Characterizing Autism Spectrum Disorder Through Fusion of Local Cortical Activation and Global Functional Connectivity Using Game-Based Stimuli and a Mobile EEG System

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***Abstract*— The deficit in social interaction skills among individuals with autism spectrum disorder (ASD) is strongly influenced by personal experiences and social environments. Neuroimaging studies have previously highlighted the link between social impairment and brain activity in ASD. This study aims to develop a method for assessing and identifying ASD using a social cognitive game-based paradigm combined with electroencephalo-graphy (EEG) signaling features. Typically developing (TD) participants and autistic preadolescents and teenagers were recruited to participate in a social game while 12-channel EEG signals were recorded. The EEG signals underwent pre-processing to analyze local brain activities, including event-related potentials (ERPs) and time-frequency features. Additionally, the global brain network's functional connectivity between brain regions was evaluated using phase-lag indices (PLIs). Subsequently, machine learning models were employed to assess the neurophysiological features. Results indicated pronounced ERP components, particularly the late positive potential (LPP), in parietal regions during social training. Autistic preadolescents and teenagers exhibited lower LPP amplitudes and larger P200 amplitudes compared to TD participants. Reduced theta synchronization was also observed in the ASD group. Aberrant functional connectivity within certain time intervals was noted in the ASD group. Machine learning analysis revealed that support-vector machines achieved a sensitivity of 100%, specificity of 91.7%, and accuracy of 95.8% as part of the performance evaluation when utilizing ERP and brain oscillation features for ASD characterization. These findings suggest that social interaction difficulties in autism are linked to specific brain activation patterns. Traditional behavioral assessments face challenges of subjectivity and accuracy, indicating the potential use of social training interfaces and EEG features for cognitive assessment in ASD.**

***Index Terms*— Electroencephalography, autism spectrum disorder, brain oscillations, functional connectivity, support-vector machine.**

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I. Introduction

AUTISM spectrum disorder (ASD) is classified as a neurodevelopmental disorder according to the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [1]. The previous diagnoses of autism, Asperger's disorder, and pervasive developmental disorder not otherwise specified are all encompassed as ASD in this version. In the United States, about 1 in 54 children has been identified with ASD according to statistics from the Autism and Developmental Disabilities Monitoring Network of Centers for Disease Control [2]. Children with ASD show difficulty in social communication and interaction, as well as repetitive patterns of behavior, interests, or activities [1]. Previous studies have suggested that there is impairment of face processing and recognition in individuals with ASD which also affects the ability of emotional expression [3], [4]. The impairment of face processing and emotional expression might be the main reasons that cause social cognition deficits.

A. Neuroimaging Evidence for ASD and Social Interaction

Neurophysiological studies have supported deficits in gaze perception, facial expression, and joint attention in autistic individuals [5], [6], [7]. Using functional magnetic resonance imaging (fMRI), researchers have reported an atypical neural network of joint attention in autistic individuals. Activation of the precuneus and temporal-parietal junction (TPJ) plays a critical role during the development of joint attention from childhood to adolescence [8]. Autistic children and adolescents have been reported to have reduced recruitment of the frontal, temporal, and parietal regions, as well as the frontal-striatal network, frontal-parietal attention networks, and visual processing regions [9], [10], in addition to abnormal activation in social cognition–related areas including the superior temporal sulcus and TPJ [11] during gaze following. These studies highlight the importance of frontal-parietal control and the amygdala salience network [8], [12]. Although altered connectivity in these networks has been suggested, more research is needed to determine the characteristic alterations of functional connectivity in ASD, including task-related investigations and the critical period at which alterations occur [13].

Compared with fMRI, which has high spatial resolution and helps to localize brain activities into distinct regions, electroencephalography (EEG) and magnetoencephalography (MEG) provide superior temporal resolution to explore the dynamics of mechanisms contributing to cognitive functions. Studies focused on brain oscillations often include time domain analysis of event-related potentials (ERPs) and time-frequency analysis of event-related spectral perturbations (ERSPs), which comprise the enhancement or reduction of brain oscillations of different frequency bands, namely event-related synchronization (ERS) or desynchronization (ERD). These regional activities, including ERPs and ERSPs, can be denoted as local cortical activations [14], [15], [16]. In contrast, global brain functional connections are concerned with functional connectivity between brain regions, mainly by estimating the coherence, amplitude correlation, and phase synchronization of brain signals [17], [18], [19], [20]. These techniques have been utilized to investigate the highly dynamic brain oscillations of mental disorders. Autistic individuals have largely been reported with atypical ERPs, ERSPs, and functional connectivity of EEG activities [6], [7], [21]. In ERP studies, smaller amplitudes and delayed latencies were consistently reported for facial emotional expressions in autistic individuals compared to controls, specifically in ERP components of P1, N170, P200, and P3 [7]. In previous time-frequency studies, researchers have consistently reported altered mu rhythm suppression (8–13 Hz) in autistic individuals [22], [23], which may indicate the impairment of the mirror neuron system.

