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Network centrality analysis of eye-gaze data in autism spectrum disorder

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ABSTRACT

Individuals suffering from autism spectrum disorder (ASD) exhibit impaired social communication, the manifestations of which include abnormal eye contact and gaze. In this study, we first seek to characterize the spatial and temporal attributes of this atypical eye gaze. To achieve that goal, we analyze and compare eye-tracking data of ASD and typical development (TD) children. A fixation time analysis indicates that ASD children exhibit a distinct gaze pattern when looking at faces, spending significantly more time at the mouth and less at the eyes, compared with TD children. Another goal of this study is to identify an analytic approach that can better reveal differences between the face scanning patterns of ASD and TD children. Face scanning involves transitioning from one area of interest (AOI) to another and is not taken into account by the traditional fixation time analysis. Instead, we apply four network analysis approaches that measure the "importance" of a given AOI: degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. Degree centrality and eignevector centrality yield statistically significant difference in the mouth and right eye, respectively, between the ASD and TD groups, whereas betweenness centrality reveals statistically significant between-group differences in four AOIs. Closeness centrality yields statistically meaningful differences in three AOIs, but those differences are negligible. Thus, our results suggest that betweenness centrality is the most effective network analysis approach in distinguishing the eye gaze patterns between ASD and TD children.

1. Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental disorder that affects around 2% of the population and is characterized by impairments in social communication and repetitive behaviors [16]. Additionally, individuals with ASD exhibit attentional biases in social situations, also known as visual social attention, that differ significantly from typical development (TD) individuals [10]. In particular, the overt attention with which individuals with ASD orient and direct to faces, as well as the manners by which they visually explore faces and interpret gaze information, appears to exhibit characteristics distinct from TD individuals [10]. Thus, visual social attention has often been studied among individuals with ASD, using human faces as the target [1,2,22]. To provide precise measurement of an individual's eye gaze to different parts of the face, eye-tracking technology can be employed [8,14]. To the extent that distinct eye-gaze patterns can be used to identify ASD individuals, eye-tracking methods have the potential to benefit ASD children in particular, who likely experience substantial difficulties in answering diagnostic screening questions, and who may have the most to gain from early diagnosis and treatment.

In visual social attention studies, subjects are typically shown pictures of people or faces, and eye gaze patterns are determined by measuring fixation times at different areas of interest on the faces. Eye gaze patterns have been found to be significantly different between ASD and TD groups [12]. Notably, studies using monitor-based eye-tracking methods [4,5] have reported that young children with ASD focus less on others' faces, particularly their eyes, compared to TD children [3,6]. Instead, ASD individuals spend significantly more time looking at the mouth, compared to TD individuals [5,20].

While the fixation time approach provides important information, that information is incomplete. A key limitation is that fixation time does not capture the transitions (saccades) from one facial feature to another, even though the transitioning between facial features is a key aspect of visual scanning of faces. Thus, a major goal of this study is to identify an analytic approach that reveals the differences in saccading patterns between ASD and TD children. To that end, we expand on the work of Guillon et al. [9], who formulated a network that represents AOIs as nodes and transitions between AOIs as links. They then computed degree centrality, a classic measure that corresponds to the degrees of each node. Their analysis indicated that the degree centrality of

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the left eye is smaller in ASD children compared to TD children, but that of the mouth is greater in ASD children [9].

The study by Guillon et al. [9] is the first published study that applies graph theory techniques to analyze eye gaze data in the ASD population. The authors used degree centrality, which, perhaps due to its simplicity, is arguably the most popular centrality measure. Nonetheless, other centrality measures may also be used to assess the importance of nodes in a network, including betweenness centrality and closeness centrality. *How effective are these network-based measures in revealing distinctive eye gaze features in ASD children?*

Given the importance of early diagnosis, a principal goal of this study is to identify a network analytic approach that can best distinguish eye gaze patterns between ASD and TD children. To accomplish that goal, we analyzed eye-tracking data in ASD and TD children using fixation time, degree centrality, betweenness centrality, and closeness centrality, and compared the extent to which each measure can distinguish between the eye gaze patterns of the two populations. To the best of our knowledge, this is the first study that analyzes eye gaze data using betweenness centrality and closeness centrality. Our results indicate that the *betweenness centrality* approach is the most effective in identifying statistically meaningful differences in eye gaze patterns of the two populations.

