# EEG signal classification using wavelet feature extraction and neural networks.

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*Abstract*—**Decision Support Systems have been utilised since 1960, providing physicians with fast and accurate means towards more accurate diagnoses and increased tolerance when handling missing or incomplete data. This paper describes the application of neural network models for classification of electroencephalogram (EEG) signals. Decision making was performed in two stages: initially, a feature extraction scheme using the wavelet transform (WT) has been applied and then a learning-based algorithm classifier performed the classification. The performance of the neural model was evaluated in terms of training performance and classification accuracies and the results confirmed that the proposed scheme has potential in classifying the EEG signals.**

*Index Terms*— **Automated Diagnosis, Discrete wavelet transform (DWT), Electroencephalogram (EEG), and Neural networks,.**

## I. INTRODUCTION

The human brain is obviously a complex system, and exhibits rich spatiotemporal dynamics. Among the non-invasive techniques for probing human brain dynamics, electroencephalography (EEG) provides a direct measure of cortical activity with millisecond temporal resolution. Early on, EEG analysis was restricted to visual inspection of EEG records. Since there is no definite criterion evaluated by the experts, visual analysis of EEG signals is insufficient. For example, in the case of dominant alpha activity delta and theta activities are not noticed. Routine clinical diagnosis needs to analysis of EEG signals. Therefore, some automation and computer techniques have been used for this aim [1]. Since the early days of automatic EEG processing, representations based on a Fourier transform have been most commonly applied. This approach is based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands—delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz). Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Parametric power spectrum estimation methods such as AR, reduces the spectral loss problems and gives better frequency resolution. Also AR method has an advantage over FFT that, it needs shorter duration data records than FFT [2]. A powerful method was proposed in the late 1980s to perform time-scale analysis of signals: the wavelet transforms (WT). This method provides a unified framework for different techniques that have been developed for various applications. Since the WT is appropriate for analysis of non-stationary signals and this represents a major advantage over spectral analysis, it is well suited to locating transient events, which may occur during epileptic seizures. Wavelet's feature extraction and representation properties can be used to analyse various transient events in biological signals. Adeli et al. [3] gave an overview of the discrete wavelet transform (DWT) developed for recognising and quantifying spikes, sharp waves and spike-waves. They used wavelet transform to analyze and characterise epileptiform discharges in the form of 3-Hz spike and wave complex in patients with absence seizure. Through wavelet decomposition of the EEG records, transient features are accurately captured and localised in both time and frequency context. The capability of this mathematical microscope to analyse different scales of neural rhythms is shown to be a powerful tool for investigating small-scale oscillations of the brain signals. A better understanding of the dynamics of the human brain through EEG analysis can be obtained through further analysis of such EEG records.

Numerous other techniques from the theory of signal analysis have been used to obtain representations and extract the features of interest for classification purposes. Neural networks and statistical pattern recognition methods have been applied to EEG analysis. Neural network (NN) detection systems have been proposed by a number of researchers. Pradhan et al. [4] used the raw EEG as an input to a neural network while Weng and Khorasani [5] used the features proposed by Gotman with an adaptive structure neural network, but his results show a poor false detection rate. Petrosian et al. [6] showed that the ability of specifically designed and trained recurrent neural networks (RNN) combined with wavelet preprocessing, to predict the onset of epileptic seizures both on scalp and intracranial recordings only one-channel of electroencephalogram. In order to provide faster and efficient algorithm, Folkers et al. [7] proposed a versatile signal processing and analysis framework for bioelectrical data and in particular for neural recordings and 128- channel EEG. Within this framework the signal is decomposed into sub-bands using fast wavelet transform algorithms, executed in real-time on a current digital signal processor hardware platform. 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

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perspective of the signal. In this work, DWT has been applied for the time–frequency analysis of EEG signals and NNs for the classification using wavelet coefficients. EEG signals were decomposed into frequency sub-bands using discrete wavelet transform (DWT). A neural network system was implemented to classify the EEG signal to one of the categories: epileptic or normal. The aim of this study was to develop a simple algorithm for the detection of epileptic seizure, which could also be applied to real-time.