Brain connectivity has been studied in autistic individuals during resting-state and task-related EEG and MEG, which can provide valuable information about task-related neuronal dynamics of functional networks. Functional connectivity studies have indicated reduced long-range connectivity in autistic individuals, whereas under-connectivity has mainly been observed in low-frequency bands [21], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38]. This neuroimaging evidence can be seen as reliable neurophysiological features for further investigation of cognitive assessment in ASD.

B. Importance of Game-Based Social Cognitive Tasks for Cognitive Assessment of Autism

Autistic individuals are commonly reported with a preference for computer technology with affect-free and highly predictable interfaces [39]. Hence, game-based interacting platforms for task-based cognitive investigation and behavioral interventions have gained momentum in recent years. The attempts to implement game-based interacting interfaces for replacing traditional stimuli have reported significant improvement in social functioning in ASD [40], [41]. Certain single-player and role-play games, such as Fearnot [42], the ECHOES project [43], JeStiMulE [44], GOLIAH [45], ALTRIRAS [46], and SSIT [47], were proposed with the possibility of intervening in emotional recognition and social skills [48], [49], as well as newly developed multiplayer [50], [51], [52], [53] and virtual reality games [54], [55], [56]. However, only a few studies have incorporated neurophysiological features for measuring a player's performance and cognitive function [41], [43], [57]. Most of the previous studies still utilized oral reports or questionnaires to verify the effectiveness of these tasks/games. In future investigations of game-based training platforms or assessment tools, the utilization of neurophysiological signals as effective biomarkers is essential for characterizing ASD.

In the past decade, more investigations have focused on utilizing neurophysiological signals for characterizing ASD [58]. High accuracies have been reported for cognitive assessment or detecting the severity of ASD. However, most of the previous studies have relied on resting datasets and subject-dependent cross-validation methods, which may overestimate the classification performance and are not suitable for cognitive environments in real life.

In this study, we developed a social interacting game designed for autistic preadolescents and teenagers. EEG signals were recorded to evaluate brain oscillations, time-frequency patterns, and functional connections during social emotional expressions. In our previous studies [59], [60], [61], we had shown that deficits in facial emotional expression and joint attention may hamper the development of social cognition in ASD. In the current study, we posited that local cortical activation, specifically altered brain oscillations, and global functional connectivity are observed during a social interacting game in autistic preadolescents. We suggest that these neurophysiological features may serve as reliable indicators for characterizing ASD.

II. Materials and Methods

A. Participants

A total of 24 participants were recruited for this study. The group consisted of twelve typically developing (TD) preadolescents and adolescents (aged 11.83 $\pm$ 1.27 years, males n = 7), and twelve autistic preadolescents and adolescents (aged 14.71 $\pm$ 2.92 years, males n = 9). Participants with a history of physiological and neurological diseases, as well as head trauma, were excluded from this study. The autistic participants were diagnosed based on the diagnostic criteria

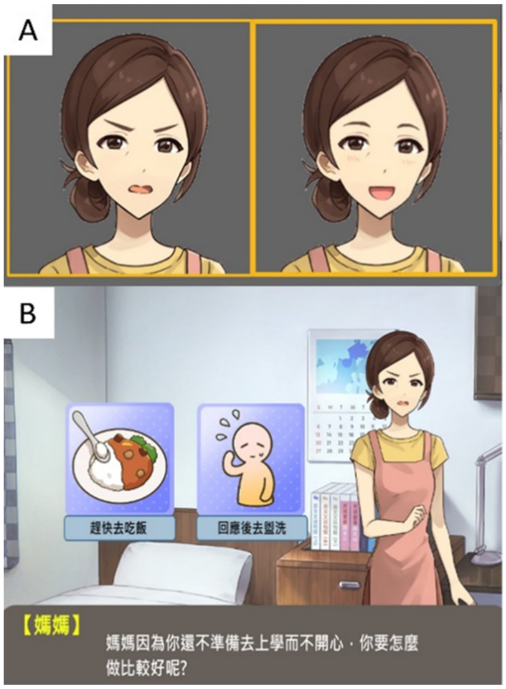

Fig. 1. Game-based social cognitive paradigm showing selections for emotional expressions (A) and appropriate behaviors (B). Translation: "Mom is upset because you're not ready for school yet. What should you do?" Left: "Hurry up and eat." Right: "Respond and then go wash up."

of the DSM-5 and ICD-10 and recruited from the National Taiwan University Hospital. All participants underwent neuropsychological tests to assess their nonverbal abilities. The Test of Nonverbal Intelligence, Fourth Edition (TONI-4), was used to measure their problem-solving and abstract reasoning capabilities [62]. The study was approved by the Research Ethics Committee at the National Taiwan University Hospital, Taiwan (REC no. 201709023RIPD and 202111075RINA), and written informed consent was obtained from the legal representatives of all participants prior to the experiment.

