Analysis of Connectivity Model to Study the Neurophysiological Process for Autism Detection

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Abstract Studying network communication within the neurons is the next step toward exploring the complexities of the human brain. In this research, we used electroencephalography (EEG) to study the neurophysiological processes because of their high temporal and spatial resolution. EEG stands out to be a vital modality in assessing patients with brain abnormalities like Autism, Epilepsy, Dementia, and Parkinson's. Nowadays, a large number of children worldwide is affected by Autism Spectrum Disorder, which impairs the ability to communicate and behave. In this research, we generate the connectivity models using the EEG signal dataset of Autism and normal children. Here, connectivity models are presented into a graphical form using different measures like phase synchronization, classical measures, granger causality, and information theory. These parameters were used to analyze the variation between Autistic and typically developed children.

Keywords Autism · EEG · Connectivity model

1 Introduction

In the recent years, researchers have showed their interest in neurodevelopmental disability due to its complexity in identifying a promising biomarker. An exceptional objective in the field is to recognize typically developing subjects and children with neuro disabilities. Relationship of human being with others and the external environment is influenced through the understanding of expressions [1]. Autism spectrum

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disorder (ASD) refers to a wider range of conditions including social skill problems, repetitive behaviors, speech, and nonverbal communication. EEG is a promising modality for contemplating neuro physiological procedures. The global prevalence rate of ASD is estimated as 1–2% in children [2]. There is a need for low-cost tool for screening children with ASD in low and middle-income countries. Diagnosis of ASD at an early age is challenging with the screening techniques available at present. This demands a distinguishing feature for children with ASD that could lead to a clarity in diagnosis and also helpful for early intervention for ASD children. An association between brain's functional connectivity and the cognitive performance leads a way to the in-depth understanding of the neurodevelopmental disorder [3]. The cognitive behavior of the brain can be well identified by EEG. Quicker advancements in clinical instruments and structures have prompted the exact and non-intrusive estimation of the mind's electrical action. EEG is considered as a potential tool for numerous neurodevelopmental studies due to its high-temporal resolution and accurate brain's response to various stimuli. The neuronal interactions in the brain are depicted as wave patterns in EEG.

The connectivity in the brain network is categorized into auxiliary, functional (FC), and effective connectivity (EC) [4–10]. Anatomical network (AN): Neighboring neurons are connected through the synaptic contacts. Functional connectivity (FC): Which is characterized as the worldly reliance of neuronal actuation examples of anatomically isolated mind areas that depends on such correlation, covariance, or phase locking [7–9]. Effective connectivity (EC): The influence of one neuron framework will depend upon another is called EC. Granger causality is indicator of effective connectivity [6].

The connection of brain regions and association among them can be represented by the connectivity model [1–3, 11]. Through this connectivity model, the investigation to identify and describe the dynamic connection and interaction among the brain region can be explored [12]. Parameters like Granger Causality, Phase synchronization, Information Theory, and Classic Measure will give various measures of dynamic behavior of the brain in different EEG channels [4]. Analyzing the brain pattern and parameters will help to develop a mathematical model to describe the difference between brain activities of autistic children and normal children. Here in this work, we have used HERMES toolbox to explore this possibilities [13]. The information flow in the human brain is analyzed through the connectivity model. Various experiments have been made to arrive different pattern and is found that proposed method is a good fit to distinguish between autism one and typical children.

This paper has been organized as: Sect. 2 gives a concise prolog to our proposed work. In Sect. 3, the experimentation technique and results are discussed. In Sect. 4, the concluding remarks and scope for future work are presented.

Fig. 1 Block diagram of proposed methodology

2 Proposed Model

This research work proposes an approach to identify the patterns present in the EEG signals and potentially detect the presence of ASD. The recognition of these patterns is conditioned on the connectivity diagram generated by HERMES toolkit. Figure 1 entitles the high-level schematic diagram of the proposed research work. Our design utilizes the information from five different parameters to fuse the time series EEG signals into the connectivity model and identify the level with corresponding the presence of Autism in a subject.

3 Materials and Methods

3.1 Electroencephalogram (EEG)

An EEG can record and track the brain wave patterns. Small electrodes are appended to the scalp with wires [1]. These electrodes investigate the electrical driving forces in the mind and impart signs to a computer that records the outcomes. The analysis and understanding of the relation between time series has gained significant traction in the recent years for EEG signals. Our research utilizes an open source HERMES toolkit for analyzing the time series data to effectively analyse the brain connectivity modeling for neurological data (e.g., MEG, EEG, iEEG) [10].

