Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients

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Abstract

Electrophysiological recordings are considered a reliable method of assessing a person’s alertness. Sleep medicine is asked to offer objective methods to measure daytime alertness, tiredness and sleepiness. As EEG signals are non-stationary, the conventional method of frequency analysis is not highly successful in recognition of alertness level. This paper deals with a novel method of analysis of EEG signals using wavelet transform, and classification using ANN. EEG signals were decomposed into the frequency sub-bands using wavelet transform and a set of statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients. Then these statistical features were used as an input to an 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 $32.4 \pm 7.3$ 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 to train the ANN. The statistics were used as a measure of potential applicability of the ANN. The accuracy of the ANN was 95\% alert, 93\% drowsy and 92\% sleep.

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

1. Introduction

One of the important applications of electroencephalogram (EEG) processing is the study of the time course of alertness and vigilance of operators who perform monotonous but attention demanding tasks (air traffic controllers, lorry drivers, etc.). The objective is to avoid potential accidents generated by decreased vigilance using a real-time system which can continuously monitor vigilance, thereby preventing accidents caused by attention deficit.

The aim of this study was to establish a method for processing input data from a set of statistical features, which was extracted from discrete wavelet transform (DWT) sub-bands of EEG recordings, by the use of an artificial neural network (ANN) that distinguishes between alert, drowsy and sleep states in arbitrary subjects. 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 $\delta$ (1–4 Hz), $\theta$ (4–8 Hz), $\alpha$ (8–13 Hz), $\beta$ (13–30 Hz) and $\gamma$ (>30 Hz) frequency ranges. Within NREM sleep, $\delta$ power (slow wave power) indicates the intensity of sleep and represents the need for sleep. During wakefulness, $\alpha$ and $\theta$ frequencies in the awake state EEG are of particular interest for research on sleepiness. During active wakefulness (with eyes open), $\alpha$ power is usually low unless the subject is severely fatigued. However, in resting conditions (with eyes closed), $\alpha$ 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 $\alpha$ power and a gradual increase in $\theta$ power occurs. Reduced $\alpha$ power and increased $\theta$ 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 $\alpha$ power and positively with $\theta$ power in the awake EEG during prolonged wakefulness (Conradt et al., 1999).

Spontaneous electrical brain activities, that are EEG signals, are dynamic, stochastic, non-linear and...
non-stationary (Guler, Kiyimik, Akin, & Alkan, 2001; Herrmann, Arnold, Visbeck, Hundemeyer, & Hopf, 2001; Peters, Pfurtscheller, & Flyvbjerg, 2001; Vuckovic, Radijovic, Chen, & Popovic, 2002). The EEG recordings depend on the location of the electrodes, their impedance and the state 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, Devulapalli, & Stolz, 1995; Doghramji, Merrill, & Sangal, 1997; Jung, Makeig, Stensmo, & Sejnowski, 1997; Principe, Gala, & Chang, 1989). 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, Humphries, Achermann, Borbely, and Sejnowski (1997) used statistical methods for the analysis of EEG signals and detection of vigilance changes. Kalayci and Ozdamar (1995) showed that an artificial neural network (ANN) performs better if the input and output data can be processed to capture the characteristic features of the signal. 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, Nobili, Gelcich, and Ferrillo (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.

As compared to the conventional method of frequency analysis using Fourier transform or short time Fourier transform, wavelets enable analysis with a coarse to fine multi-resolution perspective of the signal (Kandaswamy, Kumar, Ramanathan, Jayaraman, & Malmurugan, 2004). In this work, DWT has been applied for the time–frequency analysis of EEG signals and ANN for the classification using wavelet coefficients. EEG signals were decomposed into frequency sub-bands using discrete wavelet transform (DWT). Then a set of statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients. An ANN-based system was implemented to classify the EEG signal to one of the categories: alert, drowsy or sleep. 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.

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 $32.4 \pm 7.3$ 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 $C_3$–$A_2$ 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 and a personnel computer. 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 DAQ card which is connected to the PCI data bus of the computer. Each record was scored by two experts for alertness level staging, with a link to the recording. The system provides real-time data processing. Different EEG epochs have been given in Fig. 1. 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 $\alpha$, $\beta$, $\theta$ and $\delta$ by using DWT.

