Research Article
Volume 10:9, 2022

Journal of Cardiovascular Diseases & Diagnosis

ISSN: 2329-9517

Open Access

Diagnosis of Autism Spectrum Disorder through Complex Network Communications

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Abstract

Modular associations are structures in complex networks that are defined based on the communication density between the network elements. The difference in these structures in a complex network of human brain signals (EEG) can be used as a factor in the diagnosis of diseases. In this study, with the focus on modular associations, attempts to achieve the differences between a complex two-group of network of Normal Case (NC) and Autistic of Spectrum Disorder (ASD). Eventually, using real EEG signals, the tested groups, with no use of the pre-processing signaling, have an accuracy of 88.37% in detecting Autism Spectrum Disorder (ASD).

Keywords: Modular associations • Complex network • Electro Encephalo Graphy • Autism spectrum disorder

Introduction

One of the most important disorders in the field of growth is Autism Spectrum Disorder (ASD). This disorder, which occurs in an early age before two years of childhood, in the persons are varies. Despite these differences, the entire autistic spectrum is in a difficult to ability communicated with others. The central core of the disorder in ASD patients is the disruption of social behaviors and communication skills of individuals. Although there is no definitive cure for this disorder, but early diagnosis can have a significant impact on the training, treatment and, consequently, the improvement of the lives of these children. One of the challenges we face in diagnosing this disorder is that there is no specific medical test in this regard. Therefore, in the diagnostic examination, it may we make a mistake due to the similarity of this disorder with other diseases. So, late detection or misdiagnosis leads to postponement of the treatment process and, as a result, an increase in the problems of children with ASD.

One of the ways to diagnose diseases is the use valuable information of vital signals. If the useful information can be extracted from the correct processing of these signals, an important step has been taken to diagnosis of the disease. One of the vital signals of the body is the electrical signals of the brain known as Electro Encephalo Graphy (EEG), which are considered in the diagnosis of many brain-related diseases, such as ASD. But due to its turbulent nature and its random appearance, researchers and doctors have faced a major challenge. Most of the proposed methods for extracting information from these signals are unique to time-frequency methods. These methods have limitations due to the component's properties during signal analysis. In recent years, the analysis of non-linear series that leads to the creation of complex networks is known as an active field of study among scholars. By studying the complex structure of these series, they obtain information from the process of problem understanding, modeling, and predicted goals. Therefore, using these methods in analysis can be used by considering the EEG signal as a nonlinear time series [1]. Among the methods for extracting signal characteristics, the Visual Graph algorithm (VG) has attracted much attention. Because it has shown that the correlation in time series is indicated by this algorithm and translated into the corresponding graph. This issue makes it possible to establish a useful relationship between the series analysis and its nonlinear dynamics based on the graph theory. The visual graph, with the mapping of the signal from time space, to the information space, makes it possible without the need for preprocessing and noise elimination and the latent properties of the EEG signal are extracted using the properties of the graph domain. Can introduce the VG algorithm as a holistic approach to signal analysis. In many studies of recent years, in the medical field, the Visual Graph (VG) has been considered as a method of extracting the characteristic of vital signals. For example, in studies of epilepsy diagnosis based on the electrical characteristics of the EEG signals of the affected person, due to the non-symmetrical nature of this kind of data, the diagnosis of this disease has become is a challenge for brain specialists and nerves. In a study, used the Visual Graphic Algorithm (VG) to detect Electro Cortical-Based Epilepsy (ECOG). The model presented in the study is based on high-frequency oscillations during epileptic seizures and suggests epilepsy disease. Therefore, nonlinear characteristics of high-frequency signals may be more significant. Hence, by measuring the characteristic called the complexity of the Graph Index (GIC) based on the graph obtained from this signal (ECOG), it shows that in comparison with conventional methods of measuring complexity, such as the entropy sample, the GIC standard diagnosis of epilepsy is better. Using VG, you can discover the causes and stage of sleep disorder. Study uses this algorithm to classify the sleep stages. Most sleep classification methods are based on the characteristics of the time-frequency domain of vital signals. However, in a study, using VG and graph-domain properties such as mean degree, the analysis of EEG signal is in single-channel C3 mode. Then, using the innovative method of differentiation visual (DVG), it defines important features in determining the stages of sleep. One of the features of vital signals such as EEG is its nonlinear dynamics. This has posed a major challenge in extracting information from these signals. A complex network to maintain the weight of the edges in order to maintain this signaling property. Therefore, taking into account the Weighted Visibility Graph (WVG), two topological properties of these networks are derived from modular names and weighted degree,

