

COGNITIVE TASK PREDICTION USING PARAMETRIC SPECTRAL ANALYSIS OF EEG SIGNALS

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ABSTRACT

In this paper, we are proposing a method to predict cognitive tasks performed by the human brain using spectral analysis of electrical signals extracted from the scalp of the brain. These electrical signals, which are generated by the synapses and neurons in the brain, are also known as Electroencephalogram (EEG) signals. The EEG signals are analysed using autoregressive spectral analysis, a type of modern parametric spectral analysis method, which comparatively yield better power spectrum over the classical Fourier methods. Power spectral densities of the EEG signals are used to train a Fuzzy ARTMAP network to predict the respective cognitive tasks. In our experimental study, we have analysed 3 subjects performing 2 different cognitive tasks and our average results of 72.22% to 93.05% for each subject show that it is highly possible to predict cognitive tasks based on EEG signals. This can be used as a mode of communication or wheelchair control for paralysed patients and also in EEG biofeedback systems.

Keywords: *EEG, Autoregressive spectral analysis, Cognitive task, Fuzzy ARTMAP, Burg's algorithm*

1.0 INTRODUCTION

Although the spontaneous electrical activity of the brain or the electroencephalogram (EEG) was discovered in rabbits and monkeys more than a century ago by Caton in 1875 [7] and the first report concerning the human EEG appeared more than 60 years ago [8], much remains to be clarified about the nature and the origin of the EEG. Nonetheless, very soon after its discovery in humans, EEG became an important diagnostic tool and it has remained so. From 1924 to 1938, Berger [8] laid the groundwork of our present applications of EEG. Since then, a gradual realisation of EEG in the application of controlled information has led to significant correlations with regard to brain functioning in certain mental and behavioural states. However, in EEG, the revolution of computerisation has not turned out to be far reaching and enduring as the revolution in neuro-imaging brought about by computerised axial tomography (CAT), magnetic resonance imaging (MRI), and positron emission tomography (PET). And yet, as a non-invasive clinical tool for evaluating brain function, the EEG continues to be very useful. Furthermore, spectral analysis of EEG signals has evolved over the past three decades with much of the effort directed towards a better understanding of the functioning of the brain.

These EEG signals are composed of oscillating potentials derived from the scalp surface and originating from the electrical activity of the brain; specifically EEG signals are generated by neurons and synapses in different areas of the brain. The potentials may vary in frequency from less than 1 to 50 Hz and achieve amplitudes up to 50 μ V. However, there is a concentration of frequency ranges in normal individuals. This varies from 8 to 13 Hz, which is known as alpha rhythm, beta potentials are those higher than 13 Hz, theta rhythms are at 47 Hz and the slow delta rhythms range between 0.5 and 3.5 Hz.

In this paper, we are proposing a method to predict cognitive tasks performed by the human brain using spectral analysis of these EEG signals. A benefit of this system is as a means of communication between paralysed patients and their external environment i.e. as an interface for use by people with severe physical disabilities. As the technology advances, it is envisaged that this technique could be used by anyone for rudimentary user-interface actions, like popping up windows and making menu choices. These systems can also be used in wheelchair movement control for paralysed patients in addition to providing useful information in EEG biofeedback systems.

Digital spectral analysis using linear parametric methods like autoregressive (AR) models have proven to be superior to classical Fourier transform techniques like Discrete Fourier Transform (DFT) using the periodogram approach. This is due to the ability of Autoregressive Spectral Analysis (ARSA) models to handle short segments of data while giving better frequency resolution and smoother power spectra than Fourier methods. Furthermore, AR methods need only one or more cycles of sinusoidal-type activity to be present in the segment to produce good spectral peaks and they also provide the ability to observe small shifts in peak frequencies, which are not easily observed with periodogram derived spectra [9].

