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EEG Based ASD Diagnosis for Children Using Auto-Regressive Features and FFNN

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Abstract: Autism Spectrum Disorder is the common term given to a group of complex disorders of brain and neurodevelopment. Social interactive defects, verbal and non-verbal communication disorders and repetitive behaviours are common characteristics of autism. Electroencephalography is a medical imaging technique that has been known to be a precisely suitable tool to study the signals generated by brain signal and its activities. In this study, variations in brain EEG signals are identified based on Auto-Regressive features to find difference between normal and autistic children. Maximum classification accuracy of 92.69 % is achieved using FFNN.

Keywords: Autism Spectrum Disorder, Electroencephalography, Auto Regressive Features, Feed Forward Neural Network.

1. INTRODUCTION

Autism is a neurodevelopmental defect which starts from the childhood. It is described by impairment in language and social skills. Kanner and Asperger first explained that even if the children look slightly normal, they were not able to relate themselves on an ordinary way with other people and their surrounding from the start of their life. Repetitive behaviours and rigidity of interests were typical in all children with autism [1]. ASD is generally considered a disability which stays throughout the life, without a single precise laboratory test, and as yet without an established preventive or curative treatment [2-4]. The occurrence of autism is reported as around 1% globally and yet this disorder is given very less attention as compared to other disorders of similar prevalence. ASDs are recently diagnosed using DSM-V (Diagnostic and Statistical Manual of Mental Disorders) criteria which includes three conditions namely social interaction impairment, communication deformity and restricted repetitive and stereotypical patterns [6]. Autistic Disorder, Asperger's Disorder, Pervasive Developmental Disorder Not Otherwise Specified (PDD-NOS), Rett's Disorder and Childhood Disintegrative Disorder (CDD) are the 5 sub-groups of ASD.

2. ELECTROENCEPHALOGRAPHY

Electroencephalography (EEG) is a system which is used to study the activity of brain and its functions by recording the electrical activity developed in brain. Metal electrodes and conductive media are used to pick up the signals generated from the scalp surface [7]. EEG signals are generated in human scalp due to electrical voltages created inside the brain structure. The 2 types of activities of neurons namely action potentials and post synaptic potentials are responsible for the electric activities. When series of swift electrochemical differences takes place from the start of the axon to terminal of axon at the cell body, action potentials are formed. Postsynaptic potentials take place at the receptors on the membrane. Postsynaptic cell are bided with neurotransmitters which makes the ion channels to open and close and lead to graded change in the electrical potential across the cell membrane [8].

EEGs are mostly used non - invasively and are economical as compared to other lab test. As a result, it can be used to know in detail the activities being carried out in the brain of patient [9]. Currently, DSM- V criteria is used to diagnose autism. But it is a difficult job for the physicians without the help of any tool to manually quantify the degree of disorder by just by manually examining and evaluating the patient and his reports. Hence, more innovation and development in the field of automated autism diagnosis using EEG signals is promoted globally.

3. LITERATURE REVIEW

W. Bosl et. al., used multi-scale entropy (mMSE) and multiclass Support Vector Machine (SVM) algorithm to find a biomarker for autism in infants. They obtained an overall accuracy of 80% for both control and ASD children [10]. A. Sheikhani et. al., evaluated EEGs of 17 children with ASD and 11 control children aged 6-11years. They evaluated using spectrogram and coherence values of EEG signals. Statistical analysis showed that alpha frequency band was found to have in relaxed eye-opened condition the best differentiation level of 96.4% [11]. Wafaa Khazaal Shams et. al., used Principle Component Analysis (PCA) and Multilayer Perception Neural network (MLP). They classified the autism signals in two tasks namely task with open eyes and tasks with motor movements. Around 90-100% accuracy was found for distinction between autism and control subjects. 90% accuracy was found for normal subjects in open-eyed tasks [12].

4. DATA ACQUISITION

The major components for data acquisition stage are:

- Subjects: Sample size included 4 (3 boys and 1 girls) normal children and 6 (4 boys and 2 girls) children with autism. Age group of 6-12 years was chosen. The normal children group consisted of children with no present or past neurological disorders.
- Recording: 4 tasks namely relax, flashcards read and spell, video read and spell and video hand movement imitation were used for the study. During the recording, band pass filter with frequency band (0.1-60) Hz was used to filter the data and digitization took place at 256Hz. 50 Hz notch filter was also used.
- Selection of Electrode: Since the EEG signals of children are only taken into consideration, paediatric montage is chosen for the study. The paediatric montage consists of electrodes A1, A2, O1, O2, T3, T4, C3, C4, Fp1 and Fp2 according to 10-20 International System.

5. FEATURE EXTRACTION

The parametric spectrum estimation depends on the previous information of the system. Generally used parametric method is the Auto Regressive (AR) method. In the study, AR method is used where the coefficient of a signal at particular instance is derived by adding the coefficient of the past samples and summing the error estimation. p^{th} model order of Autoregressive (AR) process is given by

$$x[n] = i\sum_{k=1}^{p} a_k x[n-k] + e(n)$$

where, a_k indicates AR coefficients, p indicates the model order, $x(n)$ represents EEG signal at the sampled point n and $e(n)$ indicates the error term independent of previous samples.