Until now, there is no study in the literature related to the estimation of multiple-classifier accuracy in the analysis of EEG signals. In this study, a new approach based on the multiple-classifier concept will be presented for epileptic seizure detection. In the neural network techniques, both the feed-forward error back-propagation network and the Radial Basis function (RBF) network will be used. The choice of these two networks was based on the fact that the former is the most popular type of NNs and the latter is one of the most powerful networks commonly used in solving classification/discrimination problems. The accuracy of the various classifiers will be assessed and cross-compared, and advantages and limitations of each technique will be discussed.

## II. DATA SELECTION AND RECORDING

We have used the publicly available data described in Andrzejak *et al.* [8]. The complete data set consists of five sets (denoted A–E) each containing 100 single-channel EEG segments. These segments were selected and cut out from continuous multi-channel EEG recordings after visual inspection for artefacts, e.g., due to muscle activity or eye movements. Sets A and B consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardised electrode placement scheme (Fig. 1).

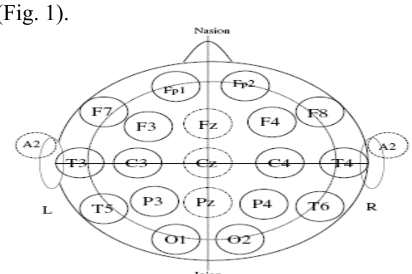


Fig. 1: The 10–20 international system of electrode placement c images of normal and abnormal cases.

Volunteers were relaxed in an awake-state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E originated from EEG archive of pre-surgical diagnosis. EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. While sets C and D contained only activity measured during seizure free intervals, set E only contained seizure activity.

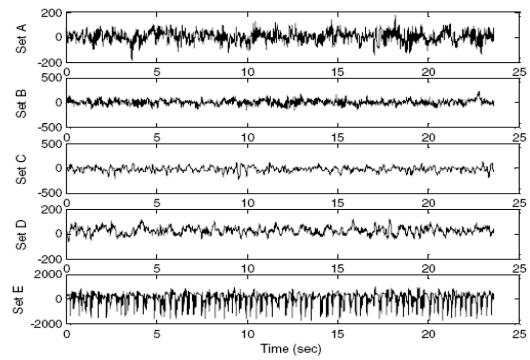


Fig. 2: Examples of five different sets of EEG signals taken from different subjects.

Here segments were selected from all recording sites exhibiting ictal activity. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitised at 173.61 samples per second using 12 bit resolution. Band-pass filter settings were 0.53–40 Hz (12dB/oct). In this study, we used two dataset (A and E) of the complete dataset. Typical EEGs are depicted in Fig. 2.

## III. ANALYSIS USING DWT

Wavelet transform is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets. The basic idea underlying wavelet analysis consists of expressing a signal as a linear combination of a particular set of functions (wavelet transform, WT), obtained by shifting and dilating one single function called a mother wavelet. The decomposition of the signal leads to a set of coefficients called wavelet coefficients. Therefore the signal can be reconstructed as a linear combination of the wavelet functions weighted by the wavelet coefficients. In order to obtain an exact reconstruction of the signal, adequate number of coefficients must be computed. The key feature of wavelets is the time-frequency localisation. It means that most of the energy of the wavelet is restricted to a finite time interval. Frequency localisation means that the Fourier transform is band limited. When compared to STFT, the advantage of time-frequency localisation is that wavelet analysis varies the time-frequency aspect ratio, producing good frequency localization at low frequencies (long time windows), and good time localisation at high frequencies (short time windows). This produces a segmentation, or tiling of the time-frequency plane that is appropriate for most physical signals, especially those of a transient nature. The wavelet technique applied to the EEG signal will reveal features related to the transient nature of the signal, which are not obvious by the Fourier, transform. In general, it must be said that no time-frequency regions but rather time-scale regions are defined [9],[10]. All wavelet transforms can be specified in terms of a low-pass filter g, which satisfies the standard quadrature mirror filter condition

$$G(z)G(z^{-1}) + G(-z)G(-z^{-1}) = 1 \qquad (1)$$

Where G(z) denotes the z-transform of the filter g. Its complementary high-pass filter can be defined as

$$H(z) = zG(-z^{-1}) \quad (2)$$

A sequence of filters with increasing length (indexed by i) can be obtained

$$G_{i+1}(z) = G(z^{2^i})G_i(z),$$
$$H_{i+1}(z) = H(z^{2^i})G_i(z), \quad i = 0, \ldots, I-1, \quad (3)$$

with the initial condition $G_0(z) = 1$. It is expressed as a two-scale relation in time domain

$$g_{i+1}(k) = [g]_{\uparrow 2^i} g_i(k), h_{i+1}(k) = [h]_{\uparrow 2^i} g_i(k) \quad (4)$$

where the subscript $[.]_{\uparrow m}$ indicates the up-sampling by a factor of m and k is the equally sampled discrete time.