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Received: 16 December, 2019, Manuscript No. jcdd-19-5624; **Editor assigned:** 19 December, 2019, Pre QC No. P-5624 (PQ); **Reviewed:** 02 January, 2020, QC No. Q-5624; **Revised:** 09 November, 2022 (R), QI No. Q-5624, Manuscript No. R-5624; **Published:** 07 December, 2022, DOI: 10.37421/2329-9517.2022.10.513

ultimately reaching 100% accuracy in the diagnosis of epilepsy disease. By studying the single-channel C3 and C4 signals from electromagnetics records of healthy and autistic children, scientists have achieved clear differences in brain connections between these two groups of children. Thus, the extraction of feature of the EEG signal and the C3 channel can be effective in detecting children in the ASD spectrum. Due to the unique nature of the EEG signals of each person, signal-based diagnostic models can greatly overcome the challenge of misdiagnosis. According to from the National Association for Autism, in one recent study, 50% of people with autism and their families believe that it is difficult to diagnose this problem, and 55% of them are from the process the very long diagnosis of this disorder has been dissatisfied. While any technique and device that helps to diagnose the disease at a child age, it potentially has the potential to affect the quality of life of people with this disease, because it causes these people from an age lower than the right support. In two studies and specifically, a similar application to the article is presented. For example, in study using the Poincare Section method, the EEG signals are modeled and, according to the events of the signals, describe the information used in the poincaré section. Then, using pattern changes in ASD samples, differentiate of them with normal case samples are showing. In study the author calculates the average of the Power Scale Freeness Visibility Graph (PSVG) for the 5 sub-bands alpha, beta, gamma, theta and delta in the EEG signal. Sub-band beta values are then used for has better result to identify the ASD samples from the NC because of better results after the introduction of the universal PSVG as an entry of the Enhanced Probabilistic Neural Network (EPNN). Hence, although the accuracy of the result's study is high, but because it uses a partial wavelet method on a particular sub-band, it has the universality necessary for all data with types no noise. The present study uses a visual graph algorithm to investigate the changes of single-channel C3 signals in two classes of Normal Children (NC) and children's autistic children (ASD). Then, using the extracted features, a model is presented for separating the complex networks of NC and ASD children [2].

Materials and Methods

Datasets

In this article, 60 children were tested in the age range of 4 to 8 years (2 ± 6). Of the 30 children in the NC group, which included 21 girls and 9 boys with a mean age and standard deviation (4. 5 ± 1.33) and 30 children in the ASD group including 22 boys and 8 girls with mean age and standard deviation (45.2 ± 9/6), all of which were right-handed, were tested. In these records, the C3 electrode is considered to represent the left hemisphere and the C4 electrode as the representative of the right hemisphere. Research has shown that areas C3 and C4 relate to voluntary movements, attention and memory of the long term, and that the central area of the head is related to the areas of mood control, executive function, and actuator performance. Of course, the temporal region is one of the important areas of the disorder, but due to the child's shaking during the recording, the probability of separation of the electrode is very high, hence the recording has taken place in the central region [3]. In this study, for sampling and recording the EEG signal, used a 10-channel flex comp Infinity instrument with a 256-Hz, 24-bit sampling frequency and a gold plated spoon electrodes, based on the standard 20-10. The recording protocol was that in the acoustic room the child had two-minute had a recording of the baseline, then the animation was broadcast to him for 5 minutes, followed by 5 minutes of silent animation. These databases are divided into 20 seconds. These files have been registered with the Mental Health License 500685/95 of Mashhad University of Medical Sciences [4].

Converting a signal to a complex network

A complex network is a definition that is provided by real-world systems and networks. These graphs do not have regular structures based on the rule. These networks, in fact, contain entities of order and disorder at the same time. EEG signals are essentially non-linear and are known as multi-fractal data in nature. Lacasa shows that time series with fractal dimensions, such as Signal signals create complex networks of scale-free features. Thus, it is possible to analyze and evaluate the desired signal using the rules governing complex networks, without necessarily requiring the removal of a part of the signal, as is customary. Most biological and technological networks have unusual topological characteristics, so that the patterns of communication between their elements are not quite regular and not merely coincidental. Some of these features are like the Heavy tail, degree distribution, high clustering and hierarchical structure (Figures 1-3) [5].