2.3. Analysis using discrete wavelet transform

2.3.1. 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.

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 \( \psi \) by dilations and translations (Cohen & Kovacevic, 1996; Daubechies, 1996; Rioul & Vetterli, 1991).

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

(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 \( a \approx 1 \) or narrow width, while low frequency wavelets have \( a \approx 1 \) 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 & 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 discrete wavelet family are given by

\[
a = a_0^j, \quad b = k b_0 a_0^j
\]  

(2)

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

\[
\psi_{j,k}(t) = a_0^{-j/2} \psi(a_0^{-j} t - k b_0)
\]  

(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

\[
d_{j,k} = \langle f_w(t), \psi_{j,k}(t) \rangle = \frac{1}{a_0^j} \int f_w(t) \psi(a_0^{-j} t - k b_0) dr
\]  

(4)

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

\[
f_w(t) = \sum_j \sum_k \langle f_w(t), \psi_{j,k}(t) \rangle \psi_{j,k}(t)
\]  

(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

\[
f_w(t) = \sum_{k=-\infty}^{\infty} c_{L,k} 2^{-L/2} \phi(2^{L} k) + \sum_{j=1}^{L} \sum_{k=-\infty}^{\infty} d_{j,k} 2^{-j/2} \psi(2^{j} k)
\]  

(6)
where scaling coefficients $c_{L,k}$ are similarly defined as

$$c_{L,k} = f_n(t), \phi_{L,k}(t) = \int f_n(t)2^{-L/2}\phi\left(\frac{t}{2L} - k\right)\,dt$$

and

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

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

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

### 2.3.2. Multi-resolution decomposition of EEG signals

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 $h(n)$ and low-pass filter $g(n)$. 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 $\pi$. The signal can therefore be sub-sampled by 2 simply by discarding every other sample. This procedure is known as multi-resolution decomposition of a signal $x[n]$ and is schematically shown in Fig. 2. Each stage of this scheme consists of two digital filters and two down-samplers by 2. The first filter, $h[\cdot]$ is the discrete mother wavelet, high-pass in nature, and the second, $g[\cdot]$ is its mirror version, low pass in nature. The down-sampled outputs of first high-pass and low-pass filters provide the detail, $D_1$ and the approximation, $A_1$, respectively. The first approximation, $A_1$ is further decomposed and this process is continued as shown in Fig. 2.

### 2.3.3. Selection of wavelet and number of levels

Selection of suitable wavelet and the number of levels of decomposition is very important in analysis of signals using DWT. The typical way is to visually inspect the data first, and if the data are kind of discontinuous, Haar or other sharp wavelet functions are applied; otherwise a smoother wavelet can be employed. Usually, tests are performed with different types of wavelets and the one which gives maximum efficiency is selected for the particular application.

The number of levels of decomposition is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. Since the EEG signals do not have any useful frequency components above 30 Hz, the number of levels was chosen to be 4. Thus the signal is decomposed into the details $D_1$–$D_4$ and one final approximation, $A_4$. The ranges of various frequency bands are shown in Table 1.

Daubechies order 2 wavelet transform was applied to the alert, drowsy and sleep signals. Figs. 3–5 shows four different levels of approximation (identified by $A_1$–$A_4$ and displayed in the left column) and details (identified by $D_1$–$D_4$ and displayed in the right column) of an EEG signal.

### Table 1

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

<table>
<thead>
<tr>
<th>Decomposed signal</th>
<th>Frequency range (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_1$</td>
<td>37.5–75</td>
</tr>
<tr>
<td>$D_2$</td>
<td>18.75–37.5</td>
</tr>
<tr>
<td>$D_3$</td>
<td>9.375–18.75</td>
</tr>
<tr>
<td>$D_4$</td>
<td>4.6875–9.375</td>
</tr>
<tr>
<td>$A_4$</td>
<td>0–4.6875</td>
</tr>
</tbody>
</table>
These approximation and detail records are reconstructed from the wavelet coefficients. Approximation $A_3$ is obtained by superimposing details $D_4$ on approximation $A_4$. Approximation $A_2$ is obtained by superimposing details $D_3$ on approximation $A_3$. Finally, the original signal is obtained by superimposing details $D_1$ on approximation $A_1$. Wavelet transform acts like a mathematical microscope, zooming into small scales to reveal compactly spaced events in time and zooming out into large scales to exhibit the global waveform patterns (Adeli, Zhou, & Dadmehr, 2003).

