data acquisition system.

Each record was scored by two experts for alertness level staging, with a link to the recording. For this system graphical programming language (LabVIEW) was used as the software development tool. The system provides real-time data processing. Different EEG epochs have been given in Fig. 2. The signals were recorded during the 7 h episodes and digital signals were taken every 20 min for each block. Then these EEG recordings were divided into 5 s epochs, and these epochs are divided into four frequency sub-bands as α, β, θ and δ by using DWT.

2.3. *Wavelet transform*

The wavelet transform specifically permits to discrimination of non-stationary signals with different frequency features (Daubechies, 1992). A signal is stationary if it does not change much over time. Fourier transform can be applied to the stationary signals. However, like EEG, plenty of signals may contain non-stationary or transitory characteristics. Thus it is not ideal to directly apply Fourier transform to such signals.

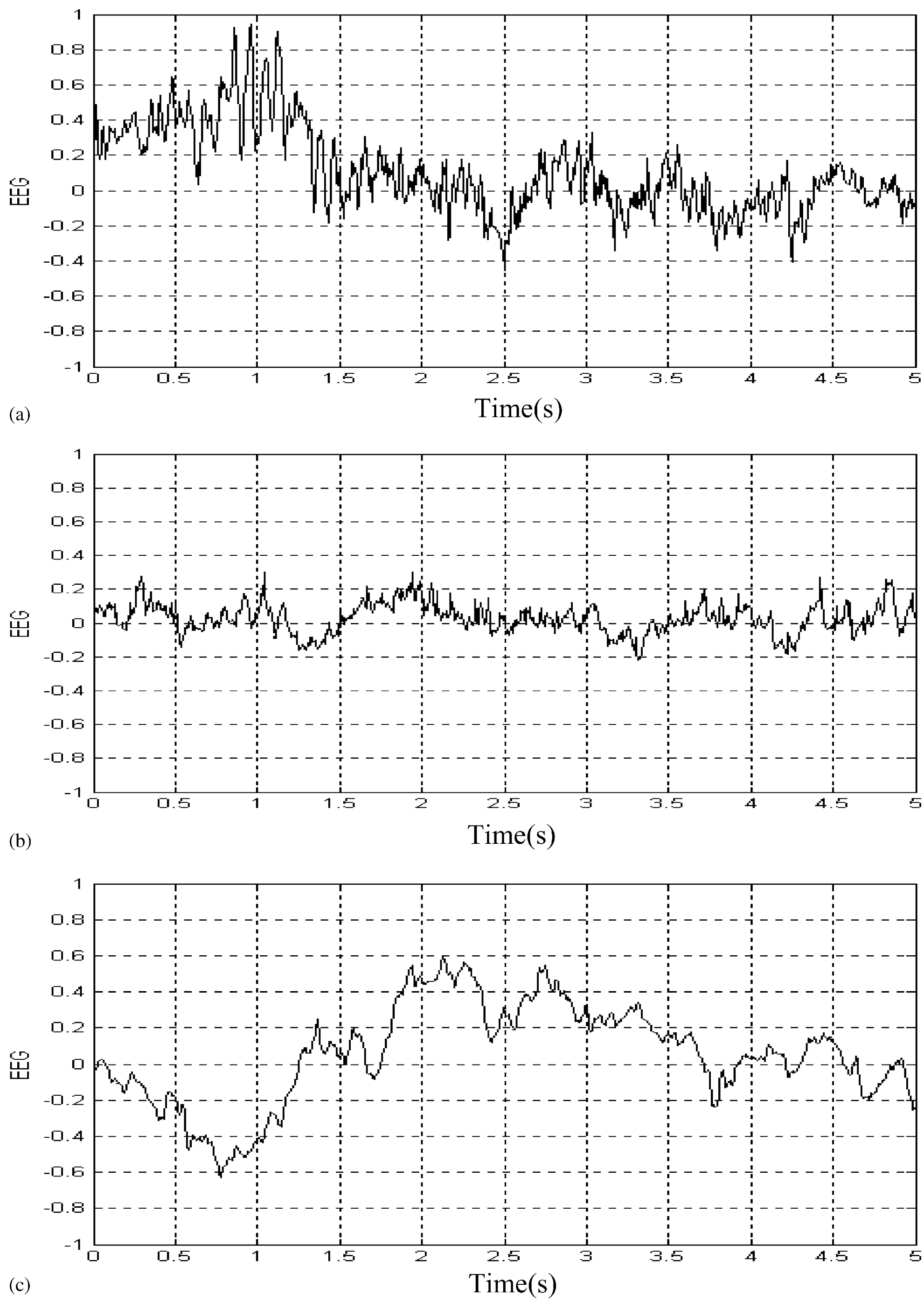

Fig. 2. Different EEG signals: (a) alert (b) drowsy (c) sleep.

The wavelet transform decomposes a signal into a set of basic functions called wavelets. These basic functions are obtained by dilations, contractions and shifts of a unique function called wavelet prototype. Continuous wavelets are functions generated from one single function ϕ by dilations and translations (Cohen and Kovacevic, 1996; Daubechies, 1996; Rioul and Vetterli, 1991).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

where b is real valued and called the shift parameter. The function set $(\psi_{a,b}(t))$ is called a wavelet family. Since the parameters (a, b) are continuous valued, the transform is called continuous wavelet transform. The definition of classical wavelets as dilates of one function means that high frequency wavelets correspond to $a < 1$ or narrow width, while low frequency wavelets have $a > 1$ or wider width. In the wavelet transform, $f(t)$ is expressed as linear combination of