One area in which the DWT has been particularly successful is the epileptic seizure detection because it captures transient features and localises them in both time and frequency content accurately. DWT analyses 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 related to low-pass and high-pass filters, respectively. The decomposition of the signal into the different frequency bands is merely obtained by consecutive high-pass and low-pass filtering of the time domain signal. The procedure of multi-resolution decomposition of a signal x[n] is schematically shown in Fig. 3. Each stage of this scheme consists of two digital filters and two down-samplers by 2. The first filter, h[.] is the discrete mother wavelet, high-pass in nature, and the second, g[.] is its mirror version, low-pass in nature. The down-sampled outputs of first high-pass and low-pass filters provide the detail, D1 and the approximation, A1, respectively. The first approximation, A1 is further decomposed and this process is continued as shown in Fig. 3.

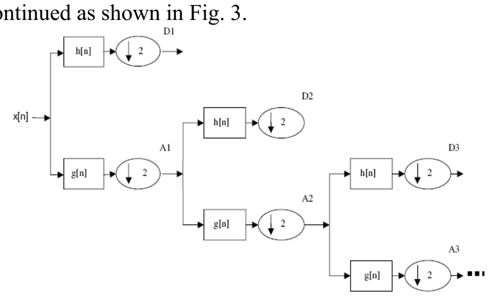


Fig. 3: Sub-band decomposition of DWT implementation; h[n] is the high-pass filter, g[n] the low-pass filter.

Selection of suitable wavelet and the number of decomposition levels is very important in analysis of signals using the DWT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlates well with the frequencies necessary for classification of the signal are retained in the wavelet coefficients. In the present study, since the EEG signals do not have any useful frequency components above 30 Hz, the number of decomposition levels was chosen to be 4. Thus, the EEG signals were decomposed into details D1–D4 and one final approximation, A4. Usually, tests are performed with different types of wavelets and the one, which gives maximum efficiency, is selected for the particular application. The smoothing feature of the Daubechies wavelet of order 2 (db2) made it more appropriate to detect changes of EEG signals. Hence, the wavelet coefficients were computed using the db4 in the present study. The proposed method was applied on both data set of EEG data (Sets A and E). Fig. 4 shows approximation (A4) and details (D1–D4) of an epileptic EEG signal.

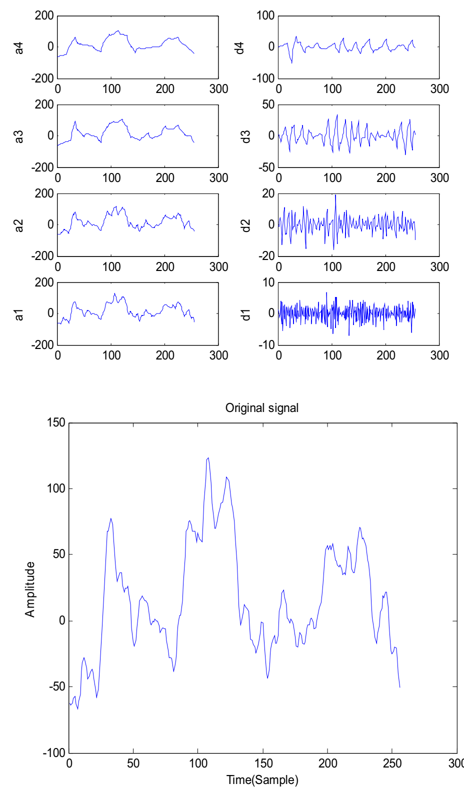


Fig. 4: Approximate and detailed coefficients of EEG signal taken from unhealthy subject (epileptic patient).

### A. *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 173.6 Hz. In order to further decrease the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients was used [10],[11]. The following statistical features were used to represent the time frequency distribution of the EEG signals:

- Maximum of the wavelet coefficients in each sub-band.
- Minimum of the wavelet coefficients in each sub-band.
- Mean of the wavelet coefficients in each sub-band
- Standard deviation of the wavelet coefficients in each sub-band

Extracted features for two recorded class A and E shown in Table 2. The data was acquired using a standard 100 electrode net covering the entire surface of the calvarium (see Figure 1).

