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Comparison Of Diagnostic Techniques Of ASD In Children Using EEG By Applying Feature Extraction Techniques Like AR Covariance And AR Yule Walker Methods Using PRNN And NARXNN

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Abstract

Investigators from Karpagam Academy of Higher Education studied about the feasibility and accuracy EEG(Electroencephalogram) signals on effectively diagnosing Autism Spectrum Disorders (ASD) in children. 4 children with already diagnosed ASD and six controls aged 6 to 12 years were enrolled in this study. EEG was done on these children and the desired features of EEG were extracted using AR(Auto-regressive) Covariance technique and AR Yule Walker Method. The acquired signals were classified using two Artificial neural networks named PRNN (Pattern recognition neural network) and NARXNN(Nonlinear Autoregressive with External Input Neural Network). Mean Recognition performance of PRNN using AR Modified covariance and AR Yule walker both accounted to 91% accuracy in diagnosing ASD. Whereas accuracy of NARXNN using AR Modified covariance and AR Yule walker techniques both scored 95% diagnosis accuracy. The results of this study provide a promising future of early diagnosis of ASD when the latter technique is used for the same purpose..

Keywords: *Autism, ASD, EEG, AR Covariance, AR Yule Walker, PRNN, NARXNN*

1. Introduction

Previously there were many classifications of autism, whereas nowadays, the fifth edition of Diagnostic and statistical manual of mental disorders (DSM V) defines the symptomatology of ASD[1].It says that, spectrum of Autism involves interacting and communicating with others and also have repetitive behaviours, loss of interest in surrounding and behavioural issues that may affect life in school and other endeavours. ASD comprises of infantile autism, atypical autism, pervasive developmental disorder not otherwise specified (PDD-nos) and Asperger syndrome [2]. ASD has a prevalence of 1 in 68 Americans [3]

Clinicians traditionally used DSM-V criteria to diagnose ASD. The behavioural abnormalities of ASD seems to start showing up from infancy itself [4]. But its very difficult for the parents to notice these symptoms at this age and show to a physician. Even if seen by doctors, it is very challenging to diagnose ASD in children less than three years of age since traditionally these diagnoses are usually behavioural and not biological [5,6]. Most of these children are usually diagnosed during preschool years or much later than that [7]. Even then diagnoses are usually done only for children with all the classical features of ASD who have many neurodevelopmental symptoms and signs, whereas milder forms of ASD are very difficult to diagnose [8]. So, it is the need of the hour to develop an appropriate and trustworthy biomarker to diagnose ASD early, so that early interventions can be developed [5].

The guidelines for screening ASD at 18 months and 2 years of age, using ASD specific screening tools were provided by Indian Academy of Paediatrics [9].

Many tools like

a. Modified Checklist for Autism in Toddlers (M-CHAT),

b. Autism Spectrum Quotient (ASQ),

c. Social Communication Questionnaire (SCQ),

d. Social Responsiveness Scale (SRS),

e. Autism Behaviour Checklist (ABC)

f. Social Communication Disorder Checklist (SCDC) are available for screening for Autism [10] are available

So, it is virtually impossible for a clinician to diagnose ASD before 18 months of age. Genes and environment play a major role in the symptomatology in children with ASD [11]. Symptoms may appear very later in life but the pathological processes start much early. Defects in social engagement which is a hallmark of ASD cannot be identified in the first year of age. These factors necessitate the need of a diagnostic tool which can be used for screening purposes of all children with or without symptoms, so that early invention can be made possible.

Even though many researches are focused to address this problem, EEG based ASD diagnosis holds promise in developing a Human-machine interface system. This paper deals about identifying an appropriate EEG based system for ASD diagnosis. Here we have evaluated certain EEG feature extraction techniques like AR Yule Walker and AR covariance. Also, we tried to find out which ANN is better for ASD diagnosis; PRNN or NARXNN.