scaling and wavelet functions. Both scaling functions and the wavelet functions are complete sets (Rioul and Vetterli, 1991). However, it is common to employ both wavelet and scaling functions in the transform representation. In general, the scale and shift parameters of the discreet wavelet family are given by

$$a = a_0^j \text{ and } b = kb_0a_0^j \quad (2)$$

where j and k are integers. The function family with discretized parameters becomes

$$\psi_{j,k}(t) = a_0^{-j/2}\psi(a^{-j}t - kb_0) \quad (3)$$

$\psi_{j,k}(t)$ is called the discrete wavelet transform (DWT) basis. Although it is called DWT, the time variable of the transform is still continuous. The DWT coefficients of a continuous time function are similarly defined as

$$d_{j,k} \leq f_{\mathrm{w}}(t), \quad \psi_{j,k}(t) \geq \frac{1}{a_0^{j/2}}\int f_{\mathrm{w}}(t)\psi(a_0^{-j}t - kb_0)\mathrm{d}t \quad (4)$$

When the DWT set $(\psi_{j,k}(t))$ is complete, the wavelet representation of a function $f_{\mathrm{w}}(t)$ is expressed as

$$f_{\mathrm{w}}(t) = \sum_j\sum_k < f_{\mathrm{w}}(t), \quad \psi_{j,k}(t) > \psi_{j,k}(t) \quad (5)$$

In general, a function can be completely represented by using L-finite resolutions of wavelet, and the scaling function with parameters value of $a_0 = 2$ and $b_0 = 1$ as

$$f_{\mathrm{w}}(t) = \sum_{k=-\infty}^{\infty} c_{L,k}2^{-L/2}\phi(2^{t/L} - k) + \sum_{j=1}^{L}\sum_{k=-\infty}^{\infty} \mathrm{d}_{j,k}2^{-j/2}\psi(2^{t/j} - k) \quad (6)$$

Where scaling coefficients $[c_{L,k}]$ are similarly defined as

$$c_{L,k} \leq f_{\mathrm{w}}(t), \quad \phi_{L,K}(t) \geq \int f_{\mathrm{w}}(t)2^{-L/2}\phi\left(\frac{t}{2^L} - k\right)\mathrm{d}t \quad (7)$$

and

$$\phi_{L,k}(t) = 2^{-L/2}\phi(2^{-L}t - k) \quad (8)$$

$$\psi = 2\sum_k h_1(k)\phi(2t - k) \quad (9)$$

$$\phi = 2\sum_k h_0(k)\phi(2t - k) \quad (10)$$

DWT analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. The decomposition of the signal into the different frequency bands is simply obtained by successive high-pass and low-pass filtering of the time domain signal.