2.4. Feature extraction

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. 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 $A_4$ decomposition are within the $\delta$ range (1–4 Hz), $D_4$ decomposition are within the $\theta$ range (4–8 Hz), $D_3$ decomposition are within the $\alpha$ range (8–13 Hz), and $D_2$ decomposition are within the $\beta$ range (13–30 Hz). Lower level decompositions corresponding to higher frequencies have negligible magnitudes in a normal EEG. In order to further reduce the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients was used (Kandaswamy et al., 2004). The following statistical features were used to represent the time–frequency distribution of the EEG signals:

1. Mean of the absolute values of the coefficients in each sub-band.
2. Average power of the wavelet coefficients in each sub-band.
3. Standard deviation of the coefficients in each sub-band.
4. Ratio of the absolute mean values of adjacent sub-bands.

Features 1 and 2 represent the frequency distribution of the signal and the features 3 and 4 the amount of changes in frequency distribution. These feature vectors, calculated for the frequency bands $A_4$ and $D_2$–$D_4$, were used for...
classification of the EEG signals. The classifier is based on a multi-layer artificial neural network.

2.5. Classification using artificial neural networks

Artificial neural networks (ANNs) are formed of cells simulating the low-level functions of biological neurons. In ANN, knowledge about the problem is distributed in neurons and connections weights of links between neurons. The neural network has to be trained to adjust the connection weights and biases in order to produce the desired mapping. At the training stage, the feature vectors are applied as input to the network and the network adjusts its variable parameters, the weights and biases, to capture the relationship between the input patterns and outputs. ANNs are particularly useful for complex pattern recognition and classification tasks. The capability of learning from examples, the ability to reproduce arbitrary non-linear functions of input, and the highly parallel and regular structure of ANN make them especially suitable for pattern classification tasks (Basheer & Hajmeer, 2000; Fausett, 1994; Haselsteiner & Pfurtscheller, 2000; Haykin, 1994; Shimada, Shiina, & Saito, 2000; Sun & Sclabassi, 2000).

ANNs are widely used in biomedical field for modelling, data analysis, and diagnostic classification (Basheer & Hajmeer, 2000; Haselsteiner & Pfurtscheller, 2000; Sun & Sclabassi, 2000). The most frequently used training algorithm in classification problems is the backpropagation (BP) algorithm which is used in this work also. As the conventional BP algorithm with gradient descent, and gradient descent with momentum are slow, a few of the modified BP algorithms were tried. Adaptive learning rate BP, resilient BP, Levenberg–Marquardt, and scaled conjugate gradient BP algorithms were examined for training the ANN.

2.5.1. 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 were used for training and the rest of them were used for testing. In order to obtain a better network generalization five training subject were used as cross-validation set.

The classification scheme of 1-of-C coding has been used for classifying the signal into one of the output categories. For each type of EEG signals, a corresponding output class is associated. The feature vector set, $x$, represents the ANN inputs, and the corresponding class, once coded, constitutes the ANN outputs. In order to make the neural network training more efficient, the input feature vectors were normalized so that they fall in the range [0,1.0]. Since the number of output classes is 3, the ANN has three outputs, which produce a code for each class. The outputs are represented by basis vectors:

- $[0.9 0.1 0.1] = \text{awake}$
- $[0.1 0.9 0.1] = \text{drowsy}$
- $[0.1 0.1 0.9] = \text{sleep}$

Each dummy variable is given the value 0.1 except for the one corresponding to the correct category, which is given the value 0.9. Using target values of 0.1 and 0.9 instead of the common practice of 0 and 1 prevents the outputs of the network from being directly interpretable as posterior probabilities (Kandaswamy et al., 2004). The output vector associated to the modified input vector $x_k$, $k=1, 2, \ldots, K$ is noted $y_k$, with $K$ the number of EEG signals.