2. Materials and methods

2.1. Experimental procedure

Seventeen children with ASD and twenty-three TD children participated in this study. All parents or legal guardians provided their written informed consent to participate in the study in accordance with the principles explained in the Declaration of Helsinki. The mean chronological ages of the ASD and TD groups were 5.5 and 4.8, respectively.

The stimuli were presented on a 19-inch screen, integrated into an eye-tracking system. Specifically, a device manufactured by SensoMotoric Instruments (SMI) with infrared technology was used. The infrared device interprets and identifies the locations on the stimuli at which the subject is looking via emission and reflection of wave from the iris. This device has a tracking resolution of 0.03°. The device includes 2 softwares: iView X for presenting and arranging the stimuli, and BeGaze for collecting and analyzing eye gaze data. Participants were seated 60–80 cm from the screen. Light levels were maintained constant during the recording.

Each participant was shown 44 photographs consecutively. Each photograph has a resolution of 72 ppi. When projected on the screen, the image has a size of 10.1×16.1 inches. This was done using iView X. The series of photographs consisted of 11 distinct photographs (6 men and 5 women of neutral expression, ages between 20 and 32) shown randomly in 4 rotations. Before the appearance of each photograph, the participant was presented with a central fixation point on a gray background. That stimulus lasted 1 s, to ensure that all participants were looking at the same location on the screen when the photographs were shown. Each photograph was presented for 3 s. Given that the participants were young children, naturally, they might have had difficulties focusing on the photograph for the full duration, especially the ASD children. Thus, post-processing was performed so that only those trials during which the participants focused on the photograph for 2.5–3 s were included in the analysis.

2.2. Eye gaze data analysis

Seven rectangular areas of interest (AOIs) were manually defined for each face: (1) under the right eye, (2) right eye, (3) under left eye, (4) left eye, (5) nose, (6) mouth, and (7) other parts of the screen. It is noteworthy that each eye AOI includes the eyes and eyelashes but not the eyebrows, whereas the mouth AOI includes the lips and teeth. The "other parts of the screen" AOI includes all areas that aren't accounted for in AOIs 1 through 6. See Fig. 1.

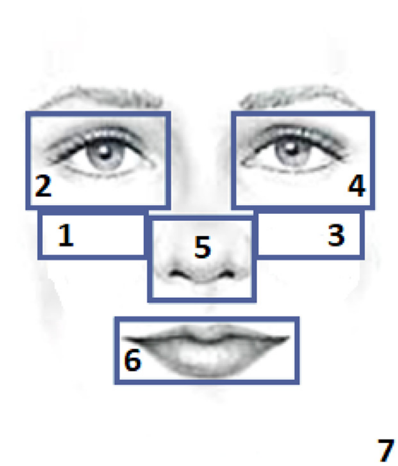

Fig. 1. Areas of interest (AOIs) on a sample face. 1, under the right eye; 2, right eye; 3, under left eye; 4, left eye; 5, nose; 6, mouth; 7, other parts of the screen.

2.2.1. Fixation time analysis

Fixation time for each AOI was determined for each participant by BeGaze (by SMI). The average fixation time was then computed over all participants for each AOI and for each group.

2.2.2. Network-based analysis

To investigate how ASD and TD children explore facial features differently, we employ the "centrality" concept from network analysis. Here, each of the seven AOIs is considered a node in our network model. Each saccadic transition between two AOIs yields a link between those two nodes. An undirected graph is assumed. Given this notation, a two-dimensional transition or adjacency matrix A is constructed for each photograph and for each participant, such that the element a_{ij} equals to the number of transitions from AOI i to AOI j and vice versa. Consider the transition matrix A:

$$A = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 3 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Here $a_{25} = a_{52} = 3$, indicating 3 transitions between AOI 2 and AOI 5.