B. Game-Based Social Interacting Interface

We developed a game-based training interface specifically designed for autistic preadolescents and teenagers to enhance their learning in areas such as recognizing facial emotional expressions and improving social interaction skills. The Unity game engine (Unity Technologies 2018.1.14f) was utilized to create the games synchronized with a mobile EEG system. The interface incorporates interactive scenarios with various topics and real-life scenes, which were divided into events to meet the requirements of an EEG experimental paradigm.

The game-based interface consists of two modules (see Fig. 1). The first module introduces a complex version of the facial emotional recognition game, encompassing fundamental techniques of facial expressions and joint attention (Fig. 1A). The second module builds upon the first one by incorporating role-playing and first-person scenarios that closely simulate real-life social interactions (Fig. 1B). To accommodate the ages and preferences of the participants, appropriate rewards, such as vouchers, were offered at the end of the game.

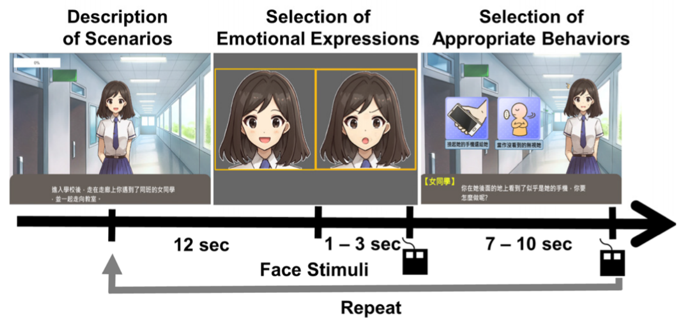

Fig. 2. Example of a trial presented in the game-base social cognitive paradigm with scenarios. Translation of the Description of Scenarios: After entering the school, you met a classmate, and you walked towards the classroom together. Translation of the Selection of Appropriate Behaviors: You see what appears to be her phone on the ground behind her. What will you do? Left: Pick up her phone and give it back to her. Right: Ignore her.

The game is an individual interactive computer game lasting for 30 minutes. It includes 84 trials of facial emotion recognition and 45 trials of selecting appropriate social/cognitive behaviors. The event triggers are communicated through the lab streaming layer to synchronize with the wireless EEG system. The primary objective of the game is to assess the participants' abilities in facial emotional recognition and social behavioral reactions. As depicted in Fig. 2, each trial consists of a 12-second description of the scenario. Participants are then requested to make eye contact with the character on the screen and select the correct facial emotional expression based on the social situation (1-3 seconds). Finally, participants are prompted to choose an appropriate behavior or reaction in response to the character's social behaviors (7-10 seconds). In this study, the facial emotional recognition module is included for further behavioral and EEG analysis, while the social interaction module is utilized to enhance the realism of the experimental situation.

C. EEG Recording and Signal Processing

While the participants were actively involved in the task, their EEG signals were recorded using a portable and dry-electrode EEG headset (Quick-20 Dry EEG Headset, Cognionics, Inc., San Diego, CA). The recording followed the 10-20 system, capturing EEG signals from 12 specific scalp locations, namely F3, F4, F7, F8, Fz, C3, C4, P3, P4, P7, P8, and Pz. A reference electrode was placed on the left earlobe, namely the A1 electrode. The EEG signals were sampled at a rate of 500 Hz and amplified.

To ensure proper synchronization, the stimulus triggers were precisely aligned with the EEG data streams and stored in a unified file utilizing the Lab Streaming Layer data acquisition and synchronization framework. Subsequently, MATLAB R2024a (The MathWorks, Inc., Natick, Mass, USA) was employed for the analysis of the EEG data. After applying band-pass filtering ranging from 0 to 50 Hz, Artifact Subspace Reconstruction (ASR) utilizing Independent Component Analysis (ICA) was employed to distinguish artifacts from brain signals. The parameter 'k' in ASR was set to 20 to achieve optimal results [63], [64], [65], [66]. ASR was performed on the data after removing bad channels, followed by reconstruction through interpolation. This approach enabled us to identify and remove artifact components and trials specific to each participant. Before proceeding with the separation of the original signals, epoching was conducted on the continuous signal, and baseline subtraction was performed to reduce mutual information [67]. Signal epochs were then extracted from -200 to 1200 ms, where 0 ms indicates the stimulus onset of the face stimuli (Fig. 2). Subsequently, epochs with signal amplitudes exceeding ± 100 were removed due to poor behavior. Following artifact removal, the cleaned and epoched EEG data underwent Morlet wavelet transformation to extract event-related potentials or time-frequency features. For each channel location, group- averaged ERSPs were computed relative to a baseline. To assess the differences in brain oscillations between the two groups across different frequency bands, the Anderson-Darling test was initially applied to evaluate the normality of the data. Subsequently, a comparison between the results from the two groups for each time-frequency interval was conducted using a Wilcoxon rank-sum test.