Once the coding processes are completed, a set of $K$ input/output pairs $D = \{x_k, y_k \mid k = 1, 2, \ldots, K\}$ is available. This data set is divided into two subsets, training set and test set.

1. $D_{\text{train}} = \{x_k, y_k \mid k = 1, 2, \ldots, K_{\text{train}}\}$ is used to perform the ANN training which consists of the determination of the ANN running parameters, i.e. the ANN connection weights and biases.

2. $D_{\text{test}} = \{x_k, y_k \mid k = 1, 2, \ldots, K_{\text{test}}\}$ is used to validate off-line classification ability and quality of the ANN once the training has been completed.
2.5.2. Cross-validation

Cross-validation (CV) (Basheer & Hajmeer, 2000; Haselsteiner & Pfurtscheller, 2000) is often used for comparing two or more learning ANN models to estimate which model will perform the best on the problem at hand. With n-fold CV, the available data is partitioned into n disjoint subsets, the union of which is equal to the original set. Each learning model is trained on n−1 of the available subsets, and then tested on the one subset which was not used during training. This process is repeated n times, each time using a different test set chosen from the n available partitions of the training data, until all possible choices for the test set have been exhausted. The n test set scores for each learning model are then averaged, and the model with the highest average test set score is chosen as the one most likely to perform well on unseen data (Kandaswamy et al., 2004).

2.5.3. 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 sum squared error (SSE) and mean squared error (MSE). SSE is the average of the squares of the difference between each output and the desired output (Basheer & Hajmeer, 2000; Fausett, 1994; Haselsteiner & Pfurtscheller, 2000; Haykin, 1994). In this study, SSE was used for measuring performance of the neural network.

3. Results and discussion

In this study, drowsiness level from EEG signals was obtained by using a set of statistical features, extracted from the sub-bands of 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. 1, and these epochs were divided into sub-band frequencies such as α, β, θ and δ by using DWT (Figs. 3–5). Then a set of statistical features was extracted from the wavelet sub-band frequencies δ (1–4 Hz), θ (4–8 Hz), α (8–13 Hz) and β (13–30 Hz).

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

1. Mean of the absolute values of the coefficients in each sub-band.
2. Average power of the wavelet coefficients in each sub-band.
3. Standard deviation of the coefficients in each sub-band.
4. Ratio of the absolute mean values of adjacent sub-bands.

After normalization, the EEG signals were decomposed using wavelet transform and the statistical features were extracted from the sub-bands. A classification system based on feed-forward ANN was implemented using the statistical features as inputs. The DWT and ANN training were performed using the toolboxes available with the technical computing software, MATLAB. In order to improve the confidence intervals on the performance estimates, six-fold cross-validation was performed. The total number of 294 samples was partitioned into three disjoint subsets and each time 198 samples were used for training, 44 for validation and the remaining 52 for test. This procedure is repeated five times, each time using a different test set chosen from the three divisions of the data, until all possible choices for the test set have been consumed. For each ANN model, this type of training and testing process was done 25 times with each set of \(D_{\text{train}}\) and \(D_{\text{test}}\) of the CV and the average value is taken.

The classification efficiency which is defined as the percentage ratio of the number of EEG signals correctly classified to the total number of EEG signals considered for classification, also depends on the type of wavelet chosen for the application. In order to investigate the effect of other wavelets on classifications efficiency, tests were carried out using other wavelets. Apart from db2, Symmlet of order 10 (sym10), Coiflet of order 4 (coif4), Daubechies of order 4 (db4) and Daubechies of order 8 (db8) were also tried. Average efficiency obtained for each wavelet when EEG signals were classified using various ANN structures. It can be seen that the Daubechies wavelet offers better efficiency than the others, and db2 is marginally better than db4 and db8. Hence db2 wavelet is chosen for this application.