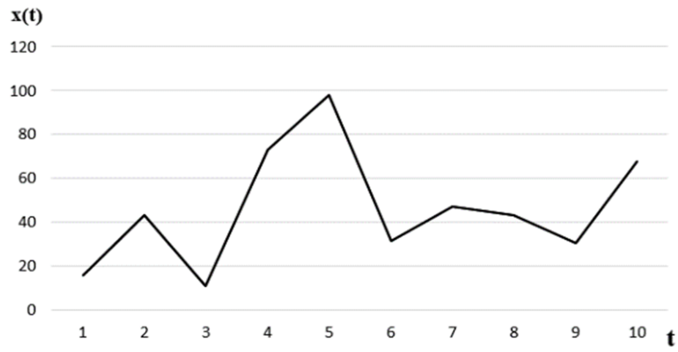

Figure 1. Classified time x (t).

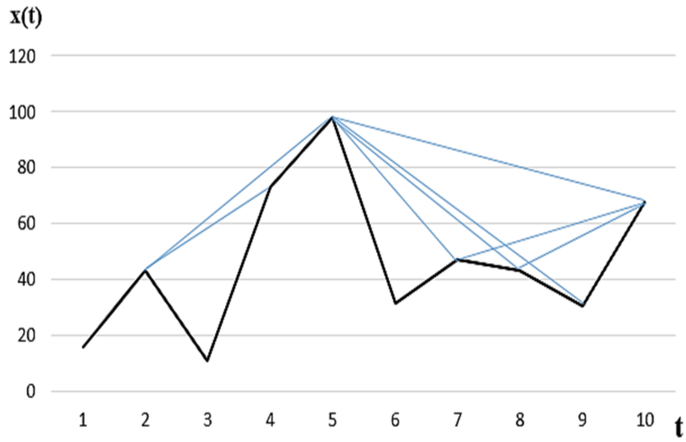

Figure 2. Visibility of each point relative to another.

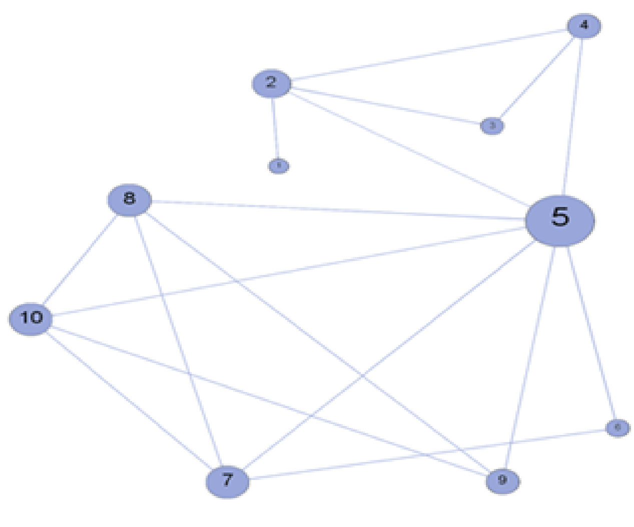

Figure 3. Visual graph of the signal x (t).

Visual graph

Suppose G (V, E) is a graph, while V and E are respectively graph and nodes. The time series {x (t)} {t=1, ..., n} is mapped to the graph G (V, E), so that a dot x_i is converted to v_i n in the graph G. For both v_i (i, x_i) and v_j (j, x_j), the edges between v_i and v_j are create of on the law Proposed by Lacasa in the study.

$$\frac{(x_j - x_k)}{j - k} > \frac{(x_j - x_i)}{j - i} \ \forall k \in (i, j)$$

In other words, the algorithm map the visual graph of each of the series digits to a node in the graph. The two nodes v_i and v_j are connected in the graph, if a direct line can be connected in the time series from x (i) to x (j), so that no altitudes like x (k) are interrupted. For example, consider the time series x (t) with the values below, Figure 1. To draw the visual graph of the time series x (t), a straight line is drawn from each x (i) to another value such as x (j), so that no intermediate height is interrupted. Each x (t) is considered as a node in the graph and its connections are the degree of that node. Using the An *n proximity matrix, links between nodes are plotted in the graph. If An *n={aij} is a neighboring matrix with n members to the number of complex network nodes, then aij becomes one when there is an edge between the two nodes i and j in the complex network and Otherwise it will be zero. The VG graph is a demonstration of node connections in the adjacency matrix an *n [6]. The visual graph extracts the different characteristics of each signal by preserving the property of time series such as periodicity, randomness and turbulence in the complex network. The mapping of vital signals such as EEG leads to create complex networking due to turbulence and having fractal dimensions [7].

