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# Classification of EEG signals using the wavelet transform

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**Abstract**

The electroencephalogram (EEG) is widely used clinically to investigate brain disorders. However, abnormalities in the EEG in serious psychiatric disorders are at times too subtle to be detected using conventional techniques. This paper describes the application of an artificial neural network (ANN) technique together with a feature extraction technique, viz., the wavelet transform, for the classification of EEG signals. The data reduction and preprocessing operations of signals are performed using the wavelet transform. Three classes of EEG signals were used: Normal, Schizophrenia (SCH), and Obsessive Compulsive Disorder (OCD). The architecture of the artificial neural network used in the classification is a three-layered feedforward network which implements the backpropagation of error learning algorithm. After training, the network with wavelet coefficients was able to correctly classify over 66% of the normal class and 71% of the schizophrenia class of EEGs, respectively. The wavelet transform thus provides a potentially powerful technique for preprocessing EEG signals prior to classification. © 1997 Elsevier Science B.V.

**Zusammenfassung**

Das Elektroenzephalogram (EEG) wird im klinischen Bereich häufig zur Untersuchung von Gehirnerkrankungen eingesetzt. Jedoch sind Abnormitäten im EEG bei ernsthaften psychiatrischen Erkrankungen gelegentlich zu subtil, um mit herkömmlichen Methoden detektiert werden zu können. Dieser Artikel beschreibt die Anwendung eines artifiziellen neuralen Netzes (ANN) in Verbindung mit einer Methode zur Merkmalsextraktion (der Wavelet-Transformation) zur Klassifizierung von EEG-Signalen. Mittels der Wavelet-Transformation wird eine Datenreduktion und Vorverarbeitung der Signale durchgeführt. Drei Klassen von EEG-Signalen wurden verwendet: von Gesunden, von Schizophrenen (SCH) und von Zwangsneurotikern (OCD). Die Architektur des zur Klassifizierung eingesetzten artifiziellen neuralen Netzes ist ein Feedforward-Netz mit drei Schichten, welches den Backpropagation-Lernalgorithmus implementiert. Nach dem Training erzielte das Netz mit Wavelet-Koeffizienten eine korrekte Klassifizierung von über 66% der EEGs von Gesunden und 71% der EEGs von Schizophrenen. Die Wavelet-Transformation ist somit eine potentiell leistungsfähige Methode für die Vorverarbeitung von EEG-Signalen vor einer Klassifizierung. © 1997 Elsevier Science B.V.

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**Résumé**

L'électroencéphalogramme (EEG) est utilisé fréquemment en médecine clinique pour étudier les dysfonctionnements du cerveau. Néanmoins, les anomalies dans l'EEG dans des cas de désordre psychiatrique sévères sont trop subtiles pour pouvoir être détectées en utilisant des techniques conventionnelles. Cet article décrit l'application de réseaux de neurones artificiels (ANN) avec une technique d'extraction d'indices caractéristiques (transformation en ondelettes) pour la classification des EEG. La réduction ainsi que le pré-traitement des signaux se font avec la transformation en ondelettes. Trois classes d'EEG ont été utilisées: normal, schizophréne (SCH), et désordre impulsif obsessionnel (OCD). La structure du réseau de neurones utilisée pour la classification comprend trois couches cachées, fonctionne en 'feedforward' et utilise la règle d'appentissage par rétropropagation de l'erreur. Après apprentissage, le réseau utilisant les coefficients d'ondelettes comme entrées a été capable de classifier correctement plus de 66% et 71% des classes normale et schizophrène. La transformation en ondelettes fourni donc un outil puissant pour le pré-traitement des EEG avant de passer à la classification. 

*Keywords*: EEG classification; Neural networks; Wavelet transform

## 1. Introduction

One of the first attempts to apply artificial neural network (ANN) techniques to the problem of electroencephalogram (EEG) signal classification in psychiatric disorders was the pilot work by Tsoi et al. [17, 20], which indicated that by using autoregressive modelling of EEG signals together with a nonlinear classification scheme, namely, the multilayer perceptron (a particular class of artificial neural network architectures), it was possible to classify EEG signals obtained from those suffering from schizophrenia and obsessive-compulsive disorder as well as EEG signals obtained from normal subjects. This study sets out to extend these initial findings.

The underlying theory behind the generation of EEG signals is far from being completely elucidated. The reader is referred to [13] for an exposition of the biophysics of the EEG and the enormous complexities involved. When the Fast Fourier transform is applied to successive segments of an EEG signal, the frequency spectrum is observed to vary over time as the Fourier coefficients vary [21]; this indicates that the EEG signal is a *non-stationary* signal. This classical analysis method assumes that the EEG signal is stationary, and ignores nonstationarity of the signal within a window. The application of an autoregressive model to a non-stationary signal also leads to the same criticisms as those outlined for the Fourier transform. The principal motivation behind the work reported here is our reasoning that if the feature extraction method could include modelling of possible non-stationary effects in the underlying signal, better classification results may be obtained than with the use of AR coefficients.

Many attempts have been made by engineers to process non-stationary signals in an appropriate manner in order to circumvent the disadvantages of the Fourier transform. Of particular interest is the wavelet transform, which provides an efficient alternative to Fourier analysis as far as the analysis of nonstationary signals is concerned. In this respect, it has been found useful in the extraction of 'features', which subsequently were used to classify to a high degree of accuracy EEG signals belonging to the normal and the schizophrenic (SCH) class, and provides a promising means of successful EEG signal classification.