Sun and Sclabassi (2000) showed that multi-layer feed-forward ANNs with at least one hidden layer of computational unit are capable of approximating any finite function to any degree of accuracy, and hence they can be regarded as universal approximators. Subsequently it was proved that a feed-forward ANN with one hidden layer having \(p−1\) neurons can exactly implement an arbitrary training set with \(p\) training samples (Kandaswamy et al., 2004). This is a sufficient condition for exactly implementing the training set. An important corollary to this result in the context of a classification problem is that ANNs with sigmoidal activation functions and two layers can approximate any decision boundary to arbitrary accuracy. Therefore, we started the simulation with a two layer ANN architecture with the hidden layer having 197 neurons, one less than the number of training samples, and both layers having sigmoidal transfer functions. The number of input nodes was fixed at 15, equal to the number of input feature vectors, and the number of output vectors as 3, equal to the number of output classes. Optimum number of neurons in the hidden layer, training algorithm, parameters of the training algorithm, and the activation functions of the two layers were determined by repeated simulation. The conventional backpropagation (BP) algorithm was found to be too slow in converging to the specified SSE. Resilient
Table 2
Performance of the various ANN architectures

<table>
<thead>
<tr>
<th>Model no.</th>
<th>ANN architecture</th>
<th>No. of weights</th>
<th>No. of epochs</th>
<th>Training time ratio with model 1</th>
<th>$\eta_1$ (%)</th>
<th>$\eta_2$ (%)</th>
<th>$\eta_3$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15-197-3</td>
<td>3546</td>
<td>185</td>
<td>1.00</td>
<td>100</td>
<td>94.52</td>
<td>91.21</td>
</tr>
<tr>
<td>2</td>
<td>15-97-3</td>
<td>1746</td>
<td>204</td>
<td>0.8124</td>
<td>100</td>
<td>92.43</td>
<td>92.15</td>
</tr>
<tr>
<td>3</td>
<td>15-70-3</td>
<td>1260</td>
<td>356</td>
<td>0.7634</td>
<td>100</td>
<td>95.32</td>
<td>92.64</td>
</tr>
<tr>
<td>4</td>
<td>15-32-3</td>
<td>576</td>
<td>431</td>
<td>0.7210</td>
<td>100</td>
<td>96.49</td>
<td>93.08</td>
</tr>
<tr>
<td>5</td>
<td>15-25-3</td>
<td>450</td>
<td>1213</td>
<td>1.6321</td>
<td>100</td>
<td>85.36</td>
<td>82.73</td>
</tr>
<tr>
<td>6</td>
<td>15-9-3</td>
<td>162</td>
<td>4953</td>
<td>8.3246</td>
<td>100</td>
<td>69.77</td>
<td>61.33</td>
</tr>
</tbody>
</table>

BP algorithm which normally performs very well on pattern recognition problems (Basheer & Hajmeer, 2000; Fausett, 1994; Shimada et al., 2000) has been selected initially for training the ANN.

It was observed that the classification efficiency and the training time were less when tan-sigmoid function was used for the first layer and log-sigmoid for the second layer. Hence the activation functions were selected accordingly. Many ANN models, having hidden layer neurons less than 200, were investigated for ascertaining how changes in the number of neurons in hidden layer contribute to the overall performance of the classification system. We noted that learning of the training set does not necessarily guarantee successful diagnostic classification of the test set. The results of neural network models trained with resilient backpropagation algorithm, which was found to be the best training algorithm, are summarized in Table 2. Average value of the classification efficiencies obtained on simulation is shown in the table. $\eta_1$ is the average efficiency when training set is presented to the trained ANN, and $\eta_2$ is that when the validation set is presented. In order to assess the performance of the trained ANN, a separate test set of 52 EEG signals is also used. $\eta_3$ is the average efficiency obtained when this test set was submitted.

It was noticed that the best performance was obtained for the training set, validation set and separate test set with those models whose hidden layer had 32 neurons or more. Thus the optimum number of neurons required in the hidden layer is 32, and hence we have chosen the ANN configuration 15-32-3.

One of the problems that occur during neural network training is called over-fitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations. One method for improving network generalization is to use a network that is just large enough to provide an adequate fit (Fausett, 1994; Kandaswamy et al., 2004). The larger the network used, the more complex the functions the network can create. If a small enough network is used, it will not have enough power to over-fit the data. Thus in this application, by using a network that is just large enough to provide an adequate fit, it could be possible to avoid any possibility of over-fitting of the training data.