To assess the importance of each node, one may apply measures of centrality. We computed four such centrality measures (see below) and compared their effectiveness in distinguishing between ASD and TD children.

Degree centrality was developed first and is arguably the simplest conceptually. It is given by the number of links associated or connected with a given node [9]. Consider a graph $G = (V, E)$, where V denotes vertices (nodes) and E denotes edges (links). The normalized degree centrality of a node k is defined as [19].

$$\bar{D}_k^w = \frac{D_k}{\max_j D_j} \times \frac{w_k}{\max_j w_j} \times 100\%, \quad (1)$$

where D_k is the number of nodes connected directly to k, and w_k is the number of links connected to k. $\max_j D_j$ and $\max_j w_j$ are maximums taken over the entire graph. Thus, $\bar{D}_k^w$ is a measure that takes into account both the number of nodes and links connected directly to k.

Betweenness centrality is given by the number of shortest paths between two other nodes that pass through a given node [17]. The betweenness of a node k in $G = (V, E)$ can be computed as follows:

1. For each pair of nodes (i, j), find the number of shortest paths between them (denoted $P(i, j)$).
2. For that pair of nodes (i, j), determine the number of shortest paths that pass through node k (denoted $P_k(i, j)$).
3. Sum the fraction $P_k(i, j)/P(i, j)$ over all possible pairs of nodes (i, j).

Thus, we define normalized betweenness centrality $\bar{B}_k$ for node k as

$$\bar{B}_k = \frac{B_k}{\max_l B_l} \times 100\%, \tag{2}$$

where

$$B_k = \frac{\sum_{i,j\neq k} (P_k(i, j)/P(i, j))}{\binom{N-1}{2}}, \tag{3}$$

N is the number of nodes in the graph.

Closeness centrality is another measure for quantifying the importance of a given node. It can be calculated from the reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the graph. Thus the more central a node is, the closer it is to all other nodes and the larger its closeness centrality value. We compute normalized closeness centrality as

$$\bar{C}_k = \frac{C_k}{\max_l C_l} \times 100\%, \tag{4}$$

where

$$C_k = \frac{N-1}{\sum_j d_{i,k}}, \tag{5}$$

$d(i, k)$ is the shortest path between node i and k.

Eigenvector centrality assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Specifically, the eigenvector centrality of node k, denoted E_k, is proportional to the weighed sum of the eigenvector centrality of the nodes to which it is connected:

$$E_k \equiv X_k^{\max} = \frac{1}{\lambda^{\max}} \sum_j a_{k,j} X_j^{\max} \tag{6}$$

where $\lambda^{\max}$ is the largest eigenvalue associated with the transition matrix A, and $\vec{X}^{\max}$ is the associated eigenvector; i.e., $\lambda^{\max} = \max_i \lambda^i$ where $A\vec{X}^i = \lambda^i \vec{X}^i$. In Eq. (6), X_j denotes the j-th entry of the vector $\vec{X}$, and $a_{k,j}$ is the (k, j)-th entry of the adjacency matrix A. Thus, E_k is given, in part, by the weighed sum of the E_j's of the neighbors of node k. The normalized eigenvector centrality $\bar{E}_k$ is given by

$$\bar{E}_k = \frac{E_i}{\max_l E_l} \times 100\% \tag{7}$$

3. Results and analysis

3.1. Fixation time results

For each AOI, we computed fixation times for the ASD and TD groups. These results are given in Table 1 and also summarized in Fig. 2. Fixation times for the "Other" region are significantly larger than other AOIs, because "Other" refers to regions of the screen, within and outside of the face, not covered by the other six AOIs and thus has a relatively large area (Fig. 1). Our statistical analysis (see p-values in Table 1) indicates that there is no significant difference in AOI fixation time between the two groups, except for the mouth. Children with ASD focused for a significantly longer time (+62%) on the mouth compared with TD children. This result is consistent with observations by Neuman et al. [18]. Also noteworthy is that both groups spent significantly more time looking at the left eye and under the left eye, compared to the right, by +360% and +215% for the TD and ASD groups, respectively. Our result for the TD group is consistent with findings by Guillon et al. [9].