2. Materials and Methods

Ten children comprising of 6 (4 boys and 2 girls) already diagnosed with ASD and 4 normal subjects (3 boys and a girl) were selected for the study. EEG were collected using RMS 24 machine (Fig 1).

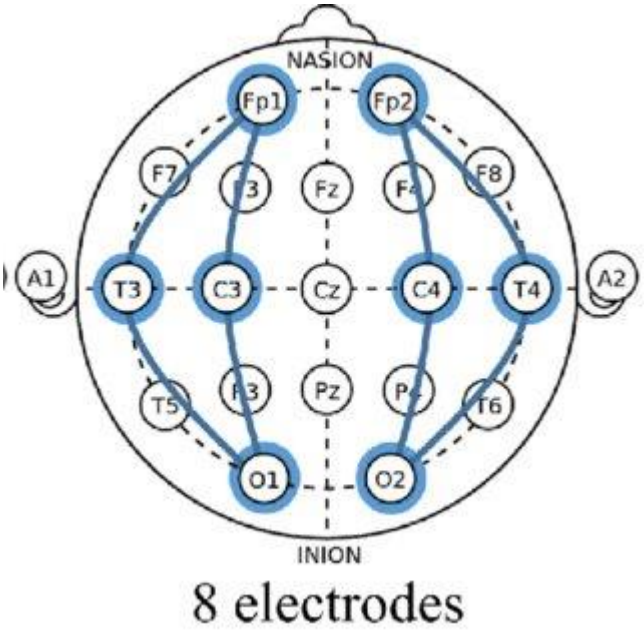

Fig 1. Electrode positioning

EEG were acquired at various levels such as relaxed state; while they read and spell words from flashcards; while watching a video of words where they have to read and spell; they have to imitate a hand movement from the video. Each recording lasted about 30 seconds. After the EEG acquisition, the following protocol is followed (Fig 2)

Fig 2. Flowchart of the study

Notch filter is applied on the raw signal to remove the 50 Hz power line artifacts from the signal. Also, Chebyshev type 2 bandpass filters are used for denoising the signal.

2.1. Feature Extraction methods

Signals must be extracted from the EEG. Two methods commonly used for this purpose are Parametric and non-parametric approaches. When signal length is short Parametric methods can give greater resolution than the non-parametric methods. So, we selected Parametric method. This method models the data as the output of a linear system driven by white noise. After which the parameters of the linear system are estimated. The most commonly used linear system model is the "all-pole model". It is a filter which has all of its zeroes in 'z' plane. When shite noise input is given to such a filter, the output is obtained Autoregressively. So, this process is called an Auto regressive process (AR). All AR methods yield a power spectral density (PSD) estimate given by equation 1.

$$\hat{P}_{AR}(f) = \frac{1}{f_s} \frac{\varepsilon_p}{\left| 1 + \sum_{k=1}^{p} \hat{a}_p(k) e^{-2\pi jkf/f_s} \right|^2} \quad (1)$$

We used both Covariance and Yule-Walker methods for feature extraction. The differences between AR Covariance and AR Yule-Walker feature extraction methods is given in table 1.

S. No	Covariance	Yule-Walker
1	Minimizes only forward prediction error	Minimizes both forward and backward prediction errors. It is also called Autocorrelation method
2	Better resolution for short data records	Better resolution for large data records
3	May produce unstable models	Always produces stable models
4	Order must be less than or equal to half the input frame size	Because of the biased estimate, the autocorrelation matrix is guaranteed to positive-definite, hence non-singular

Table 1. Differences between Covariance and Yule-Walker methods

Power spectral density facilitates how signal power density or time series is dispersed with frequency. It identifies data periodicities by sensing frequency peak corresponding to specific periodicities. Therefore, to acquire estimates PSD we have utilized two feature extraction algorithms like AR Yule Walker, and AR Covariance. PSD using AR covariance and Yule-Walker are given in equations 2 and 3.

$$p_{cov}(f) = \frac{\sigma^2}{1 + \sum_{k=1}^{p} a_k \exp - j2\pi fk^2} \quad (2)$$

$$p_{yule}(f) = \frac{\sigma^2}{1 + \left| \sum_{k=1}^{p} a_k \exp\left(-j2\pi fk\right) \right|^2} \quad (3)$$

2.2. Signal Classification methods

We used PRNN and NARXNN types of ANN in this study.