The phase lag index (PLI) of artifact-corrected EEG signals was employed to quantitatively evaluate functional connectivity, which represents the interaction between two brain regions [68]. PLI is a widely used measure that provides quantitative phase relationships between signals and has been proposed as an important index in various cognitive processes [69]. To determine the functional connectivity of brain oscillations within specific frequency bands of interest, PLI was computed between pairs of EEG channels, with the detailed methodology described in references [68], [70]. Prior to computing PLIs, the time courses of each channel pair were filtered using a narrow-band convolution filter centered at a specified EEG frequency range (e.g., delta, theta, alpha, and gamma). The resulting PLIs were then averaged over 100 ms intervals and compared between the two groups.

Statistical analyses were conducted to assess the differences in behavioral results, ERPs, ERSPs, and PLIs between TD individuals and autistic preadolescents. The Wilcoxon rank-sum test was utilized for the group comparison. MATLAB R2024a (The MathWorks, Inc., Natick, Mass, USA) was used for all statistical analyses.

D. Machine Learning for Characterizing ASD

The machine-learning based assessment consists of three parts: feature engineering, classification, and performance validation. A filter method of analysis of variance (ANOVA) univariate test was used to determine the optimal number of features for the subsequent classification processes. The neurophysiological features mentioned, including the ERP components, time-frequency features, and PLI, were all subjected to the ANOVA test for feature sorting and the optimization of parameters. The optimal number of neurophysiological features used for classification was defined by varying the F-value of the ANOVA test.

To optimize the classification framework, the performance of six different classifiers, including the k-Nearest Neighbor (kNN) with a neighbor number of ten ($k = 10$), Binary Decision Tree (BDT), Gentle Adaptive Boosting (GAB), and Support Vector Machine (SVM) with three kernels of polynomial, radial, and sigmoid function, were assessed and compared. The optimization for classification was resolved using the SVM toolbox function LibSVM [25] and the Statistics and Machine Learning Toolbox incorporated in MATLAB R2024a.

The leave-one-out cross-validation (LOOCV) method was used to ensure subject-independent validation of classification performance. The categorization performance of the proposed framework is measured using sensitivity, specificity, and accuracy, which are fundamental metrics in classification tasks. Sensitivity, often referred to as the true positive rate, represents the proportion of actual positive cases that are correctly identified by the framework. It is calculated as the number of true positives divided by the sum of true positives and false negatives. Specificity, also known as the true negative rate, measures the proportion of actual negative cases that are accurately classified by the framework. It is computed as the number of true negatives divided by the sum of true negatives and false positives. Accuracy quantifies the overall correctness of the classification results by considering both true positive and true negative cases relative to the total number of cases. It is determined by the ratio of the sum of true positives and true negatives to the total number of cases.

III. Results

A. Task Performance

The average TONI-4 nonverbal ability test score for TD preadolescents was 115 ± 15, while for preadolescents with autism it was 102 ± 15. There was no significant difference observed between the two groups ($p = 0.105$). In terms of reaction time, the average response time in the social interaction game for autistic preadolescents was 2.28 ± 0.58 seconds, significantly slower than the TD preadolescents who had an average response time of 1.64 ± 0.39 seconds ($p = 0.019$). The mean accuracy rates for TD and autistic preadolescents were $98\% \pm 2\%$ and $93\% \pm 7\%$, respectively. The accuracy between the two groups differed significantly ($p = 0.018$).

B. ERP Features

The averaged ERPs between the two groups were compared during the condition of facial emotional recognition in the social training game, as shown in Fig. 3. The largest difference in the average ERPs was observed in the parietal regions, specifically at the Pz and P7 electrodes. Significant differences were observed at the time intervals around 160-220 and 550-750 ms, namely the P200 component and late positive potential (LPP), indicating divergent neural responses between the two groups.

Regarding the P200 component, which reflects the visual complexity in language processing or memory processing, increased amplitudes were observed between 160 and 220 ms after the onset of stimuli at the P7 electrode in autistic preadolescents and adolescents (Fig. 3A). The grand averages of the P200 waveform at the P7 electrode and the corresponding mean amplitudes are depicted in the lower portions of Fig. 3A. In comparison to TD participants