Signal analysis aims to extract appropriate information from a signal – this may be achieved through a *transformation* of the signal which enables a detailed study of relevant properties. An assumption is made that the transformation is also *invertible*. A transform, $\mathscr{F}$, such that $Y = \mathscr{F}x$, where $x$ is the signal to be transformed, and $Y$ is the transformed variable, is said to be invertible, if $\mathscr{F}^{-1}$ exists such that $x = \mathscr{F}^{-1}Y$. In this case, the analysis can be shown to represent the signal unambiguously, and more involved operations such as feature extraction and parameter estimation can be performed on the 'transform side'. [15]. This paper describes one such technique – the wavelet transform.

The wavelet transform can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the wavelet transform allows the decomposition of a signal into a number of scales, each scale representing a particular 'coarseness' of the signal under study [12]. This essentially decomposes the signal into a set of signals of varying 'coarseness', ranging from low frequency components progressively to high frequency components. Thus, if one can make some decision concerning the underlying frequency components of the signal, one may choose the appropriate scale in the wavelet transform, whilst ignoring the contribution of the other scales. This decomposition of the signal into different scales is particularly useful if the wavelet transform is performed on an orthogonal basis. [1] Hence, one may think of the high frequency components as representing the 'noise' content in a signal, and which may therefore be ignored. It is this concept of decomposing the signal into a number of scales, and the ability to ignore some of the decomposed signals which recommend the wavelet transform as a possible method for signal processing.

Wavelet transform theory has found many interesting applications in digital signal processing [12]. It provides very general techniques which can be applied to many tasks in signal processing. One very important application is the ability to compute and manipulate data in compressed parameters. These compressed parameters are often called 'features'. Thus, the signal, consisting of many data points, can be 'compressed' into a few parameters. These parameters characterise the behaviour of the signal. This feature of using a smaller number of parameters to represent the signal is particularly important for recognition and diagnostic purposes.

The structure of this paper is as follows. In the next section, we will briefly describe the method for computing the wavelet coefficients, and their interpretation, of a given signal. Then, we will use the wavelet coefficients as features for the classification of EEG signals using an artificial neural network. The results on the performance of the wavelet transform method are shown. These results are then compared with those obtained by using an autoregressive model as a feature extraction method. Finally, some conclusions are drawn concerning this classification methodology.

## 2. Computation of wavelet coefficients

The wavelet transform decomposes a signal onto a set of basis functions called *wavelets*. These are obtained from a single prototype wavelet, called a *mother wavelet*, by dilations and contractions, as well as shifts.

Wavelets may be used to decompose a signal at various resolutions; this process is referred to as *multiresolution signal decomposition*. A general signal, e.g. an EEG, can be considered as a superposition of different structures occurring on different time scales at different times (or spatial scales at different locations). For example, the classic understanding of EEG signals is to consider the EEG signal as consisting of a number of underlying oscillating frequency components, e.g., alpha frequency, beta frequency, etc. There is also a noise component superimposed on these oscillating frequency components. Thus, ideally, one may wish to filter the EEG signals using a filter bank, with centre frequencies located at the same frequencies as these presupposed oscillating frequency components, and each filter bandwidth equal to the separation between the frequency components. Then, in this manner, the superimposed noise component can be filtered out. Unfortunately, this scheme does not work satisfactorily, as the wavelet transform theory has shown; such a filter bank must be carefully designed. The oscillating frequency components effect cannot be easily 'isolated'.

One purpose of wavelet analysis is to separate and sort these underlying structures of different time scales. The details of a signal at different resolutions generally characterize different physical structures. For example, in an EEG signal, some of the observed signal may be due to the filtering effect of the 'white' matter in the brain, and some of the observed signal may be due to the 'noise' being generated from the ways in which the synapses work. These signals may operate at different frequencies, although this has not been conclusively demonstrated. But, it would be useful if a way can be found to progressively and systematically 'decompose' the signal into multi-scaled

[1] The wavelet transform may be performed on a set of orthogonal or non-orthogonal basis. The orthogonal basis transform is more compact in its representations, as it allows the decomposition of the underlying space into a set of orthogonal subspaces, thus making it possible to ignore some of the decomposed signals.

components. Such a coarse-to-fine strategy may be useful for pattern recognition purposes.

In this paper, we describe briefly how the wavelet transform can be applied to extract the wavelet coefficients of discrete time signals [6, 12]. This procedure makes use of multirate signal processing techniques [3]. The proposed scheme is the *subband* coding [2, 4, 5] or multiresolution signal analysis. For a detailed description, the reader is referred to [7]

The signal $f(x)$ is decomposed onto an orthonormal basis, as mentioned previously. Given an original sequence $f(n)$, $n \in \mathbf{Z}$, where $f(n)$ is the discrete version of $f(x)$, we derive the difference of information between the approximations of the signal at the resolutions $2^j$ and $2^{j+1}$. [2] In order to compute this difference, we build an orthonormal basis by dilating and translating a particular function $\psi(x)$, called an *orthogonal wavelet*, or alternatively, a *mother wavelet*, where

$$\psi_{2^j}(x) = \sqrt{2^j}\,\psi(2^j x). \tag{1}$$

Eq. (1) is the central equation in the wavelet transform theory. It is observed that if the mother wavelet $\psi(x)$ is given, then the other wavelet functions can be computed from (1) by dilation and translation. Different mother wavelets give rise to different classes of wavelets, and hence the behaviour of the 'decomposed' signal could be quite different [6]. There are a number of methods for obtaining an appropriate mother wavelet design. For details, the reader is referred to [8, 12]. The mother wavelet should be chosen carefully, such that it exhibits good localization properties in both the frequency and spatial domains [12]. One such wavelet is the Lemarie wavelet [11]. We used this wavelet basis in the current work. The Lemarie mother wavelet $\psi(x)$ is shown in Fig. 1. It is noticed that its Fourier transform has the shape of a band pass filter. Thus, the wavelet function can be interpreted as the impulse response of a band pass filter.