Feature extraction

In the data analysis, during the process of extracting the characteristic, it attempts to identify the characteristics of the data by performing operations on the data. The goal is to extract the raw data preparation feature into an effective data output. In this study, using the topological properties of a complex network derived from the EEG signal, such as the Community Detection (CD), analyzes and classifies the networks of both NC and ASD classes. Finally, it is shown that the CD topological feature can help identify hidden patterns in EEG signals for children with ASD [8].

Community detection

Complex networks such as biological networks have similar characteristics, such as small world, free-scale, and modular (group) structures. In this regard, the study of complex networks has attracted the attention of many researchers in recent years. Community detection is difficult in arbitrary network, because there is no comprehensive and accurate definition of society in a network, and various algorithms have been proposed for community detection. Modular structure (Modular) is one of the most important features of real networks. In the modular structure, we see communities that have a high social interpersonal density and, conversely, population congestion is minimized. Finding optimal communities that can be used to extract useful information has always been challenging. Typically, in bio-networks, proteins that have the same function can form a community (Meybodi). In this study, using the CD feature, the relationship between nodes in a complex network derived from the EEG signal of normal and ASD children is investigated [9].

Modularity

One of the common models in community detection is the modular maximization model. Modularity is the most well-known method of qualitative comparison in the discovery of associations, which uses this method in isolation in community detection. In this model in (2), the matrix A is the adjacency matrix, m is the number of edges, k_i is the vertex i and the function δ (ci, cj) if each darya i and j are in the same society. Equal to one and otherwise equal to zero. The higher the Q value, shown the more optimal modular it is. The ultimate modular value is ultimately defined between 1 and -1 (Figure 4) [10].

$$Q = \frac{1}{2m}\sum_{ij} A_{ij} - \frac{k_i k_j}{2m}\delta(c_i, c_j)$$

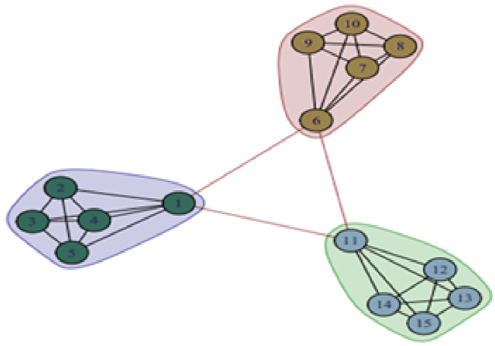

Figure 4. Girvan-Newman's modularity.

Community detection based on the maximum communication density within the community and the minimum contiguity of communication outside the community.

Feature selection

The visual graph, as a method of extracting attributes from time series, can extract the unique topological properties of each signal. Among the topological differences, those features that have a significant impact on classifying classes are selected in the feature selection step. How to select these features in the section of the findings and discussion is presented in detail. In this study, using the modular community detection algorithm, the number of community (Comm-Num) in each graph is extracted and considered as the main attribute. Then, the size of the community (Comm-Siz) (the number of constituent nodes in each community) is also computed. Finally, the two features of Mean of communities Size (Meancomm-Siz) and the community size variance (Varcomm-Siz) of each graph are also calculated as secondary and effective attributes [11].

Number of community

As the name attribute feature the number of Community (Comm-Num), this property measures the number of Community in each graph. When using the modular community algorithm, identity for each Community in the graph, a counter is considered to hold the number of community assigned to each graph.

Mean of size the community

The average is one of the most common criteria for center-centeredness. This feature shows that the community for each graph is in the gap scattered over time. Hence, based on the mean definition, the relation (3) is defined.

$$Mean_{\ COMM\_SIZ} = \frac{1}{(\text{Comm\_Num})}\sum_{i=1}^{\text{Comm\_Num}}(\text{Comm\_Siz})$$

However, the mere fact that this indicator cannot provide an accurate picture of our problem. Hence, in order to understand how the community are located, around its average, the size of the variance of community (Varcomm-Siz) is also calculated.

Variance of community size

In data mining, it helps to get variance to determine how much the records of a column are distributed. In other words, the records of a dataset are far from the average distance. In this study, the variance is calculated according to relation (4).

$$VAR_{COMM\_SIZ} = \frac{\sum(\text{COMM\_SIZ} - \text{MEAN}_{\text{COMM\_SIZ}})^2}{\text{COMM\_NUM}}$$

Average grade

The degree of a node in the graph means the number of connections available between a node with other nodes. If K_i is considered as the degree of each node, it can be written as relation (5) based on the adjacency matrix A_{ij}. Most of the nodes in the network are of a small degree, so the graph of the time series of these nodes is not worth much.

