TIME SERIES ANALYSIS OF EEG SIGNALS

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Abstract

Time series analyses have a broad spectrum of applications ranging from identification, prediction and control of dynamical systems. The application areas range from medical signal processing to stock market prediction. In this paper, we analyse time series modelling using autoregressive techniques for extracting features to represent electroencephalogram (EEG) signals. We extract EEG signals for different mental tasks. These EEG signals are segmented and Burg's method is used to obtain the AR coefficients. Next, a Fuzzy ARTMAP neural network classifies the mental tasks into their respective categories. Our results show that it is highly possible to discriminate between different mental tasks for each subject using the proposed technique.

Keywords: EEG; Autoregressive Time Series; Fuzzy ARTMAP; Burg

1 Introduction

Time series analysis using autoregressive (AR) models have a broad spectrum of applications ranging from identification, prediction and control of dynamical systems and digital analysis using these models have proven to be superior to classical Fourier transform techniques like Discrete Fourier Transform (DFT) or the computationally efficient Fast Fourier Transform (FFT). This is due to the ability of AR models to handle short segments of data. In addition, computation of AR coefficients are faster than to compute the Fourier spectra. The AR model coefficients can be easily estimated by solving a set of linear equations using the Yule-Walker method or solving recursively for higher orders using Burg method.

In this paper, we focus our attention on analysing electroencephalogram (EEG) signals for different mental tasks using AR time series with Burg method and we classify these signals using a Fuzzy ARTMAP classifier.

A real valued, zero mean, stationary, non-deterministic, autoregressive process of order *p* is given by

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + e(n), \qquad (1)$$

where p is the model order, $x(n)$ is the data of the signal at sampled point n, a_k are the real valued AR coefficients and $e(n)$ represents the error term independent of past samples.

Many different techniques have been proposed to estimate a_k, each with its own merits and demerits. The most common method is to use the autocorrelation technique of solving the Yule-Walker equations. We can solve the Yule-Walker equations directly using conventional linear equation solutions like Gaussian elimination but a shortcoming of this approach lies in its huge computational time. Thus, recursive algorithms have been developed which are based on the concept of estimating the parameters of a model of order p from the parameters of a model of order $p-1$. One of these methods is Burg's algorithm.

Burg's method is common is AR literatures and as such, we'll only discuss briefly the algorithm behind this method. The algorithm is as follows:

1. Calculate initial values

- Error variance, $\hat{\sigma}_e^2(0) = \frac{1}{N}\sum_{0}^{N-1}[x(n)]^2$

  where $x(n)$ is the n^{th} sampled data with mean value subtracted
- Forward error, $e_n(0) = x(n)$
- Backward error, $b_{n-1}(0) = x(n-1)$

2. Calculate reflection coefficient and error variance

- Reflection coefficient,

$$\pi_m = -2\frac{\sum_{n=m}^{N-1} b_{n-1}(m-1)e_n(m-1)}{\sum_{n=m}^{N-1}[e_n^2(m-1)+b_{n-1}^2(m-1)]}$$

- Error variance,

$$\sigma_e^2(m) = [1-|\pi_m|^2]\sigma_e^2(m-1)$$

3. Update Error and AR coefficients

- AR coefficients,

$$\left.\begin{aligned} a_k(m) &= a_k(m-1)+\pi_m a_{m-k}(m-1) \\ a_m(m) &= \pi_1 \end{aligned}\right\} \begin{aligned} m &> 1 \\ m &= 1 \end{aligned}$$

- Forward Error Update,

$$e_n(m) = e_n(m-1)+\pi_m b_{n-1}(m-1)$$

- Backward Error Update,

$$b_n(m) = b_{n-1}(m-1)+\pi_m e_n(m-1)$$

4.Repeat steps 2 and 3 (with m incremented by one) until the selected model order p is reached.

Proofs and details of this algorithm can be found in [2].