Table 1
Fixation times (in ms) for autism spectrum disorder (ASD) and typical development (TD) groups. SD, standard deviation.

	ASD		TD		p-value
	Mean	SD	Mean	SD	
Under right eye	37.6	66.5	60.6	55.4	0.25
Right eye	79.7	105.6	95.2	98.9	0.64
Under left eye	312.1	275.4	393.1	233.3	0.34
Left eye	239.3	232.7	323.6	253.3	0.28
Nose	240.9	174.6	324.8	223.8	0.19
Mouth	744.9	392.4	449.7	194.6	0.01
Other	985.3	355.3	991.3	421.5	0.96

3.2. Degree centrality

For each AOI, we computed the normalized degree centrality (Eq. (1)) for the ASD and TD groups. These results are given in Table 2 and also summarized in Fig. 3. Our results suggest that degree centrality of under right eye, under left eye, and left eye (but not the right eye) in ASD children is less than TD children (by 54%, 30%, and 37%, respectively). In contrast, the degree centrality of the mouth is 24% greater in ASD children compared to TD children. For the nose and the rest of the face, the degree of centrality is similar between the two groups. Despite these seemingly notable differences, our statistical analysis indicates that under the right eye is the only AOI where the difference is statistically meaningful between groups (p = 0.024; Table 2).

A positive correlation can be identified between fixation times and degree centrality. The two measures share the similarity of depending on the number of fixations associated with a given AOI. However, They differ in that fixation time is given by the sum of all fixations, whereas degree centrality considers primarily fixations that are exploratory.

3.3. Betweenness centrality

For each AOI, we computed the normalized betweenness centrality (Eq. (2)) for the ASD and TD groups. These results are given in Table 3 and also summarized in Fig. 4. Similar to the degree centrality results, the betweenness centrality of under right eye, under left eye, and left eye (but not the right eye) in ASD children is less than TD children (by 27%, 53%, and 42%, respectively), whereas the betweenness centrality of the mouth is 61% lower in ASD children compared to TD children. Betweenness centrality for the nose is similar between the two groups.

Unlike degree centrality, which reveals statistically meaningful difference between the two groups for only one AOI ("under the right eye"), betweenness centrality yields statistically meaningful differences between the two groups in four AOIs: in "under right eye" (p-value 0.01), "under left eye" (p-value = 0.02), "left eye" (p-value = 0.01), as well as "other" (p-value = 0.01). This result suggests that betweenness centrality may be a more effective approach in distinguishing the eye gaze patterns between ASD and TD children.

3.4. Closeness centrality

Table 4 and Fig. 5 show normalized closeness centrality (Eq. (4)) for each AOI for the ASD and TD groups. Notably, the p-values associated with "under right eye," "right eye," and "mouth" are sufficiently small to indicate statistically meaningful differences between the means.