Since we are using the subsampling by 2 method, it would be useful to consider the length of a segment of signal as $2^N$. In this case, there are a total of $N+1$ levels of resolution, containing respectively, $2^N$ points, $2^{N-1}, \ldots, 2^0 = 1$ point. The total number of coefficients in a wavelet transform is the sum of all the transformed points at all the levels, including the original signal itself, i.e., $\sum_{i=0}^{N} 2^i$. It can be shown that, given all the wavelet coefficients at all levels $N+1$, it is possible to reconstruct the original *exactly* [12]. It is this *exact* reconstructability which underpins the value of the wavelet transform as a signal processing tool. This means that the wavelet transform is 'invertible', and hence one may safely operate on the 'transformed' variables, as so elegantly argued by Rioul and Vetterli [15].

Often, as we are using an orthogonal wavelet basis, it is possible to 'ignore' some of the 'upper' levels of the wavelet transforms, e.g., we may ignore the contribution of the wavelet transforms for level $i > M$, where $M < N$. This is based on the assumption that the 'upper' levels of the wavelet transform consist of mainly 'noise' components, and hence can be 'ignored'. The result is a set of wavelet coefficients of an approximation of the original signal. In the present work, the results are confined to the discrete case. There are $n = 2^N$ values $f_1, f_2, \ldots, f_n$, which are equally spaced values of a function $f(x)$. The goal, then, is to split $f$ into its components at different scales. We shall use the superscript $N$ to indicate the level of decomposition. At each new level, the meshwidth is cut in half and the number of wavelet coefficients is doubled. The decomposition can then be represented as

$$\begin{aligned} f^{(N)} &= g^{(N-1)} + g^{(N-2)} + \ldots \\ &\quad + g^{(N-M)} + f^{(N-M)}, \end{aligned} \tag{2}$$

where $g^{(\cdot)}$ is called the 'detail' signal [18]. $M$ is so chosen that $f^{(N-M)}$ is sufficiently 'blurred' [2]. Fig. 2(a) shows the multiresolution discrete approximations of a typical segment of EEG signal at the resolutions $M = 1$, 2, 3 and 4 using the Lemarie mother wavelet. The original signal $f^{(N)}$ is also shown. Fig. 2(b) shows the corresponding wavelet representation of the signal. Here, the dots give the amplitude of each detail signal. It is noticed that the detail signal samples have a high amplitude when the approximations at level $M$ and $M+1$ shown in Fig. 2(a) are locally different.

Further, since we are using an orthogonal wavelet basis, hence, by ignoring the 'upper' levels, e.g., $i > M$

[2] Note that, here, we have assumed for simplicity that the resolutions are 'doubled' or 'halved'. In the literature, there is some work on the possibility of using resolutions which are non-commensurate ratios, but this work is still in its early days, and hence it is not yet clear how they can be applied to the wavelet basis chosen for this paper.

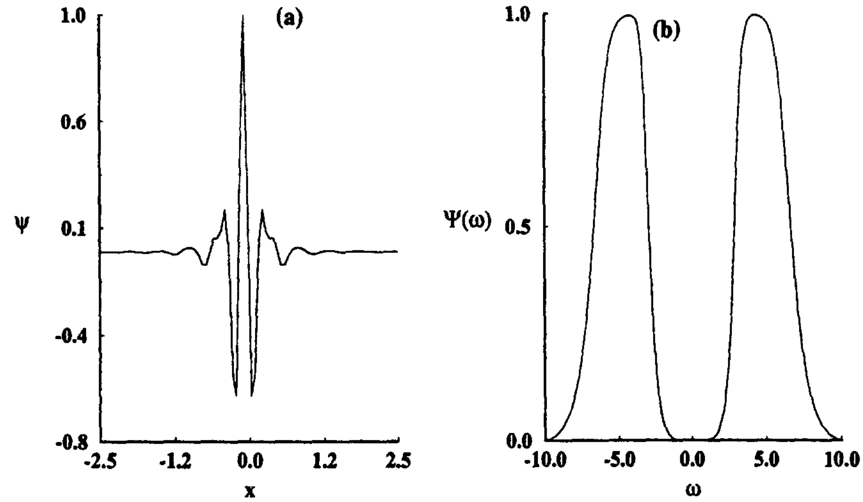


Fig. 1. (a) The Lemarie wavelet $\psi(x)$. (b) Modulus of the Fourier transform of $\psi(x)$.