What emerged from the experimental observational graphs in the test dataset shows that 75% of normal EEG signals of child normal, lead to graphs with high-grade hubs.

$$k_i = \sum_{j=1}^{n} A_{ij} \quad (5)$$

This is while the visual graphs of children with ASD are formed from lower-order hubs degree than the NC sample graphs. The feature of average grade for each visual graph (ADVG) is presented in accordance with relation (6).

$$AD_{VG} = \frac{1}{n}\sum_{i=1}^{n} k_i$$

Based on the extracted attributes of COMM-NUM, COMM-SIZ, MEANCOMM-SIZ, VARCOMM-SIZ and the feature mean value of the visual graph (ADVG), two new features are defined as relations 7 and 8. As the value of feature ADVG increases, the VARCOMM-SIZ value decreases, hence, based on this relationship, the new VAD feature is presented in accordance with equation (7).

On the other hand, due to the apparent difference in the number of Community of NC and ASD graphs, the second power is used to enhance the effect of the COMM-NUM attribute in calculations.

Classification nearest neighbors algorithm

Among the pattern recognition algorithms, the K-NN algorithm is used as a non-parametric method for classification and regression. This algorithm is an optimization problem for finding the nearest points in the metric space. The problem is that the set s contains a number of points in a metric space such as M and also a search point called q such that q∈M, the goal is to find the nearest point to q in the set s. In most cases, the space M is a d-dimensional Euclidean space and the distance between points is determined by criteria such as the Euclidean distance, the Manhattan distance (relation 8), the cosine distance, or other metric distances. The classifier K-NN, K returns the neighbor closer to the hypothetical point. K is a positive integer and usually small. This method works according to the majority voting mechanism of the neighbors for prediction, estimation and classification. Classifier K-NN increases the computational speed due to lack of training. In this study, K-NN was used for k=6 (Figure 5).

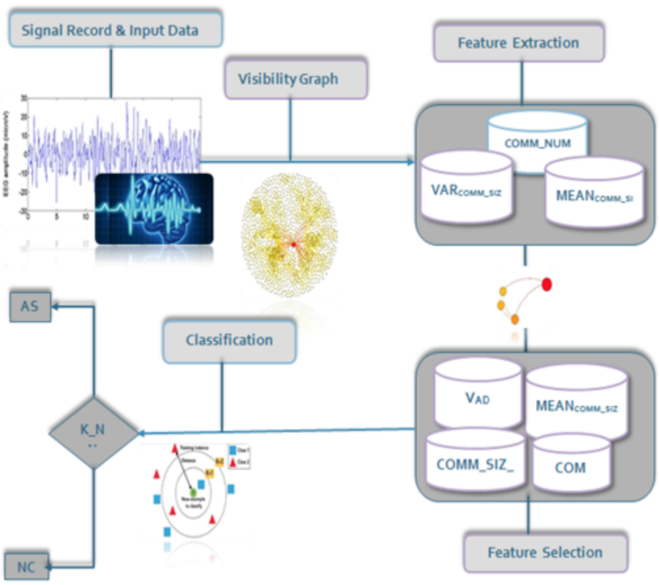

Figure 5. Diagram of the proposed method.

Discussion

Characteristics community detection of nodes and its choice importance

In Section 1, it is noted that the graph obtained from vital signals becomes complex networks with a free-scale feature. This attribute shows that the degree distribution in these networks follows the power rule and has a long-order graduated distribution diagram. The free-scale feature indicates that the nodes with a higher degree are less than the number of nodes with less degree. This behavior is observed in the grading distribution graph of the test data of both NC and ASD classes (Figures 6 and 7).

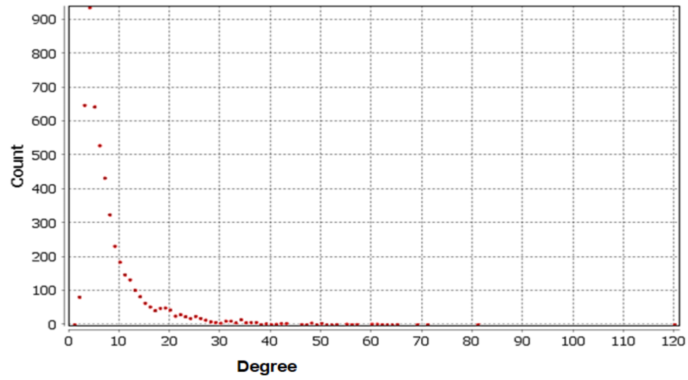

Figure 6. Grade Distribution Graph. Normal class grade sample distribution chart (NC).