The original signal $x(n)$ is first passed through a half band high-pass filter $g(n)$ and low-pass filter $h(n)$. After filtering, the half of the samples can be eliminated according to the Nyquist criteria, since the signal now has the highest frequency of $\pi/2$ radians, instead of π. The signal can therefore be sub-sampled by 2 simply by discarding every other sample. This procedure constitutes one level of decomposition and can mathematically be expressed as follows:

$$Y_{\mathrm{high}}[k] = \sum x[n]g[2k - n] \quad (11)$$

$$Y_{\mathrm{low}}[k] = \sum x[n]h[2k - n] \quad (12)$$

where $Y_{\mathrm{high}}[k]$ and $Y_{\mathrm{low}}[k]$ are the outputs of the high-pass and low-pass filters, respectively, after sub-sampling by 2 (Khahill and Duchene, 1999).

The above procedure, which is also known as subband coding, can be repeated for further decomposition. At every level, the filtering and sub-sampling will result in half of the number of samples and half of the frequency band spends (Khahill and Duchene, 1999).

Daubechies order 2 wavelet transform was applied to the alert, drowsy and sleep signals. Fig. 3 shows five different levels of approximation (identified by a1–a5 and displayed in the left column) and details (identified by d1–d5 and displayed in the right column) of an EEG signal. These approximation and detail records are reconstructed from the wavelet coefficients. Approximation a4 is obtained by superimposing details d5 on approximation a5. Approximation a3 is obtained by superimposing details d4 on approximation a4, and so on. Finally, the original signal is obtained by superimposing details d1 on approximation a1. Wavelet transform acts like a mathematical microscope, zooming into small scales to reveal compactly spaced events in time and

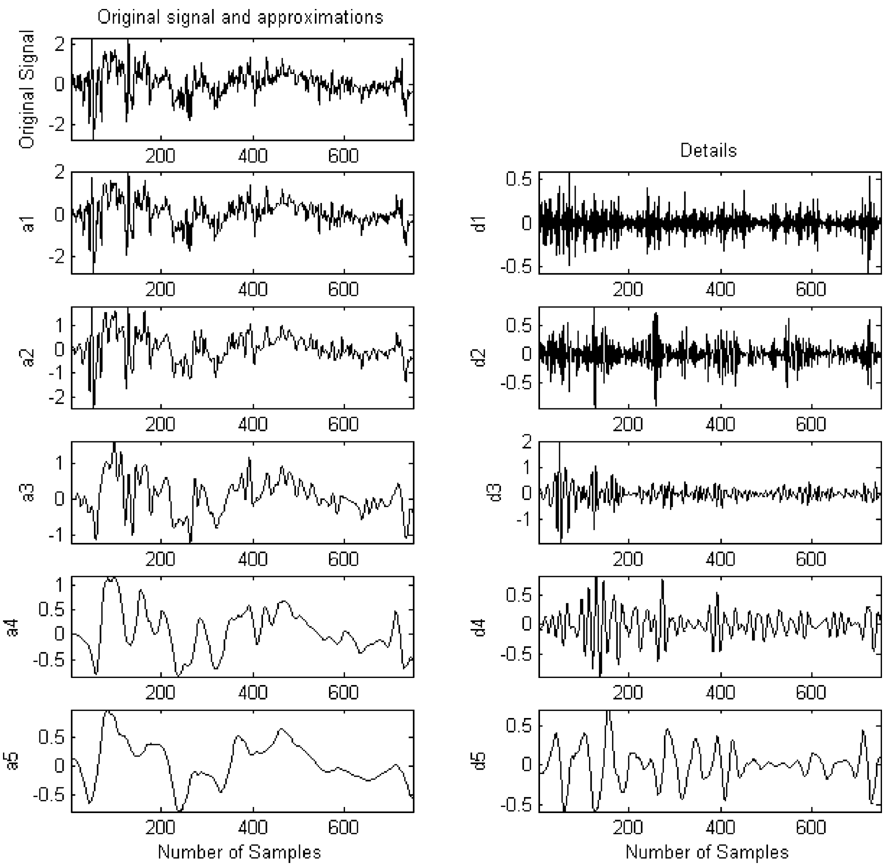

Fig. 3. Daubechies order 2 wavelet transform of an EEG signal.

zooming out into large scales to exhibit the global waveform patterns (Adeli et al., 2003).

