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The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data

自闭症谱系障碍

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ABSTRACT

Objective: To identify autistic children, we used features extracted from two modalities (EEG and eye-tracking) as input to a machine learning approach (SVM).
Methods: A total of 97 children aged from 3 to 6 were enrolled in the present study. After resting-state EEG data recording, the children performed eye-tracking tests individually on own-race and other-race stranger faces stimuli. Power spectrum analysis was used for EEG analysis and areas of interest (AOI) were selected for face gaze analysis of eye-tracking data. The minimum redundancy maximum relevance (MRMR) feature selection method combined with SVM classifiers were used for classification of autistic versus typically developing children.
Results: Results showed that classification accuracy from combining two types of data reached a maximum of 85.44%, with AUC = 0.93, when 32 features were selected.
Limitations: The sample consisted of children aged from 3 to 6, and no younger patients were included.
Conclusions: Our machine learning approach, combining EEG and eye-tracking data, may be a useful tool for the identification of children with ASD, and may help for diagnostic processes.

1. Introduction

Autism spectrum disorder (ASD) is a very complex neurodevelopmental disorder. It affects the developmental trajectory in several behavioral domains including social and communication abilities, and stereotyped and repetitive activities [1]. The etiopathogenesis is still unclear, but is generally believed to be related to biological factors such as genetic defects, brain inflammation, and abnormal conditions during pregnancy [2]. Incidence is sharply increasing according to the National Health Interview Survey, the estimated prevalence based on 2014 data is about 1 in 45 [3]. The sharp increase in the number of children diagnosed with ASD highlights the need for further research on this population. In particular, accurate clinical methods are necessary. At present, clinical diagnosis is mainly based on behavioral scale tests including the autism behavior checklist [4]; and Childhood Autism Rating Scale [5]. Due to subjectivity, evaluation results may not be very accurate. The diversity of phenotype in ASD results in impairments varying among different individuals, and this heterogeneity indicates various forms of ASD with biological processes and neurodevelopmental pathways.

Biomarkers are objective indicators which can reflect typical biological processes. Biomarkers are used for diagnosis, outcome predictions, and treatment prediction. High accuracy, reliability, and validity of biomarkers are essential for clinical field. With the development of neuroimaging and eye-tracking technology, many researchers are working towards more objective diagnostic indices for ASD based on electroencephalograph (EEG) or eye-tracking to improve diagnosis accuracy.

EEG, a non-invasive acquisition method, is mainly used to measure neural activity signals, with high time resolution; and has been shown to be a powerful tool for the study of complex neuropsychiatric disorders [6–8]. Previous researches on autism has suggested that cortical rhythmic oscillations in children with autism are abnormal. It has been hypothesized that these oscillations are correlated to brain functions, especially associative and communication functions [9]. Previous developmental research on typically developing (TD) children showed that low frequency rhythms gradually decrease [10] and high frequency rhythms increase with age at the same time [11]. However, the

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characteristics of EEG power spectrum in autistic children showed some developmental differences from typically developing children [12,13]. Wang's review research suggested that the resting-state EEG of ASD showed a U-shaped profile of electrophysiological power alterations, with excessive power in low-frequency and high-frequency bands, and inadequate power in alpha band [14]. Therefore, power in various frequency bands have potential to be used as characteristic indices to identify autistic children.

The attentional behavior of ASD children to social stimuli is defective, mainly in team of gaze. Eye-tracking technology can directly measure social visual attention. Normal adults show a specific gaze pattern when viewing faces, fixating mainly on the eyes, but also on the nose and mouth [15]. However, patients with autism spent a smaller percentage of time fixating on the core features of the face [16]. The eye avoidance hypothesis provides us with an explanation for facial recognition defects in ASD [17], and it has been proposed that people with ASD avoid eye contact because they may consider it an unbearable social threat and experience uncomfortable physiological responses. Eye tracking technology can not only record eye movement tracks, but also analyze Areas of Interest (AOI) and differences in fixation regions, which may reflect the processing of visual information in the brain. Infants with deficits in eye contact at 6 months of age were diagnosed with ASD later [18], suggesting that atypical face processing has potential to be a diagnostic index.

We are not aware of any studies combining EEG and eye-tracking data to identify the autistic children. In the present study, features extracted from the two modalities were used as input to a machine learning approach. The results show this approach is better suited for extracting objective indicators for comparison and classification.