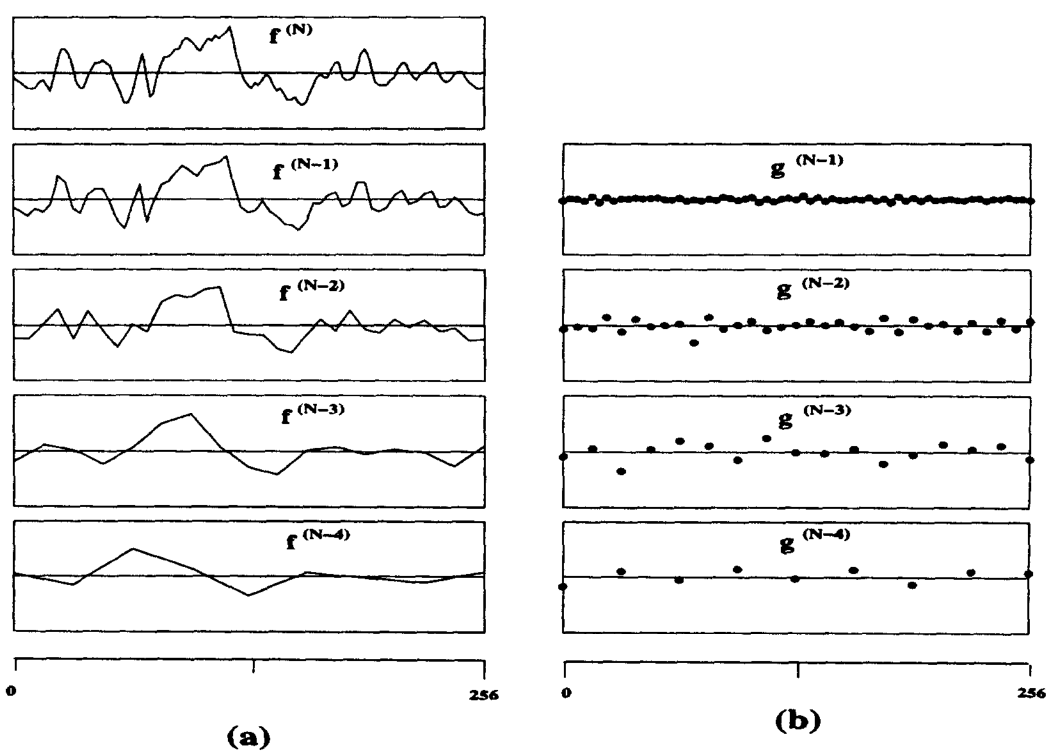


Fig. 2. (a) Multiresolution discrete approximations of a typical segment of EEG signal. (b) Wavelet representation of the signal.

level, of the wavelet transform, the reconstructed signal will be the *best* representation of the signal upto that particular level, $i$. Thus, the wavelet transform can be used to obtain the best representation of the underlying signal at different scales, upto a particular level. It is this reconstructability, together with the orthogonal wavelet basis decomposition, which readily recommend the wavelet transform as a signal processing tool.

One way of reducing the number of wavelet coefficients to be used as features representing each segment of the EEG signals is to prescribe a 'stopping criterion' for the value of $M$ in Eq. (2) – this can be achieved through a thresholding operation [9]. Note that, in Eq. (2), for each $j = N - M, \ldots, N - 1$, $g^{(j)}$ gives localized time-frequency information of $f^{(N)}$ in the $j$th octave [2]. The advantage of this method of computing the wavelet coefficients is that the details of the sampled signal $f^{(N)}$ are sorted out and stored in different subspaces, thereby enabling better analysis. This implies that it is possible to delete information of very small magnitudes in each subspace, resulting in much less data information being needed to reconstruct a very good approximation of the original signal.

## 3. Analysed EEG signals and their classification

The classification of the EEG signals comprises of the following steps:

- Preprocessing of the signals. In the present work, this comprises determination of the wavelet coefficients, using the subband coding scheme described above. These coefficients will be used as 'features' describing the signal.
- The features thus extracted from the preprocessing operation are input into an artificial neural network which carries out a classification over the set of extracted parameters, in this case, the set of wavelet coefficients.

Three data types were selected. Each data type comprised of EEG signals recorded from subjects from one of three diagnostic groups: normal control subjects, patients diagnosed with schizophrenia (SCH), and patients diagnosed with obsessive-compulsive disorder (OCD). All EEG recordings were performed in the Clinical Electrophysiology Unit at Wolston Park Hospital, in Wacol, Queensland, with hospital ethics approval given and informed consent obtained from all subjects.

The diagnoses of psychiatric patients were made by qualified neurologists and psychiatrists using standard DSM-IIIR diagnostic criteria [1]. Patients with OCD were recruited as outpatients, and further details have been published elsewhere [14, 16]. All of the OCD patients studied had been suffering from severe and intractable OCD for at least one year, but most were not on medication. Patients with schizophrenia were mainly recruited from non-acute new inpatient admissions to the Clinical Studies Unit at Wolston Park Hospital. Most of these patients were diagnosed as having a paranoid subtype of schizophrenia, and most were taking neuroleptic medication. The type and dosages of medication varied widely between subjects, but was required to be in steady state at the time of the EEG recording. Normal subjects were selected from healthy individuals recruited from the medical and nursing staff.

Details of the recording methodology used for all subjects are given elsewhere [21, 16]. EEG recordings were performed essentially as for a typical neurological recording session, with the subjects 'at rest' in a state of moderate alertness, and no specific cognitive 'activating' tasks were employed. All EEG signals were acquired at 128 Hz and digitised with 8-bit resolution using a Bio-Logic Brain Atlas III system. Each recording used a gain of 30,000 and a 1–30 Hz band pass filter. Only data taken with eyes open was subsequently analysed, and of the 19 channels of data actually acquired, only data recorded from the vertex of the scalp was used for this study. All EEG data was visually inspected off-line and data contaminated by artefacts was manually rejected. Personal identification information was stripped from all EEG data files, and only the first 2 minutes of data recorded during the 'eyes open' phase was submitted for subsequent analysis.

