Linguistic Comparison of Children with and without ASD through Eye-Tracking Data

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ABSTRACT

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder that affects a child's social communication development, and early assessment is a challenging and time-consuming practice. Over the years, research has shown that eye-tracking (ET) data provides valuable information for clinical practice. Many data analytics methods have been developed to assess ASD in young children. Although mainly predictive techniques are used in the literature, it has also been shown that using descriptive techniques can lead to a common understanding in this specific area. Well-known statistical analyses are insufficient to provide explicit knowledge compatible with human understanding. Therefore, linguistic summarization techniques are helpful in meeting this need. The dataset provided by the ETJASD Project has been utilized in this study to create human-friendly fuzzy linguistic summaries. To the best of our knowledge, it is one of the first studies that linguistically summarize eye tracking data. The outcomes are presented in a comparative manner between children with and without ASD.

CCS CONCEPTS

• **General and reference**; • **General conference proceedings**;

KEYWORDS

Linguistic summarization, autism spectrum disorder, eye-tracking, fuzzy logic

ACM Reference Format:
Demet Ozturk*, Sena Aydogan, Ibrahim Kok, Isik Akin-Bulbul, Selda Ozdemir, Suat Ozdemir, and Diyar Akay. 2023. Linguistic Comparison of Children with and without ASD through Eye-Tracking Data. In *2023 9th International Conference on Computer Technology Applications (ICCTA 2023), May 10–12, 2023, Vienna, Austria.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3605423.3605457

ICCTA 2023, May 10–12, 2023, Vienna, Austria

ACM ISBN 978-1-4503-9957-9/23/05.
https://doi.org/10.1145/3605423.3605457

1 INTRODUCTION

Autism Spectrum Disorder (ASD) is one of the neurological and developmental disabilities caused by differences in the brain. It impacts behavior of people with ASD while they are interacting with others, paying attention, moving, and learning. Social communication, repetitive behaviors or interests are distinctive features of ASD assessment. Eye tracking (ET) studies are important in detecting differences in the visual-social attention of people with ASD. Specifically, visual attention has become a recent topic of intense research in understanding the developmental pathways of young children with autism. A growing evidence base of ET studies confirms differential visual attention patterns specific to young, high-risk children with ASD versus typically developing (TD) or low-risk children [1].

Ozdemir et al. [1] suggested that visual attention is a unique, promising biomarker for the early assessment of ASD. Visual attention captured by ET technologies provides ease of work with Data Analytics (DA) on early assessment of ASD. Tasks related to DA can be divided into four categories, from descriptive and diagnostic analytics to more advanced predictive and prescriptive analytics [2]. Descriptive analytics includes linguistic summarization as well as statistical summarization. Linguistic summarization of databases, where outputs in a linguistic structure are more favorable because it can provide richer and more easily understandable information [3]. Linguistic summarization can extract potential useful and abstract knowledge from numeric and categoric data. Therefore, it has received much attention from various areas [4]. Linguistic summarization of the structured datasets gives practical insights to experts in the way of common understanding with nonexperts. Therefore, it provides the possibility to gather fast and proper knowledge that can be understood in the same way. This feature offers a wide area of working to linguistic summarization in the health industry or clinical research. Children with ASD have different characteristics of visual attention from TD children. Retrieval of this information from ET studies applied to decision support systems based on machine learning designed in [1] shows that decision support systems and data analytics are important and widely studied topics in ASD assessment. Early assessment of ASD is based on characteristics in the ET dataset between children with ASD and TD children. With linguistic summarization, it is possible to retrieve information about the distinguishing behaviors of children with ASD from ET data. Unlike other methods, linguistic summarization allows the understanding of distinctive features of children in visual attention-based ASD screening by quantified sentences.

For those not subject matter experts, linguistic summarizing provides summaries so that the output sentences' analysis can be understood. It has allowed combining distant disciplines, such as special education and data mining. In this study, we provide insights into natural language that identifies characteristics of children with ASD and TD children based on linguistic summarization techniques through supplied social interaction and animation datasets. The following sections cover a literature review of the methods used, linguistic summarization, application, and conclusion.