The following formula can be used when frequency information is needed instead of the scales (Adeli et al., 2003):

$$F_a = \frac{F_c}{\delta a} \tag{13}$$

where F_a is the pseudo-frequency corresponding to scale a, in Hz, a the scale, δ the sampling period, and F_c the center frequency or dominant frequency of a wavelet in Hz, defined as the frequency with the highest amplitude in the Fourier transform of the wavelet function. Table 1 presents frequencies corresponding to different levels of decomposition for Daubechies order 2 wavelet with a sampling frequency of 150 Hz. It can be seen from Table 1 that the components from level 5 decomposition are within the δ (1–4 Hz), level 4 decomposition are within the θ range (4–8 Hz), level 3 decomposition are within the α range (8–13 Hz), and level 2 decomposition are within the β range (13–30 Hz). Lower level decompositions corresponding to higher frequencies have negligible magnitudes in a normal EEG.

Table 1
Frequencies corresponding to different levels of decomposition for Daubechies order 2 wavelet with a sampling frequency of 150 Hz

Level of decomposition	0	1	2	3	4	5
Scale (2^i)	1	2	4	8	16	32
Frequency (Hz)	100	50	25	12.5	6.25	3.125

2.4. Neural network classifier

Three-layer feed-forward artificial neural network with one hidden layer and one output layer as shown in Fig. 4 was

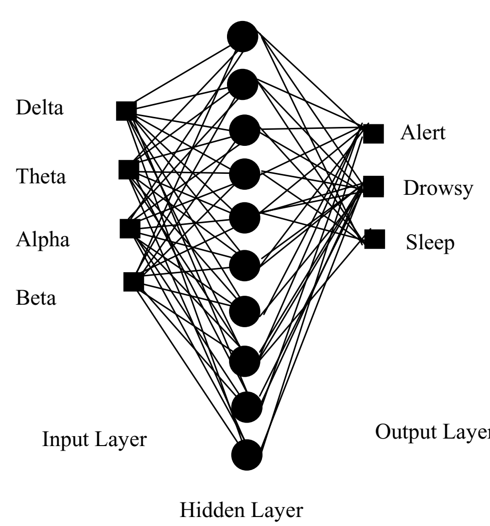

Fig. 4. Multi-layered neural network model.

trained using standard back-propagation algorithm. An input vector is applied to the input layer, where all of the inputs are distributed to each unit in the hidden layer. All of the units have weight vectors which are multiplied by these input vectors. Each unit sums these inputs and produces a value that is transformed by a nonlinear activation function, for which we used the common asymmetric sigmoid function. The output of the final layer is then computed by multiplying the output vector from the hidden layer by the weights into the final layer. More summations and activations of these units then give the actual output of the network.

The determination of appropriate number of hidden layers is one of the most critical tasks in neural network design. Unlike the input and output layers, one starts with no prior knowledge as to the number of hidden layers. A network with too few hidden nodes would be incapable of differentiating between complex patterns leading to only a linear estimate of the actual trend. In contrast, if the network has too many hidden nodes it will follow the noise in the data due to over-parameterization, leading to poor generalization for untrained data. With increasing number of hidden layers, training becomes excessively time-consuming. The most popular approach to finding the optimal number of hidden layers is by trial and error (Basheer and Hajmeer, 2000; Fausett, 1994; Haykin, 1994). In this study, the neural network consisted of one input layer, one hidden layer, and one output layer.

