Fuzzy Artmap Classification of Mental Tasks using Segmented and Overlapped EEG Signals

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Abstract: Visual inspection of EEG signals in their unprocessed form is still the predominant way of discriminating EEG patterns in the medical community and requires highly trained medical professionals. To overcome this problem, automatic EEG analysis using Fourier Transform methods are popular since most EEG signals consist of spectral power in the range of δ, θ, α and β i.e from 0 to 30 Hz. But this method suffers from high noise sensitivity and is not suitable for short and variable length of signal segments. In this paper, we analyse EEG signals with time series analysis using autoregression techniques. We classify these extracted features for different mental tasks using a Fuzzy ARTMAP classifier. We study the effects of different EEG segment or window lengths and different overlapping lengths on the overall performance of the classifier. Our results show that the segment length affects the performance and that overlapping the segments improves the performance greatly.

Keywords
EEG, Autoregressive Spectral Analysis, Fuzzy ARTMAP, Overlapping, Segmentation

I. INTRODUCTION

Autoregressive (AR) processes are as their name implies – regressions on themselves. In this paper, we analyse AR models with modern spectral analysis for EEG signals. Different mental tasks are represented by spectral values obtained from EEG-AR models and a Fuzzy ARTMAP network [3] is used to classify these signals into their respective mental tasks. Specifically, the purpose of the work described in this paper is to investigate the effects of segmentation length i.e. window length and overlapping of the EEG signals on the overall classification performance.

The EEG signals are represented by AR models of order p, which 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 AR coefficients and $e(n)$ represents the error term independent of past samples. The obtain a_k, we can solve the Yule-Walker equations directly using conventional linear equation solution 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 order p-1. Some of these methods are like the Levinson–Durbin and Burg algorithm. Burg algorithm is used in this paper since this algorithm uses not only the forward prediction error but also the backward prediction error and minimises the sum of both of them. Therefore, in general it has proven to be a much more accurate method than other algorithms like Levinson-Durbin which uses only the forward prediction error [7].

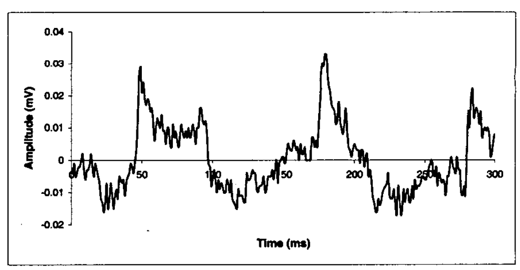

Figure 1. An EEG signal

Once the appropriate model order has been determined, the AR parameters are obtained. Using these AR coefficients, the power spectral density (PSD) function can be obtained by using the equation

$$S(f) = \frac{s_p^2 T}{\left| \sum_{k=0}^{p} a_k e^{-i2\pi fkT} \right|^2} \tag{2}$$

where $S(f)$ represents the power spectral density function and T is the sampling period and s_p^2 is the total squared error divided by N and is given by

$$s_p^2 = \frac{1}{N} \sum_{p}^{N-1} e^2(n) \tag{3}$$

II. 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 Grass 7P511 amplifiers and bandpass filtered from 0.1--100 Hz. The data was sampled at 250 Hz with a Lab Master 12 bit A/D converter mounted in an IBM-AT computer.

For this paper, the data from four subjects performing two different mental tasks are analysed.

- Geometric figure rotation, for which the subjects were asked to visualize a particular three-dimensional block figure being rotated about an axis
- Math task, for which the subjects are given nontrivial multiplication problems, such as 34 times 48, and are asked to solve them without vocalizing or making any other physical movements

The experiments are repeated for a second session. The EEG signals are recorded for a period of 10 seconds. With a 250 Hz sampling rate, each 10 second trial produces 2,500 samples per channel. Overall, there are 16 different EEG files (2 tasks x 4 subjects x 2 sessions).

A study is performed on the effects of the segment (window) length and of the length of overlap between the segments on the performance of the AR model with FA classification. In the experimental study, the 10 second EEG signals are segmented into smaller manageable lengths with different overlap lengths. These are

1. Half second window segment producing 20 segments for each EEG channel (without overlapping)
2. One second window segment with an overlap of half second producing 19 segments for each EEG channel
3. Quarter second window segment producing 40 segments for each EEG channel (without overlapping)
4. Half second window segment with an overlap of quarter second producing 39 segments for each EEG channel

In this paper, we have chosen a model order of 6 based on the results of studies performed by Keirn and Aunon [6] and therefore the EEG feature vector consists of six coefficients for each of the C3 C4, P3, P4, O1, and O2 channels i.e. a total of 36 features to represent each task.