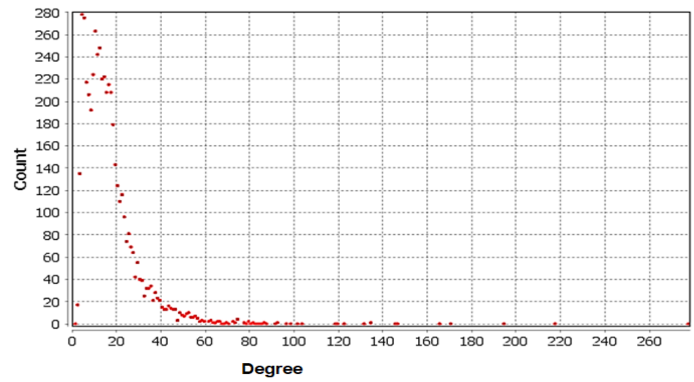

Figure 7. Grade Distribution Graph. Autism Spectrum Disorder (ASD) class grade sample distribution chart.

The difference in the gradual distribution graphs of these two classes is the existence of nodes with higher degrees in NC specimens than the nodes of non-standard samples (ASDs), which is easily evident in images of degrees distribution graphs. Another feature of complex networks is the small-world feature, which is shown feature in VG graphs of vital signals. The characteristics of the small-world networks, the high clustering coefficient and the average path length are low. This problem is clearly visible in the VG graphs of NC children samples (Figure 8).

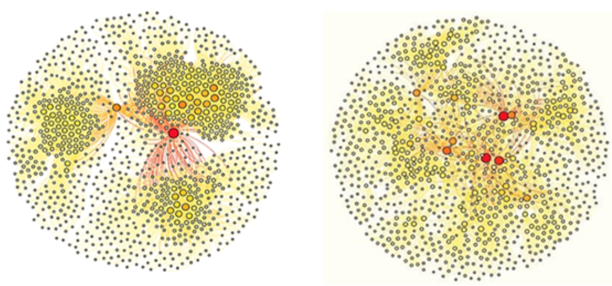

Figure 8. The graphs of samples with ASD, nodes in these graphs do not tend to cluster together and are usually placed in small community.

So, after seeing the graphs of samples with ASD, nodes in these graphs do not tend to cluster together and are usually placed in small community. Hence, this node performance results in the formation of a population of full number clusters with fewer numbers in the NC graph than the ASD graph. In the ASD graph, there are obviously low populations with high numbers, except in the case of exceptions that are considered as overlapping examples with the NC. This behavior is observed in 75% of the test sample graphs. Thus, in the EEG signals of the two NC and ASD classes, both the characteristics of the free-scale networks and the small-world networks are intuitive. Another noteworthy point in observation is that, in a class NC association, the average nodal grades are higher than the ASD class. Hence, in the NC class, hubs with more power in the connections are seen. The degree difference of nodes is shown with different color and size. The color of the nodes, the closer the red is to its larger size, indicates the degree of power it is nod (Figures 9 and 10, Table 1).

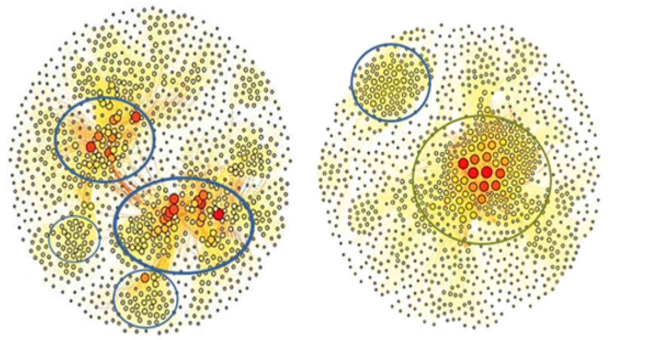

Figure 9. Community detection Visibility Graph (VG) in normal case class.

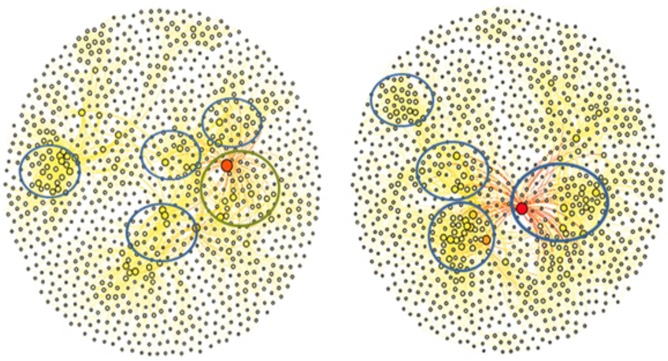

Figure 10. Community detection Visibility Graph (VG) Autism Spectrum Disorder (ASD).

	True ASD	True NC	Class Precision
Pred. ASD	21	4	0.84
Pred. NC	9	26	74/29%
Class Recall	0.7	86/67%	
Accuracy		78/33%	

Table 1. Simulation results based on K-NN classification (K=6). Features used: $MEAN_{COMM\_SIZ}$, V_{AD}, COM.

Results

In this study, using the differences between complex networks derived from EEG signals, a method for classifying two classes of NC and ASD children was presented. The topological differences in these networks, such as the number of community per network (COMM-NUM), the size of each association (COMM-SIZ), and the average and variance of the size of each community (MEANCOMM-SIZ, VARCOMM-SIZ), are used as indicators for distinguishing between these two the class was introduced. Based on these features, two new features are called VAD and COM. Then, the MEANCOMM-SIZ, VAD, and COM attributes were used as inputs of the K-NN classifier.

According to the number of NC and ASD children tested, a total of 60 signal pieces, with a length of 5120 samples, were used in the mapping to network and feature extraction. Then, using the proximity matrix, the visual graph is formed. The visual graph for samples with a 1024-bit data (4-second signal with a frequency of 256 Hz) for the two ASD and NC target classes. The important point at this stage is that the single-channel C3 signal is mapped to the graph raw and without any frequency pre-processing. The K_fold validation method was used to evaluate the performance of the proposed method in order to obtain reliable results. In this study, in order to generalize the results, K=60 is considered. This special mode of K_fold evaluation is called LOOCV. The results of the evaluation of the proposed method, the accuracy and accuracy of the model. The accuracy of 78.33% without signal filtering indicates the effectiveness of the VG feature extraction method in brain signal processing and the separation of the NC and ASD groups.

Analysis of the effect of unique community in result

The community feature in complex networks can be considered as a factor in separating the two NC and ASD children classes. In followed to improve the assessment results, the impact of each graph as a single community, been investigated. At first, the forums are sorted in descending order by size (COMM-SIZ). The reason for this sort is the impact of the large size community on the classification results. Because our guess for this process is the existence of a large, populous community in NC class graphs than the ASD class graphs. Studies show that the community number 21 (COMM-SIZ-21) is more effective than other forums in dividing both NC and ASD classes. COMM-SIZ-21 changes for the 60 tested children. As seen in the picture, the COMM-SIZ-21 attribute for NC children has more nodes than ASDs, hence, with a slope less than zero. This feature is added to the other features tested in the proposed method. The results show that the unique feature of COMM-SIZ-21 can be effective from the COMM-SIZ feature set on the accuracy of NC and ASD class detection and can increase the accuracy to 80%. The properties used in the K-NN classifier. (Figure 11 and Tables 2, 3).

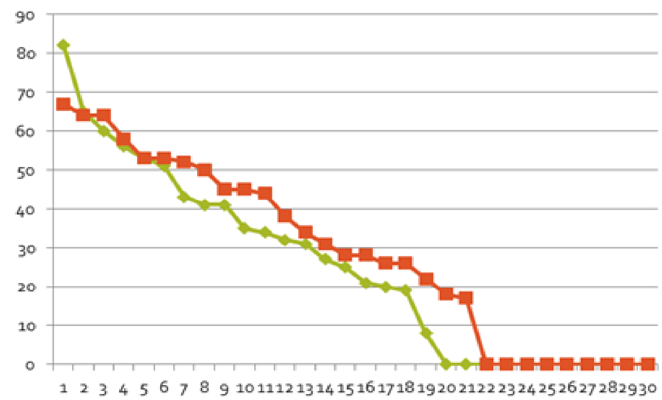

Figure 11. Change of the community 21st for all samples of the two NC and ASD classes.

	True ASD	True NC	Class Precision
Pred. ASD	22	4	84/62%
Pred. NC	8	26	76/47%
Class Recall	73/33%	86/67%	-
Accuracy		0.8	

Table 2. Simulation results based on K_NN classification (K=6). Features used: MEANCOMM_SIZ, VAD, COM, COMM_SIZ-21.