Pattern recognition neural network (PRNN)
Pattern recognition is a process in which, raw data from signals are taken and appropriate action taken based on the category of the pattern. A type of PRNN is feed forward network. It contains two layers of processing units. One layer to receive input and another layer to deliver output (Figure 3).

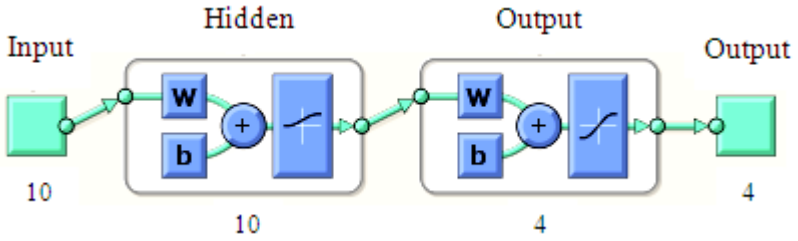

Figure 3. Architecture of Pattern Recognition Neural Network Model

NonlinearAutoregressive with External Input Neural Network (NARXNN)
NARXNN is dynamic network that is more powerful than static networks. It has three layers like hidden, input, and output layers (figure 4). NARX neural system is the kind of recursive neural network and it has feedbacks from output layer. NARX network accumulates delayed input-output and facilitates network to calculate time series value.

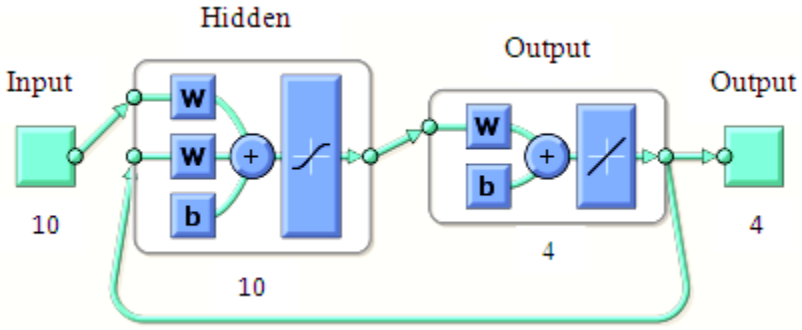

Figure 4. Architecture of NARXNN Model

3. Results and Discussion

EEG signals for four tasks were acquired using a sixteen channel EEG equipment from ten subjects (6 Autistic and 4 Non-autistic). Two feature extraction algorithms based on frequency domain were used to extract the features from pre-processed signals. Two neural networks were used to classify EEG signals of Autistic and non-Autistic subjects.

PSD plots for a single subject are given in figures 5 and 6.