Six parameters are analyzed in this work namely, Granger causality, PS records ("Phase Synchronization Indexes"), Classical measures, Information theoretic files ("Data Theoretic Measures"), and GS indexes ("General Synchronization Indexes").

3.2 Data Acquisition

EEG data from 3 typically developing children and 3 children with ASD were acquired through Nihon Kohden MEB9000 with sensitivity of 7 μv. With the sampling frequency of 500 Hz, 21 channel signal are recorded and 13,000 samples of EEG signals are acquired and filtered with low pass channel & high pass channel at a range of 0.53–70 Hz frequencies. These electrodes placements are Fp1, F7, T3,

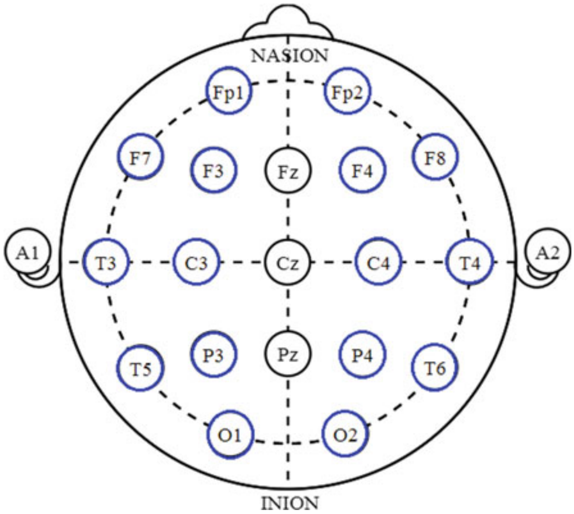

Fig. 2 Electrode positions applied for this research [10–20 system]

T5, F3, C3, P3, O1, Fp2, F8, T4, T6, F4, C4, P4, O2, Fz, Cz, Pz, A1, A2 (ch21) as shown in Fig. 2.

The children are made to sit and watch a cartoon video for 10 min. The cartoon is played with audio and without audio. The children are exposed to rhymes alone for 10 min. The response of the children is recorded in the EEG. This signal is preprocessed for eye blink removal, power line artifact removal.

Six different data sets are available for analysis as shown below.

1. EEG recording with only rhymes for Autism children and Normal children.
2. EEG recording while viewing cartoon video for Autism children and Normal children.
3. EEG recording with combined audio and video for both Autism children and Normal children.

Using HERMES tool, connectivity model is generated with the above mentioned signals. The parameters as directionality phase index, Grangner causality, phase locking value, correlation coefficient, and Mutual information are calculated from the connectivity model. The different parameters are explained below.

3.3 Directionality Phase Index (DPI)

Directionality measure among two signs $X(t)$ and $Y(t)$ can be acquired by the addition of the periodic elements of the two phases of the signals. This is measured by DPI parameter [10]. Three methods available to calculate directionality phase index are EMA (Evolution map approach), instantaneous period approach (IPA) and information theoretic approach (ITA). The DPI measure by ITA approach is expressed by

Eq. (1).

$$d^{xy} = \frac{C_x - C_y}{C_x + C_y} \tag{1}$$

Where, C_x = cross reliance of the elements of $X(t)$ on the period of signal $Y(t)$.
C_y = cross reliance of the elements of $Y(t)$ on the period of signal $X(t)$.
This cross coupling records C are then calculated for a group of substitutes and associate with the original information.

3.4 Granger Causality (GC)

Granger causality is a measure of causality that depends on expectation. Granger causality, predicts the value of a signal X_2 from the past values of a signal X_1, if X_1 contain some data that to predicts X_2 well beyond the data contained in past estimations of X_2 alone [3]. Granger causality depends on linear auto-regression modeling. Granger causality (GC) predicting x from y is given in below Eq. 2:

$$GC_{y \to x} = \ln\left(\frac{V_{x|\overline{x}}}{V_{x|\overline{x,y}}}\right) \tag{2}$$

Where, $V_{x|\overline{x}} = \mathrm{var}(U_x)$ and $V_{x|\overline{x,y}} = \mathrm{var}\left(U_{xy}\right)$, where var() is the difference after some time and where $x|x,y$ is the gage of signal $x(t)$ by the past example of estimations of signals $x(t)$ and $y(t)$. Range of GC is from 0 to ∞ and if GC is equal to 0 then the $Y(t)$ does not improve the prediction from $X(t)$ and also, for more than 0 the past of $Y(t)$ is improves the forecast of signal $X(t)$.