2.5. Performance indicators of the neural network

2.5.1. Measuring error

Given a random set of initial weights, the outputs of the network will be very different from the desired classifications. As the network is trained, the weights of the system are continually adjusted to reduce the difference between the output of the system and the desired response. The difference is referred to as the error and can be measured in several ways. The most common measurement is SSE and MSE. SSE is the average of the squares of the difference between each output and the desired output (Basheer and Hajmeer, 2000; Fausett, 1994; Haykin, 1994). In this study, SSE was used for measuring performance of the neural network.

2.5.2. Cross-validation

Cross-validation is a highly recommended criterion for stopping the training of a network. During performance analysis of network, cross-validation can be used for determining the final training. In general, it is known that a network with enough weights will always learn the training set better as the number of iterations is increased. However, neural network researchers have found that this decrease in the training set error was not always coupled to better performance in the test. When the network is trained too much, the network memorizes the training patterns and does not generalize well. The training holds the key to an accurate solution, so the criterion to stop training must be very well described. The aim of the stop criterion is to maximize the network's generalization (Basheer and Hajmeer, 2000).

We performed the following cross-validation procedure for training the network as a way to control the over-fitting of training data. We randomly select 13 subjects' data set (60% of overall data) for training the network and 5 subjects' data set (10% of overall data) for validation after each training epoch. The error of the network on the validation data is calculated after every pass, or epoch, through the training data. After a 5416 epochs, the network state (its weight values) at the epoch for which the validation error is smallest is chosen as the network that will most likely perform the best on novel data. This best network is then applied to the remaining 12 subjects' data (30% of overall data), referred to as the test set. All representations were classified 30 times using different random selections of train, validation, and test sets and initial weight values (Sun and Sclabassi, 2000). ANN performance was assessed on both the training and the validation set.

2.5.3. Classification and regression

Neural networks are used for both classification and regression. In classification, the aim is to assign the input patterns to one of several classes, usually represented by outputs restricted to lie in the range from 0 to 1, so that they represent the probability of class membership. While the classification is carried out, a specific pattern is assigned to a specific class according to the characteristic features selected for it. In regression, desired output and actual network output results can be shown on the same graph and performance of network can be evaluated in this way (Basheer and Hajmeer, 2000; Fausett, 1994; Haykin, 1994).

3. Results and discussion

This study presents a method for classifying a state of vigilance to alert, drowsy or sleepy states based on an ongoing EEG for an arbitrary healthy subject. A wavelet analysis of EEG recordings (Jung et al., 1997; Doghramji et al., 1997; De Carli et al., 1999) was proven to be a powerful tool for determining sleep stages and transitions from an alert to a drowsy state. The wavelet analysis used the fact that such an EEG comprises of a characteristic rhythm that will disappear when the subject becomes drowsy. The statistical classification of EEG signals (McKeown et al., 1997) could be an effective method for classification and detection of changes in vigilance, though it was not used for distinguishing between the alert and drowsy states.

In this study, drowsiness level from EEG signals was obtained by using discrete wavelet transform (DWT) and ANN. The signals were recorded during the 7 h episodes and digital signals were taken every 20 min for each block. Then these EEG recordings were divided 5 s epochs as shown in Fig. 2, and these epochs were divided into sub-bands frequencies such as α, β, θ and δ by using DWT. Then power