2 LITERATURE REVIEW

The literature review was carried out to reveal the existing studies on data analytics of ASD screening. For this purpose, first, an article search was done. Then, studies considered important in the current literature are examined and given in this section. The literature review is limited to Scopus, a scientific database on the internet. In Scopus database search, 17897 documents were first found using the keyword "autism spectrum disorder". By refining the research with the keywords "eye tracking" 30964, then with the keywords "data analytics" 1065 and "visual attention" 609 results are found, afterward these results are limited to only articles and conference papers published in the last five years. The final 19 articles were placed in this section.

In the literature, as well as ET data, electroencephalography (EEG) data has been used as a biomarker of ASD diagnosis. Haputhantri et al. [5] presented an approach to classify ASD using Random Forest and Correlation-based Feature Selection based on EEG signal processing. A preliminary analysis of parents' experiences from participating in a study on infant siblings was published in [6], including high risk and low risk parents' groups divided according to familial history diagnosed with ASD. Rahman et al. Using the recorded eye-fixation data, [7] proposed a feature extraction technique for classifying ET data that may be used in predicting the tasks in the act of viewing. With data collected across multiple sites and using a manualized training and acquisition protocol, the Autism Biomarkers Consortium for Clinical Trials (ABC-CT) reported high levels of acquisition success using behavioral video and environmental tracking, EEG in a large sample of children with ASD and TD [8]. Vettori et al. [9] recorded ET and EEG during visual stimulation to address the issue which eye tracking and revealed that using only ET data is not enough to track covert orienting processes. Xu and Chen [10] used EEG data to examine differences between children with ASD and TD in power spectrum analysis. Various data types, including clinical assessment, neuroimaging, gene mutation and expression and response signal data are used in the classification model to predict ASD clinical diagnostic status in [11] showed competing outcomes. ET and neural response combination showed no support for the increased mouth decreased eye gaze hypothesis in ASD [12]. But asynchronously collected EEG and visual attention to faces bio-signals usage in Convolutional Neural Network (CNN) method with random forest achieved high accuracy in ASD detection. [13]. A gaze prediction framework based on a prepared internal data set in [14] proved that the mutual gaze is one of the most significant social cues in social interactions. Stuart et al. [15] demonstrated that attention detection within TD children and low-attention tasks is more generalizable using the geometric feature transformation with Support Vector Machine (SVM) classifier, which performs better than CNN. Liao et al. [16] reviewed evaluated studies that measured the relationship between eye gaze and activity in visual attention on facial stimuli. Results of [17] demonstrated that a hybrid fusion approach based on a weighted naive Bayes algorithm using eye fixation, facial expression, and EEG is effective for the early detection of ASD.

[18] established a framework to assess the link between the 3D head pose angles and object displacement. [19] revealed that Artificial Neural Networks (ANN) overcame other methods, such as decision tree and SVM, k-Nearest Neighbors in ASD prediction by using ET technology [20]. In realistic circumstances, combining ET-EEG, ET, and EEG data produces diagnostic biomarkers and aids in identifying cognitive impairment linked to a particular visual pattern [21]. Using a small dataset [22] identified differences between the gestural patterns of children with ASD and neurotypicals. A recent study in [23] proved that the transfer learning AlexNet could perform better than other ASD detection models.

In conclusion, ASD is a complex neuro-development disability affecting the child's reading, speech, word or route learning, mathematical calculation, social communication, motor learning, and logical thinking abilities. The early assessment of ASD is essential for delivering effective, timely interventions. The studies in the literature show that different machine learning models using ET data combined with other discriminative data could facilitate the early detection of ASD in clinical practice. But it is also retrieved that data collection in ASD screening is time-consuming, expensive and complicated. Studies using small datasets require additional expert knowledge or further hybrid models to achieve better accuracy in the detection of ASD. Understanding data features in ET datasets of children with ASD and TD children is also challenging for researchers who are not experts in ASD. As a result, linguistic summarization is crucial to providing concise and intelligible linguistic summaries in the form of sentences in natural language. The need for expertise to understand outcomes from data features can be reduced by extracting quantified sentences from linguistic summarization. Since the output of linguistic summarization can be easily understandable by experts or non-experts on account of being natural language, the study of linguistic summarization of ET data in ASD screening is important and valuable.