2. Methods

2.1. Participants

A total of 97 children were enrolled in the present study. Participants consisted of children aged between 3 and 6 years with a confirmed diagnosis of ASD (N = 49; 10 females and 39 males; M = 4.29, SD = 1.07) and TD children (N = 48; 12 females and 36 males; M = 4.26, SD = 1.00). There were no statistical differences in age and gender between the two groups. All the ASD participants were diagnosed by the experienced Chinese psychiatrists based on the psychoeducational profile (Third Edition) [19] and Diagnostic and Statistical Manual of Mental Disorders-V criteria [20]. The typically developing children were recruited from a local kindergarten and had no genetic history of autistic family members. The children's parents provided informed consent before participation. The present study was conducted according to the Declaration of Helsinki and approved by the ethics committee of Beijing Normal University.

2.2. Data recording

EEG was recorded in a shielded room, the participating children sat on a comfortable chair with eyes open. We made efforts to keep them quiet and reduce movements, including head movement, teeth gritting and blinking. EEG was recorded for about 6 min. A 128-channel HydroCel Sensor Net System (Electrical Geodesics, Inc) was used for data recording. The EEG sampling rate was 1000 Hz. We chose 62 electrodes for analysis and all 62 channels were re-referenced to an ear-linked reference.

After EEG data recording, the children had a break and then performed eye-tracking tests individually. They sat about 60 cm from the display screen, and TX300 eye-tracking system (Tobii, Danderyd, Sweden) was used in this experiment. The sampling frequency was 300 Hz. Before the formal experiment, a five-point calibration program was performed; the experiment proceeded after all five points were captured with small error vectors. The children were presented with a series of face photos in random order. The face photos were of an own-race young girl or an other-race young girl. Each type of photo would appear 6 times, each time for 10s. During the interval between trials, a dynamic kitten with sound was presented to attract children's attention. During the whole experiment, no response was required from the children.

2.3. Data analysis

2.3.1. EEG data preprocessing

Data preprocessing was performed via Matlab R2016a and EEGlab. The original EEG data were re-referenced with the average signal from the left and right mastoid sensors as they recorded less signal from the brain. Data were band-pass filtered between 0.5 and 45 Hz. To improve computing speed, EEG data were then down-sampled to 250 Hz. Power line noise in EEG was removed by a notch filter centered at 50 Hz. Artifacts (such as electrooculogram and electromyogram) in EEG were removed using an ICA approach. In addition, visual inspection was performed to reject data segments contaminated with noise. Data were divided into 4 s segments with no overlap.

2.3.2. Power spectrum analysis

Power spectrum analysis is a conventional analysis for artifact-free EEG data. The analysis was performed by the Matlab function pwelch. The data were divided into eight segments with equal length, each with 50% overlap. Each segment was then windowed with a Hamming window and spectral density was calculated using a fast Fourier transform (FFT). The relative power is the ratio of each frequency band's power to the total power over the whole power spectrum, and reflects the proportion a certain frequency band's fluctuation is to the total fluctuation. The purpose of calculating the relative power is to explore abnormalities in the rhythmic fluctuations of EEG from autistic patients. Relative power indices were divided into five frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (30–45 Hz).

2.3.3. Eye-tracking data analysis

Raw data were analyzed in Matlab software. Eight areas of interest (AOI) were selected for face photos analysis: background, body, face, eyes, right eye, left eye, mouth, and nose. To quantify the child's engagement for each AOI, we define the analysis index as the percentage of fixation time in the AOI versus the total fixation time: fixation time in AOI/total fixation time. A 60 ms threshold was applied to avoid counting unconscious gazing. Fig. 1 shows the areas of interest.

2.3.4. Feature selection

The minimum-redundancy-maximum-relevance (MRMR) feature selection method was proposed by Ding and Peng et al. [21], It considers both maximum relevance with class labels and minimum redundancy among features and selects features according to the maximal statistical dependency criterion based on mutual information. The MRMR feature selection is one of the most powerful methods for selecting a subset of features from the feature pool (dimensionality reduction). Previous studies indicate that mRMR leads to promising improvements in classification accuracy [22,23].