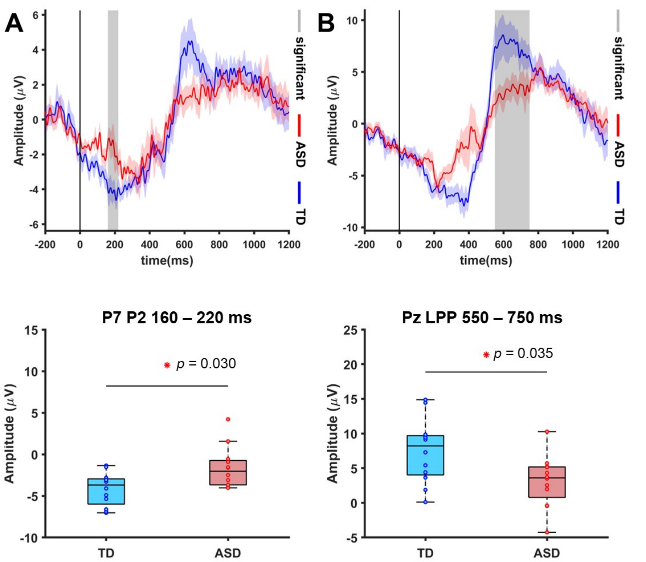

Fig. 3. The average ERPs during the module of facial emotional recognition in the social interacting game (upper row) and statistical results (lower row) within the following time intervals in the parietal regions: (A) 160-220 ms (P200 component) at the P7 electrode, and (B) 550-750 ms (LPP component) at the Pz electrode.

(-4.17 $\pm$ 1.99 μV), the autistic preadolescents (-1.65 $\pm$ 2.50 μV) exhibited a tendency towards larger P200 amplitudes ($p = 0.030$), suggesting disruptions in their facial feature processing.

The LPP component is associated with attention allocation towards emotionally salient stimuli [71], [72], [73]. The grand averages of the LPP component at the Pz electrode and the corresponding mean amplitudes are presented in the lower portion of Fig. 3B. Autistic participants displayed smaller LPP amplitudes (3.10 $\pm$ 3.68 μV) compared to TD participants (7.50 $\pm$ 4.61 μV, $p = 0.035$), suggesting difficulties in attentional allocation toward the target among autistic preadolescents and adolescents.

C. Time-Frequency Analysis of Brain Oscillations

The average ERSPs of time-frequency analysis in the frontal, central, and parietal regions of the TD and autistic preadolescents were compared in Fig. 4. The largest difference was observed at the C4, P3, P4, and Pz electrodes. The increments and decrements of the power, namely ERS and ERD, in different frequency bands and time intervals relative to the pre-stimulus baseline are represented by red and blue colors. Theta synchronization is observed around the frontal regions in the first 500-ms window after the stimulus onset in TD preadolescents. Delta synchronization in the frontal, central, and parietal regions was also observed especially in the autistic group. Alpha and beta desynchronization, which indicate the intention of motor activity, were found in the time interval after 200 ms.

A significant difference in ERSPs was observed between the two groups in the delta (1-4 Hz) and theta (5-8 Hz) frequency bands (Fig. 5). Autistic preadolescents exhibited greater theta synchronization in the parietal regions of electrodes P3 (Fig. 5A; p = 0.046), P4 (Fig. 5B; p = 0.023), and

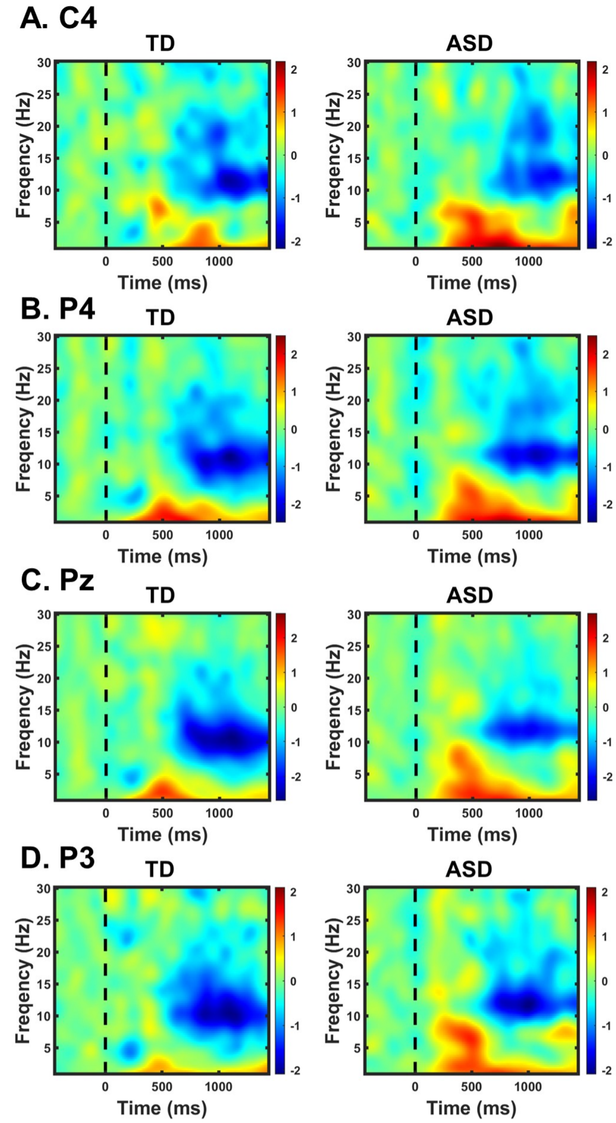

Fig. 4. The average ERSP results of time-frequency analysis from TD (left column) and autistic participants (right column) in the central and parietal regions. The largest difference was observed at the (A) C4, (B) P4, (C) Pz and (D) P3 electrodes.