3 LINGUISTIC SUMMARIZATION

Linguistic summarization of data is based on the theory of fuzzy sets. The linguistic summarization procedure gives text results of the data and is useful for both numeric and non-numeric data. It summarizes the data using three components: a summarizer, a linguistic quantifier, and a truth degree [24]. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function which assigns to each object a degree of membership ranging between zero and one [25]. There are different methods to define membership functions of fuzzy sets. Fuzzy c-means (FCM) clustering is one of these methods developed by Bezdek et al. [26]. At the end of the algorithm centers of each cluster and the membership degree of each element of the set are obtained. Although there are many membership functions in the literature, discrete, triangular, and trapezoidal functions are mainly used due to the low processing load [27, 28].

The linguistic summarization of data based on fuzzy sets was presented by Yager in 1982 [29]. Fundamentally type I and type II quantified sentences were introduced, and new methods have been developed over the years. These two types of sentences are based on absolute and relative quantifiers proposed by Zadeh [30]. "Approximately five" and "most" are examples of absolute and relative quantifiers, respectively.

Type-I summary structure is in the form of "Q Y s are/have S. [T]". Absolute quantifiers can only be used in Type-I sentences. According to this structure, "Most of the participants have low attention [0.85]" can be given as an example. In this type-I sentence, most, participants, low attention, [0.85] refers to quantifier (Q), subjects (Y), summarizer (S), and truth degree, respectively.

Type-II summary structure is in the form of "Q S_g Y s are/have S. [T]". According to this structure, if the age of the participants is also in the dataset, "Most of the young participants have low attention [0.70]" can be given as an example. In this type-II sentence, most, young, participants, rich, [0.70] refers to quantifier (Q), pre-summarizer (S_g), subjects (Y), summarizer (S), and truth degree, respectively.

The number of summary sentences equals the combination of the number of quantifiers, pre-summarizers, and summarizers. The most meaningful and valuable sentence shows the highest truth degree. Generally, sentences above a specific threshold value are selected [31, 32].

The most important part of the generation of linguistic summaries is the evaluation of the sentences. The more reliable sentences are generated, the more real insight from the data is reflected. The degree of truth is used to measure whether enough data supports the obtained linguistic summary. Therefore, most theoretical studies on linguistic summarization have focused on the degree of truth. The way to compute the degree of truth is classified into two groups according to the type of cardinality: scalar cardinality-based methods and fuzzy cardinality-based methods. First, the scalar cardinality-based methods are proposed for computing the degree of truth. The scalar cardinality-based methods have been widely used in linguistic summarization as their computational cost is very low [33, 34].

The basis of the scalar cardinality-based truth degree calculation methods is the methods suggested by Zadeh [11]. The calculation method for type I quantified sentence is given in Eq. 1. as Q: linguistic quantifier (e.g., most, about three, etc.), Y: subjects $(m = 1, \ldots, m)$, S: summarizer (e.g., age, salary, etc.), T: truth degree [0,1], $R = M$ for relative quantifier or $R = 1$for absolute quantifier, μ: membership function, $d_{m:}$ the value of the feature d of the m^{th} object.

$$\mathrm{T} = \mu_Q\left(\frac{\sum_{m=1}^{M} \mu_s\left(d_m\right)}{R}\right) \tag{1}$$