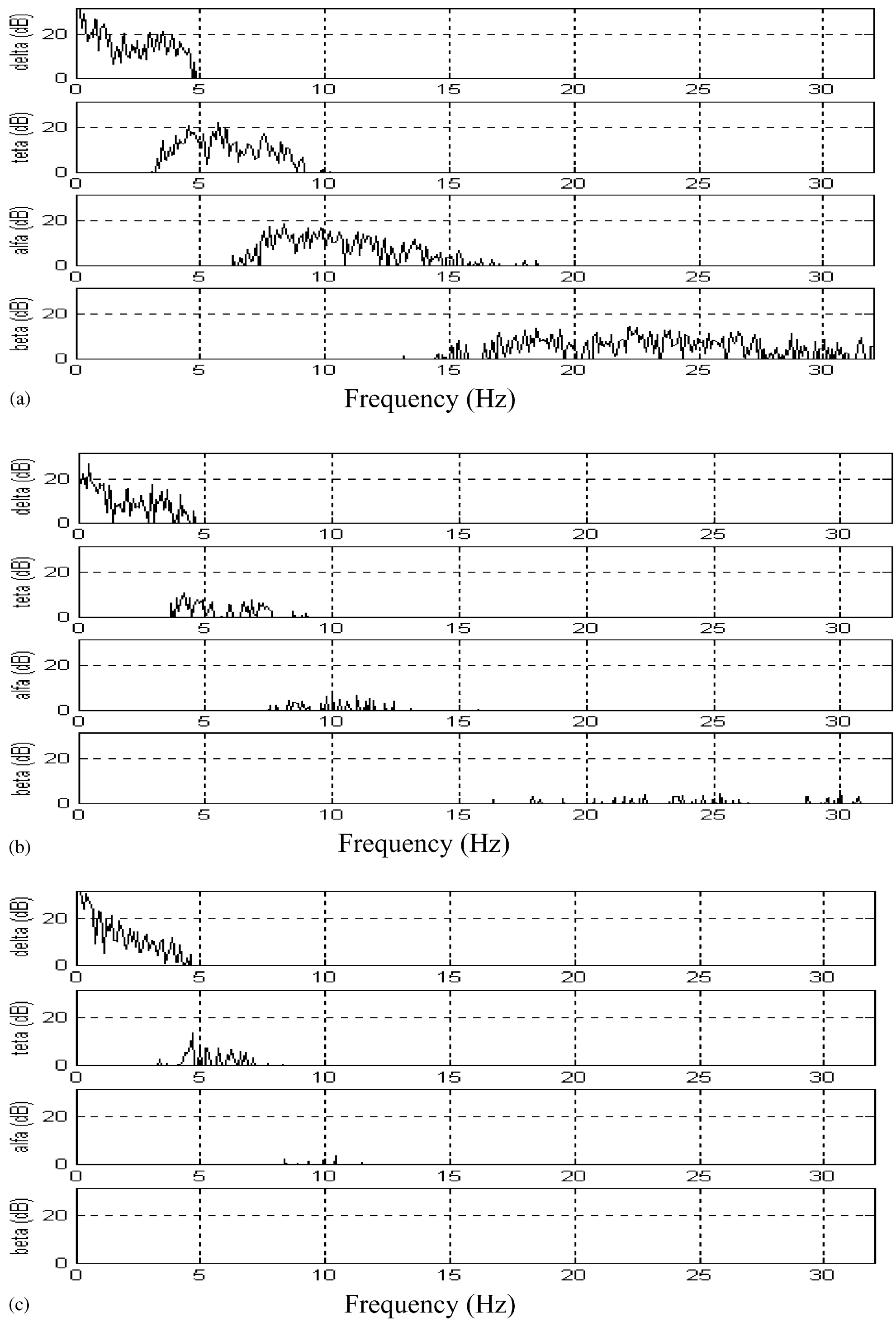

Fig. 5. Power spectral densities of the alert, drowsy and sleep using Daubechies wavelet coefficients: (a) alert, (b) drowsy, (c) sleep.

spectral densities (PSDs) of wavelet sub-band frequencies δ (1–4 Hz), θ (4–8 Hz), α (8–13 Hz) and β (13–30 Hz) are applied to ANN. PSDs of DWT of alert, drowsy and sleep state are shown in Fig. 5.

As seen in the Fig. 5 which is drawn by using Daubechies 2 wavelet coefficients, alert state has mixed frequencies; α and β are seen. In the drowsy state, the α will disappear. In the sleep α and β are lost δ and θ are observed. We used these signals as an input to ANN to classify the state of vigilance.