In this study, EEG signals from 3 subjects are extracted while performing 2 different cognitive tasks. The signals are segmented and two different statistical model order criteria are applied namely Akaike Information Criterion (AIC) and Final Prediction Error (FPE) before the AR coefficients are obtained. The AR model coefficients can be estimated by solving a set of linear equations using the Yule-Walker method or solving recursively for higher orders using Levinson-Durbin [2] or Burg method [3]. Burg's method is used in this paper since it minimises not only forward prediction error but also backward prediction error unlike Levinson-Durbin (LD), which minimises only the forward prediction error. This method also derives AR coefficients directly from the data where as LD method requires the use of autocorrelation (AC) method, which is erroneous for small length of data. Next, ARSA method is used to generate power spectral densities (PSD) of these EEG segments. These PSD values are then used to train a Fuzzy ARTMAP (FA) neural network to predict the cognitive tasks for the test EEG patterns. FA network is used instead of other popular neural networks since it has low training time and gives good accuracy in addition to being plastic while maintaining stability.

Section 2 gives an introduction to EEG signals. In section 3, we give a description of the ARSA method including the statistical model order criteria and AR coefficient estimation using Burg's algorithm. Section 4 discusses Fuzzy ARTMAP while Section 5 treats the experimental study and results. The paper is concluded in Section 6.

2.0 EEG SIGNALS

Electroencephalogram (EEG), is a measure of brain activity. The word comes from the Latin 'encephalon', which means 'brain'. EEG is measured using electrodes (small metal pieces) attached to the skull surface. Nerve cells in the brain constantly create very small electrical signals. The actual generator of these potentials is thought to be neurons in the cortex (the outer part of the brain). The electrode is however large in comparison to the neurons, so what can be seen on an EEG signal is a summation of the activity of thousands or millions of neurons. The EEG machine contains amplifiers, which amplifies these brainwaves signals, large enough so that we can see them. The electrical signals are picked up by electrodes glued to the scalp, and travel to the amplifiers of the EEG machine and then are either written out on paper or saved on the hard drive of a computer and displayed on the computer's monitor or used in computerised signal analysis.

2.1 Method of Deriving EEG Signals (Montages)

There are three traditional methods of deriving electrical signals from an electrode array. These *montages* are commonly described as bipolar, unipolar (or monopolar) and average reference methods. However, it must be remembered that all derivations are essentially bipolar in the sense that the detecting device must be connected between two points and will indicate the potential difference between them. The average reference method is not very popular and will not be discussed further.

In the bipolar method, each channel is connected between two electrodes both of which are likely to be affected by appreciable EEG potentials i.e. active areas of the brain. Monopolar method however, uses two electrodes – one connected to the EEG active area and another from a reference of zero potential (typically placed at the earlobe). In certain literatures, we find the term common reference is used. It actually denotes monopolar readings but with all the reference channels located on a common electrode. This common reference method is employed in this paper since it reduces the number of electrodes required.

Note that the amplifier looks at the two electrode signals coming into it and cancels out signals that are the same. So, the signal that is seen on the paper or on the computer screen is actually the difference between the electrical activities picked up by the two different electrodes. Fig. 1 shows an example of EEG waveform obtained in the experimental study of this paper.