Pz (Fig. 5C; p = 0.023), particularly evident around 230 to 300 ms after stimulus onset. Additionally, a slightly larger delta synchronization was observed in the autistic group in the right central regions (Fig. 5D), although this difference was not statistically significant.

D. Functional Connectivity

ASD preadolescents demonstrate altered connectivity patterns in both the theta (Fig. 6A) and alpha (Fig. 6B) frequency bands, with the most pronounced difference between the two groups observed between 300 and 500 ms in the alpha frequency band ($\geq$ 5 channel pairs). These findings align with previous EEG studies investigating functional connectivity during various cognitive tasks, which have consistently indicated hypo-connectivity in autistic individuals.

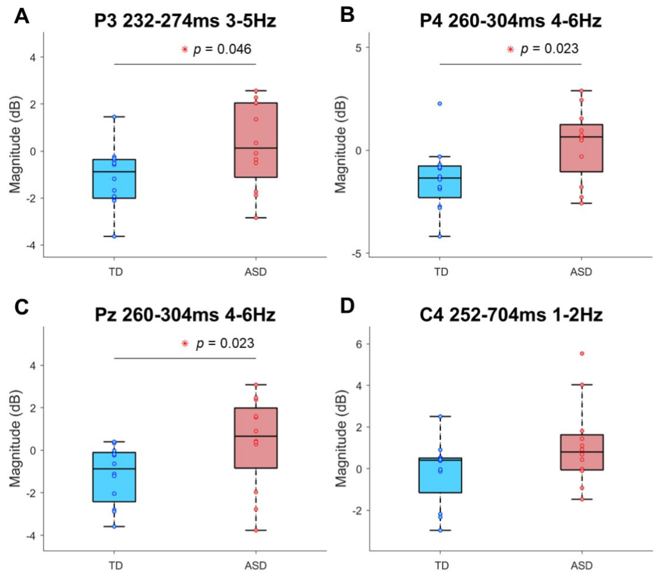

Fig. 5. The ERSP results of time-frequency analysis within the following time intervals in the central and parietal regions: (A) 232 - 274 ms (delta and theta band) at P3, (B) 260 - 304 ms (theta band) at P4, (C) 260 - 304 ms (theta band) at Pz, and (D) 252 - 704 ms (delta band) at C4.

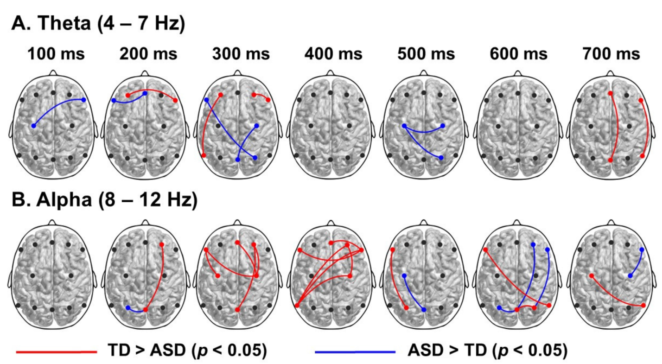

Fig. 6. The results of brain functional connectivity calculated by phase-lag indices in the (A) theta and (B) alpha frequency bands. The red lines indicated the significant lower phase synchronization of autism than the TD group. Hypo-connectivity is observed in the alpha band during the first 700 ms following stimulus onset in autistic preadolescents and teenagers, particularly notable within the time interval of 400 to 500 ms.

E. Results of Machine Learning for Characterizing ASD

The performance of the six machine-learning-based classification methods was compared using subject-independent LOOCV for validation. The optimal number of local and global features used for classification was determined by adjusting the F-value. The overall performance of the six classifiers, including sensitivity, specificity, accuracy, and average feature number, is presented in Table I.

The performance of the six classifiers was evaluated separately using the local features of brain activations and oscillations, global features of brain functional connectivity, and all neurophysiological features. Table I illustrates that SVM exhibited a sensitivity higher than 90%, while BDT and GAB showed lower sensitivity. Conversely, GAB and SVM demonstrated high specificity values, exceeding 90%, while kNN and BDT had the lowest specificity values, below 75%.

In summary, the SVM-based approach using a sigmoid kernel function achieved the highest sensitivity of 100% and overall performance, with an accuracy of 95.8% when only local features were utilized.