NUM	COMM-21	MEANCOMM-SIZ	VAD	COM
A-1	43	119.0697674	5655.409173	1849
A-2	82	86.77966102	2053.569499	3481
A-3	0	284.4444444	3035.396137	324
A-4	35	134.7368421	5599.984252	1444
A-5	19	170.6666667	7485.59123	900

Table 3. Features used in K-NN classi ication.

A-6	0	269.4736842	6042.822204	361
A-7	65	102.4	2712.174676	2500
A-8	56	196.9230769	3441.308943	676
A-9	53	72.11267606	2492.328452	5041
A-10	0	284.4444444	3202.519042	324
A-11	20	176.5517241	6212.286663	841
A-12	34	146.2857143	6617.41085	1225
A-13	41	243.8095238	3950.78431	441
A-14	32	160	7052.94636	1024
A-15	31	213.3333333	3591.063703	576
A-16	60	183.8214286	3666.409063	729
A-17	0	256	6483.352436	400
A-18	41	160	5743.813119	1024
A-19	0	301.1764706	3143.582039	289
A-20	27	176.5517241	5747.406763	841
A-21	0	256	3375.621001	400
A-22	0	320	3447.681996	256
A-23	51	213.3333333	3291.15026	576
A-24	21	232.7272727	5251.09535	484
A-25	0	301.1764706	8291.600814	289
A-26	8	243.8095238	2536.392304	441
A-27	25	111.3043478	5344.018418	2116
A-28	0	269.4736842	6138.752029	361
A-29	0	269.4736842	7186.582952	361
A-30	0	256	5977.851185	400
N-1	0	512	8080.597928	100
N-2	0	465.4545455	4368.849499	121
N-3	0	301.1764706	5060.195515	289
N-4	45	138.3783784	3503.716119	1369
N-5	17	182.8571429	5271.509026	784
N-6	0	269.4736842	3689.819099	361
N-7	67	102.4	2260.005805	2500
N-8	45	150.5882353	4110.216919	1089
N-9	26	196.9230769	4906.536707	676
N-10	0	256	3432.233223	400
N-11	22	222.6086957	3993.441284	529
N-12	26	232.7272727	3522.576229	484
N-13	18	243.8095238	3690.764104	441
N-14	0	284.4444444	5433.273468	324
N-15	34	243.8095238	3517.190864	441
N-16	0	301.1764706	4073.765264	289
N-17	53	182.8571429	4435.471137	784
N-18	28	176.5517241	4813.972654	841
N-19	53	142.2222222	3992.785494	1296
N-20	58	213.3333333	2642.946433	576
N-21	31	213.3333333	3591.063703	576
N-22	0	269.4736842	2239.564674	361
N-23	0	320	4418.798239	256
N-24	50	232.7272727	3552.146552	484
N-25	52	182.8571429	3821.96419	784
N-26	28	196.9230769	5495.549653	676
N-27	64	189.6296296	3765.211688	729
N-28	38	204.8	3689.822261	625
N-29	64	106.6666667	3165.703044	2304
N-30	44	119.0697674	9778.777939	1849

Conclusion

In this study, using the visual graph method, as a new method for extracting the characteristic of EEG signals, it was shown that the difference in the number and size of modular associations in graphs can be used as a criterion for classifying NC and ASD target class samples. One of the advantages of the VG algorithm is to automatically remove the noise from the signal. This causes the speed of computing to change with the removal of the signal filtering stage, in addition to maintaining the fundamental characteristics of the vital signals. This study focuses on other studies in the field of diagnosis of (ASD), in the simultaneous use of analytic methods of graph theory and the use of modular associations in complex networks. Another advantage of the proposed method in detecting ASD is that, because it is based on the analysis of EEG signals, it can therefore be used as an effective diagnostic method before the onset of clinical symptoms and secondary problems in the child. One of the most prominent features of this research is the use of real data related to the Autism Noor Hedayat School in Mashhad, which was registered by the research team of the Center for Computational Neuroscience Research at Imam Reza International University. To evaluate the proposed method, NC and ASD children were used with the same record conditions. Finally, using the K_Fold evaluation technique, accuracy of 84.62% was found in the ASD class diagnosis.

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How to cite this article: Irankhah, Elyas. "Diagnosis of Autism Spectrum Disorder through Complex Network Communications." *J Cardiovasc Dis Diagn* 10 (2022): 513.