# Nonlinear Approach to Brain Signal Modeling

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## INTRODUCTION

Biological signal is a common term used for time series measurements that are obtained from biological mechanisms and basically represent some form of energy produced by the biological mechanisms. Examples of such signals are electroencephalogram (EEG), which is the electrical activity of brain recorded by electrodes placed on the scalp; electrocardiogram (ECG), which is electrical activity of heart recorded from chest, and electromyogram (EMG), which is recorded from skin as electrical activity generated by skeletal muscles (Akay, 2000).

Nowadays, biological signals such as EEG and ECG are analysed extensively for diagnosing conditions like cardiac arrhythmias in the case of ECG and epilepsy, memory impairments, and sleep disorders in case of EEG. Apart from clinical diagnostic purposes, in recent years there have been many developments for utilising EEG for brain computer interface (BCI) designs (Vaughan & Wolpaw, 2006).

The field of signal processing provides many methods for analysis of biological signals. One of the most important steps in biological signal processing is the extraction of features from the signals. The assessment of such information can give further insights to the functioning of the biological system.

The selection of proper methods and algorithms for feature extraction (i.e., linear/nonlinear methods) are current challenges in the design and application of real time biological signal analysis systems. Traditionally, linear methods are used for the analysis of biological signals (mostly in analysis of EEG). Although the conventional linear analysis methods simplify the implementation, they can only give an approximation to the underlying properties of the signal when the signal is in fact nonlinear. Because of this, there has been an increasing interest for utilising nonlinear analysis techniques in order to obtain a better characterisation of the biological signals.

This chapter will lay the backgrounds to linear and nonlinear modeling of EEG signals, and propose a novel nonlinear model based on exponential autoregressive (EAR) process, which proves to be superior to conventional linear modeling techniques.

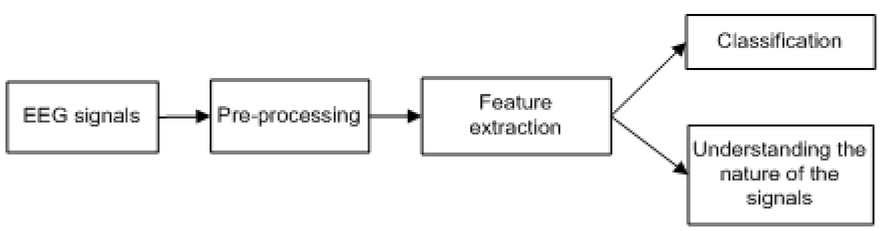
## BACKGROUND INFORMATION

### EEG Signal Processing

In recent years, the field of biological signal processing has seen an explosive growth. In particular, there have been many research studies on EEG signals for:

- Diagnosis of certain neurological conditions such as sleep disorders, memory impairments and epilepsy;
- Extracting relevant features for classification of different mental states;

*Figure 1. The basic steps in EEG signal analysis*



- Understanding the dynamics and underlying mechanisms of the brain.

Figure 1 shows the basic steps in the analysis of EEG signals, these are: *preprocessing* which includes the removal of noises such as the baseline noise, powerline interference and eye blink contamination; *feature extraction,* which extracts representative values of the signals through modeling techniques, and *classification,* where the extracted features are classified in specific for the application, such as discrimination between different mental states or neurological conditions. Note that the feature extraction step is not necessarily followed by classification—the features can also be used in understanding the nature and underlying dynamics of the signals, for example in investigating a certain brain disorder. The selection of appropriate feature extraction methods for obtaining a better representation of the EEG signals is the most challenging step in EEG signal processing. This can be approached in two ways namely the linear and nonlinear modeling techniques.

## Utilising Linear Modeling Techniques for Analysis of EEG Signals

Since its discovery by Hans Berger in 1929 (Sanei & Chambers, 2007) the EEG signals have been used extensively in research studies for diagnosis of certain neurological conditions (such as memory impairments, sleep disorders, and epilepsy). Traditionally linear modeling techniques like autoregressive (AR) modeling and power spectral estimation (PSD) have been extensively used for the analysis of EEG signals (Sanei & Chambers, 2007).

Palaniappan (2005) used second order AR model coefficients as features for the classification of EEG signals recorded from alcoholic and control subjects. The EEG signals were recorded from subjects while they were exposed to visuals selected from Snodgrass and Vanderwart picture set. The feature sets were classified using three different classification algorithms namely the simplified Fuzzy ARTMAP (SFA) neural network (NN), multilayer-perceptron trained by the backpropagation algorithm (MLP-BP) and Linear Discriminant (LD). The results of this study indicated that the classifiers were able to discriminate the alcoholic and control subjects with average discrimination error of 2.6%, 2.8% and 11.9% for LD, MLP-BP and SFA classifiers respectively.

In another study, Subasi, Kiymik, Alkan, and Koklukaya (2005) characterised and classified EEG segments recorded from epilepsy patients and healthy subjects using PSD values as feature sets. Two different methods were utilised for PSD estimation namely the AR spectral estimation and FFT-based spectral estimation. The feature sets were classified using multilayer feedforward neural network with backpropagation algorithm (MLP-BP). The results of this study indicated an average classification accuracy of 92.3% for AR spectral estimation and 91.6% for FFT-based spectral estimation. The authors also suggested that utilizing nonlinear methods instead of the conventional linear methods would improve the classification accuracy.

Apart from diagnostic purposes, in the last decade there has been an increasing interest in utilising EEG for Brain Computer Interface designs. Keirn and Aunon (1990) were one of the first groups that suggested using EEG as an alternative mode of communication between disabled people and their environment. The different pairs of mental tasks were classified (i.e., baseline, maths, letter composing, geometric figure rotation, and visual counting) using a Bayesian quadratic classifier. They used power asymmetry ratio for creating the feature sets since the mental tasks were identified as belonging to right or left hemisphere of the brain. In addition, they used AR model coefficients as feature sets. Their study showed that the AR method was superior to asymmetry ratios where the most significant result was 84.6% classification accuracy for discrimination of two different mental tasks.

## Utilising Nonlinear Modeling Techniques for Analysis of EEG Signals

The individual neurons in the brain behave in a nonlinear manner. There are many research studies reporting more or less successful attempts to apply nonlinear methods to biological time series data (Babloyantz, Salazar & Nicolis, 1985; Bukkapatnam et al, 2002; Gautama, Van Hulle & Mandic, 2003; Lehnertz, Mormann, Kreuz, Anderzak, Rieke & David, 2003; Stepien, 2002).

One of the first studies on nonlinear EEG analysis was by Babloyantz et al. (1985). In this study it was shown that certain nonlinear measures (i.e., Correlation Dimension) change during low-wave sleep patterns. In other words, different sleep stages could be discriminated using these nonlinear measures. After this study the nonlinear methods began to attract the interest of many researchers. Nonlinear methods have been applied mainly to areas such as diagnosis of epileptic seizures and sleep disorders (Chippa & Bengio, 2003).

Bukkapatnam (2007) characterized and classified two different mental conditions from EEG signals using the theory of nonlinear dynamical systems. In this study, 64 channel signals of length 256 samples recorded from 20 people were used. Out of 20 EEG signals used, 10 were obtained from people under alcoholic influence and the remaining ten were recorded from people in a normal (non-alcoholic) condition. The feature sets were created by calculating the correlation dimension of the EEG segments (where this measure quantifies the nonlinear complexity of the signals) (Sanei & Chambers, 2007). The created feature sets were used as an input to a two layer back propagation neural network. The