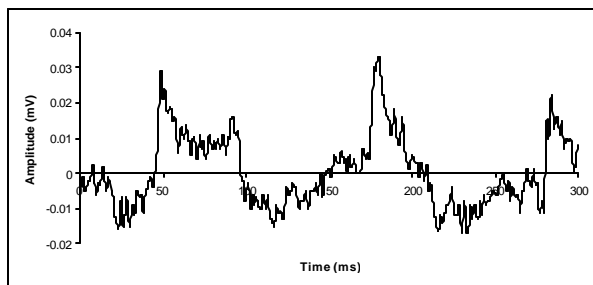


Fig. 1: An extracted EEG segment

2.2 Electrode Placement

Electrode placement is also an important topic in EEG analysis. The placement of the electrodes is important because the closer the electrodes are to each other, the less are the differences in their brainwaves. Therefore, if the electrodes are too close, the EEG will look like a straight line instead of showing the brainwaves. However, this problem does not arise for monopolar readings using common reference scheme since the reference channel is of zero potential. In this research, we have used the 10-20 international method [10] to place the electrodes, which consists of 19 active channels plus 2 reference channels. There is also the 64-channel EEG electrode placement using Standard Electrode Position Nomenclature, American Electroencephalographic Association but this method was opted out due to high number of channels, which is unnecessary for the application discussed in this paper. Fig. 2 shows the 10-20 international system of EEG electrode placement. In this system, we have used 6 active channels plus 2 reference channels (refer to Section 5).

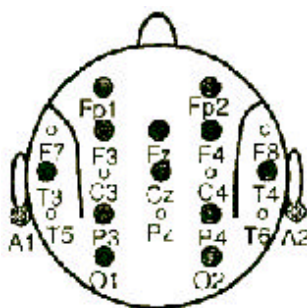


Fig. 2: 10-20 International system for EEG electrode placement

2.3 Artifacts

Another, not always wanted, source of these potentials is muscular activity such as eye and head movements, also known as artifacts. However, eye movements can be filtered using additional electrodes placed above and below the eye. This process of detecting eye movements is known as electroculography (EOG). When the reading from these electrodes show high potentials in less than 100 ms, then an eye movement has occurred and the EEG signals from the brain for that particular period of time should be removed from the analysis. Muscle artifacts from other parts of the body i.e. Electromyogram (EMG) can be removed using digital filtering in the frequency domain. This is since most normal EEG signals do not exceed 50 Hz. Therefore, a low pass filter designed to cut off at this frequency would filter out these unwanted higher frequency spectrum.

Electrical interferences also do pose a treat to corrupt EEG signals. But these are easily filtered out since they show up with a peak according to their power distribution frequency. For example, in Malaysia, the frequency of the electrical power is about 50 Hz and frequency peaks close to this value can be filtered out.

3.0 SPECTRAL ANALYSIS OF EEG SIGNALS

Interpretations of EEG signals visually often require expert medical or technical professionals. To overcome this problem and to automate EEG analysis, spectral analyses of EEG signals have been proposed [9, 13]. This is since an EEG signal can be regarded as a time series, which can be analysed mathematically. Usually, this analysis cannot be applied exactly because the necessary theoretical conditions cannot be met in practice. However, with some minor modifications and assumptions, these methods provide a useful approach to studying EEG signals. This is similar to the analysis of signals in other branches of science like seismography and in the study of ocean waves.

3.1 Theoretical Basis of EEG Frequency Analysis

Frequency analysis is the process of separating a signal into its frequency components. Each frequency component in the spectrum has an associated phase, which can be expressed as a function of frequency; the result is called a phase spectrum. Therefore, to describe a signal uniquely, both an amplitude spectrum and a phase spectrum are required. Often, the amplitude values are squared and the result of analysis is called a power spectrum. The sum of the values of the power spectrum is equal to the total power or mean squared value of the original signal (Parseval's theorem). This is why power or variance measures often used instead of amplitude measures in signal analysis since the sum of component amplitudes is not equal to the total amplitude because of phase effects.

Using frequency analysis, the proportion of a signal attributable to a particular frequency or range of frequencies can therefore be measured. In our case, the power spectrum is scaled so that the area under the spectrum is equal to the mean squared value of the original signal and the spectrum is called a power density spectrum or power spectral density (PSD).

3.2 Fourier Analysis vs Parametric Spectral Analysis

Frequency analysis using Fourier methods are popular. DFT or the computationally efficient FFT with periodogram method are commonly applied for EEG spectral analysis. However, there are numerous disadvantages with these non-parametric methods as compared to parametric spectral methods like AR method¹. Parametric methods also give smoother spectrums as compared to non-parametric methods. Although using data windows can smooth Fourier spectrum (which is the Blackman-Tukey method), it must be noted however that this does distort the true spectrum due to side lobe leakages.

