THE USE OF WAVELET TRANSFORM AS A PREPROCESSOR FOR THE NEURAL NETWORK CLASSIFICATION OF EEG SIGNALS

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ABSTRACT
In this study, Wavelet Transform (WT) is used to analyze EEG data as an input to a feed forward neural network for signal classification of individuals at high risk (HR) for alcoholism. We used two types of mother wavelets for the mathematical processing of EEG data: (a) Biorthogonal (Bior) and (b) Daubechies (Db). The results show that the wavelet transform can be used to provide a better classification by artificial neural network (ANN). Both ANN, trained with wavelet coefficients of Bior and Db, provided good performances (70%) in the classification task.

KEY WORDS
EEG, Artificial Neural Network, Wavelet Transform, Alcoholism.

1. Introduction

Alcoholism is a disease that runs in families and is one of the leading health problems in the Western world with a high incidence, vast economic costs, and notably, a poor treatment response. Beirut (2002) suggests a “strong evidence from twin and adoption studies suggests that alcoholism is in part caused by genetic predisposition”. Many other traits that are associated with the risk for alcoholism also cluster in families and have genetic underpinnings. These traits, or phenotypes, include a person’s response to alcohol and biological measurements, such as brain electrophysiological measures [1].

Neurofisiological deficits in chronic alcoholism have been well documented, especially in spatial working memory, problem solving, and cognitive flexibility. Supporting functional evidence indicates that a diminished activation of the frontal cortical system probably underlies attention and visual working memory deficits in chronic alcoholics. In the case of offspring of alcoholics, deficits in visuospatial skills, verbal performance, categorization or organization, attention, and memory indices have been consistently reported. This detailed review also suggests that these cognitive deficits can predate chronic alcohol use [2].

EEG signals are not deterministic and they have no special formation. Wavelet Transform (WT) does not require stationarity; because of this, the WT is more suitable for the analysis of EEG signals.

This paper deals with a novel method of analysis of EEG signals using wavelet transform (WT) and classification using artificial neural network (ANN). The specific hypothesis assessed was that by using a nonlinear classification scheme, namely the multi-layer perceptron (a particular class of ANN architectures) trained with wavelet coefficients (WC) of EEG signal would distinguish subjects with low risk (LR) from high risk (HR) for alcoholism.

2. Methods and materials

Data Recording: EEG data used in this work arises from a large study to examine EEG correlates of genetic predisposition to alcoholism, and were available for Lester Ingber [3]. These data were collected by Henri Begleiter and associates at the Neurodynamics Laboratory at the State University of New York Health Center at Brooklyn. In this experiment 122 subjects participated. All subjects were right-handed and had normal vision or corrected normal vision.

Each subject in the experiment was fitted with a 61-lead electrode cap (ECI, Electrocap International). The entire 10/20 International montage was used along with an additional 41 sites as follows: FPz, AFz, AF1, AF2, AFz, AF8, F1, F2, F5, F6, FCz, FC2, FC3, FC4, FC5, FC6, FC7, FC8, C1, C2, C5, C6, CPz, CP1, CP2, CP3, CP4, CP5, CP6, TP7, TP8, P1, P2, P5, P6, Poz, PO1, PO2, PO7, and PO8 (Standard Electrode Position Nomenclature, American Electroencephalographic Association 1990). All scalp electrodes were referred to Cz. Subjects were grounded with a nose electrode, and the electrode impedance was always below 5 kΩ. Two additional bipolar deviations were used to record vertical and horizontal EOG. The signals were amplified with a gain of 10,000 by Ep-A2 amplifiers (Sensorium, Inc) with a bandpass between 0.02 and 50 Hz, and recorded on a Concurrent 55/50 computer. The amplified signals were sampled at a rate of 256 Hz during an epoch of 190 ms of prestimulus baseline and 1440 ms following each
stimulus presentation. Trials with excessive eye and body movements (>73.3 µV) were rejected on-line.

In this experiment, the subject was stimulated with pictures that were chosen from 1980 Snodgrass and Vanderwat picture set to identify an ERP component correlating with visual memory. Both the spatial and temporal characteristics of this component, which is generally located in the occipito-temporal region, are in keeping with single cell studies in monkeys [4], [5]. This component is named visual memory potential (VMP) because it indexes properties to visual memory.