2.3.5. Classification

In this study, support vector machine (SVM) was used for classification. The main objective of data fitting for SVM is to find the separating hyperplane with the largest margin distance between categories in feature space, so that instances of two classes can be divided as widely as possible. The hyperplane depends on the closest data points, the support vectors [24]. SVM is a common method used to deal with linear and non-linear classification problems in machine learning [25,26].

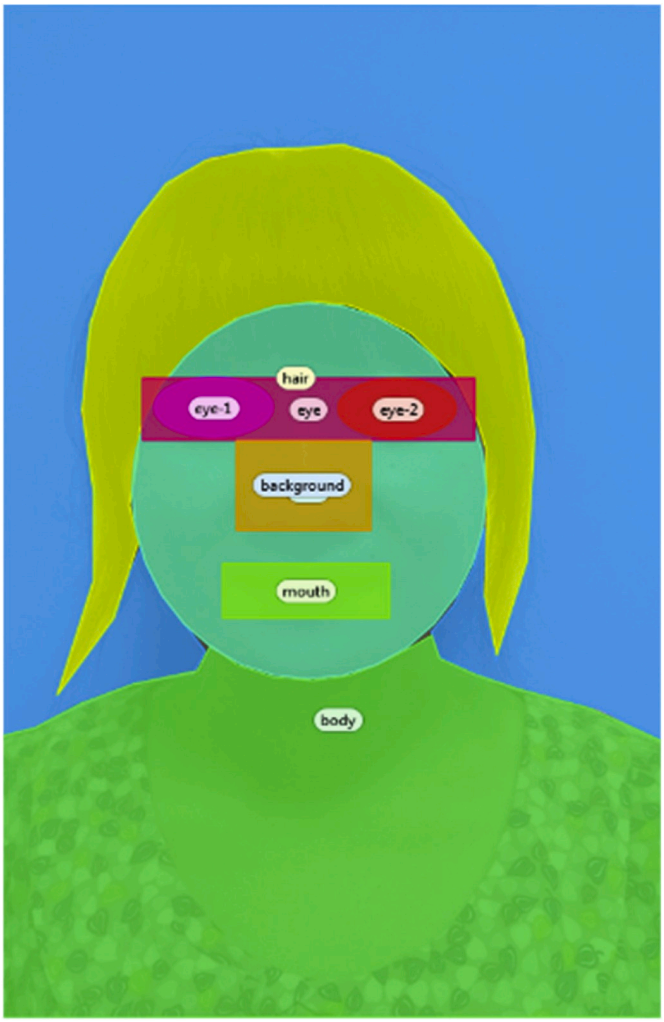

Fig. 1. Areas of interest illustration. We divided each face picture into eight parts, here shown with in different colors.

3. Results

3.1. Comparison of EEG data from ASD and TD children

We calculated the relative power of delta, theta, alpha, beta and gamma bands over all electrodes. Table 1 shows the mean EEG relative power in five frequency bands in ASD and TD children. Independent t-tests revealed that children with ASD showed significantly higher EEG power in theta bands and lower in beta and gamma bands than controls. We obtained a 68% accuracy classification using the five frequency bands' relative power as input to SVM.

3.2. Comparison of eye-tracking data from ASD and TD children

In Table 2 shows the percentage of fixation duration in each AOI.

Table 1
Means (standard deviation) of relative power in various bands. Right column shows t-tests t-statistic values and corresponding p-value in parentheses.

	ASD	TD	T
Delta	8.16 (0.98)	8.22 (9.23)	−0.303 (p = .762)
Theta	1.96 (0.43)	2.27 (0.51)	−3.220 (p = .002)
Alpha	0.87 (0.34)	0.95 (0.28)	−1.120 (p = .232)
Beta	0.28 (0.09)	0.22 (0.08)	3.875 (p = .000)
Gamma	0.12 (0.06)	0.08 (0.04)	4.352 (p = .000)

Table 2
The percentage of fixation duration in each AOI. Mean (standard deviation).