The calculation method for type II quantified sentence is given in Eq. 2. as Q linguistic quantifier (e.g., most, about three, etc.), S_g pre-summarizer (e.g., age, salary, etc.), Y: subjects $(m = 1, \ldots, m)$, S: summarizer (e.g., age, salary, etc.), T : truth degree [0,1], $d_{m:}$ the value of the feature d of the m^{th} object, v_g^m: the value of the feature g of the m^{th} object

$$\mathrm{T} = \mu_Q\left(\frac{\sum_{m=1}^{M}\left(\mu_{S_g}\left(v_g^m\right) \otimes \mu_s\left(d_m\right)\right)}{\sum_{m=1}^{M} \mu_{S_g}\left(v_g^m\right)}\right) \tag{2}$$

The degree of membership of the element x to the fuzzy set A is indicated by the membership function $\mu(x)$, which takes the value between 0 and 1. The set A is defined in the universal set E, and the membership function of the fuzzy set A is defined as $\mu A(x) : E \longrightarrow [0, 1]$ for $\forall x \in E$

If a pre-summarizer is created in the quantified sentence, their intersection is obtained with the t-norm operator and included in the truth degree calculation. Generally, the minimum operator is used as a t-norm.

4 APPLICATION

Diagnosing ASD can be difficult because there is no medical test, like a blood test, to diagnose the disorder. Experts look at the child's developmental history, current behavioral patterns and social communicant skills to make an ASD diagnosis. ASD can sometimes be detected at 18 months or younger [35]. For the past several decades, visual-social attention differences of individuals with ASD have been widely documented in the literature through ET studies [1].

The aim of this study is the linguistic summarization of the ET data set of Ozdemir et al. [1] based on type I and type II quantified sentences. Generated sentences in natural language give an apparent aspect of ET skills specific to ASD as well as different characteristics of visual attention between children with ASD and TD children. In this application, sentences are evaluated based on Zadeh's scalar cardinality method, given in the previous section. This method has been chosen because of its computational advantages.

4.1 Dataset

The data set of the ETJASD Project [36] is used in this study. The dataset includes two groups of children, 61 young children with ASD with a mean age of 34.85 months (Range: 28–36 months) and 72 TD children with a mean age of 32.90 months (Range: 26–36 months), from a university-based research center in metropolitan and rural areas in Ankara. Children with ASD had been previously diagnosed by licensed child psychiatrists using the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (2013) criteria [37]. Children with ASD were matched with the TD group based on their chronological age, since the study used a passive viewing paradigm that did not require any language processing skills. All