Artificial neural networks: Artificial Neural Networks (ANNs) are complex mathematical models that are based on the human neuronal structure. They are capable of modeling elaborate biologic systems without making assumptions based on statistical distributions. Even though the increasing acceptance of ANNs in medicine is a recent phenomenon, many applications have been or are being developed. These applications are in the areas of diagnosis, imaging, cardiographic waveform analysis, outcome prediction (prognosis), pharmacology, and identification of pathologic specimens. Given the strength of ANNs in performing pattern recognition tasks, early clinical applications were in diagnostic testing. Since then, ANNs have been used in the diagnosis of dementia, myocardial infarction, psychiatric disorders, acute pulmonary embolism, and temporal arteries [6].

ANNs are computational tools that utilize a combination of many elementary processing units (cells). Each unit is connected to a number of network units to process information by a transfer function. The relationship between input and output determines the network behavior. Contrary to conventional computing methods, ANNs are ‘trained’ to produce the desired input-output relationship [7]. During the training phase, a number of examples are given to the net altogether with the desired output for each example of training set. At this stage, the numerical values of weights are established by the ANN according to the principle of minimizing. For each example, the difference between the output given by the ANN and the one provided by the trainer will be named error. When the training is over, the final set of weights represents the base of knowledge of the ANN. A trained network is able to analyze other traces, different from those of the training set [8]. The principal applications of ANNs are related to the area of pattern recognition. The pattern is turned into a feature vector used as the ANN input. The output is interpreted as identifying the input to be a member of one of a number of classes of possible inputs. Neural networks do not need any specific rules but only examples for training. Thus, neural networks are very attractive in recognition and classification tasks where complete rules cannot be written.

A subsample of subjects at high risk (HR) for alcoholism, and other subsample of (LR) were selected randomly from the available database [5]. The HR group consisted of 30 individuals and the LR group 30 individuals as well. We used 40 files for training the ANN and the rest of the 20 files for the testing purposes. The testing data files were never used in the training process.

Wavelet Transform: The Wavelet Transform (WT) is of interest for the analysis of non-stationary signals, because it provides an alternative to the classical STFT. The wavelet transform (WT) 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 WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study [9]. The basic difference is in contrast to the STFT, which uses short windows at high frequencies and long windows at low frequencies. This is in the spirit of the so-called “constant-Q” or constant relative bandwidth frequency analysis. It is desirable to see the WT as a signal decomposition onto a set of basis functions. In fact, as mentioned previously, these basis functions are called wavelets. They are obtained from a single prototype wavelet by dilations and contractions (scaling) as well as shifts. The prototype wavelet can be thought of as a band-pass filter, and the constant-Q property of the other band-pass filters (wavelets) follows because they are scaled versions of the prototype. Therefore, in WT, the notion of scale is introduced as an alternative to frequency, leading to a so called time-scale representation. This means that a signal is mapped into a time-scale plane. The mother wavelet should be chosen carefully in order to exhibit good localization properties in both the frequency and spatial domains [9]. We used in this work two types of mother wavelet functions to preprocess the EEG data: Birothogonal (Bior) and Daubechies (Db).

3. Results

We have built one ANN for each channel of EEG, that is, we have built 64 ANNS using the wavelet coefficients (WC) computed in the pre-processor step. Thus, each channel was evaluated independently with the aim of comparing both performances.

The layered feedforward net was trained using standard backpropagation [10] with different number of neurons in the hidden layers. The output activation is considered to be unknown if all the values of the activations at the output node are less than 0.01. The use of 200 hidden neuron numbers gave the most successful results in terms of general performance.

The neural networks identified differences between LR and RH subjects in most of electrodes of the parietal, occipital and temporal scalp, but electrodes of the frontal and central region failed in most of the identifications. These initial results were expected because the stimuli received stimulated the occipito-temporal region, according with [2], and [10].
The tables I to VI provide the classification results using the 2 types of mother wavelets, Daubechies (Db) and Birothogonal (Bior), from parietal, occipital and temporal scalp.

Table I, II and III: Classification results using Daubechies (Db). Table IV, V and VI: Classification results using Birothogonal (Bior).

### 3. Discussion

Ethanol is the object of a great deal of scientific investigation. Thus, enormous efforts reflect the need for understanding the biological basis of alcoholism and for to establish analysis tools, which can help in the diagnosis of predisposition for alcoholism, with aim to prevent the development of substance abuse in predisposed youths.

With an ANN built and trained with WC, and the computing of data from EEG electrodes, it was possible to reveal functional differences in the cortex of HR subjects. We suggest that this procedure would be considered as one clinical tool for the diagnosis of predisposition for alcoholism.

The WT technique offers a more general approach to parameter extraction than previously used parametric methods that rely on the expert selection relevant features. Thus, it can be readily generalized to the recognition and classification of other biomedical signals.

In future studies, other mother wavelets function can be investigated for better LR and RH subjects differentiation and the recognition performance of ANN further improved.

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References: