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.

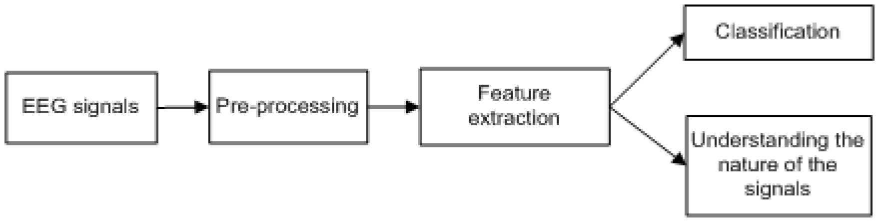
BACKGROUND INFORMATION

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 (Snodgrass & Vanderwart, 1980). 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) (Haykin, 1998). 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 classifier was able to distinguish between subjects under alcoholic influence and the control subjects with 90% accuracy. The results of this study indicated that EEG signals could be described as noise-contaminated, nonlinear, and perhaps chaotic dynamic systems.

In Stepien et al. (2002), an analysis of spontaneous EEG of 21 healthy subjects recorded when they were resting was conducted. The EEG signals were tested if they were generated by a nonlinear process using surrogate data method (Theiler, Eubak, Longtin, Galdrikian & Farmer, 1992), where the nonlinear prediction error was used as a test statistic. Out of 336 (from 21 subjects with 16 channels) EEG segments, only 17 (5%) of them were found to be nonlinear. The results of this study indicated very low percentage of nonlinearity in the EEG signals recorded from healthy subjects. However, the existence of nonlinearity in various pathological states like epilepsy is indicated by Lehnertz et al. (2003) and Gautama et al. (2003). The existence of this distinguishing feature between normal and diseased cases would allow improved classification of EEG signals using nonlinear methods.

In another previous study done by Gautama et al. (2003), the nonlinearity of EEG signals recorded from healthy and epilepsy patients was investigated. In total, five sets of EEG data were utilised where the sets A and B were recorded from healthy subjects with eyes open and closed, the sets C and D were recorded from epilepsy patients during seizure-free interval from epileptogenic zone and from outside of epileptogenic zone, respectively. And the set E contained the EEG segments recorded from epilepsy patients during seizure activity recorded from seizure generating areas. The nonlinearity of the EEG segments was assessed by surrogate data method (Theiler et al., 1992) where the delay vector variance, third order autocorrelation and asymmetry due to time reversal methods were used for the characterisation of time series (Gautama et al., 2003). The results of this study indicated that the percentage of nonlinearity is lower for EEG segments recorded from healthy subjects (i.e., with eyes open and closed: sets A and B) compared to epilepsy patients (i.e., during seizure and seizure free intervals: sets C, D, and E). These results show that there are clear differences in dynamical properties of the electrical activity of the brain recorded from different physiological and pathological brain states.

Lehnertz et al. (2003) indicated in his article that there are plenty of evidences in the literature that nonlinear EEG analyses are able to characterize the neuronal behavior in the brain and provide a tool for detecting the preictal state in the epilepsy patients. However the sufficiency of sensitivity[a] and specificity[b] of these analysis techniques are still subject to current research. The development of new time series analysis techniques that will sufficiently represent the nonlinear, chaotic and multidimensional behavior of the EEG signals will improve the understanding of the brain dynamics. Once enough specificity and sensitivity is obtained from these analysis techniques, more extensive clinical studies and the implementation of such systems can be considered in the future.

EXPONENTIAL AUTOREGRESSIVE MODEL–A RECENT NONLINEAR MODELING TECHNIQUE FOR ANALYSIS OF EEG SIGNALS

Haggan and Ozaki (1981) introduced EAR algorithm for modeling nonlinear fluctuations in time series. They stated that the analysis of stochastic processes have been mostly done using some form of linear time series modeling and this can only provide an approximation to the underlying properties of the signals. Besides, it is found that many signals exhibiting random vibrations display nonlinear behavior; hence a nonlinear model that gives a good approximation to the underlying properties of a signal is required.

The EAR model exhibits certain features of random vibrations that do not occur in linear models namely the amplitude-dependent frequency, jump phenomena and limit cycle (Haggan & Ozaki, 1981).

An EAR model of order p is defined by;

$$x_t = \sum_{k=1}^{p} (\varphi_k + \pi_k \cdot e^{-\gamma x_{t-1}^2}) \cdot x_{t-k} + e_t \tag{1}$$

where φ, π, γ are autoregressive coefficients, x_t is data at sampled point t, p is the model order and e_t is Gaussian white noise with mean zero.

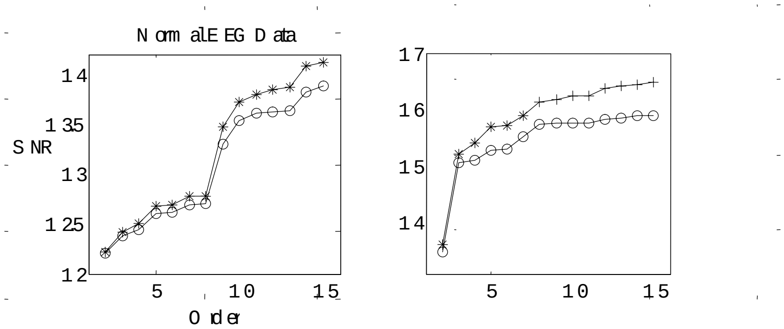
The nonlinearity of the EAR model comes from the exponential term, $e^{\gamma \cdot x(n-k)^2}$, which makes the series globally nonlinear. If nonlinear parameter γ is set to 0, the equation will become an ordinary linear AR model with coefficients $a_p = \varphi_p + \pi_p$ such that;

$$x_t = \sum_{k=1}^{p} a_k \cdot x_{t-k} + e_t \tag{2}$$

The estimation of the 2p+1 coefficients {γ, (φ_i, π_i, i=1,2,…,p)} of the EAR model is a nonlinear optimisation problem, hence is complicated especially with increasing model order. In order to achieve this task, binary genetic algorithms (BGA) hybridized with recursive least squares (RLS) algorithm can be used (Shi & Aoyama, 1997).

Genetic algorithms are search algorithms inspired by the natural selection and natural genetics which can be used to solve optimisation problems. Initially, there is a population of candidate solutions to the optimisation problem and the

Figure 2. Example of SNR result when linear/nonlinear methods were applied to EEG modeling



solutions evolve toward better solutions according to the principles of natural selection (i.e., survival of the fittest) (Goldberg, 1989). For the selection of the fittest chromosome, a fitness function that measures the performance of a chromosome in the population must be defined according to the optimisation problem to be solved.

In our study here, the nonlinear coefficient γ of the EAR model is determined by BGA and once the nonlinear coefficient is obtained, the model will become a linear regression problem in which the linear coefficients, $\{\varphi_i, \pi_i, i=1,2,\ldots,p\}$ will be determined by RLS algorithm. Moreover, the model order is selected as the order with minimum Akaike Information Criterion (AIC) value (Akaike, 1974).

Figure 2 shows an example of signal to noise ratio (SNR) results obtained by applying conventional linear AR modeling and EAR modeling to EEG data from a healthy subject and an epilepsy patient. Note that the SNR values were calculated by reconstructing time series with corresponding AR coefficients (for both AR and EAR modeling techniques) and calculating the SNR between original and reconstructed signals. The figure clearly indicates an improved modeling when EAR was used.

These initial results are promising since it appears that the EAR method can provide an improved characterisation of time series. It is hoped that this method will lead to a better representation of the EEG signals when used in various applications.

FUTURE TRENDS

The preliminary results obtained from EAR model are promising since they indicated an improved modeling of EEG signals recorded from healthy subjects and epilepsy patients. However, further experiments should be conducted to investigate the representative ability of EAR method for the classification of different classes of EEG data (i.e., EEG data from epilepsy patients during seizure and seizure free intervals, EEG data from healthy subjects, mental task EEG data, etc).

The proposed improved EAR method could also be explored for other biological signal analysis applications, such as electrophysiological analysis of cognitive processes, prediction of epilepsy onset, abnormal heart sound and beat detection, heart rate variability monitoring, and so forth.

CONCLUSION

The characterisation (i.e., feature extraction) of EEG signals is one of the most challenging steps towards the design of a real time biological signal analysis system. In order to achieve that task, knowledge of the underlying dynamics of the EEG signals is necessary so that suitable modeling techniques could be utilised for characterisation of the EEG signals. In recent years, nonlinear time series analysis techniques in particular largest Lyapunov exponent, correlation dimension and nonlinear prediction error measures along with surrogate data method were repeatedly applied to some of the biological signals (specifically, EEG) in order to understand the nature of the signals. The results of these studies suggested presence of highly significant nonlinearities in EEG signals, especially the signals recorded from patients with neurological disorders. However the sensitivity and specificity of the utilized nonlinear measures are still subject to current research. It is believed that the development of new time series analysis techniques that will sufficiently represent the nonlinear, chaotic and multidimensional behavior of the EEG signals will improve the understanding of the brain dynamics.

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KEY TERMS

AR: Autoregressive model, a linear prediction model where each data point in time series is defined to be linearly related to its previous data points.

EAR: Exponential Autoregressive model, a nonlinear extension of Autoregressive model.

Linear Regression: A technique that attempts to model a set of data points by fitting a linear equation to the data.

Linear System: A system f(·) that obeys the superposition and scaling property is said to be linear such that; for $a, b \in R : f(a\cdot x + b\cdot y) = a\cdot f(x) + b\cdot f(y)$.

Linear Signal: A linear signal is generally defined as the output of a linear shift invariant system that is driven by Gaussian white noise.

Nonlinear Signal: A nonlinear signal is generally defined as the signal generated by the system that does not obey superposition and scaling properties.

Power Spectral Density: Power spectral density shows the power per unit frequency of a signal.

Shift-Invariant System: A shift-invariant system is known as a system that input-output relationship does not vary with time such that; let $y[n]$ be the response of the system to input $x[n]$, for any delay t, the response of the system to input $x[n-t]$ will be $y[n-t]$.

Stochastic (Random) Process: Opposite of deterministic processes in which the future states of the system can not be predicted precisely. In other words, even if the initial states of the process are known there are many states that the process can go where some states are more probable than others.

White Noise: A random signal that has equal amount of power at all frequency bands.

ENDNOTES

[a] Sensitivity is a statistical measure of how well a classification test correctly identifies a condition.

[b] Specificity is a statistical measure of how well a classification test correctly identifies the negative cases, or those cases that do not meet the condition under study.