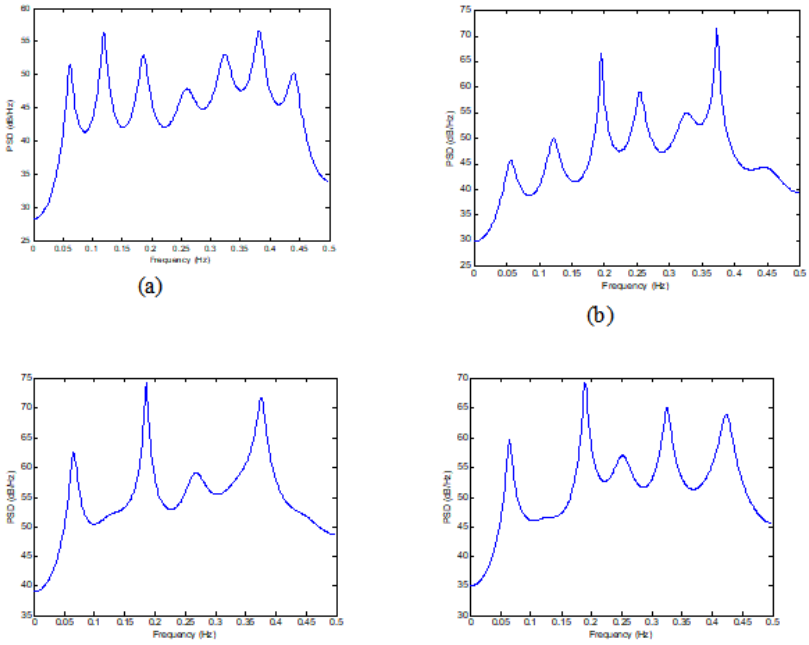

Figure 5.PSD plots for Subject N2 for 4 tasks (a) Relax, (b) Alphabet read and spell, (c) Video read and spell and (d) Motor task; using AR Covariance Method

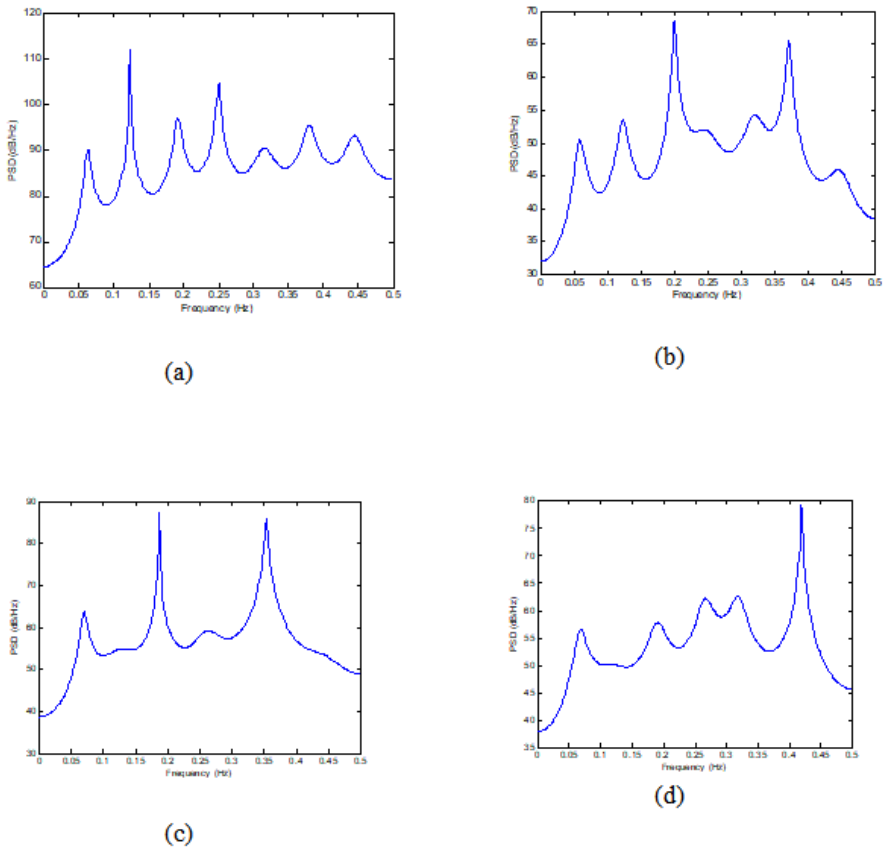

Figure 6.PSD plots for Subject N2 for 4 tasks (a) Relax, (b) Alphabet read and spell, (c) Video read and spell and (d) Motor task; using AR Yule Walker Method

Classification accuracy using PRNN and NARXNN are given in figures 7 and 8.