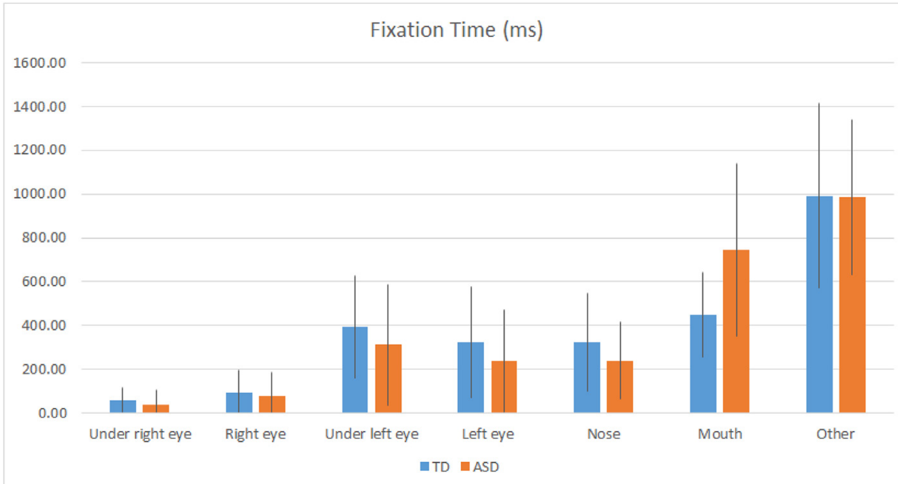

Fig. 2. Fixation times determined for each area of interest, for the autism spectrum disorder (ASD) and typical development (TD) groups.

Table 2
Normalized degree centrality for autism spectrum disorder (ASD) and typical development (TD) groups. SD, standard deviation.

	ASD		TD		p-value
	Mean	SD	Mean	SD	
Under right eye	2.6	3.4	6.0	5.7	0.02
Right eye	7.9	10.9	7.7	8.0	0.94
Under left eye	23.9	16.8	34.3	19.2	0.08
Left eye	17.4	16.4	27.6	19.9	0.09
Nose	23.3	17.1	25.1	16.9	0.74
Mouth	52.2	19.6	42.1	17.4	0.10
Other	65.9	13.8	66.0	12.4	0.98

Table 3
Normalized betweenness centrality for autism spectrum disorder (ASD) and typical development (TD) groups. SD, standard deviation.

	ASD		TD		p-value
	Mean	SD	Mean	SD	
Under right eye	0.9	1.6	3.4	4.1	0.01
Right eye	4.1	7.2	4.6	5.1	0.81
Under left eye	10.4	8.9	19.6	13.9	0.02
Left eye	6.6	8.1	15.8	13.0	0.01
Nose	10.4	10.4	11.6	11.0	0.72
Mouth	22.3	14.8	24.1	16.4	0.72
Other	28.9	10.5	39.3	13.8	0.01

However, the between-group relative differences in mean closeness centrality are small: 6.6%, 7.8%, and 4.3% for "under right eye," "right eye," and "mouth," respectively. Thus, while these differences are statistically meaningful, their practical value is likely limited.

3.5. Eigenvector centrality

As an additional example, we consider eigenvector centrality (Eq. (6)). We compute normalized eigenvector centrality for our eye gaze data; results are shown in Table 5 and Fig. 6. The only AOI with statistically meaningful difference is the "right eye," for which the eigenvector centrality is about 15% higher in the TD group. Statistically meaningful results are not obtained for any of the other AOIs. Thus, eigenvector centrality doesn't yield significantly more information than other centrality measures such as betweenness centrality.

4. Discussion

A key diagnostic feature of ASD is impaired social communication, which manifests in behaviors including the abnormal eye contact that ASD people make when interacting with others and the abnormal eye gaze when looking at faces. The overarching goal of this study is to

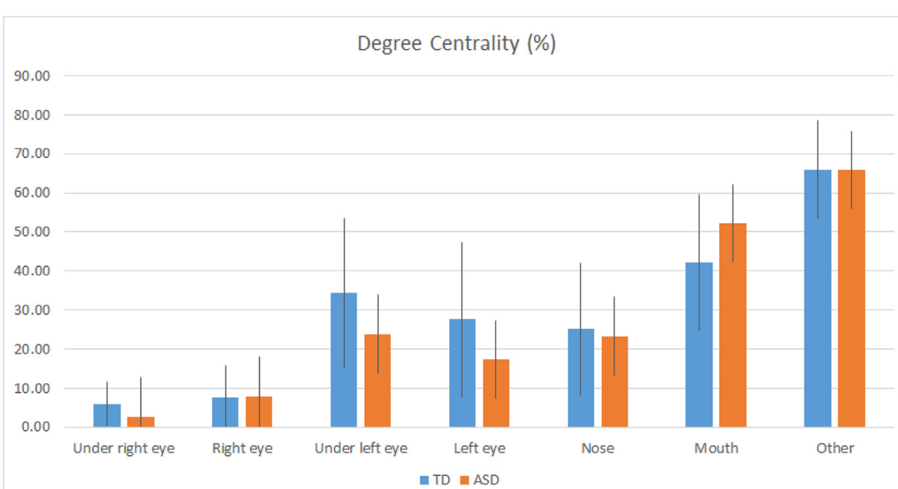

Fig. 3. Normalized degree centrality determined for each area of interest, for the autism spectrum disorder (ASD) and typical development (TD) groups.