Fourier analysis requires multiple periods for the particular spectral peak to appear unlike the ARSA using Burg's method, which requires the data segment to contain only a single period to produce a pronounced peak [9].

ARSA methods also give better frequency resolution while avoiding picket fence and scalloping loss effects faced by Fourier methods. DFT consists of harmonic amplitude and phase components regularly spaced in frequency. The spacing of the spectral lines depends on the number of data samples, decreasing with the number of data. Therefore, we will not be able to estimate accurately the frequency component of the signal in between these two adjacent harmonic frequency components. This problem is better known as picket fence effects. The solution to this problem lies in augmenting zeros to the data. However, this results in scalloping loss, which is designed to represent the maximum reduction in processing gain, which occurs mid-way between the harmonically related frequencies.

3.3 Autoregressive Spectral Analysis

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

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

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. In some literatures, the error term is also known as residual, random shock or innovation. The term autoregressive implies that the process $x(n)$ is seen to be regressed

¹ Parametric models like AR require only a small set of parameters to fit the model. However, non-parametric models like Fourier spectrum require infinite number of parameters to specify the process.

upon previous samples of itself. The error term is assumed to be a zero mean white noise with finite variance, \mathbf{s}_e^2 . In applications, the values of a_k and \mathbf{s}_e^2 have to be estimated from finite samples of data $x(1), x(2), x(3), \dots, x(N)$.

Many different techniques have been proposed to estimate a_k , each with its own merits and demerits. However, the most common method is to use the autocorrelation technique of solving the Yule-Walker equations [2]. 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 $p-1$. Some of these methods are like Burg's algorithm [3] and Levinson-Durbin (LD) algorithm [2].

Burg's method is more accurate than LD since it uses the data points directly unlike the latter method, which relies on the estimation of the autocorrelation function, which is generally erroneous for small data segments. The earlier method also uses more data points simultaneously by minimizing not only a forward error (as in the Levinson-Durbin case) but also a backward error. This algorithm will be discussed later.

3.4 Statistical Model Order Selection Methods

Before an AR process could be used, there is a prerequisite of having to know the order of the model. Most order selection criteria are transformations of the mean squared error², \mathbf{s}_e^2 which is computed as a function of the order in model estimation. These techniques employ a multiplication of this error and a cost function, which increases monotonically with order p . Methods pioneered by Akaike [1] are popular and two model order selection criteria developed by him i.e. AIC and FPE are based upon concepts in mathematical statistics. FPE method gives the model order, which minimises the function below:

$$FPE(p) = \hat{\mathbf{s}}_e^2(p) \frac{N+p}{N-p}, \quad (2)$$

where p is the model order, N is the number of data points, $\hat{\mathbf{s}}_e^2(p)$ is the estimated error variance for the model. If the mean value of the data has been subtracted, then the unbiased estimate of this error variance is given as [12]:

$$\hat{\hat{\mathbf{s}}}_e^2(p) = \hat{\mathbf{s}}_e^2(p) \frac{N}{N-p-1}, \quad (3)$$

and the FPE is now given by:

$$FPE(p) = \hat{\hat{\mathbf{s}}}_e^2(p) \frac{N+p+1}{N-p-1}. \quad (4)$$

The fractional portion of FPE increases with p and as such represent the inaccuracies in estimating the AR parameters. The principle behind the FPE criterion is that the unbiased estimate of the error variance is multiplied by the factor:

$$1 + p/N, \quad (5)$$

where p is the number of parameters to be estimated and N is the number of points observed. This factor allows for the increase in the error variance when the estimated coefficients are used to make predictions on new, independent data.

² In this paper, mean squared error is used interchangeably with error variance. This is since the error is assumed to be white noise where the mean value is zero.

