RECURRENT NEURAL NETWORK FOR DISORDER DETECTION IN EEG SIGNAL

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Abstract

Autism Spectrum Disorder is the general term given to a diverse group of neurodevelopment and brain disorders. The main symptoms of autism are relational interactive defects, verbal and non-verbal deficiencies of speech and repercussion. Electroencephalography is a method known for medical imaging as a detailed instrument for the analysis of signals produced by brain impulses and their behaviour. In this study, changes in brain EEG signals dependent on Recurrent Neural Network (RNN) was established to differentiate between normal and autistic children. The RNN achieves overall accuracy in classification of 92.7%.

Keywords:

Autism, Recurrent Neural Network, Electroencephalography

1. INTRODUCTION

Autism is a neurodevelopmental defect that occurs in infancy. The vocabulary and social skills are affected. Kanner and Asperger clarified that, while they seem a little average, they have never been able to react to others and their environments from the beginning of their lives in an ordinary fashion. In all children with autism repetitive behaviour and rigidity of interests is typical [1]. ASD is widely treated as a lifelong disorder, with no particular exact laboratory examination and no preventive or curative therapy identified yet [2-4]. Autism exists worldwide as about 1%, but this condition is less considered than other related incidence disorders [6].

Electroencephalography (EEG) is a device that studies brain activity and works by registering brain electrical activity. The signals produced from the scalp surface are collected by metal electrodes and conductive media [7]. EEG impulses in the human scalp are produced because of electrical voltages within the brain system. The electric activities are distinguished by two forms of neuronal activation, namely action potentials and post synaptic potential. As sequence of swift electrochemical differences occur between axon beginning and axon terminal in the cell body, the potential for action is produced. Potentials of postsynaptic exist in membrane receptors. Neurotransmitters are offered for the post-synaptic cell to open and close the ion channels, which induce incremental shift to the electrical potentials in cell membrane [8].

EEGs are often non-invasive and cost-effective in contrast with other laboratory studies. As a consequence, the operation in the patient's brain can be known in detail [9]. DSM-V guidelines are commonly used for autism diagnosis. However, it is impossible for doctors to manually measure the extent of illness by observing and analysing the patient and his notes without the use of any instrument. In the area of automatic autism detection by EEG signifies further creativity and growth is then encouraged worldwide.

SVM algorithm multi-scale entropy (mMSE) is used to identify an autism biomarker in children. In all controls and ASD children they have reached an average precision of 80% [10]. EEGs are evaluated for 17 ASD and 11 controls for 6-11 years old and they measured the EEG signals using spectrograms and coherence values. Statistically, the highest distinction degree of 96.4% was observed in comfortable eye-opening conditions [11]. Multilayer Neural Perception Part Analysis is used to classify the autism signs as two tasks, namely open-eyes and engine activity tasks. About 90%-100% accuracy has been shown to differentiate between autism and controls. For normal subjects in open-eye activities, 90% precision has been found [12].

2. DATA ACQUISITION

For the data acquisition stage, the main components are:

- *Subjects*: Sample size contains 4 average children (three boys and one girl) and 6 children (four boys and two girls) with autism. The 6-12 year age range has been selected. The regular group of children consisted of children without neurological disorders, either present or past.
- *Recording*: 4 tasks were employed, namely relaxation, reading and spelling flashcards, video reading, spelling and imitation of video hands. The frequency band (0.1-60) Hz band pass filter was used during the recording to filter data and the digitalization was performed at 256Hz. Also used was the 50 Hz nozzle filter.
- *Electrode Selection*: Since EEG signals are taken into account only, paediatric mounting for this analysis is selected.

3. FEATURE EXTRACTION

The spectrum calculation relies on the system's previous data. The Auto Regressive (AR) approach is commonly used as a parametric method. The AR procedure is used in the analysis to obtain the signal coefficient at a given instance by applying the previous sample coefficient and adding the error estimate to the estimate.

In order to minimise forward and backward prediction errors in AR coefficients by fitting AR model with EEG signals, this method uses lower-quadratic sense techniques. High frequency resolution, stability and very efficient calculations are the major advantages of the AR Burg estimate. Without interference with the autocorrelation function, the AR burg method automatically produces the reflection coefficient.

In addition, this method uses less square sensory techniques to minimise forward and behind-the-scenes prediction errors by matching the AR model with the EEG signals. In addition, autocorrelation matrix window calculation is not necessary in this method. Spectral line-splitting does not occur but it can produce unstable models.

Coefficients of AR are found by using fewer square meaning methods in order to eliminate mistakes in forward prediction. This is then fitted to the EEG Signals AR Versions. The AR Covariance calculation provides better spectrum resolution for short data records compared to the yule-walker AR estimate. The windows of the autocorrelation matrix are not required in this process.