	Own-race strange face		Other-race strange face	
	ASD	TD	ASD	TD
Background	19.40 (24.49)	3.27 (5.63)	9.62 (17.79)	1.53 (2.26)
Body	29.47 (19.59)	33.17 (16.70)	26.49 (17.96)	27.15 (15.31)
Face	51.13 (24.39)	63.56 (16.03)	63.89 (26.20)	71.32 (15.73)
Eyes	8.84 (10.10)	10.57 (14.24)	15.60 (17.73)	18.98 (17.16)
Left eye	2.58 (5.64)	1.90 (3.83)	4.79 (9.97)	4.61 (6.54)
Right eye	1.82 (3.28)	2.58 (5.39)	3.99 (5.40)	7.25 (9.99)
Mouth	4.33 (5.83)	8.35 (7.44)	4.10 (5.93)	6.79 (6.25)
Nose	16.94 (13.00)	24.88 (12.73)	9.20 (9.24)	14.53 (10.45)

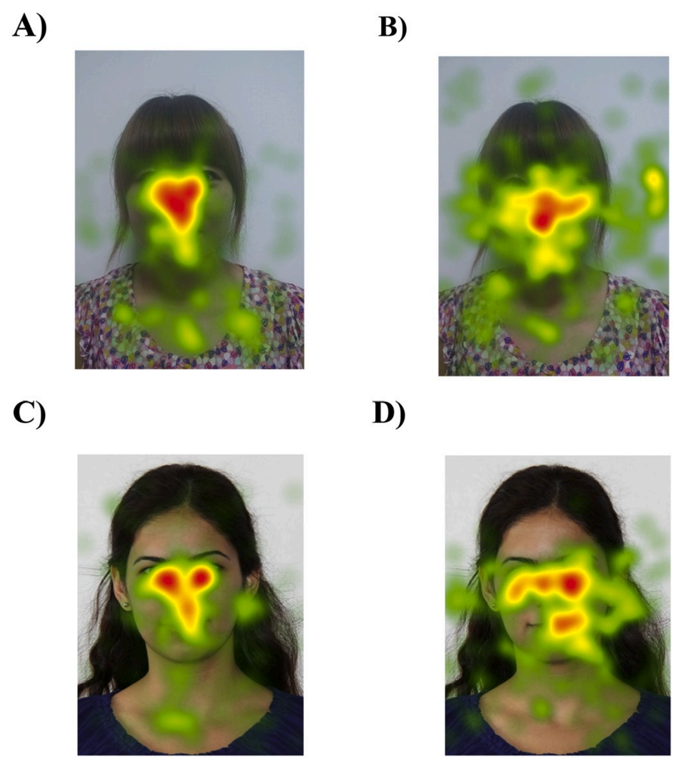

Fig. 2. The differences map of two kinds of facial stimuli in two groups. A) showed the hotspot map in TD children when gazing own-race face and B) showed the hotspot map in children with ASD when gazing own-race face; C) showed the hotspot map in TD children when gazing other-race face and D) showed the hotspot map in children with ASD when gazing other-race face.

Table 3
Classification accuracy of SVM using AOI durations when gazing at own-race and other-race facial stimuli and their combination.

	ACC	AUC
Own-race stranger's faces	72.33%	0.8269
Other-race stranger's faces	66.67%	0.7460
Both types of stranger's faces	75.89%	0.8652

Independent t-tests revealed significant differences between ASD and TD in fixation duration percentage for background, face, mouth, and nose. ASD gazed more at the background of own-race stranger's faces, and less at the face, nose, and mouth. Meanwhile, ASD group gazed more at the background of other-race stranger's faces, and less at the nose and mouth. The hotspot map of differences between the two groups is shown in Fig. 2. We also calculated the classification accuracy based on the AOI gaze durations of own-race and other-race facial stimuli and their combination (Table 3).