Akaike then extended this model selection criterion to any maximum likelihood situation. This other criterion is called AIC and is given by:

$$AIC(k) = -2 \ln(\text{maximum likelihood}) + 2k, \quad (6)$$

where k is the number of parameters estimated. Using this method, the order of the model is selected which minimises the following function:

$$AIC(p) = N \ln \hat{\mathbf{S}}_e^2(p) + 2p. \quad (7)$$

The term $2p$ represents the penalty for selecting higher orders. The two criteria are asymptotically equivalent and in the limit of large N , FPE and AIC will predict the same optimal order.

3.5 Burg's Method

Burg's method is common in 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, $\hat{\mathbf{S}}_e^2(0) = \frac{1}{N} \sum_0^{N-1} [x(n)]^2$ 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, $\mathbf{P}_m = -2 \frac{\sum_{n=m}^{N-1} b_{n-1}(m-1)e_n(m-1)}{\sum_{n=m}^{N-1} [e_n^2(m-1) + b_{n-1}^2(m-1)]}$

3. Update Error and AR coefficients

- AR coefficients, $\left. \begin{aligned} a_k(m) &= a_k(m-1) + \mathbf{P}_m a_{m-k}(m-1) \\ a_m(m) &= \mathbf{P}_1 \end{aligned} \right\} \begin{aligned} m > 1 \\ m = 1 \end{aligned}$
- Forward Error Update, $e_n(m) = e_n(m-1) + \mathbf{P}_m b_{n-1}(m-1)$
- Backward Error Update, $b_n(m) = b_{n-1}(m-1) + \mathbf{P}_m e_n(m-1)$

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 [3].

3.6 Autoregressive Spectral (ARSA) Estimation

After selecting the order of the model by the any one of the discussed criterion, we can proceed with the estimation of the AR coefficients using Burg's algorithm. These coefficients are then used to obtain the power spectral density (PSD) values by using the equation:

$$S(f) = \frac{S_e(f)}{\left| \sum_{k=0}^p a_k e^{-i2\pi f k T} \right|^2}, \quad (8)$$

where $S(f)$ represents the power spectral density function, T is the sampling period and $S_e(f)$ represents the power spectrum of the error sequence. Since the term $S_e(f)$ applies to the errors or residuals which are in theory white, the resulting power spectrum should be flat and therefore $S_e(f)$ should be a constant independent of the frequency. Ideally, the value of this constant (noting that the mean of the residuals are zero) will be directly proportional to the variance of the residuals. Hence, the final expression for the conventional AR spectral estimate is obtained by replacing $S_e(f)$ with $\hat{\sigma}_e^2(p)T$ where $\hat{\sigma}_e^2(p)$ is the unbiased estimated variance of the residuals and the term T is included so that the true power of the signal will be represented digitally. The final PSD equation is given by:

$$S(f) = \frac{\hat{\sigma}_p^2 T}{\left| \sum_{k=0}^p a_k e^{-i2\pi kT} \right|^2} \quad (9)$$

4.0 FUZZY ARTMAP

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

ARTMAP is a class of neural network that performs incremental supervised learning of recognition categories. 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. This system learns to classify inputs by using fuzzy set features i.e. the input features are from 0 to 1. This 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 analog or binary valued input patterns. It consists of two modules (Fuzzy ART_a and Inter ART) 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 Inter ART module maps the output of Fuzzy ART_a to the respective target of the pattern. It is actually an associative controller that creates a minimal linkage of recognition categories between the Fuzzy ART_a module and target classes to meet a certain accuracy criteria. This is accomplished by realizing a learning rule that minimizes predictive error and maximizes predictive generalization. It works by increasing the vigilance parameter r_a of Fuzzy ART_a by a minimal amount needed to correct a misclassification or predictive error.

Parameter r_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 r_a enable larger categories to form and lead to a broader generalization and higher code compression. A predictive failure increases the minimal confidence r_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 generalization 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. Further details of this method can be found in [4, 5, 6].

5.0 EXPERIMENTAL STUDY

In this paper, we study the ability of the FA network using ARSA method to predict two types of cognitive tasks. The performance of different types of order selection criteria for ARSA models to represent EEG signals are also experimented. These statistical criteria are AIC and FPE. In addition, an experiment is also conducted with a fixed 6th order model since Keirn and Anun [13] have used it in their experiments.