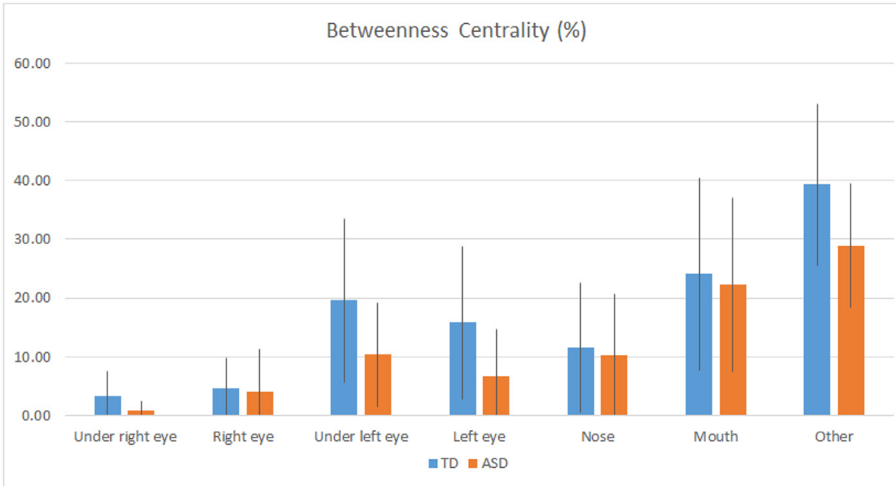

Fig. 4. Normalized betweenness centrality determined for each area of interest, for the autism spectrum disorder (ASD) and typical development (TD) groups.

Table 4
Normalized closeness centrality for autism spectrum disorder (ASD) and typical development (TD) groups. SD, standard deviation.

	ASD		TD		p-value
	Mean	SD	Mean	SD	
Under right eye	75.8	4.0	71.2	8.5	0.03
Right eye	78.2	4.8	72.6	8.7	0.01
Under left eye	85.8	5.8	87.0	6.4	0.53
Left eye	83.5	6.6	83.9	7.6	0.87
Nose	85.2	4.8	83.5	6.6	0.35
Mouth	92.8	4.7	89.0	4.8	0.02
Other	95.7	2.7	94.9	3.0	0.41

Table 5
Normalized eigenvector centrality for autism spectrum disorder (ASD) and typical development (TD) groups. SD, standard deviation.

	ASD		TD		p-value
	Mean	SD	Mean	SD	
Under right eye	50.60	13.96	57.61	11.80	0.09
Right eye	51.69	13.76	60.80	11.89	0.03
Under left eye	68.50	12.80	68.79	13.17	0.95
Left eye	62.19	15.12	66.30	13.99	0.38
Nose	61.10	13.90	68.11	10.65	0.08
Mouth	70.81	11.66	78.21	12.71	0.07
Other	81.23	8.36	84.57	6.85	0.17

identify analytic techniques to better distinguish ASD individuals from TD individuals. Such techniques can be used as an essential component in a comprehensive ASD diagnostic toolkit. To accomplish that goal, we first seek to characterize the spatial and temporal attributes of the impaired eye gaze of ASD individuals. Specifically, we obtain, analyze, and compare eye-tracking data of ASD and TD children. Our results indicate that ASD children exhibit a distinct gaze pattern when looking at faces, spending significantly more time looking at the mouth, compared with TD children, and less at the eyes; see Table 1 and Fig. 2 for the fixation time results. These results are consistent with previous studies [14,20].