TABLE 1: FREQUENCIES CORRESPONDING TO DIFFERENT LEVELS OF DECOMPOSITION

| Decomposed signal | Frequency range (Hz) |
|---|---|
| D1 | 43.4–86.8 |
| D2 | 21.7–43.4 |
| D3 | 10.8–21.7 |
| D4 | 5.4–10.8 |
| D5 | 2.7–5.4 |
| A5 | 0–2.7 |

The total recording time was 23.6 seconds, corresponding to a total sampling of 4,096 points. To reduce the volume of data, the sample (time points) was partitioned into 16 windows of 256 times points each. From these sub-samples, we performed the DWT and derived measures of dispersion statistics from these windows (each corresponding to approximately 1.5 seconds). The DWT was performed at 4 levels, and resulted in five sub-bands: d1-d4 and a4 (detail and approximation coefficients respectively). For each of these sub-bands, we extracted four measures of dispersion, yielding a total of 20 attributes per sample window. Since our classifiers use supervised learning, we must also provide the outputs, which was simply a class label (for the experiments presented in this paper, there were 2, corresponding to classes A and E).

TABLE2: THE EXTRACTED FEATURES OF TWO WINDOWS FROM A & E CLASSES

| Data | Extracted features | Sub-band D1 | Sub-band D2 | Sub-band D3 | Sub-band D4 | Approxi-mation |
|---|---|---|---|---|---|---|
| Set A | Max. | 28.1094 | 101.757 | 131.0846 | 124.377 | 114.138 |
| | Min. | -28.4010 | -60.813 | -149.072 | -158.797 | -109.521 |
| | Mean | -0.0022 | 0.0058 | -0.0035 | 0.0388 | 3.7950 |
| | Std dev. | 5.1818 | 13.6442 | 23.3685 | 24.7933 | 35.1465 |
| | | | | | | |
| Set E | Max | 123.3921 | 278.924 | 429.6621 | 375.0564 | 582.3167 |
| | Min | -90.7055 | -238.51 | -417.120 | -468.064 | -361.2154 |
| | Mean | 0.0131 | -0.0281 | -0.0359 | -0.0071 | -5.5526 |
| | Std dev. | 11.8488 | 35.9941 | 73.7659 | 78.1432 | 180.4493 |

## IV. INTELLIGENT CLASSIFIERS

Recently, the concept of combining multiple classifiers has been actively exploited for developing highly reliable "diagnostic" systems [11]. One of the key issues of this approach is how to combine the results of the various systems to give the best estimate of the optimal result. A straightforward approach is to decompose the problem into manageable ones for several different sub-systems and combine them via a gating network. The presumption is that each classifier/sub-system is "an expert" in some local area of the feature space. The sub-systems are local in the sense that the weights in one "expert" are decoupled from the weights in other sub-networks. In this study, 16 subsystems have been developed, and each of them was associated with the each of the windows across each electrode (16/electrode). Each subsystem was modelled with an appropriate intelligent learning scheme. In our case, two alternative schemes have been proposed: the classic MLP network and the RBF network using the orthogonal least squares learning algorithm. Such schemes provide a degree of certainty for each classification based on the statistics for each plane. The outputs of each of these networks must then be combined to produce a total output for the system.

### A. *MLP and RBF networks*

The Multilayer Perceptron Network (MLP), which has the ability to learn and generalise, smaller training set requirements, fast operation, ease of implementation and therefore most commonly used neural network architectures, have been adapted for describing the alertness level of arbitrary subject. We have used in this case, the classic gradient descent-learning scheme for the training of this particular network.