This approach also uses fewer sensory strategies to reduce forward prediction errors by mounting the AR model to the EEG signal. In order to measure coefficients, skewed calculations of the signal's autocorrelation function distinguish AR-yule walkers from other approaches. It is also often called the method of self-correlation. AR Yule Walker gives all polar models a reliable performance.

3.1 CLASSIFICATION

The RNN, a static network, was used to interpret the signals. RNN is an algorithm of classification based on living organology. The fundamentals of this network are plain neuron-like processing units. There are layered systems. In each layer, whole units of the preceding layer are connected. Each relation can vary in strength and weight. The weight of each relation is understood for the network awareness. The data is entered in the input. It goes across the network layer by layer. Finally, the performance was achieved. When the standard operation is done, no feedback is provided between layers. They are therefore referred to as RNN.

4. RESULTS AND DISCUSSION

For any EEG signal, the function extraction gives 16 features. The neural network will be supplied with these values. To build the RNN, sixteen input neurons, three output neurons and ten cached neurons are employed. In the collection of hidden neurons the test and error process. Network monitoring and preparation is carried out using 75% and 100% of the respective data collection. The tolerance rate of 0.001 is set as a training mistake. Testing error threshold is 0.6. The precision of the classification for the four AR-Features called AR-Burg, AR-modified, AR-covariances, and AR-Yule Walker is shown in Fig.1 and Fig.2. Subject 1 to subject 4 shall be natural and subject 5 to subject 10 shall be autism.

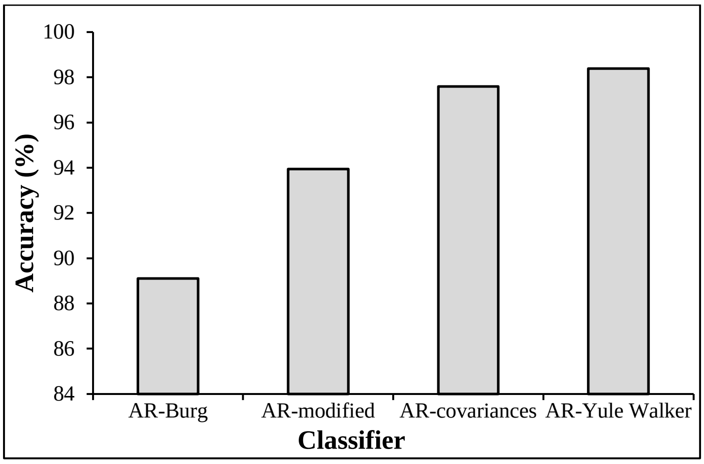

Fig.1. Detection Accuracy

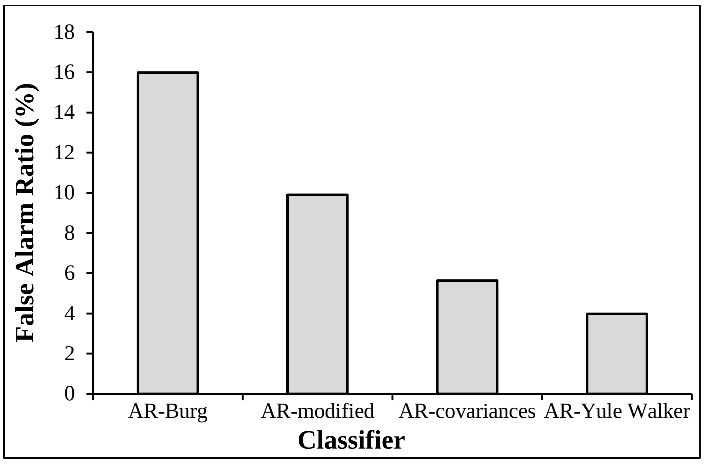

Fig.2. False Alarm Ratio

As seen in Fig.1 and Fig.2 for the subject 9 with the AR-Burg function standard deviation as 2.18 a maximum classification accuracy of 93% was achieved. For topic 2 the AR-Yule Walker function with standard deviation as 2.35 was achieved with a minimum classification accuracy of 87%. For children with autism, better classification accuracy than ordinary children is seen which indicates more variations between neural activities in any task in comparison to ordinary children. In comparison, the maximum accuracy of classification is attained with the AR-Burg function and the lowest accuracy of classification with the AR-Yule - Walker. This shows that AR-Burg is better adapted for autism children and regular RNN children.

5. CONCLUSION

The research used RNN and 4 AR-to discriminate between children with autism and regular children using EEG. The research used 10 participants, four regular subjects and 6 autistic subjects. For autism subjects using AR-Burg function, 92.9% were of the highest classification rate. The results of the experiments showed that the function AR-Burg is relatively stronger than the methods of extraction of AR-Covariance, AR-modified Covariance and Yule Walker. The findings indicate that children with autism have greater accuracy in the classification than typical children.

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