3.1. Visual inspection and validation

Two neurologists with experience in the clinical analysis of polygraphic sleep tracings independently inspected every recording included in this study to evaluate vigilance changes. Each event was filed into the computer memory and linked to the tracing with its start and duration. These were then revised by the two experts jointly to solve any disagreements and to set up the training set for the program, consenting on the choice of the threshold for the alertness level detection. The agreement between the two experts was evaluated for the testing set as the rate between the numbers of alertness level detected by both experts. A further step was then performed with the aim of checking the disagreements and setting up a "gold standard" reference set (De Carli et al., 1999). A computer program collected all the marked vigilance states from each recording into one set (alert, drowsy and sleepy). When revising this unified event set, the human experts, by mutual consent, marked each state as alert, drowsy or sleepy. They also reviewed each recording entirely for vigilance states that had been overlooked by all during the first-pass and marked them as definite or possible. This validated set provided the reference evaluation to estimate the sensitivity and selectivity of computer scorings. Sensitivity and selectivity measures are given in the Appendix A. Nevertheless, a preliminary analysis was carried out solely on events in the training set as each stage in these sets had a definite start and duration.

3.2. Selection of network parameters

For solving pattern classification problem ANN employing back-propagation training algorithm was used. Effective training algorithm and better-understood system behaviour are the advantages of this type of neural network. Selection of network input parameters and performance of neural network are important to distinguish between states of vigilance, that is, wakefulness and sleep.

During training, the input and desired data will be repeatedly presented to the network. When using a neural network, decisions must be taken on how to divide data into a training set and a test set. In this study, 18 of 30 subjects (70% of overall data) were used for training and the rest of them (30% of overall data) were used for testing. In order to obtain a better network generalization 5 training subject were used as cross-validation set. In classification, the aim is to assign the input patterns to one of several classes, usually represented by outputs restricted to lie in the range from 0 to 1, so that they represent the probability of class membership. The outputs are represented by unit basis vectors:

[1 0 0] = awake

[0 1 0] = drowsy

[0 0 1] = sleep

3.3. Performance analysis of ANN

Neural networks employing back-propagation were trained with a training set and checked with a test set. The neural network will find the input–output maps by analyzing the training set repeatedly. This is called the network training phase. Most of the neural network design effort is spent in the training phase. Training is normally slow because the network weights are updated based on the error information. It is necessary to monitor how well the network is learning. One of the simplest methods is to observe how the square difference between the network's output and the desired response changes over training iterations. The curve of the SSE versus iteration is called as the training curve. Training SSE curve of neural network in 5416 epochs is shown in Fig. 6. As the network learns, the error converges to zero.

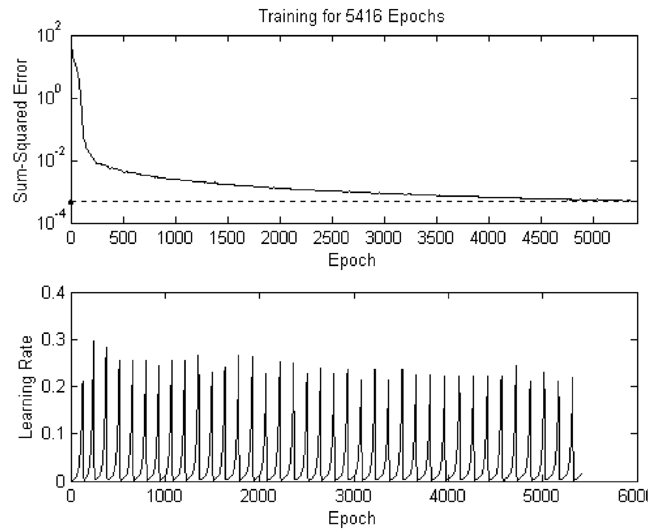

Fig. 6. Graphics of sum-squared error and learning rate.