The second classification scheme utilised here is a Radial Basis Function Network (RBF) scheme. RBF networks train rapidly, usually orders of magnitude faster than MLP, while exhibiting none of its training pathologies such as paralysis or local minima problems. Such a system consists of three layers (input, hidden, output). The activation of a hidden neuron is determined in two steps: The first is computing the distance (usually by using the Euclidean norm) between the input vector and a centre $c_i$ that represents the $i^{th}$ hidden neuron. Second, a function h that is usually bell-shaped is applied, using the obtained distance to get the final activation of the hidden neuron. In this case the Gaussian function G(x)

$$G(x) = \exp(-\frac{x^2}{\sigma^2}) \qquad (5)$$

was used. The parameter σ is called unit width and is determined using the heuristic rule "global first nearest-neighbour". The activation of a neuron in the output layer is determined by a linear combination of the fixed nonlinear basis functions, i.e.

$$F^*(x) = \sum_{i=1}^{M} w_i \phi_i(x) \qquad (6)$$

where $\phi_i(x) = G(\|x - c_i\|)$ and $w_i$ are the adjustable weights that link the output nodes with the appropriate hidden neurons. The orthogonal least squares (OLS) method has been employed as a forward selection procedure that constructs RBF networks in a rational way. The algorithm chooses appropriate RBF centres one by one from training data points until a satisfactory network is obtained.

## V. RESULTS

The proposed diagnostic system consists of a pre-processing /feature selection and one classifier subsystem. Duabechies Wavelets order-2 with 4 levels have been used for pre-processing in order to achieve the same dimensionality reduction of wavelet coefficients. In this work, the 100 time series of 4096 samples for each class windowed by a rectangular window composed of 256 discrete data and then training and test sets were formed by 3200 vectors (1600 vectors from each class) of 20 dimensions (dimension of the extracted feature vectors).

The proposed multi-classifier scheme consists of 16 sub-systems/classifiers. For each one of these sub-systems, an MLP or RBF network structure has been utilized. The average concept of combining the individual output of the 16 classifiers has been adopted in this study. The architecture of MLP is based on straightforward approach with 20 input with two hidden layer of 24 and 14 nodes respectively, and two outputs, with 2000 epochs training. The 20 inputs correspond to the four features times the number of wavelet decomposition (D1-D4 & A4). The results using MLP were encouraging. After combining the outputs of the 16 classifiers, the classification accuracy for this two-class problem found to be 97%. More specifically, out of 3,200 (classes A and E), only 96 was incorrectly labelled (i.e. misclassified).

Similarly, the RBF network using the OLS algorithm has been used in this case study. Each sub-system consisted of 20 again inputs and the result was a classification accuracy of 98%. One of the advantages of RBF over the MLP is the extremely fast training which is due to the OLS algorithm.

## VI. CONCLUSIONS

The results from this study indicate that the hybrid approach to the classification of a complex dataset such as an EEG time series can be achieved with a high degree of accuracy. This dataset contains both a spatial and a temporal component – the electrodes are placed on spatially distinct regions of the calvarium. There are several diseases that yield a characteristic signature that can be detected reproducibly using standard EEG equipment. For instance epilepsy yields a characteristic change in the power spectrum within the temporal lobe region. This would indicate that there will be a spatial signal that requires proper spatial localisation within the appropriate brain region. In addition, symptoms may change over time – and thus the temporal resolution of the recording must be such that it is samples at the correct frequency – without yielding Nyquist or other sampling errors. In the present work, we employed a discrete wavelet transform to the dataset in order to extract temporal information in the form of changes in the frequency domain over time – that is they are able to extract non-stationary signals embedded in the noisy background of the human brain. In this study, we examined the difference(s) between normal and epileptic EEG signals – over a reasonable duration of 24 seconds approximately. We extracted statistical information from the wavelet coefficients, which we used as inputs to a set of supervised learning algorithms – MLP and RBF based neural networks. The attributes (inputs) used were measures of dispersion – which captured the statistical variations found within the particular time series. Both classifiers were able to correctly map the inputs to the desired outputs with appropriate and typical training periods – indicating that local minima were not a major factor in training – although the RBF training period was substantially less than that for MLP.

The results from this preliminary study will be expanded to include a more complete range of pathologies. In this work, we focused on the extremes that are found within the EEG spectrum – normal and epileptic time series. These two series were chosen as they would more than likely lead to the maximal dispersion between the 2 signals and be amenable for training of the classifiers. In the next stage of this research, we have datasets that are intermediate in the signal changes they present. This will provide a more challenging set of data to work with – and will allow us to refine our learning algorithms and/or approaches to the problem of EEG analysis. We will also consider additional attributes - are these attributes the most critical in terms of classification? These are interesting research questions that need to be addressed. Lastly, we may also investigate additional pre-processing steps such as clustering and related techniques.

## ACKNOWLEDGEMENTS

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