Each EEG signal was divided into segments, with each segment comprising $2^7 = 128$ samples, i.e. each segment was 1 s in duration. 120 such segments were taken from each subject. Thus, up to seven levels of decomposition of the signal onto the wavelet basis are possible. The reason why we selected a 1 s duration as a segment is to enable a comparison of the results obtained using the present technique with those obtained previously using autoregressive coefficients. Our basis of comparison is the predictive capability of an artificial neural network using an autoregressive model for the signal, where the EEG signals are assumed to be stationary within this segment. Our preliminary work [16, 19, 21], in which we studied the effects of varying segment lengths and applied a likelihood ratio analysis, indicated that these EEG signals were generally approximately stationary within one second segments.

A total of 41, 60 and 35 EEG files were obtained respectively from normal, schizophrenic and OCD subjects. We used 26, 39 and 24 EEG files, respectively, for training, and the rest of the files for testing purposes. The testing data files were never used in the training process.

As described above, it is possible to apply thresholding at each level of decomposition to reduce the number of coefficients which are used as features describing the signal. However, as this is an initial study on the feasibility of wavelet coefficients as features for EEG signal classification, we used a simpler approach. We chose the value $M = 4$ in Eq. (2), ignoring the higher levels of decomposition of the wavelet transform. We chose the Lemarie wavelet [11] as the basis for decomposition of the EEG signals. At each level of decomposition, we measured the absolute value of the detail signals, and retained the two coefficients with the highest magnitude. Thus, for $M = 4$, there were $4 \times 2 = 8$ coefficients for each segment of the EEG signals.

An artificial neural network that employs multilayer perceptrons [10] with a single hidden layer using a gradient search technique is used to classify the signals. We will not describe the training algorithm used here as it is the standard backpropagation of error type algorithm, but we refer the readers to [10] for details.

Developing an ANN architecture appropriate to the task under consideration was a major concern. A good choice of network architecture increases the probability that the trained network generates the right output for an unknown input. There are constructive algorithms such as Fahlman and Lebiere's Cascade Correlation algorithm [10] which are capable of evolving a suitable architecture as part of the training procedure. However, these constructive algorithms do not work well when there is significant amount of noise in the training data and hence they will not be used in this study. Furthermore, since this is a study of the performance of ANNs as a classifying tool for EEG signals, we used a simple trial and error approach of changing the number of hidden layers and hidden units to determine the most suitable ANN architecture for the different EEG data sets under consideration. Based on this approach, it was found that, using 8 signal feature parameters as the input, a network with a single hidden layer containing fifty hidden units and three output units performed well for each of the data sets under consideration. The activations of the output nodes, using the one-in-$N$ coding scheme, were as follows:

1\. 0. 0. : Normal
0\. 1. 0. : Schizophrenia (SCH)
0\. 0. 1. : Obsessive-Compulsive Disorder (OCD)

The learning rate was fixed at 0.1, with a momentum factor of 0.9.

Note that, in the training of the multilayer perceptron, we could have used the entire subject's complement of $120 \times 8$ parameters as inputs, together with the associated output classification. However, this would have caused the training process to be extremely slow, as the resulting network would have had a large number of weights. Instead, we have treated each segment as independent, hence we only had 8 input parameters and an associated output classification. This resulted in a much smaller neural network.

## 4. Results

The layered feedforward net was trained using the standard backpropagation of error method [10]. The output activation is considered to be unknown if all the values of the activations at the output nodes are less than 0.5, or if there is a tie in the number of output activations for each class of EEG.

The output activations and the classifications based on the activations of the output nodes using the method described in this paper are shown in Fig. 3. Each bar represents the ANN classification of 120 segments of data taken from a subject or case. Each bar is divided into a number of blocks representing the total number of output node activations in each of the following classes: Normal (N), Schizophrenia (S), Obsessive-Compulsive Disorder (O) and Unknown (U). The classification result is shown on top of each bar.