A neural network is subject to what is known as the memorization of training data. Also it is known as the statistical phenomenon of over-fitting when it is over-trained. If a network over-fits or memorizes the training data, its generalized performance on other sample populations, such as, the test file or on records for which prospective predictions are to be made, is likely to be severely compromised. Therefore, the most important criterion is choosing the number of iterations for training. Cross-validation is one of the most powerful methods to stop the training. In principle, the training curve decreases exponentially to zero or a small constant. Just how small in magnitude this constant depends on the situation and judgement must be used to find what error value is appropriate for the problem. When the error in the cross-validation has increased, the training should be stopped because the point of best generalization has been reached. In this study, training was done using 5416 epochs, and number of epochs was determined according to cross-validation. Since SSE is converging to a small constant, approximately zero in 5416 epochs, training of the neural network is determined to be successful.

After the training phase, testing of the ANN was done. The data that the network had not seen before was applied to the network for testing the network performance. Since training was successful and the network's topology was

Table 2
Alert, drowsy and sleepy state classification performance of the ANN

	Accuracy (%)	Sensitivity (%)	Selectivity (%)
Alert	96 ± 3	94	93
Drowsy	95 ± 4	96	91
Sleep	94 ± 5	93	89

correct, it was then used to test data and thus resulted in a good solution.

3.4. Applying test data

After training and cross-validating this network, it was determined that the network adequately classified data. Then 12 subjects' records were applied to this network. In this experiment network inputs of 12 subjects' records were entered, and desired outputs for these subjects were not given to the network. The results of network for each subject are compared with the experts' prediction.

A classification rate of higher than 95% was achieved by using artificial neural network as a classifier. The total number of feature vectors for each data was about 300. Depending on which output neuron had a value of 1, the EEG recording was classified as alertness ([1 0 0]), drowsiness ([0 1 0]) or sleepiness ([0 0 1]). The percentage of matches between ANN and experienced neurologists for alertness and drowsiness of ANN trained using data on a single subject, training and validation set, mean value for repeated training using data on three different subjects. In all experiments, network scoring was presented as a mean value ± standard deviation (S.D.). The measure of accuracy, sensitivity and selectivity are given in the Appendix A. Also the accuracy, sensitivity and selectivity of the ANN were given in Table 2. As seen in table, the sensitivity is the highest in drowsy signal (96%); the selectivity is the highest in alert signal (94%). The accuracy is 96 ± 3% alert, 95 ± 4% drowsy and 94 ± 5% sleep signals. The classification percentages of ANN with wavelet transform on test data are above 95%. Hence application of this study will be helpful for the neurologists to analyze the awake-sleep correlations.

4. Conclusion

In this study, prediction of the level of drowsiness was examined. δ, θ, α, and β sub-frequencies of the EEG signals were extracted by using wavelet transform. The wavelet spectra of EEG signals are used as an input to artificial neural networks that could be used to discriminate between alert, drowsy and sleep states. This process is realized by LabVIEW software development tool and online data acquisition system. Depending on these sub-frequencies, ANN have been developed and trained. The accuracy of the ANN was 96 ± 3% alert, 95 ± 4% drowsy and 94 ± 5% sleep state. Also, it was observed that while a person changes from the alert state to sleep state, the EEG spectrum changes from high to low frequency. When the frequency components of the sub-frequencies were checked, the β and α activities were decreased during the transition from awake to sleep. Thus it can be concluded that the application of this study will be useful for the neurologists to analyze awake-sleep correlations.

Appendix A. The measure of sensitivity, selectivity and specificity

The performance of a particular run of the program, or a particular reading by an expert was evaluated in terms of sensitivity, selectivity and specificity, where:

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\%$$
$$\text{selectivity} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\%$$
$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\%$$
$$\text{accuracy} = \frac{\text{sensitivity} + \text{specifity}}{2} \times 100\%$$

The specificity was computed only in the context of the discriminant analysis, in which each fixed length basic epoch was classified as true positive (TP), false positive (FP), true negative (TN) or false negative (FN). In subsequent analyses, variable length vigilance states, marked by one observer, were compared to the reference set and the individual events were considered as TP (if an overlapping occurred), FP or FN. We believed that in this case TN counting, and consequently specificity evaluation, was non-sensical (De Carli et al., 1999).

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