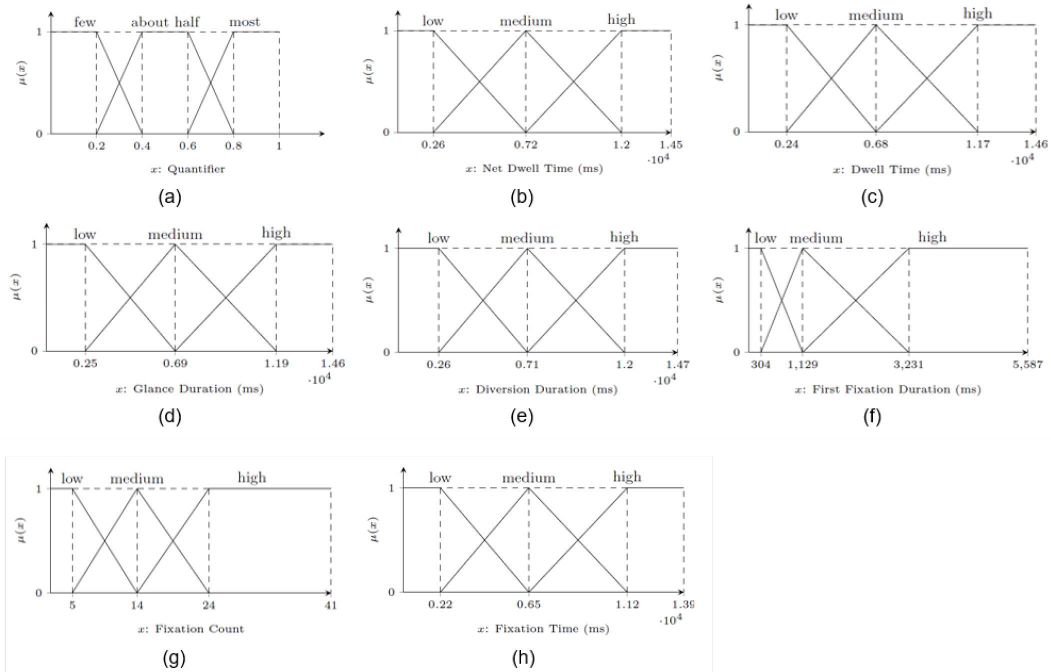

Figure 1: (a) Linguistic quantifier and fuzzy sets of numerical variables: (b) net dwell time, (c) dwell time, (d) glance duration, (e) diversion duration, (f) first fixation duration, g) fixation count, and (h) fixation time

participants had to meet specific criteria, such as being between 18 and 36 months old, not having a seizure disorder or known genetic disorder, and not having an uncorrectable hearing or visual impairment.

Eye movements were recorded at a sampling rate of 250 Hz using an SMI-Red250 [38] remote eye tracker placed below a 17-in. The eye movements of the participants were measured using passive viewing ET tasks. Two sets of paired preference viewing tasks were created in this experiment; all were presented to the participants within the same session. These two sets are pairs of social and non-social stimuli. The first set included three pairs of social interaction videos (social stimuli) and toy videos (non-social stimuli). In contrast, the second set included three social interaction videos (social stimuli) and animation videos (non-social stimuli) [1]. In this dataset, 14 features were available. The definitions of the features are given in the manual of SMI [38].

In their study considering feature selection methods, Ozdemir et al. [1] found in the context of Animation AOI (area of interest) features, fixation count, and dwell time as discriminative features. Fixation Count is the number of fixations inside the AOI. Dwell Time is the sum of durations from all fixations and saccades that hit the AOI. According to the overall results of their study, multiple classification algorithms showed higher classification success in the Social Interaction - Animation dataset. These results indicated that the visual sets containing animations were more distinctive than those with toys. For these reasons, they have suggested that using animated stimuli in experimental design is promising for future studies. Moreover, as shown in feature selection methods, some features, such as Net Dwell Time, are highly discriminative in identifying young children with ASD. Therefore, this study uses the Social Interaction - Animation dataset and discriminative features from this dataset.

4.2 Results

The generation of Type I and Type II summary structures is based on the animation social interaction dataset. The features are selected according to features suited as discriminative based on feature selection methods used in [1]. These features are net dwell time, dwell time, glance duration, diversion duration, first fixation duration, fixation count, and fixation time, which belong to social interaction and animation visual attention of children.

Features have been divided into three fuzzy sets with the FCM algorithm. The fuzzy sets are given in Fig. 1. The quantified sentences are based on quantifier Q:{most, half, few}, summarizer S: {high, low, medium}, and pre-summarizer S_g={low, medium, high} are selected as the same feature gathered from SI (social interaction) and A (animation) video. For instance, there is an A dwell time, which is measured while the participant watches an animation video. There is also SI dwell time, which is measured while the participant is watching SI video. The children watched these two types of videos simultaneously, but the data were recorded separately.

All the combinations of variables and quantifiers are generated and evaluated according to Zadeh's method by Python programming. Selected linguistic summaries and their truth degrees are given in Table 1.