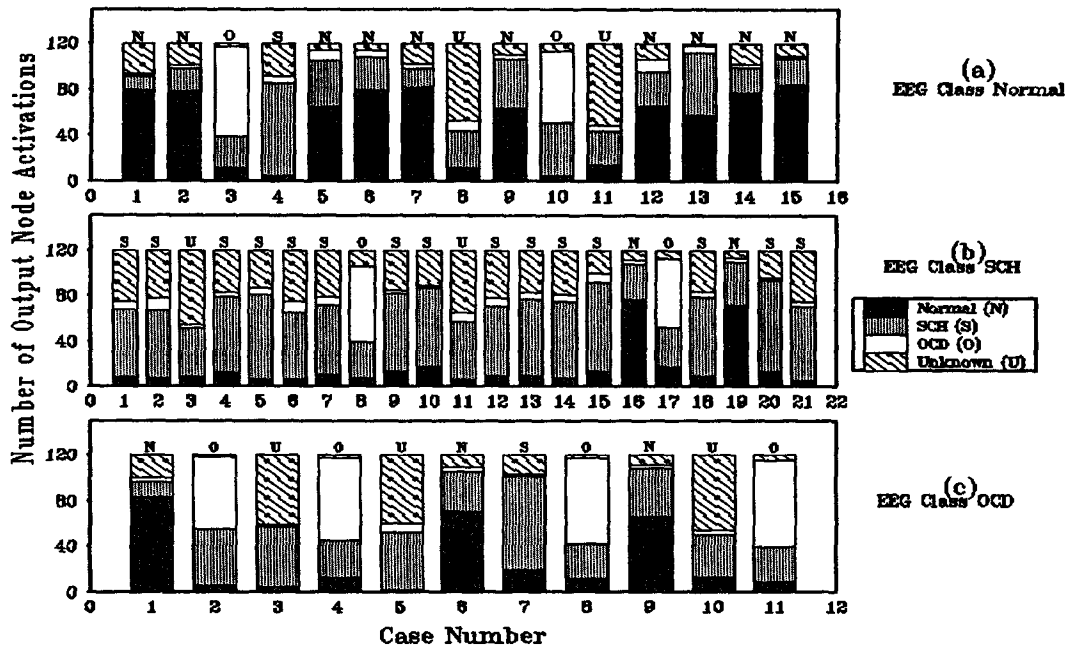


Fig. 3. Classification of EEG signals using an ANN with wavelet coefficients using a 128 point segment for all test cases.

We elected to designate the predicted classification of a given test case by taking the majority of classifications of the 120 segments from that test case. For example, for the testing data set 1 in Fig. 3(a), it is found that out of a total 120 segments, 80 have been classified as 'N,' 12 as 'S,' 2 as 'O', and 26 as 'U'. Since the majority of the predicted classification is in the 'N' category, we designate the predicted classification as 'N'. Thus, the classification of each test case is based on the largest number of output activations in each class. In the case of a tie, it is classified as 'U'.

Table 1 shows the confusion table of the classification.

The results show that it is possible to classify about 71% schizophrenia class EEG signals, and 66%

Table 1
Confusion table of the classification results based on wavelet coefficients using a 128 point segment

| | Classification result → | | | | |
|---|---|---|---|---|---|
| | EEG class | Normal | SCH | OCD | Unknown |
| Actual | Normal | 10/15 | 1/15 | 2/15 | 2/15 |
| category ↓ | SCH | 2/21 | 15/21 | 2/21 | 2/21 |
| | OCD | 3/11 | 1/11 | 4/11 | 3/11 |

Normal class EEG signals using wavelet coefficients, and that the results for the OCD class of EEG signals are rather poor.

As stated earlier, signal preprocessing using autoregressive (AR) coefficients [20] was used as the comparison benchmark for the present work. The method using AR coefficients is exactly the same in all respects as that followed with the wavelet coefficients except that, instead of applying the wavelet transform to each segment of 128 points, we assume that the segment can be modelled by an autoregressive model:

$$y(t) = \sum_{i=1}^{n_{AR}} a_i y(t-i) + \varepsilon(t), \tag{3}$$

where $y(t)$ represents the signal at time $t$, $a_i$ are constants, and $\varepsilon(t)$ is a Gaussian noise with zero mean and unknown variance $\sigma^2$. $n_{AR}$ is the order of the AR model used. In our case, we have chosen $n_{AR} = 8$, determined [16] by using a number of information criteria such as Akaike information criterion and Bayesian information criterion. The coefficients $a_i$ in each segment are then used as features. In other words, apart from the method of extraction of the features, where one method uses an AR model and the other uses the

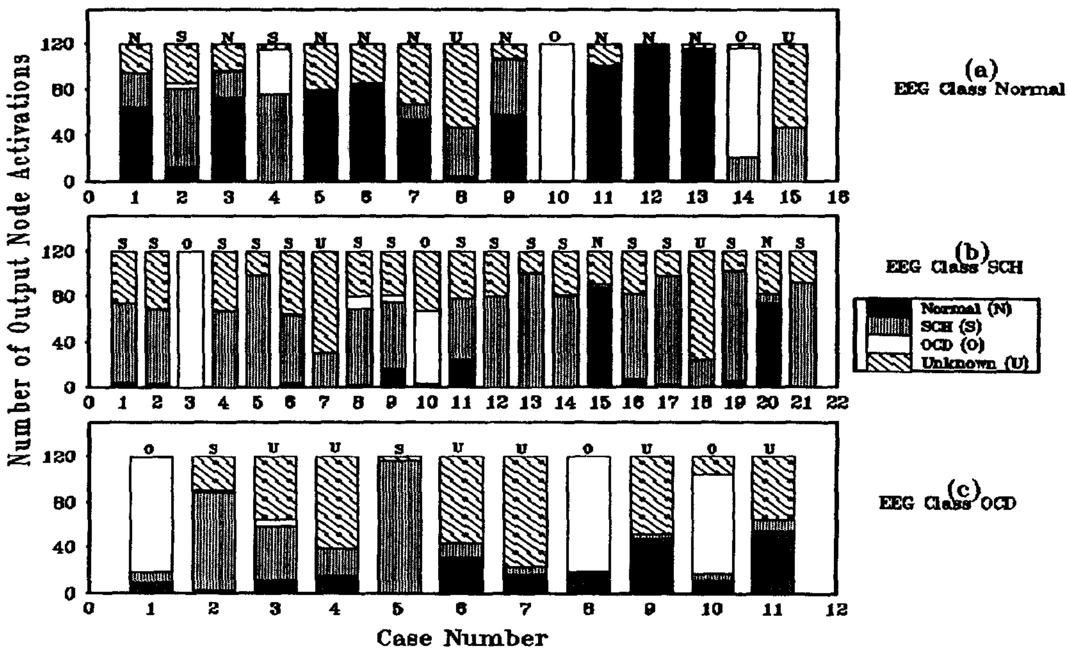


Fig. 4. Classification of EEG signals using an ANN with linear AR coefficients using a 128 point segment for all test cases.

wavelet transform, all the other aspects of both cases are exactly the same. In the AR case, too, it is found that a multilayer perceptron with a single hidden layer containing fifty hidden neurons can adequately classify the given set of training data.