For all the experiments, 50% of available patterns are used for training while the rest 50% are for testing. Since we are interested in classifying EEG signals, we only extract PSD values in the range of δ, θ, α and β i.e from 0 to 30 Hz. Since we have 6 channels, we have a total of 180 inputs. Next, Fuzzy ARTMAP network is used with these PSD values for classifying different mental tasks. The performance of the classifier is used to show the difference in the ability of the different model order selection criteria.

III. FUZZY ARTMAP

This section introduces Fuzzy ARTMAP network. Fuzzy ARTMAP belongs to the ART family. There are several variations of these ART neural networks, namely ART1, ART2, ART3, Fuzzy ART, Fusion ART, Fuzzy ARTMAP and ART-EMAP. These systems were initially developed by Carpenter and Grossberg [2-4].

ARTMAP is a class of neural network that performs incremental supervised learning of recognition categories in response to input vectors presented in arbitrary order [4]. Earlier Adaptive Resonance Theory models like ART1 and ART2 consisted of unsupervised learning systems. In this paper, a more general ARTMAP system known as Fuzzy ARTMAP is used [3]. This system learns to classify inputs by using fuzzy set features i.e. the input features are from 0 to 1. This generalisation is accomplished by replacing the ART1 module of the binary ARTMAP system with Fuzzy ART module.

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 Minimax Learning 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. In this paper, we have used ρ_a of 0.9 for all the experiments.

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 2 shows the Fuzzy ARTMAP network model used in this study.

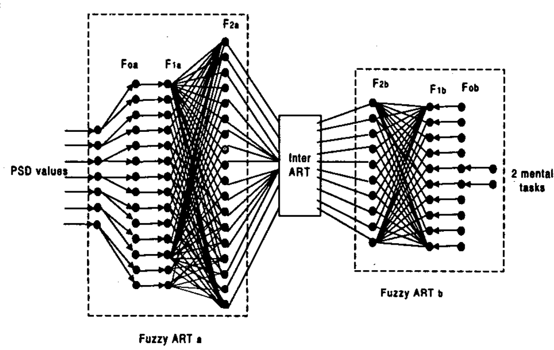

Figure 2. Fuzzy ARTMAP structure as used in this paper

IV. RESULTS

Table 1 shows the results of an experimental study conducted with different number of subjects for two mental tasks, i.e. rotation and math task. The results are shown for session 1, session 2 and both session combined. It can be seen that the segment lengths affect the performance but the results are not conclusive i.e. for some experiments, half-second window performs better while for some cases, the quarter second window performs give better results.

Next, we look at the effects of overlapping the EEG segments. To ensure fair comparison, results in row 1 should be compared with results in row 2 and similarly for rows 3 and 4 for each session. This is since the first two rows (in each session) have nearly similar amount of patterns for training and testing and likewise for the last two rows. Comparison of results in this way shows that overlapping the segmented signals improves the AR representation and FA classification performance greatly. In general, the best overall performance is obtained for a segment window of one second and an overlap of half-second.

Table 1: Results of the experimental study

Segmentation/ Overlap	1 user	2 users	3 users	4 users
Session 1				
0.5 s no overlap	70.00	85.00	88.33	78.75
1.0 s 0.5 s overlap	78.95	94.74	94.74	93.42
0.25 s no overlap	57.5	88.75	80.00	73.75
0.5 s 0.25 s overlap	87.18	94.87	94.87	89.75
Session I1				
0.5 s no overlap	70.00	90.00	66.67	65.00
1.0 s 0.5 s overlap	94.74	97.37	91.23	88.16
0.25 s no overlap	67.5	81.25	73.33	72.5
0.5 s 0.25 s overlap	89.74	94.87	87.18	75.00
Both Session Combined				
0.5 s no overlap	72.5	67.5	87.5	68.75
1.0 s 0.5 s overlap	78.9	94.74	92.11	83.53
0.25 s no overlap	67.5	77.5	73.75	63.75
0.5 s 0.25 s overlap	85.9	92.31	85.9	73.72

V. CONCLUSION

In this paper, we have studied autoregressive-modelling techniques for EEG spectral analysis and the effects of segmentation and overlapping of EEG signals on Fuzzy ARTMAP classification performance for different mental tasks. Our results show that overlapping the EEG signals improves the results. However, the effects of the segment length (i.e. window length) are inconclusive. The results also show that it is possible to differentiate between mental tasks to a high degree of accuracy using EEG signals for each subject and this can be used, say as a mode of communication for paralysed patients [6].

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