Table 1: Linguistic Summaries

Linguistic Summary		T
Type-I	Few of the children have high glance duration on animation video.	1.00
	Half of the children have low fixation time on animation video.	0.93
	Few of the children have high diversion duration on animation video.	1.00
	Few of the children have high dwell time on animation video.	1.00
Type-II	Most of the ASD children with high net dwell time on animation video have low net dwell time on SI video	1.00
	Most of the TD children with low net dwell time on animation video have high net dwell time on SI video	0.80
	Most of the ASD children with high dwell time on animation video have low dwell time on SI video	1.00
	Most of the TD children with low dwell time on animation video have high dwell time on SI video	0.96
	Most of the ASD children with high glance duration on animation video have low glance duration on SI video	1.00
	Most of the TD children with low glance duration on animation video have high glance duration on SI video	1.00
	Most of the ASD children with high diversion duration on animation video have low diversion duration on SI video	1.00
	Most of the TD children with low diversion duration on animation video have high diversion duration on SI video	1.00
	Most of the ASD children with low first fixation duration on animation video have low first fixation duration on SI video	1.00
	Most of the TD children with low first fixation duration on animation video have low first fixation duration on SI video	1.00
	Most of the ASD children with high fixation count on animation video have low fixation count on SI video	1.00
	Most of the TD children with medium fixation count on animation video have medium fixation count on SI video	1.00
	Most of the ASD children with high fixation time on animation video have low fixation time on SI video	1.00
	Most of the TD children with low fixation time on animation video have high fixation time on SI video	0.86

Type-I linguistic summaries show the main features of the dataset of children with and without ASD. It is interpreted from the summaries that children don't have high values of fixation time, fixation count, glance count, diversion duration, and dwell time, especially for the animation video. Few of the children only reach higher values. More precisely, an understanding of the higher value effect in children with ASD and TD Type-II sentences are generated. These summaries show that when a higher value is reached in animation video, lower values are reached in SI video. Therefore, the features of dwell time, glance duration, diversion duration, and fixation time are discriminative in visual attention-based ASD screening. In contrast, the first fixation duration and fixation count have the same orientation.

ET studies have also demonstrated that children with ASD display reduced attention to social information and increased preference to non-social elements of social scenes (e.g., outside area or objects vs. faces) [1]. This difference is proved in the comparison sentences, which reflect the children's attention to the two types of videos. The study results showed clear distinctions in visual attention between children with ASD and TD children. Type-II findings indicated that most of the ASD children who had high net dwell time, dwell time, glance duration, and fixation count on animation videos also had low net dwell time, dwell time, glance duration, and fixation count on SI videos.

These findings suggest that young children with ASD have a passive visual attention preference for animation videos instead of SI videos. On the other hand, most TD children showed increased visual attention to SI videos and preferred to watch them. Therefore, our results suggest that while children with ASD preferred animation videos, TD children preferred SI videos. The findings also suggest that the eye movement parameter, first fixation duration, may not indicate visual attention differences between the groups. Overall, these results highlight the importance of understanding the visual attention differences between children with ASD and TD children, and how these differences can affect their preferences for certain types of videos.

5 CONCLUSION

ASD is one of the major research topics in clinical research. Assessment of ASD in young children is conducted by autism screening clinical practices. The purpose of ASD screening is to identify common early signs of the disorder. Young children with ASD display diminished visual attention and have limited social communication skills. ET technologies are valuable for screening early visual attention differences and developing autism screening protocols.

In this study, ET data was used to develop a decision support system for early ASD assessment, and human-friendly linguistic summaries were provided based on type I and type II fuzzy quantified sentences. The results revealed that children with ASD and TD children have different visual attention characteristics. Specifically, their visual interests in animation and social interaction videos show significant contrast in eye movement features. This finding also supports the use of ET features for early ASD screening. The results of this study are consistent with previous studies using the same dataset. The key value of the linguistic summarization of ET data in ASD diagnosis is providing a clear, accurate, and accessible understanding of the data. Otherwise, interpreting ET data can be challenging for professionals unfamiliar with this type of data, which could hinder the detection of ASD in young children. Therefore, this study confirmed the feasibility of using ET for ASD diagnosis by professionals. It proves that descriptive techniques can be applied in other clinical researches.

This study has several limitations. Firstly, it only uses a particular dataset and one methodology, which may not provide comprehensive results. A complete understanding of the data can be achieved by using the entire dataset. Additionally, other linguistic summarization methods could yield different explanatory statements. Future studies could also be conducted on an extended dataset that includes the demographic and developmental features of the children, allowing for the interpretation of developmental and behavioral data on children with ASD and TD. Despite these limitations, this study contributes to the existing literature by supporting previous research and laying the groundwork for further research.

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