Results using autoregressive coefficients, trained using the same training data set and tested on the same testing data set as the wavelet coefficient case, are shown in Fig. 4, and the corresponding confusion table is shown in Table 2. It is seen that classification based on signal features derived from the wavelet transform method is on a par with, and in some cases (e.g. normal and OCD), are slightly better than classification based on signal features derived from the AR method. The results are possibly more apparent if we compare the confusion Tables 1 and 2. There is an improvement in performance for the two types of data files, from 9 to 10/15 for the normal cases, and 3 to 4/11 for the OCD cases. Another advantage of the present method over the AR method is its ability to analyse non-stationary signals.

The prospective accuracy of the present method compares very well with previous efforts at classifying psychiatric EEG data. Thus, the present method is a promising means of successful EEG signal classification.

Table 2
Confusion table of the classification results based on standard AR parameters using a 128 point segment

| | Classification result → | | | | |
|---|---|---|---|---|---|
| | EEG class | Normal | SCH | OCD | Unknown |
| Actual | Normal | 9/15 | 2/15 | 2/15 | 2/15 |
| category ↓ | SCH | 2/21 | 15/21 | 2/21 | 2/21 |
| | OCD | 0/11 | 2/11 | 3/11 | 6/11 |

## 5. Conclusions

In this paper, we have introduced a method which can be used to preprocess non-stationary EEG signals using the wavelet transform. It is shown that extraction of EEG signal features using this method enables classification, by a multilayer perceptron, of EEG recordings obtained from subjects with schizophrenia and obsessive-compulsive disorder, and normal subjects, with an equal or higher degree of accuracy than classification using a standard autoregressive model to preprocess the same EEG signals. We suggest that this method therefore has merit as a method for preprocessing EEG signals.

One may argue that we have not fully utilised the power of the wavelet transform. As indicated previously, the wavelet transform is useful in processing nonstationary signals. However, at least in the format used here, we have only considered the wavelet transform of a 'stationary' segment, as we argue that an EEG signal with 128 data point can be considered as stationary. Hence, by restricting ourselves to analysing 128 points, we have not indeed considered the capability of the wavelet transform to process non-stationary signals.

This criticism is valid to some extent in that our choice of 128 point segment is dictated by our need to compare our results with those obtained using other methods. Since a possible datum for comparison is feature extraction using AR methods, and since it is known that the AR models can only be used for stationary segments, this makes the situation a bit difficult. We have two possibilities:

(1) Compare the results on the same basis as we had deployed the AR model method, i.e., to assume a 128 point segment. This is the approach which we have taken in this paper.

(2) To use a larger segment length, and then compare the performance of AR model and the corresponding wavelet method. However, in this case, a valid conclusion cannot be inferred, as the AR model is known to be only strictly applicable to 'stationary' segments.

We have chosen to use approach (1) above instead of (2), as we are concerned with comparing the wavelet method with the best that the AR model can produce. The wavelet transform method, because it can process both stationary and non-stationary signals, should produce slightly better results than the AR methods. This is because the assumption of stationarity of the segment may not be satisfied with every segment. Thus, if the signal is approximately stationary then the results using the AR method and the wavelet transform method should be quite close, with the wavelet method giving slightly better results. This slightly better result accounts for the possible 'odd' non stationary segments in the signal. This is indeed observed in our results.

Using approach (2) would mean that the AR modelling method would no longer be valid as a comparison benchmark. In the absence of other models for comparison in the literature, this may not reveal the true capability of the wavelet methods. However, as a test case, the experiment was repeated using a longer segment length of 2 seconds duration, i.e. a 256 point segment. In this case, since only the first 2 minutes of recorded data are analysed, there are 60 segments of EEG data per subject. The results using linear AR coefficients with 256 point segments is shown in Fig. 5, and the corresponding confusion table is shown in Table 3. Results using wavelet coefficients using the same training data set and tested on the same testing data set as the AR coefficient case with 256 point segments are shown in Fig. 6, and the corresponding confusion table is shown in Table 4. It is seen that, using a larger segment length, the performance of the AR method actually decreases, while the wavelet-coefficient method shows a slight increase in performance in normal and schizophrenia cases. This is perhaps to be expected, since the AR method is valid only for stationary signals.