The biological and psychological basis for this distinctive ASD gaze pattern has remained elusive. There is evidence that links eye contact with hyperactivation of the subcortical regions of the brain in ASD population [7,11]; the subcortical regions of the brain are primarily responsible for processing facial expressions and recognition. Likewise, it has been conjectured that ASD people look less into the eyes to avoid any distress caused by eye contact [7,15]. Alternatively, ASD people may be attracted to the mouth, instead of the nose, because the movements and sounds of the mouth offer hints of social meaning [18].

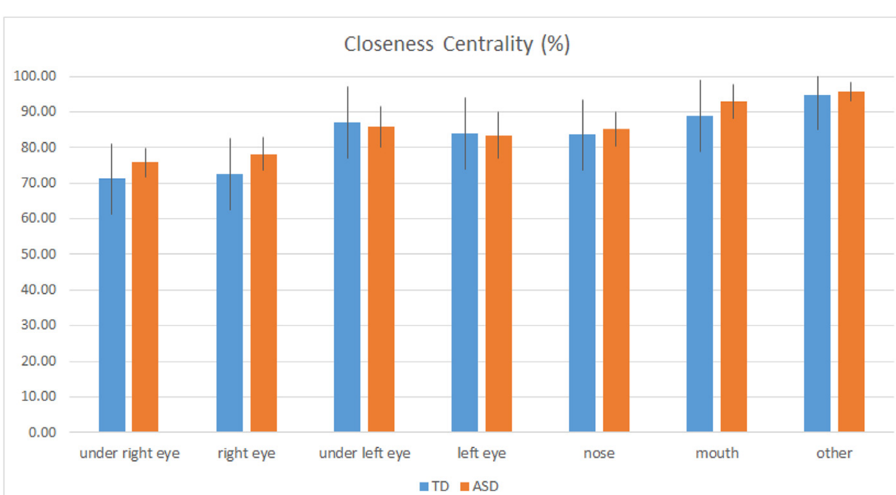

Fig. 5. Normalized closeness centrality determined for each area of interest, for the autism spectrum disorder (ASD) and typical development (TD) groups.

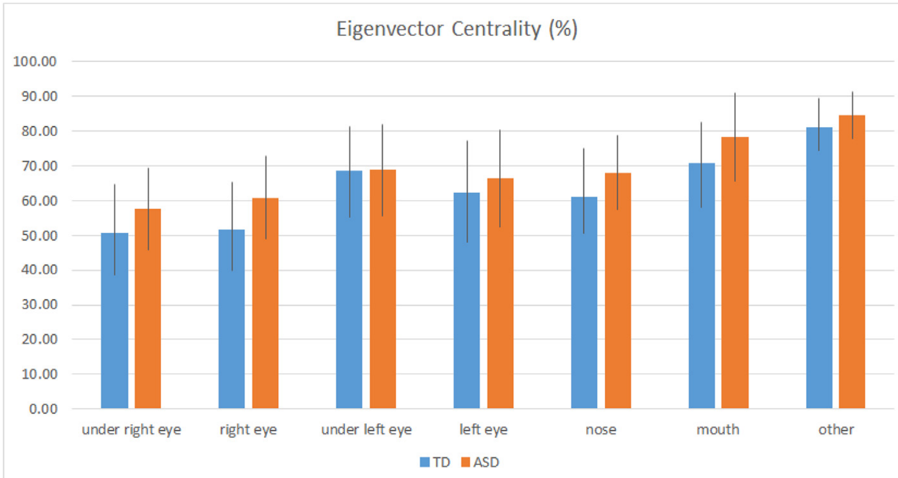

Fig. 6. Normalized eigenvector centrality determined for each area of interest, for the autism spectrum disorder (ASD) and typical development (TD) groups.