3.5 Phase Locking Value (PLV)

The PLV evaluates how the relative stage is set over the unit circle. When the relative stage includes a little piece of the circle and the PLV is almost 1 then we say that there is a strong PS among X and Y. [10]. PLV is an estimation that can used to look at task-actuated changes in long-extend synchronization of neural development from the EEG data. Equation 3 is used to find the PLV value.

$$\mathrm{PLV} = \left|\mathrm{e}^{i\Delta\emptyset_{\mathrm{rel}}(t_n)}\right| = \left|\frac{1}{N}\sum_{n=1}^{N}\mathrm{e}^{i\Delta\emptyset_{\mathrm{rel}}(t_n)}\right| \tag{3}$$

RANGE: $0 \leq \mathrm{PLV} \leq 1$ here 0 for unsynchronized frameworks. For example, this spread has two high values which are differentiated by π and 1 if the condition of demanding phase locking is aggregated then phase distinction is consistent, and subsequently called total phase synchronization.

3.6 Pearson's Correlation

Pearson's correlation is a measurement that estimates direct association between two variables $X(t)$ and $Y(t)$ and that can be calculated from Eq. 4. RANGE: $-1 \leq$ Rxy ≤ 1_-1 for reverse connection among $X(t)$ and $Y(t)$, 0 for no straight relationship and 1 for complete straight connection between the $X(t)$ and $Y(t)$.

$$R_{xy} = \frac{1}{N}\sum_{k=1}^{N} x(k)y(k) \tag{4}$$

3.7 Transfer Entropy (TE)

Transfer entropy is estimating the measure of coordinated move of information between two irregular Processes.

$$T_{X\to Y} = \sum_{y_{t+1}, y_t^n, x_t^m} p(y_{t+1}|y_t^n, x_t^m) \log\left(\frac{p(y_{t+1}|y_t^n, x_t^m)}{p(y_{t+1}|y_t^n)}\right) \tag{5}$$

Equation 5 shows the measure of data stream from $X(t)$ to $Y(t)$. This parameter is theoretically the same as the possibility of Granger Causality. The range of TE is from 0 to ∞, here on the off chance that 0, at that point there is no causality among $X(t)$ and $Y(t)$ and if greater than 0 then $X(t)$ is 'causing' $Y(t)$.

3.8 Mutual Information (MI)

When two different variables is proportion by the common dependence between the two factors that is called mutual information [10]. Mutual information is used to identify high correlation between two channels and this value is calculated by Equation 6. The range of MI is from 0 to ∞ and if equal to 0 then $X(t)$ and $Y(t)$ both are totally autonomous and for greater than 0 $X(t)$ and $Y(t)$ signals are dependent on each other.

$$\mathrm{MI}_{xy} = \sum_{i} p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \tag{6}$$

4 Result and Discussion

The objective of this examination was to show the potential of nonlinear characteristics of the EEG signal in discriminating the normal and autistic response for various stimuli. This will serve as an early identifier and for designing customized training for the children with autism. Figure 3 shows the 3 columns and 2 rows where three column represent three different stimuli like only video, only audio, and audio + video and rows are for normal children and autistic children.

DPI and PLV are phase synchronization parameter and these are used to get local and long rage connectivity. PLV is not strong against the nearness of normal sources. Correlation gives the linear relation between two signals it is consider under the classical measures parameter and it will be used to get low-level relationship between channels. TE and MI are the information theory measures where TE is the conditional MI and it gives the directed information flow from one signal to another, where MI is used to get mutual dependency as discussed earlier and main use of MI is gives the higher order relationship between two signal therefore it does not depends

