Classification of EEG using PCA, ICA and Neural Network

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ABSTRACT
The processing and analysis of Electroencephalogram (EEG) within a proposed framework has been carried out with DWT for decomposition of the signal into its frequency sub-bands and a set of statistical features was extracted from the sub-bands to represent the distribution of wavelet coefficients. Reduction of the dimension of the data is done with the help of Principal component analysis and Independent components analysis. Then these features were used as an input to a neural network for classification of the data as normal or otherwise. The performance of classification process due to different methods is presented and compared to show the excellent of classification process. These findings are presented as an example of a method for training, and testing a normal and abnormal prediction method on data from individual petit mal epileptic patients.

Keywords
Electroencephalogram (EEG), Principal component analysis (PCA), Independent components analysis (ICA), DWT, ANN.

1. INTRODUCTION
About 1% of the people in the world suffer from epilepsy and 30% of epileptics are not helped by medication. Research is needed for better understanding of the mechanisms causing epileptic disorders. Careful analyses of the electroencephalograph (EEG) records can provide valuable insight into this widespread brain disorder. Wavelet is an effective time_/frequency analysis tool for analyzing transient signals. Its feature extraction and representation properties can be used to analyze various transient events in biological signals. In this work, wavelet transform is used to analyze epileptiform discharges in recorded brain waves (EEG) for patient with absence seizure (petit mal). Absence seizure is one of the main types of generalized seizures and the underlying pathophysiology is not completely understood. Neurologists make the absence seizure epileptic diagnosis primarily through visual identification of the so-called 3-Hz spike and wave complex. Epileptic seizure is an abnormality in EEG recordings and is characterized by brief and episodic neuronal synchronous discharges with dramatically increased amplitude. This anomalous synchrony may occur in the brain locally (partial seizures), which is seen only in a few channels of the EEG signal, or involving the whole brain (generalized seizures), which is seen in every channel of the EEG signal [2].

Electroencephalograms (EEGs) are recordings of the electrical potentials produced by the brain. In 1924, Hans Berger reported the recording of rhythmic electrical activity from the human scalp. In the past, interpretation of the EEG was limited to visual inspection to qualitatively distinguish normal EEG activity from localized or generalized abnormalities contained within relatively long EEG records. This approach left clinicians and researchers alike buried in a sea of EEG paper records. The advent of computers and the technologies associated with them has made it possible to effectively apply a host of methods to quantify EEG changes [4].

The EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands: delta (<4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz). Since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals. 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 analyze various transient events in biological signals. Adeli et al. [2] gave an overview of the discrete wavelet transform (DWT) developed for recognizing and quantifying spikes, sharp waves and spike-waves. They used wavelet transform to analyze and characterize epileptiform discharges in the form of 3-Hz spike and wave complex in patients with absence seizure.

The techniques have been used to address this problem such as the analysis of EEG signals for epileptic seizure detection using the autocorrelation function; frequency domain features, time–frequency analysis, and wavelet transform (WT). The results of the studies in the literature have demonstrated that the WT is the most promising method to extract features from the EEG signals. In this respect, in the present study for epileptic seizure detection in patients with absence seizures (petit mal), the WT was used for feature extraction from the EEG signals belonging to the normal and the patient with absence seizure [11].

2. FEATURE EXTRACTION METHODS

2.1 The Wavelet Transform

A signal is said to be 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. In such a situation time–frequency methods such as wavelet transform must be used. In wavelet analysis, a variety of different probing functions may be used. This concept leads to the defining equation for the continuous wavelet transform (CWT):

$$W(a, b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi \left(\frac{t - b}{a} \right) dt$$

where b acts to translate the function across x(t), and the variable a acts to vary the time scale of the probing function,ψ. If a is greater than one, the wavelet function, ψ, is stretched along the time axis, and if it is less than one (but still positive) it contacts the function. While the probing function ψ could be any of a number of different functions, it always takes on an oscillatory form, hence the term ''wavelet.'' The normalizing factor ensures that the energy is the same for all values of a. In applications that require bilateral transformations, it would be preferred a transform that produces the minimum number of coefficients required to recover accurately the original signal. The discrete wavelet transform (DWT) achieves this parsimony by restricting the variation in translation and scale, usually to powers of 2. For most signal and image processing applications, DWT-based analysis is best described in terms of filter banks. The use of a group of filters to divide up a signal into various spectral components is termed sub-band coding. This procedure is known as multi-resolution decomposition of a signal x[n]. 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 [2].

Selection of appropriate wavelet and the number of levels of decomposition is very important in analysis of signals using DWT. 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 5. Thus the signal is decomposed into the details D1–D5 and one final approximation, A5. The ranges of various frequency bands are shown in Table 1. The approximation and detail records are reconstructed from the Daubechies 4 (DB4) wavelet filter [2]. 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 4 wavelet with a sampling frequency of 173.6 Hz.