TABLE I
SUBJECT-INDEPENDENT PERFORMANCE OF CLASSIFYING METHOD FOR CHARACTERIZING AUTISM (kNN: k-NEAREST NEIGHBORS; BDT: BINARY DECISION TREE; GAB: GENTLE ADAPTIVE BOOSTING; SVM: SUPPORT VECTOR MACHINE)

Classifier	Average feature number		Sensitivity (%)	Specificity (%)	Accuracy (%)
kNN	Local	14	100.0	66.7	83.3
	Global	61	75.0	50.0	62.5
	All	27	91.7	66.7	79.2
BDT	Local	17	75.0	66.7	70.8
	Global	14	66.7	41.7	54.2
	All	53	58.3	66.7	62.5
GAB	Local	8	83.3	91.7	87.5
	Global	6	41.7	66.7	54.2
	All	13	75.0	58.3	66.7
SVM-sigmoid	Local	**18**	**100**	**91.7**	**95.8**
	Global	16	83.3	75.0	79.2
	All	**29**	**83.3**	**100**	**91.7**
SVM-radial	Local	**17**	**91.7**	**91.7**	**91.7**
	Global	13	58.3	83.3	70.8
	All	28	83.3	83.3	83.3
SVM-polynomial	Local	19	91.7	83.3	87.5
	Global	13	75.0	58.3	66.7
	All	23	91.7	83.3	87.5

IV. DISCUSSION

This study proposes a social cognitive game synchronized with portable EEG systems to extract local and global features of brain activities, aiming to characterize autistic preadolescents and teenagers. The future potential of this investigation lies in evaluating the effectiveness of social training through cognitive assessment. In comparison to previous studies that claim high accuracies of ASD detection [58], the importance of this study is discussed in the following three aspects. Firstly, the neurophysiological features extracted in this study are provided based on the neural mechanism of social cognitive activities. The features, including local cortical activations and global functional connections, are verified based on previous neuroscience studies. Secondly, the validation method used for classification in the current study is subject-independent. We utilized our own dataset with LOOCV to ensure that the performance is not overestimated by the influence of subject-dependent data, and reasonable accuracy was achieved in this study.

Finally, a game-based social interacting game is provided based on the preference of autistic teenagers. In contrast to resting state analysis or traditional paradigms for cognitive evaluation, the game-based design is closer to a real-life social environment, allowing for the further application of cognitive assessment.

A. Features of Local Brain Activations and Oscillations

We mainly focused on two ERP components, P200 and LPP, associated with local brain activations during social interaction. Our previous findings already addressed evidence regarding the role of P200 in the attention characteristics of ASD, suggesting that P200 parameters are associated with difficulties in attention switching [74]. Therefore, ASD individuals with P200 gating deficits imply altered attention allocation in ASD, consistent with previous studies on ASD and P200 [75]. The second ERP component, LPP, is a centro-parietally distributed positive component often observed after 300 ms of stimulus onset. The decreased amplitudes of the LPP component in ASD may reflect aberrant dynamic allocation of increased attention [71], [72], [73].

B. Features of Global Functional Connectivity

Hypo-connectivity was observed in autistic individuals in the current study. Decreased functional connections were reported in the alpha frequency bands, especially within the first 700 ms after the stimulus onset of social emotional recognition. Over the past decade, brain connectivity has been extensively studied in autistic individuals using resting-state and task-related fMRI, EEG, and MEG studies [13], [21]. Abnormal functional connectivity has been found in resting-state fMRI studies, with evidence suggesting that ASD is characterized by instances of both under- and over-connectivity [13], [76]. In comparison to fMRI, connectivity analysis of EEG/MEG can provide valuable information about task-related neuronal dynamics of functional networks. EEG and MEG studies have also indicated reduced long-range connectivity in individuals with ASD, while the status of local connectivity remains unclear [21]. Our finding of alpha hypo-connectivity during the social interacting game supports the notion of decreased long-range functional connectivity in autistic preadolescents and teenagers. This finding also verifies that patterns of global brain functional connections can serve as reliable features for characterizing ASD.

C. Characterizing Autism With A Game-Based Task and Fusion of Local and Global Features

Neurophysiological signals have been widely incorporated in characterizing autism in recent years [58]. Table II shows that previous studies targeting ASD in different age groups have utilized various tasks, features, and classifiers for detecting autism. Accuracies ranging from 70% to 99% have been reported for identifying ASD. However, many of these studies did not mention the dependency of subjects in their

TABLE II

COMPARISON WITH EXISTING METHODS (kNN: k-NEAREST NEIGHBORS; DT: DECISION TREE; IMF: INTRINSIC MODE FUNCTIONS; ET: EYE-TRACKING; TF: TIME-FREQUENCY FEATURES; FC: FUNCTIONAL CONNECTIVITY;; SVM: SUPPORT VECTOR MACHINE; ANN: ARTIFICIAL NEURAL NETWORK)