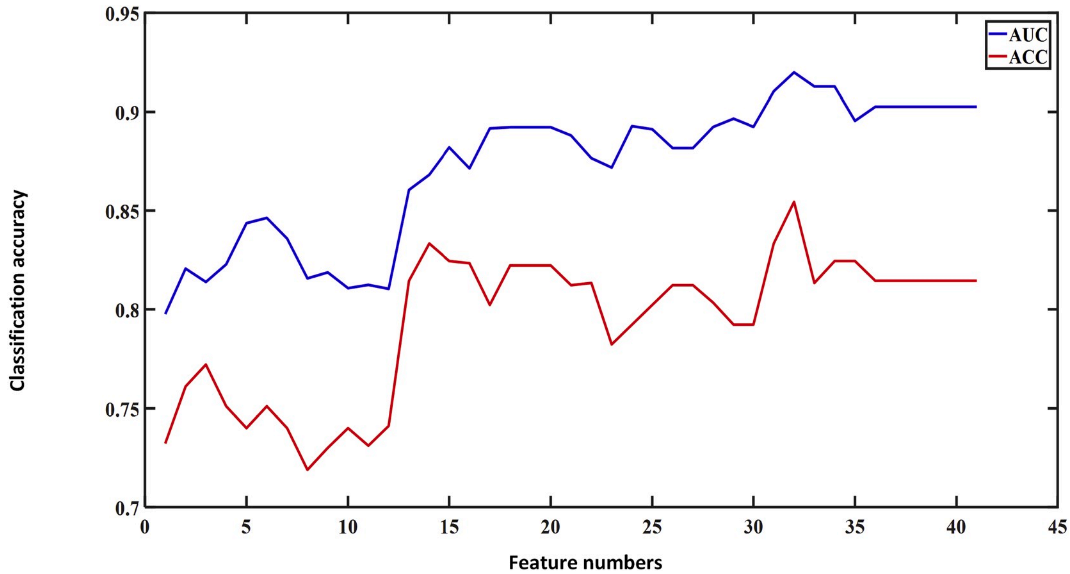

Fig. 3. Classification accuracy using one to forty-five features and SVM classifier.

3.3. *Classification using both EEG and eye-tracking*

When we combined EEG and eye-tracking data as input to the classifier, the classification accuracy reached a maximum of 85.44% with AUC = 0.93 when 32 features were selected. Fig. 3 shows the results.

4. Discussion

In this study, we classified ASD and typically developing children using linear SVM, combining EEG and eye-tracking data. Satisfactory classification results were obtained. To our knowledge, there are no other studies using EEG and eye-tracking data to discriminate between autistic and healthy children.

When using only the EEG power, we obtained a 68% classification. When only eye-tracking data was used for classification, the accuracy was 72.33% for own-race faces and 66.67% for other-race faces. When the two types of faces were combined, the accuracy was 75.89%. With a combination of EEG and eye-tracking data, the accuracy of classification reached 85%.

We found significant differences in relative power in theta, beta and gamma band, which are consistent with previous studies [12,27], showing that brain rhythms of autistic children are abnormal. EEG theta oscillations are related to working memory processes, not only retrieval but also encoding process [28]. Beta oscillations are associated with alertness and motor behavior [29]. Gamma oscillations and its synchronization are closely related to many cognitive activities, such as sensory processing, working memory, attention, and arousal [30,31]. Corresponding behavioral problems appear in some autistic children. However, no differences in EEG were found in some previous studies, especially for high functioning autism [32,33]. We think the reason is that ASD is a complex disease with large individual differences. Autism can be divided into low function and high function according to behavioral ability. Therefore, using only EEG evaluation may be insufficient to identify children with this complex disease.

Eye-tracking technology was added for evaluation, since some previous studies have found atypical face processing for all types of ASD. We fused the two types of data and obtained a more accurate classification.

Analyzing the eye-tracking data, we found that, compared with normal children, autistic children paid less attention to the core areas of the face, including eyes and mouth, consistent with previous research results [34,35]. The "eye avoidance" hypothesis provides us a reasonable explanation for abnormal facial recognition of ASD [17]. ASD children avoid gazing at eyes because this may lead to feelings of social threat, leading to physiological responses. Eye avoidance is then an adaptive strategy for autism; however, this influences their ability to deal with facial identity and intention suggestion, which negatively impacts autistic children.

We explored how autistic children gaze at other-race faces and the results were similar with the own-race face processing. Classification accuracy when using AOI gaze durations on own-race faces was higher than other-race faces, in line with the other-race effect. Most researchers agree that this effect results from differential experience with own-race and other-race faces, and compared with own-race faces, the ability to distinguish and recognize other-race face was slightly weaker [36,37].

In this study, we recruited a relatively large sample size for the sake of classification, and data from two modalities also increased accuracy. However, there are some limitations to our study. First, diagnosis of autism at earlier ages is a pressing clinical need, and we only enrolled children aged 3–6 years in this study. We plan to recruit younger children, aged 2 years or younger, to participate in the next study. Second, more features need to be extracted from EEG and eye-tracking data; multi-modal, multi-feature fusion will likely improve classification accuracy further.

Data availability

The EEG and eye-tracking data used to support the findings of this study are available from the corresponding author upon request.

Declaration of competing interest

All authors declared that they have no conflicts of interest to this work.

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