Table 1.Frequencies corresponding to different levels of decomposition for Daubechies 4 filter wavelet with a sampling frequency of 173.6 Hz.

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

2.2 Independent component analysis

We assume that we observe n linear mixtures x1,.....,xn of n independent components:

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \cdots + a_{jn}s_n, j = \overline{1, n} \qquad (1)$$

In this equation the time has been ignored. Instead, it was assumed that each mixture xj as well as each independent component si are random variables and xj(t) and si(t) are samples of these random variables. It is also assumed that both the mixture variables and the independent components have zero mean.
If not subtracting the sample mean can always center the observable variables xi. This procedure reduces the problem to the model zero-mean:

$$\hat{x} = x - E(x) \qquad (2)$$

Let x be the random vectors whose elements are the mixtures and let s be the random vector with the components s1,....,sn. Let A be the matrix containing the elements aij. The model can now be written:

$$x = As \qquad \text{or} \quad x = \sum_{i=1}^{n} a_i s_i \qquad (3)$$

The above equation is called independent component analysis or ICA. The problem is to determine both the matrix A and the independent components s, knowing only the measured variables x. The only assumption the methods take is that the components si are independent. It has also been proved that the components must have nongaussian distribution [10]. ICA looks a lot like the "blind source separation" (BSS) problem or blind signal separation: a source is in the ICA problem an original signal, so an independent component. In ICA case it is also no information about the independent components, like in BSS problem.
Whitening can be performed via eigenvalue decomposition of the covariance matrix:

$$VDV^T = E[\hat{x}\hat{x}^T] \qquad (4)$$

where V is the matrix of orthogonal eigenvectors and D is a diagonal matrix with the corresponding eigenvalues. The whitening is done by multiplication with the transformation matrix P:

$$\tilde{x} = P\hat{x} \qquad (5)$$
$$P = VD^{\frac{1}{2}}V^T$$

The matrix for extracting the independent components from $\tilde{x}$ is $\widetilde{W}$, where $P = \widetilde{W}P$.

2.3 Fast Ica for N Units

A unit represents a processing element, for example an artificial neuron with its weights W. To estimate several independent components, the weights w1,....w2 must be determined. The problem is that the outputs $w_1^T x$, ..., $w_n^T x$ must be done as independent as possible after each iteration in order to avoid the convergence to the same maxima. One method is to estimate the independent components one by one [1, 8].

Algorithm:

i) Initialize wi

ii) Newton phase

$$w_i = E\{\tilde{x}g(w_i^T\tilde{x})\} - E\{\acute{g}(w_i^T\tilde{x})\}w_i \qquad (6)$$

where g is a function with one of the following form:

$$g_1(y) = \tanh(a_1 y),$$

$$g_2(y) = y \exp\left(-\frac{1}{2}y^2\right),$$

$$g_3(y) = 4\,y^3 \qquad (7)$$

iii) Normalization

$$w_i = \frac{1}{\|w_i\|}w_i \qquad (8)$$

iv) Decorrelation

$$w_i = w_i - \sum_{j=1}^{i-1} w_i^T w_j w_j \qquad (9)$$

v) Normalization (like in the step iii)

vi) Go to step ii) if not converged.

2.4 Principal component analysis

Given a set of centered input vectors xt (t = 1,. . . ,l and $\sum x_{t=0}$) , each of which is of m dimension $x_t = (x_t(1), x_t(2), ..., x_t(m))^T$(usually m < l), PCA linearly transforms each vector xt, into a new one st, by

$$s_t = U^T x_t \qquad (1)$$

where U is the mxm orthogonal matrix whose ith column ui is the ith eigenvector of the sample covariance matrix $C = \frac{1}{l}\sum_{t=1}^{l} x_t x_t^T$.

In other words, PCA firstly solves the eigenvalue problem (2).

$$\lambda_i u_i = C u_i, i = 1, ..., m \qquad (2)$$

where λi is one of the eigenvalues of C . ui is the corresponding eigenvector. Based on the estimated ui, the components of st are then calculated as the orthogonal transformations of xt,

$$s_t = u_i^T x_t, i = 1, ..., m \qquad (3)$$

The new components are called principal components. By using only the first several eigenvectors sorted in descending order of the eigenvalues, the number of principal components in st can be reduced. This is the dimensional reduction characteristic of PCA [6].

2.5 Support vector machines

Support vector machines (SVMs) are one of the most recently developed classifiers and build on developments in computational learning theory. They are finding applications in bioinformatic applications, because of their accuracy and their ability to deal with a large number of predictors. Most of the previous classifiers separate classes using hyperplanes that split

the classes, using a flat plane, within the predictor space. SVMs extend the concept of hyperplane separation to data that cannot be separated linearly, by mapping the predictors onto a new, higher-dimensional space (called the feature space) in which they can be separated linearly. The method's name derives from the support vectors, which are lists of the predictor values obtained from cases that lie closest to the decision boundary separating the classes and are, therefore, potentially the most difficult to classify.