Author/ year	N (ASD/ TD)	Age (years)	Task	Features	Method
Abdulhay, 2018 [85]	60/60	4-13	Resting	IMF	PCA, neural network
Heunis, 2018 [86]	7/7	2-6	Resting	PCA and recurrence quantification analysis	LDA, MLP, SVM
Fan, 2018 [87]	20	Mean 15.29	Task	Spectra and fractal dimension	KNN
Simões, 2018 [81]	17/17	Mean 16.4	Visual Stimulati on Task	TF, non-linear, spectra	SVM
Abdolzadeg an, 2020 [82]	34/11	3-12	5-min cartoon	Spectra, TF, entropy	kNN, SVM
Kang, 2020 [88]	49/48	3-6	Resting	Spectra and ET	SVM
Pham, 2020 [89]	40/37	4-13	Resting	Spectra	Neural network
Alotaibi, 2021 [83]	12/12	6-13	Emotion-al face	FC	Cubic SVM
Dong, 2021 [90]	86/89	3-6	Resting	Spectra	CNN
Ranjani, 2021 [91]	8/18	11-17	Resting	Spectra	Deep CNN
Baygin, 2021 [92]	61/61	4-13	Resting	TF and hybrid deep lightweight features	DT, kNN, SVM
Tawhid, 2021 [93]	9/10	10-16	Resting	TF	CNN, RF, kNN, LR, SVM
Bakheet, 2021 [84]	12/12	6-13	Emotion-al face	IMF	DA, SVM, kNN
Gui, 2021 [77]	77/91	0.5-0.9	Resting	Global Field Power	SVM
Liao, 2022 [79]	40/40	3-6	Videos	ET and spectra	Bayes
Ari, 2022 [94]	20/9	6-20	Resting	Sparse coding-based imaging	CNN
Barik, 2022 [78]	30/30	4-7	Resting	Spectra and phase	ANN
Han, 2022 [80]	40/50	Mean 4	Resting	Spectra, entropy, and FC	Multi-modal
Our Method	**12/12**	**Mean 13**	**Social game**	**ERP, TF, and FC**	**kNN, DT, GAB, SVM**

cross-validation methods, which can lead to an overestimation of classification performance. In recent years, several studies have focused on the practical application of identifying children with ASD and have clarified that their validation methods are subject-independent [77], [78], [79], [80]. These studies have reported more reasonable performances with accuracies ranging from 70% to 95%. In this study, our focus was on preadolescents and teenagers with ASD for the cognitive assessment of their social cognitive abilities. We reported a reasonable performance with an accuracy of 95.8% and a sensitivity of 100% using the SVM classifier and subject-independent LOOCV validation.

It is worth mentioning that many of the previous studies have reported their performance by using online databases or conducting resting EEG experiments (Table II). Only a few studies have reported their datasets with task-related stimuli for characterizing ASD [79], [81], [82], [83], [84]. Consistent with these studies, our focus was on the assessment of ASD during cognitive tasks to maximize the differences in the effects during specific social cognitive control of ASD.

Furthermore, there is wide variation in the feature extraction methods used in previous studies, as shown in Table II. Most studies focused on spectral parameters of frequency domain information, while some incorporated time-frequency analysis and provided corresponding parameters. Only a few studies considered global brain network parameters and utilized functional connectivity measurements as features. To the best of our knowledge, this is the first study that combines both local brain activities and global functional networks as features to create a knowledge-based feature space.

A major limitation of this study is the small sample size of autistic preadolescents and teenagers. Individuals with a severe degree of ASD may encounter challenges in comprehending games designed for their chronological age group. Consequently, achieving a large sample size and balanced age distribution between the ASD and TD groups has proven difficult. However, despite this constraint, our findings in TD and ASD preadolescents and teenagers revealed significant differences in local brain activations and global functional connectivity. Despite the small sample size, the findings are reliable and consistent with those of previous studies, even when using a more complex serious game platform.

V. Conclusion

In contrast to relying solely on behavioral questionnaires, we designed a social interaction game with EEG recorded during facial emotional recognition for the cognitive assessment of preadolescents with ASD. By analyzing the altered local features of brain activations and oscillations, namely ERPs and ERSPs, our study reveals that abnormal EEG responses can serve as reliable biomarkers for evaluating cognitive functions associated with social information processing and emotion recognition in autistic preadolescents and teenagers. We observed significant differences in the amplitudes of the P200 and LPP components, as well as increased theta and delta synchronization in autistic individuals. Aberrant global features of brain functional connectivity were also observed, with consistent findings of hypo-connectivity of autistic individuals during social-related cognitive tasks.

For characterizing ASD, our computer-aided assessment using SVM with both local features achieved high performance, reaching an accuracy of 95.8% in the cognitive assessment of autism. This study demonstrates the potential of incorporating EEG as an objective indicator for assessing cognitive performance and even computer-aided diagnosis during real-life scenarios of game playing. The flexibility and portability of EEG make it a promising tool compared to other neuroimaging techniques in this context.

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