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 is used to record EEG signals from positions C3, C4, P3,

P4, O1 and O2, defined by the 10-20 system of electrode placement. The electrodes are connected through a bank of amplifiers and band-pass filtered from 0.1-100 Hz. The data is 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 were chosen by Keirn and Aunon to invoke hemispheric brainwave asymmetry [13]. These tasks are:

- Math task, for which the subjects were given nontrivial multiplication problems, such as 12 times 18, and were asked to solve them without vocalizing or making any other physical movements;
- Geometric figure rotation, for which the subjects were asked to visualize a particular 3D block figure being rotated about an axis.

Data was recorded for 10 seconds during each task and each task was repeated for two sessions. With a 250 Hz sampling rate, each 10 second trial produces 2,500 samples per channel. Overall, there are 16 different EEG files. Each EEG signal is segmented with a half-second window, i.e. for a length of 125 points giving 20 patterns for each file with a total of 320 patterns. For all the experiments, 50% of available patterns are used for training, while the rest 50% are for testing. The patterns for each data set are chosen randomly at the beginning and are fixed for all the experiments. Three different experiments are run, each with different Fuzzy ART_a vigilance parameter, r_a values of 0.0, 0.5 and 0.9 for all the cases.

First, the different model order selection criteria like AIC, and FPE are used to give the appropriate order of the model. Next, Burg's algorithm is used (throughout the experiments) to derive the AR coefficients. After this, we derive the PSD values in the range of 0.50 Hz per channel and using these spectral values (the PSD values for all the 6 channels are concatenated into one vector), we train a FA network and use it to predict the cognitive tasks. The entire process is then repeated for the case with a fixed 6th order AR model. Fig. 3 illustrates this process.

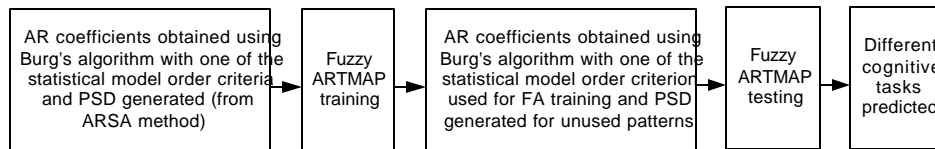


Fig. 3: Fuzzy ARTMAP training and testing

Table 1 shows the FA prediction performance for subjects 1, 2, 3 and all 3 subjects combined for the 3 cases of order selection criteria. These results are for classification of two different mental tasks i.e. computing arithmetic and geometric figure rotation for combined two sessions. Three different experiments with Fuzzy ART_a vigilance parameter, r_a values of 0.0, 0.5 and 0.9 are conducted.

Table 1: Results of FA prediction percentage during experimental study

Statistical criteria	r_a	Subject 1	Subject 2	Subject 3	All 3 subjects
AIC	0.0	79.17	70.83	95.83	54.17
	0.5	75.00	70.83	95.83	54.17
	0.9	79.17	75.00	87.50	66.67
FPE	0.0	79.17	75.00	91.67	56.94
	0.5	91.67	75.00	91.67	56.94
	0.9	83.33	75.00	83.33	72.22
6 th order	0.0	79.17	83.33	91.67	62.50
	0.5	83.33	83.33	87.50	62.50
	0.9	100.00	83.33	91.67	72.22

Table 2 shows average performance of FA for the 3 different vigilance parameter values. From these two tables, we can see that for most cases, FA can predict the cognitive tasks to a good accuracy using ARSA method. As far as the statistical model order criteria are concerned, it is difficult to conclude which criterion is best since the performance varies for different subjects. A similar conclusion can be arrived for the performance with different r_a values. However, we are able to conclude that subject 3 performs better than the other two subjects in most of the cases.