It is reasonable to assume that these cases have the greatest impact on the location of the decision boundary.

Computationally, finding the best location for the decision plane is an optimisation problem that makes uses of a kernel function constructs linear boundaries through non-linear transformations, or mappings, of the predictors. The 'clever' part of the algorithm is that it finds a hyperplane in the predictor space which is stated in terms of the input vectors and dot products in the feature space. A dot product is the cosine of the angle between two vectors (lists of predictor values) that have normalised lengths. The dot product can then be used to find the distances between the vectors in this higher dimensional space. A SVM locates the hyperplane that separates the support vectors without ever representing the space explicitly. Instead a kernel function is used that plays the role of the dot product in the feature space.

The support vector classifier has many advantages. A unique global optimum for its parameters can be found using standard optimization software. Nonlinear boundaries can be used without much extra computational effort. Moreover, its performance is very competitive with other methods. A drawback is that the problem complexity is not of the order of the dimension of the samples, but of the order of the number of samples.

3.   Experimental Result

The datasets used in this research are selected from the Epilepsy center in Bonn, Germany by Ralph Andrzejak. Five data sets(A-E) containing quasi-stationary, artifact, e.g., due to muscle activity or eye movements, free EEG signals both in normal subjects and epileptic patients. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12 bit resolution. Band-pass filter settings were 0.53–40 Hz (12 dB/oct). In this study, we used two dataset (A and E) of the complete dataset [3].

The data taken from the dataset A & E is being decomposed using DWT. Fig. 1 & 2 shows the detailed & approximate decomposed coefficients of healthy & unhealthy patients using DWT.
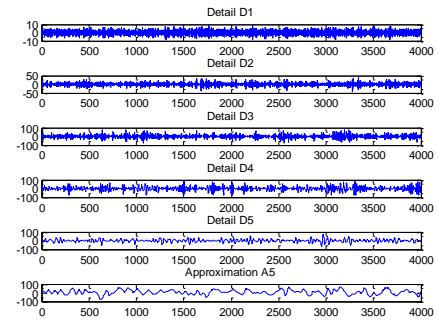
Fig. 1 Approximate and detailed coefficients of EEG signal taken from a healthy subject.
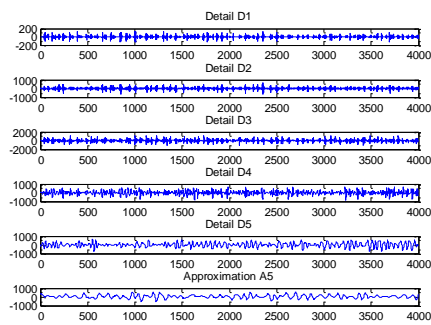

Fig. 2 Approximate and detailed coefficients of EEG signal taken from unhealthy subject (epileptic patient).

The dimension of the data is reduced using feature extraction techniques. The statistical features such as mean, variance, standard deviation of component vectors are extracted which are used to train the neural network which classifies the data as normal or epileptic. Two layered, five perceptron neural network classifier was trained with feed forward algorithm. The training was implemented to distinguish between identification of normal and abnormal electroencephalograph on the basis of comparison of coefficients. Table 2 shows the comparison of the two feature extraction techniques used along with neural network. Table 3 shows the improvement in result with support vector machine.

Table2. The values of statistical parameters of the PCA, ICA models for EEG signal classification using neural network

Feature extraction method	Accuracy (%)	Sensitivity (%)	Specificity (%)
PCA	93.63	62.93	98.83
ICA	96.75	96.75	96.75

Table3. The values of statistical parameters of the PCA, ICA models for EEG signal classification using SVM.

Feature extraction method	Accuracy (%)	Sensitivity (%)	Specificity (%)
PCA	97.75	96.15	99.48
ICA	99.50	99.50	97.05

4. CONCLUSION

Diagnosing epilepsy is a difficult task requiring observation of the patient, an EEG, and gathering of additional clinical information. Conventional classification methods of EEG signal using mutually exclusive time and frequency domain representations shows in-efficient results. In proposed framework, DWT was used to decompose the EEG into time–frequency representations. Statistical features were calculated to represent the distribution of coefficients. Using statistical features extracted from the DWT sub-bands of EEG signals, two feature extraction method; namely PCA, ICA, were used

with ANN and cross-compared in terms of their accuracy relative to the observed epileptic/normal patterns. The comparisons were based on two scalar performance measures derived from the test vectors; namely specificity and sensitivity. The result of EEG signal classification shows that nonlinear feature extraction can improve the performance of classifier. The result of EEG signal classification using SVMs shows that nonlinear feature extraction can improve the performance of classifier with respect to reduction in the number of support vectors. According to this result, the application of nonlinear feature extraction can serve as a promising alternative for intelligent diagnosis system in the future.

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