2 Fuzzy ARTMAP

Fuzzy ARTMAP (FA) system learns to classify inputs by using fuzzy set features i.e. the input features are from 0 to 1. FA incorporates fuzzy set theory in its computation and as such it is able to learn stable responses to either analogue or binary valued input patterns. It consists of two Fuzzy ART modules (Fuzzy ART_a and Fuzzy ART_b) that create stable recognition categories in response to sequence of input patterns. During supervised learning, Fuzzy ART_a receives a stream of input features representing the pattern and Fuzzy ART_b receives a stream of output features representing the target class of the pattern. An Inter ART module links these two modules, which is actually an associative controller that creates a minimal linkage of recognition categories between the two Fuzzy ART modules to meet a certain accuracy criteria. This is accomplished by realising a rule that minimises predictive error and maximises predictive generalisation. It works by increasing the vigilance parameter ρ_a of Fuzzy ART_a by a minimal amount needed to correct a predictive error at Fuzzy ART_b.

Parameter ρ_a calibrates the minimum confidence that Fuzzy ART_a must have in a recognition category, or hypothesis that is activated by an input vector in order for Fuzzy ART_a to accept that category, rather than search for a better one through an automatically controlled process of hypothesis testing. Lower values of ρ_a enable larger categories to form and lead to a broader generalisation and higher code compression. A predictive failure at Fuzzy ART_b increases the minimal confidence ρ_a by the least amount needed to trigger hypothesis testing at Fuzzy ART_a using a mechanism called match tracking. Match tracking sacrifices the minimum amount of generalisation necessary to correct the predictive error. Match tracking leads to an increase in the confidence criterion just enough to trigger hypothesis testing which leads to a new selection of Fuzzy ART_a category. This new cluster is better able to predict the correct target class as compared to the cluster before match tracking. Figure 1 shows the network structure of FA as used in this paper. Further details of this method can be found in [3-4].

3 Experimental Study

The subjects are seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noiseless fans for ventilation. An Electro-Cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2, defined by the 10-20 system of electrode placement [5]. The electrodes are connected through a bank of amplifiers and bandpass filtered from 0.1--100 Hz. The data was sampled at 250 Hz with a 12-bit A/D converter mounted on a computer. For this paper, the data from three subjects performing two different mental tasks are analysed. These tasks are

- Baseline task, for which the subjects are asked to relax as much as possible and

- Multiplication task such as 23 x 97.

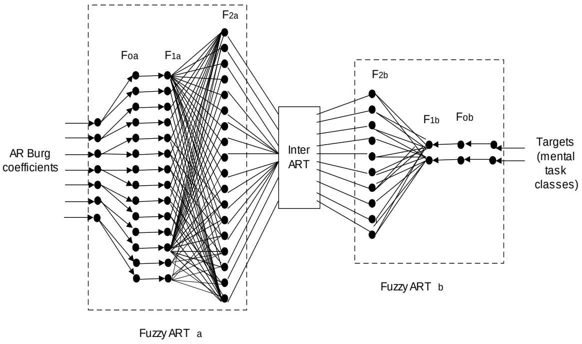

Figure 1: Fuzzy ARTMAP structure as used in this paper

The EEG signals are segmented with a half second window i.e. each segment consists of 125 points. In other words, each EEG signal will be segmented into 20 segments. In this paper, we have experimented with model orders 25, 30 and 35. EEG feature vectors consist of concanated AR coefficients for each of the 6 channels. FA classifier is used to classify these features into their respective tasks. For all the experiments, 50% of available patterns are used for training while the rest 50% are for testing. We have also experimented the effects of varying vigilance parameter ρ_a on classification of these signals.

4 Results

Table 1 shows the results of the experimental study conducted with different subjects for two mental tasks, namely baseline and math task. From this table, we can see that it is easy to differentiate EEG signals for subject 3 using the proposed method. Subject 1 performs the worse among the three. However, with more data for training, these results would give a higher classification percentage. In general, the results also show that Fuzzy ARTMAP gives best performance with ρ_a value of 0. This is since ρ_a value of 0 gives maximum generalization ability to the network and as such performs better.

5 Conclusion

In this paper, we have considered using autoregressive time series analysis to discriminate between mental tasks. We have extracted AR coefficients from the EEG signals using Burg's method and classified the signals using a Fuzzy ARTMAP classifier. The results show that it is possible to differentiate between mental tasks using the proposed method.

Table 1: Results of experimental study

	model order 25		
	S1	**S2**	**S3**
pa=0.0	70	100	100
pa=0.5	65	90	95
pa=0.9	70	80	85
	model order 30		
pa=0.0	55	85	100
pa=0.5	75	85	100
pa=0.9	60	65	95
	model order 35		
pa=0.0	65	95	100
pa=0.5	65	80	100
pa=0.9	70	80	90

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