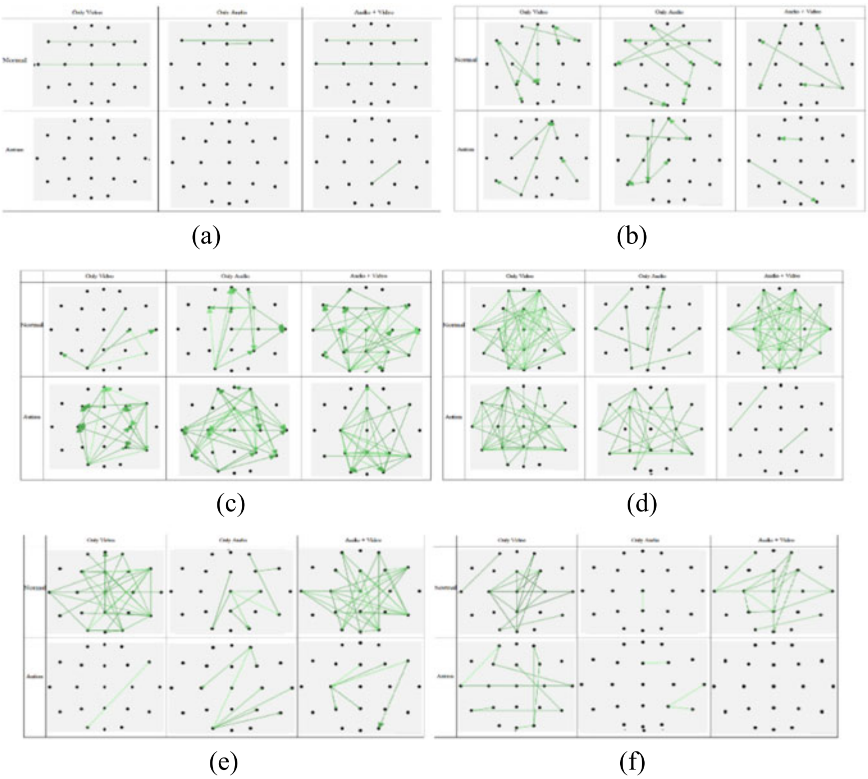

Fig. 3 These figures show the connectivity model of each measure **a** PLV, **b** GC, **c** PLV, **d** COR, **e** TE, **f** MI