It is also very difficult to know which training algorithm will be the fastest for a given problem. It will depend on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition or function approximation. In order to obtain the most efficient training algorithm for this work, we have investigated four high performance BP algorithms, namely, adaptive learning rate BP (GDA), resilient BP (RP), scaled conjugate gradient (SCG), and Levenberg–Marquardt (LM) algorithms. For the ANN architecture 15-32-3, the resilient BP is the fastest algorithm for this classification problem; hence its selection is justified. The SCG algorithm seems to perform well; it is almost as fast as the RP. The GDA algorithm is much slower than the SCG and RP algorithms and LM algorithm seems to be the slowest.

Thus the EEG signal classification system proposed in this paper uses db2 wavelet for time–frequency analysis of EEG signals. 15-32-3 ANN architecture was found to be the optimum model for classification using the statistical features extracted from wavelet coefficients. RP algorithm was used for training the ANN. This system was tested using a new set of EEG signals.

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 Appendix. 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. 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 93% was achieved by using artificial neural network as a classifier. The total number of feature vectors was 294. Depending on which output neuron had a value of 0.9, the EEG recording was classified as alertness ([0.9 0.1 0.1]), drowsiness ([0.1 0.9 0.1]) or sleepiness ([0.1 0.1 0.9]). 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 (SD). The measure of accuracy, sensitivity and selectivity are given in Appendix. Also the accuracy, sensitivity and selectivity of the ANN are given in Table 3. As seen in table, the sensitivity is the highest in alert signal (93.4%); the selectivity is the highest in sleep signal (91.7%). The accuracy is 95 ± 3% alert, 93 ± 4% drowsy and 92 ± 5% sleep signals. The classification percentages of ANN with wavelet transform on test data are above 92%. Hence application of this study will be helpful for the neurologists to analyze the awake–sleep correlations.

4. Conclusion

EEG signals give important information about the vigilance states of any subject. Conventional method of classification of EEG signals using mutually exclusive time and frequency domain representations does not give efficient results. In this work, a novel method of diagnostic classification of EEG signals is proposed.

Apart from serving as an aid for physician change in vigilance state, the proposed method could prove particularly useful for the time course of alertness and vigilance of operators who perform monotonous but attention demanding tasks (air traffic controllers, lorry drivers, etc.).

The EEG signals were decomposed into time–frequency representations using wavelet transform and statistical features were calculated to depict their distribution. An ANN-based system was implemented for the classification of EEG signals using the statistical features extracted from wavelet coefficients as inputs. Simulation results showed that Daubechies wavelet of order 2 gives better classification efficiency than some of the other common wavelets. ANN architectures having two layers were chosen for the application. Some of the high performance backpropagation algorithms, namely, adaptive learning rate BP, resilient BP, scaled conjugate gradient, and Levenberg–Marquardt algorithms were tested for training the ANN. It was concluded after many simulations with various combinations of ANN architectures, activation functions, and training algorithms, that an ANN architecture 15-32-3, with tan-sigmoid transfer function for the first layer and log-sigmoid function for the second layer, is the optimum structure for this application. Of the various training algorithms tested, resilient BP was found to be the best algorithm, taking least time for meeting the error goal. The accuracy of the ANN was 95 ± 3% alert, 93 ± 4% drowsy and 92 ± 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, 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.

### Table 3
Alert, drowsy and sleepy state classification performance of the ANN

<table>
<thead>
<tr>
<th></th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Selectivity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alert</td>
<td>95 ± 3</td>
<td>93.4</td>
<td>90.9</td>
</tr>
<tr>
<td>Drowsy</td>
<td>93 ± 4</td>
<td>88.1</td>
<td>89.2</td>
</tr>
<tr>
<td>Sleep</td>
<td>92 ± 5</td>
<td>89.3</td>
<td>91.7</td>
</tr>
</tbody>
</table>

**Appendix. 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:

Sensitivity = \( \frac{TP}{TP + FN} \times 100\% \)

Selectivity = \( \frac{TP}{TP + FP} \times 100\% \)

Specificity = \( \frac{TN}{TN + FP} \times 100\% \)

Accuracy = \( \frac{Sensitivity + Specificity}{2} \times 100\% \)
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).

References