Thus, in order to obtain the estimates of AR coefficient four feature extraction algorithms have been used, such as AR Burg, AR Modified Covariance, AR Covariance and AR Yule Walker.

- **AR Burg Method:** This method uses least squares sense techniques to minimize the forward and backward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. The major benefits of the AR Burg estimation are high frequency resolution, stability and very efficient computation. The AR burg method generates the reflection coefficient automatically without the interference of autocorrelation function.
- **AR Modified Covariance Method:** This method uses least squares sense techniques to minimize the forward and backward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. In this method, for calculating autocorrelation matrix windowing is not necessary. It doesn't suffer spectral line-splitting but may produce unstable models.
- **AR Covariance Method:** This method uses least squares sense techniques to minimize the forward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. When compared to the Yule-Walker AR estimation, AR Covariance estimation produces higher resolution spectrum for short data records. In this method, for calculating autocorrelation matrix windowing is not necessary.
- **AR Yule-Walker Method:** This method uses least squares sense techniques to minimize the forward prediction errors for identifying AR coefficients by fitting AR model to the EEG signals. Biased estimates of the signal's autocorrelation function are also used to calculate coefficients. Hence, it is also called as "autocorrelation method". AR Yule Walker technique gives a stable output for all pole models.

6. CLASSIFICATION

Classification of signals was performed using Feed Forward Neural Network (FFNN) which is a static network.

FFNN is a classification algorithm is aspired from biology of living being. Simple neuron-like processing units form the basics of this network. These structures are formed as layers. Every unit in a layer are connected with entire units of the previous layer. Strength and weight of every connection may vary. The network knowledge is known by the weights on each connection. Input is where the data is entered. It then passes layer by layer through the network. Finally, it reached the output. No feedback is given between layers when normal operation is performed. As a result, they are named as FFNN.

7. RESULTS AND DISCUSSION

Feature extraction gives 16 features for each EEG signal. These values become the input to the neural network. Sixteen input neurons, 3 output neurons and 10 hidden neurons are used to design the FFNN. Trial and error method is used to select the values for hidden neurons. Testing and training of the network are performed using 75% and 100% of the data set respectively. 0.001 is fixed as training error tolerance rate. Error tolerance rate for testing is 0.6. The classification accuracy for the four AR-Features namely AR-Burg, AR-modified Covariance, AR-Covariance and AR-Yule Walker for 4 normal and 6 children with autism is shown in Table 1. Subject 1 to subject 4 are normal subjects while subject 5 to subject 10 are autistic subjects.

Table 1
Classification Accuracy For 10 Subjects Using 4 AR Features

Subjects	*Hidden neuron*	*AR-Burg*		*AR- Modified Covariance*		*AR- Covariance*		*AR-Yule Walker*	
		Standard Deviation	*Average Accuracy (%)*	*Standard Deviation*	*Average Accuracy (%)*	*Standard Deviation*	*Average Accuracy (%)*	*Standard Deviation*	*Average Accuracy (%)*
1	10	2.35	88.45	2.75	88.10	2.85	88.30	2.71	87.91
2	10	2.31	87.79	2.90	87.48	2.49	87.17	2.35	87.08
3	10	2.23	90.29	2.72	89.98	3.17	89.62	2.95	89.46
4	10	2.26	89.16	2.40	88.94	2.86	88.61	2.44	88.34
5	10	1.99	91.11	2.44	90.90	2.63	90.97	2.97	90.57
6	10	2.38	91.21	2.31	91.11	2.71	90.90	2.63	90.48
7	10	2.14	90.64	2.54	90.38	3.17	90.23	2.98	89.72
8	10	2.33	90.93	2.45	90.50	3.04	90.47	2.93	90.14
9	10	2.18	92.69	1.91	91.33	2.66	91.21	2.70	90.99
10	10	1.85	91.14	2.01	91.02	2.80	90.69	2.63	90.48

As observed from above Table 1, maximum classification accuracy of 92.69 % was achieved for Subject 9 using AR-Burg feature with standard deviation as 2.18. Minimum classification accuracy of 87.08 % was achieved for Subject 2 using AR-Yule Walker feature with standard deviation as 2.35. Higher classification accuracy is found for children with autism as compared to normal children which indicate more difference of behavior of neurons under each task as compared to the normal children. Moreover, highest classification accuracy is obtained using AR-Burg feature while least classification accuracy is obtained using AR-Yule Walker. This shows that AR-Burg is best suited for classification of children with autism and normal children using FFNN.

8. CONCLUSION

In the study, FFNN and 4 AR-features were used to differentiate normal children and children with autism using EEG signals. The study used ten subjects among which 4 were normal and 6 autistic. 92.9% was the maximum classification rate for subject with autism using AR-Burg feature. The experimental results show that AR-Burg feature is comparatively better than AR-Covariance, AR-modified Covariance and AR-Yule Walker feature extraction methods. We can also observe from the results that higher classification accuracy is found for children with autism as compared to normal children. However, better recognition rates have to be obtained in future using better features and classifiers for practically implementing an automated EEG based Autism diagnosis system.

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