Classification of EEG Signals Using the Wavelet Transform

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Abstract—**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. 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 EEG's. The wavelet transform thus provides a potentially powerful technique for preprocessing EEG signals prior to classification.**

Keywords— **EEG Classification, Neural Networks, Wavelet Transform**

I. 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 [13], 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.

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 [15]; this indicates that the EEG signal is a *non-stationary* signal. 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.

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Many attempts have been made by engineers to process non-stationary signals in an appropriate way 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.

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, $\mathcal{F}$, such that $Y = \mathcal{F}x$, where x is the signal to be transformed, and Y is the transformed variable, is said to be invertible, if $\mathcal{F}^{-1}$ exists such that $x = \mathcal{F}^{-1}Y$. 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." [11]. The wavelet transform is an example of such an invertible 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 [9]. 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

[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

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.

The structure of this paper is as follows: in section II, 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 in section III. The results on the performance of the wavelet transform method are shown in section IV. Finally, some conclusions are drawn concerning this classification methodology.

II. 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.

In this paper, we describe briefly how the wavelet transform can be applied to extract the wavelet coefficients of discrete time signals [5], [9]. The signal $f(x)$ is decomposed onto an orthonormal basis. 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

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

Equation (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 [5]. There are a number of methods for obtaining an appropriate mother wavelet design. For details, the reader is referred to [9]. The mother wavelet should be chosen carefully, such that it exhibits good localization properties in both the frequency and spatial domains [9]. One such wavelet is the Lemarie wavelet [8]. We will use this wavelet basis in the current work.

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* [9].

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, 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

$$f^{(N)} = g^{(N-1)} + g^{(N-2)} + \ldots + g^{(N-M)} + f^{(N-M)} \quad (2)$$

where $g^{(\cdot)}$ is called the "detail" signal [9]. M is so chosen that $f^{(N-M)}$ is sufficiently "blurred" [2].

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

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

decomposed signals.

[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.

"stopping criterion" for the value of M in equation 2 — this can be achieved through a thresholding operation [6].

III. 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, described in section II. 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).

Details of the recording methodology used for all subjects are given elsewhere [15], [12]. 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 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.

Each EEG signal was divided into segments, with each segment comprising $2^7 = 128$ samples, *i.e.* each segment was 1 second 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. Our preliminary work [15], [12], [14], 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.

We chose the value $M = 4$ in Equation 2, ignoring the higher levels of decomposition of the wavelet transform. We chose the Lemarie wavelet [8] as the basis for decomposition of the EEG signals. At each level of decomposition, we measured the absolute value of the wavelet coefficients, 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 multi-layer perceptrons [7] 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 [7] for details.

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.

Note that, in the training of the multilayer perceptron, we could have used the entire subject's complement of 120×8 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.

IV. Results

The layered feedforward net was trained using the standard backpropagation of error method [7]. 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 figure 1 [3]. Each bar represents the ANN clas-

[3]Due to page limitations, this figure unfortunately is not

EEG Class	Normal	SCH	OCD	Unknown
Normal	10/15	1/15	2/15	2/15
SCH	2/21	15/21	2/21	2/21
OCD	3/11	1/11	4/11	3/11

TABLE I

THE CONFUSION TABLE OF THE CLASSIFICATION RESULTS ON THE TESTING DATA SET USING THE WAVELET TRANSFORM.

sification 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.

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 figure 1 (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% Normal class EEG signals using wavelet coefficients, and that the results for the OCD class of EEG signals are rather poor.

V. 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 normal subjects, with a high degree of accuracy. We suggest that this method therefore has merit as a method for preprocessing EEG signals.

included in the printed proceedings. Interested readers can contact the first or the third author for a copy of the figure.

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