Historically, fixation time has been used as the primary approach to analyze eye gaze patterns [7]. However, this classic approach may not be able to distinguish certain important features of the scanning strategies employed by ASD and TD individuals. For instance, our results indicate that, except for the mouth, there is no statistically important difference between the fixation times in other AOIs. Indeed, a survey by Thompson which considered a large number of eye gaze analysis studies revealed substantial inconsistencies among relative fixation times between the ASD and TD populations [21]. This observation suggests that fixation time alone may not be adequate as a means, or even as a supplemental tool, for identifying ASD children.

Given the deficiency of fixation time analysis, we seek to identify alternative analytic approaches that can better reveal differences, subtle or otherwise, between the face scanning patterns of ASD and TD children. Face scanning involves transitioning from one AOI to another, a process that lends itself to network analysis. Hence, we present four network analysis approaches that measure the "importance" of a given AOI: degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. The present study is the first to apply betweenness centrality, closeness centrality, and eigenvector centrality to ASD eye-tracking pattern analysis.

Degree centrality was the first centrality concept to be used in network analysis [9], and is conceptually simple. It measures the importance of a node in a network by the number of edges linked to that node. Our analysis yields a greater degree centrality of the mouth in ASD children relative to TD children (Table 2), consistent with the fixation time result. Moreover, that difference in degree centrality is statistically significant. However, while there are between-group differences in degree centrality in other AOIs, those differences are not statistically significant. Hence, degree centrality confirms the fixation time result that the mouth plays a larger role in the face scanning process of ASD children, compared to TD children, but does not appear to provide additional (statistically important) information about other parts of the face.

Another network centrality measure considered is betweenness centrality, which quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. Our analysis using betweenness centrality reveals statistically meaningful differences between the ASD and TD groups that were not uncovered by either fixation time or degree centrality. The betweenness centrality values of four AOIs (under right eye, left eye, under left eye, and other) are significantly larger in TD children compared to the ASD group; see Table 3 and Fig. 4.

One notable result is that almost all AOIs are associated with degree and betweenness centrality values that are higher in the TD group compared to ASD (Tables 2 and 3). The lone exception is the mouth, which has a higher degree centrality for the ASD group. These findings suggest that TD individuals have more frequent saccades, which translates into a graph with more edges. The higher degree centrality for the mouth for ASD demonstrates the strong preference of the ASD group for that particular AOI. Note that the difference in saccade frequency between the two groups does not directly impact fixation times or closeness centrality.

Also considered are closeness centrality and eigenvector centrality. Closeness centrality measures how close a given node (AOI) is to other nodes. Analysis of our face scanning data yields three sufficiently small p-values (see Table 4), which indicate statistically meaningful differences between the mean closeness centrality values of the associated AOIs. However, those differences are small (<8%), and hence likely of limited practical value. The negligibility of these differences may be attributable to the relatively short test time in our experiment, i.e., the length of time during which each participant focused on each picture (2–3 s). As a result, each graph, for the ASD and TD groups, consists of relatively few edges. It is possible that in experiments with longer test times, the differences between ASD and TD groups in normalized closeness centrality may be augmented and become more useful. However, conducting eye gaze experiments with young children with ASD for a sufficiently long period of time is not without challenges. Eigenvector centrality quantifies the influence of a node. It is sometimes used in network analysis even though it is less popular than the other measures examined in this study. Our analysis (Table 5) suggests that eigenvector centrality doesn't yield new information that isn't already provided by betweenness centrality.

Diagnosing ASD can be difficult, since there is no medical test, like a blood test, to diagnose the disorder [13]. The diagnosis typically involves two steps: (i) developmental screening, which determines if the young child exhibits any developmental delays, and (ii) comprehensive diagnostic evaluation, which is a thorough review that may include assessing the child's behavior and development, interviewing the parents, hearing and vision screening, genetic testing, neurological testing, and other medical testing. Clearly, the eye gaze pattern analysis cannot replace the comprehensive diagnostic evaluation. It might, however, be used as an additional screening tool. In this regard, the results of this study suggest that betweenness centrality is the most effective network analysis approach in distinguishing the eye gaze patterns between ASD and TD children, and is thus a promising ASD screening tool.

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