Table 2: Average results of FA prediction percentage during experimental study

	Model Order Criteria	FA Performance
Subject 1	AIC	77.78
	FPE	84.72
	6 th order	87.5
Subject 2	AIC	72.22
	FPE	75
	6 th order	83.33
Subject 3	AIC	93.05
	FPE	88.89
	6 th order	90.28
All 3 subjects combined	AIC	58.34
	FPE	62.03
	6 th order	65.74

6.0 CONCLUSION

We have proposed a method to predict cognitive tasks performed by the human brain using spectral analysis of EEG signals. The EEG signals are analysed using autoregressive spectral analysis, a type of modern parametric spectral analysis method, which comparatively yield better power spectrum over the classical Fourier methods. Power spectral densities of the EEG signals are used to train a Fuzzy ARTMAP network to classify these signals into the respective cognitive tasks. The average results of 72.22% to 93.05% for each subject from our experimental study show that it is highly possible to predict cognitive tasks based on EEG signals. This can be used as a mode of communication or wheelchair control for paralysed patients and also in EEG biofeedback systems.

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REFERENCES

- [1] H. Akaike, "A New Look at the Statistical Model Identification". *IEEE Transactions on Automatic Control*, Vol. 19, December 1974, pp. 716-723.
- [2] G. E. P. Box, and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*. Holden Day, San Francisco, 1976.
- [3] J. P. Burg, "A New Analysis Technique for Time Series Data", in *NATO Advanced Study Institute on Signal Processing with Emphasis on Underwater Acoustics*, Netherlands, August 1968. Also in Childers, D.G. (Ed), "Modern Spectrum Analysis", New York, IEEE Press, 1978.

- [4] G. A. Carpenter, and S. Grossberg, "A Massively Parallel Architecture for a Self-Organizing Neural Pattern Recognition Machine". *Computer Vision, Graphics, and Image Processing*, Vol. 37, pp. 54-115, 1987.
- [5] G. A. Carpenter, S. Grossberg, and J. H. Reynolds, "A Fuzzy ARTMAP Nonparametric Probability Estimator for Nonstationary Pattern Recognition Problems". *IEEE Transactions on Neural Networks*, Vol. 6 No. 6, 1995, pp. 330-1336.
- [6] G. A. Carpenter, S. Grossberg, N. Markuzon, J. H. Reynolds, and D. B. Rosen, "Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps". *IEEE Transactions on Neural Networks*, Vol. 3, No. 5, September 1992, pp. 698-713.
- [7] R. Caton, "The Electric Currents of the Brain". *Brit. Med. Journal*, 2:278, 1875.
- [8] P. Gloor, "Hans Berger on the Electroencephalogram: The Fourteen Original Human Reports on the Electroencephalogram". *Electroencephalogram and Clinical Neurophysiology*, Suppl.28, 1969.
- [9] B. H. Jansen, J. R. Bourne, and J. W. Ward, "Autoregressive Estimation of Short Segment Spectra for Computerized EEG Analysis". *IEEE Transactions on Biomedical Engineering*, Vol. 28, No. 9, September 1981, pp. 630-638.
- [10] H. Jasper, "The Ten Twenty Electrode System of the International Federation". *Electroencephalographic and Clinical Neurophysiology*, 1958, 10: 371-375.
- [11] G. M. Jenkins, and D. G. Watts, *Spectral Analysis and Its Applications*. Holden-Day, San Francisco, 1968.
- [12] R. H. Jones, "Identification and Autoregressive Spectrum Estimation". *IEEE Transactions on Automatic Control*, Vol. 19, December 1974, pp. 894-897. Also in Childers, D.G. (Ed), "Modern Spectrum Analysis", New York, IEEE Press, 1978.
- [13] Z. A. Keim, and J. I. Aunon, "A New Mode of Communication Between Man and His Surroundings". *IEEE Transactions on Biomedical Engineering*, Vol. 37, No. 12, December 1990, pp. 1209-1214.

BIOGRAPHY

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