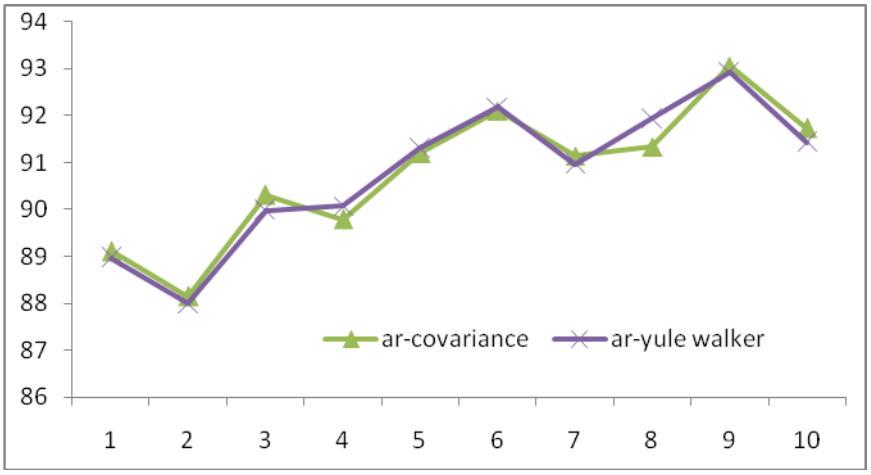

Figure 7. Classification Accuracy for 2 PSD Features Using Pattern net

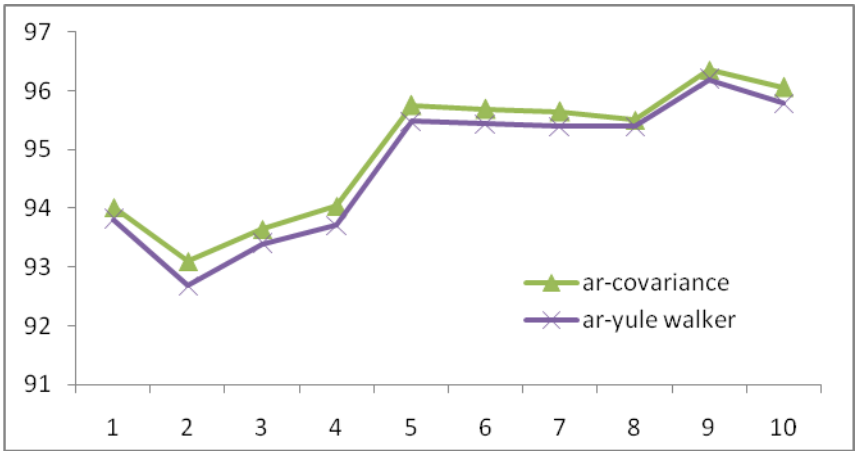

Figure 8. Classification Accuracy for Two PSD Features Using NARXNN

From the above figures it can be seen that classification accuracy of ASD when AR covariance used with NARXNN is more than other methods (94.5%). Whereas PRNN resulted in a classification accuracy of 90.5%.

This study was done to explore the potential Brain-computer interface to diagnose a complex problem called ASD in children. We developed four machine learning systems like AR covariance with PRNN and NARXNN; and AR Yule walker with PRNN and NARXNN. Our results highlight the advantages of NARXNN over PRNN in diagnosing ASD. Neural networks had higher computational costs than other models. With advanced in Deep learning techniques, it has reduced providing us with lesser training time. The main limitations of our study are the low sample size and study confined to few feature extraction methods and classifiers. Optimal would be doing this experiment with large number of cases and controls, many extraction methods and many ANNs. Another minor bias is more number of males selected than females, it can be attributed to difference in the incidence.

4. Conclusion

Our study has demonstrated that classification accuracy of ASD using NARXNN with Covariance or Yule-Walker is about 94.5% when compared to PRNN using same feature extraction methods which stood at 90.5%. Future efforts must be taken in using other extraction methods like AR burg, modified covariance, etc., along with feedback neural networks, Elman neural networks, Layered recurrent neural network, etc., We hereby conclude that relying upon clinical diagnosis of ASD for children under one year age is not possible and in future EEG based Brain-Computer interface models like the one we discussed here must be used as screening tool for all children for early diagnosis of ASD.

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