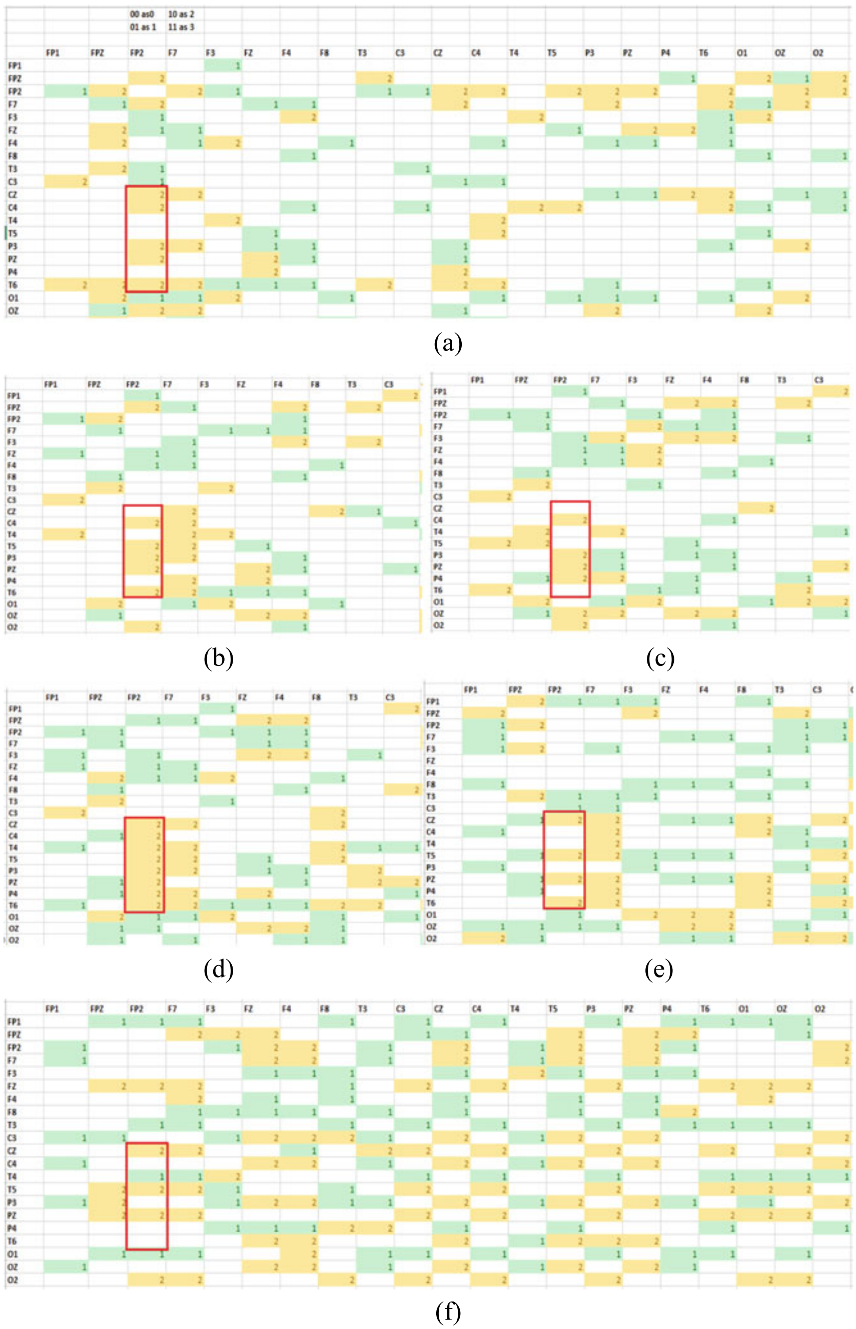

Fig. 4 **a–g** Shows the normalized averaged values of COR for each 21 × 21 channels

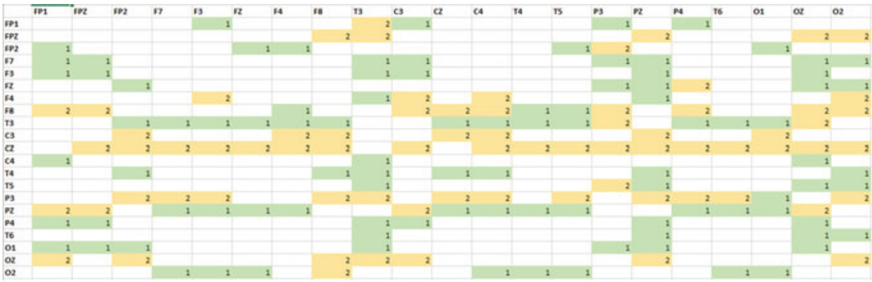

Fig. 5 Shows the normalized averaged value of MI for each 21 × 21 channels

on any specific model. The above connectivity diagrams are converted into weighted graphs. Dissimilar patterns between normal and autistic children are observed.

For pattern detection, we observed only audio + video stimuli with the different datasets to detect better patterns. Here, we have used 7 datasets for both autistic and normal children with the help of showing audio + video stimuli to 3 autism and 3 normal children. Then by applying Correlation connectivity measures to that dataset and we got the value of correlation for each specific 21 channel in the form of a 21 × 21 matrix. Average normalization is applied by getting the average value for each node then whichever has less average value is replaced with 0 and whichever has greater value is replaced by 1 and at the end, the last step is to combine both autism and normal values to distinguish their differences. Here, Fig. 4 shows the combined data which has value for 00 as 0, 01 as 1, 10 as 2, and 11 as 3, and here value 3 and 0 is removed because both autism and normal has the same relationship where 1 and 2 have differences.

The yellow-colored blocks having the value ‘2’ means ‘10’ and green-colored blocks having the value ‘1’ means ‘01’. In this binary pattern, 1 represents the greater value than average and 0 represents the lesser than average. In Fig. 4, we have inferred that FP2 node has all the connectivity with the parietal cortex so it represents that dense network is present around the prefrontal cortex. These correlation gives the linear relationship and it is also depends on the position and distance between two nodes of scalp. Figure 5 shows the value of mutual information for 21 × 21 channels and in MI here no any such common pattern like correlation is observed so here no possibility to focus any particular node.

5 Conclusion

There are many researches trending toward ASD, which can be useful and provides a broad knowledge about the pathological condition. At present, there is no known cure for ASD, but the level of the pathological condition can be reduced when it is detected early. Early detection of this disorder is complicated and challenging till date. In this work, the connectivity model is transformed into a graphical representation and different objective measures like Phase synchronization, Classic Measure, Granger Causality, and Information Theory-based parameters were extracted from it. These parameters were examined to study the variation between autistic and typically developing controls. Higher correlation value in autistic children represents that similar activities are present in brain and less value represents the independent activities. The behavioral, planning and communication skill will more affected by the frontal part of brain and that is clarify in this research. Also, we conclude that parietal part of brain is more useful to analyze connectivity because of low noise into the central brain region and it gives more accurate connectivity than other regions. Analysis with more parameters will lead to better results in the early identification of autism.

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