The results indicated in this paper may be further improved by substituting a recurrent neural network [10] for the multilayer perceptron. A recurrent neural network is similar in nature to the multilayer perceptron, except that it may include feedback paths with trainable weights, and it may also include time-delay. This architecture can be used to classify data which depends on past information. In the results reported

Table 3
Confusion table of the classification results based on standard AR parameters using a 256 point segment

| | Classification result → | | | | |
|---|---|---|---|---|---|
| | EEG class | Normal | SCH | OCD | Unknown |
| Actual | Normal | 7/15 | 1/15 | 2/15 | 5/15 |
| category ↓ | SCH | 0/21 | 13/21 | 4/21 | 4/21 |
| | OCD | 1/11 | 3/11 | 2/11 | 5/11 |

Table 4
Confusion table of the classification results based on wavelet coefficients using a 256 point segment

| | Classification result → | | | | |
|---|---|---|---|---|---|
| | EEG class | Normal | SCH | OCD | Unknown |
| Actual | Normal | 10/15 | 1/15 | 1/15 | 3/15 |
| category ↓ | SCH | 2/21 | 16/21 | 1/21 | 2/21 |
| | OCD | 1/11 | 2/11 | 4/11 | 4/11 |

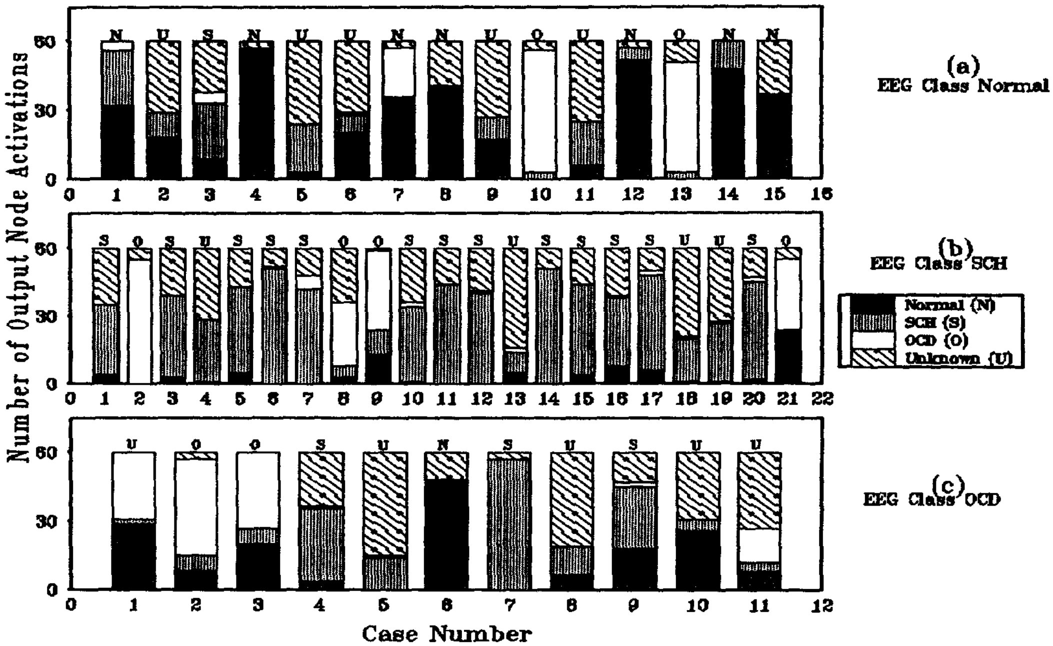


Fig. 5. Classification of EEG signals using an ANN with AR coefficients using a 256 point segment for all test cases.

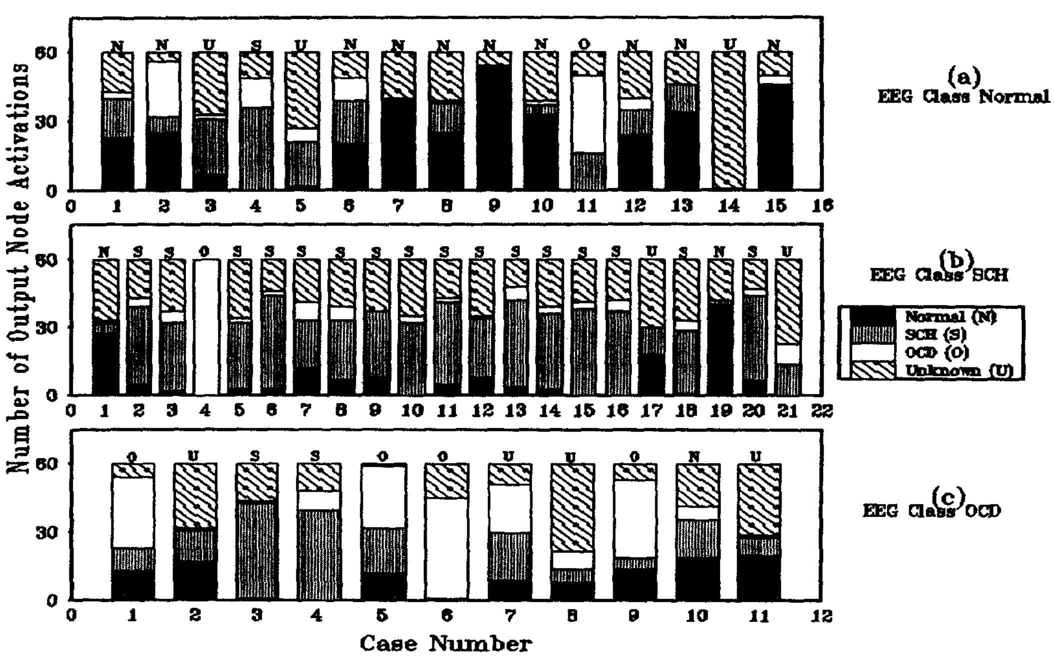


Fig. 6. Classification of EEG signals using an ANN with wavelet coefficients using a 256 point segment for all test cases.

in this paper, we have assumed that all data segments are independent, ignoring their possible sequential nature. The use, instead, of a recurrent neural network which takes account of this data structure may result in further improvement in the classification accuracy. This remains as a topic for further research.

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