Diagnosis and Intervention for Children With Autism Spectrum Disorder: A Survey

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***Abstract*—In recent years, the prevalence of autism spectrum disorder (ASD) has been proliferating rapidly around the world. This article aims to provide a comprehensive survey of the diagnosis and intervention for autistic children. Two assessment frameworks are introduced first to provide theoretical support for autistic engineering technologies: 1) international classification of diagnosis (ICD) and 2) international classification of functionalities (ICF). Then, autistic diagnosis and intervention techniques are presented respectively with different modalities. Multimodal sensing strategies for autism assessment are summarized subsequently. Finally, this article is concluded with future directions and challenges. This article overviews state-of-the-art research in the field of autistic diagnosis and intervention theory and applications giving priority to ICF-based solutions.**

***Index Terms*—Autism spectrum disorder (ASD), diagnosis and intervention, engineering technologies.**

I. Introduction

AUTISM, first proposed by Kanner in 1943, is a pervasive developmental disorder involving various anomalies in social relations, language, behavior, cognition, etc. [1]. In recent years, the prevalence of autism spectrum disorder (ASD) has been enormously increasing. The prevalence rate of ASD in America is 1/5000 in 1975, while a recent report (2018) from the Centers for Disease Control (CDC) estimates that the prevalence of ASD in the United States is 1/59 (or 16.8 per 1000 8-year old), which gets a dramatic increase in the past decades [2]. It approximates to 1/100 in China, and the number of patients is about 10 million in total, of which more than 2 million patients are children from 0 to 14 years old. The increase in the number of patients hints at a large group of sufferers, which may also reflect people's increasing awareness of the disorder. Although the exact cause of autism is unclear, the heritability of ASD was proved to be 0.82, and the effect of nonshared genetic factors was 0.18 [3]. Research indicates that appropriate and scientific intervention can improve the condition, especially in early childhood. Early diagnosis and intervention of ASD have a positive effect on improving ASD symptoms [4], [5].

ASD is mainly manifested in two core symptoms: communication and social difficulties, stereotypical and repetitive interests and behaviors based on the International Classification of Diseases (ICD-10) and Diagnostic and Statistical Manual of Mental Disorders (DSM-TR) [6], [7]. The ICD is considered an internationally accepted standard and tool for clinical diagnosis, epidemiological investigation, health management, and research across the world. It is organized as a hierarchical, categorical system, grouped by "epidemic disease," "systemic or general disease," "localized disease by site," "developmental disease," and "injury." Every physical or mental condition included is assigned a unique alphanumerical code, and the ASD is classified as F84 [8]. Social impairments mean that children have a qualitative defect in reciprocal social interaction. In infancy, children avoid eye contact, lack interest and reaction to human voices, do not expect to be held or have a stiff body, and are unwilling to be close to people when held, which exists huge difference from typically developing kids. In early childhood, children with ASD still avoid eye contact and often do not respond to calls. Besides, they have no attachment with their parents and cannot play or interact with children of the same age. Communication difficulties include nonverbal communication disorders and verbal communication disorders. Narrow interests appear as they always show great interest in a fixed type of thing such as wheels, bottle caps, etc. Stereotypical and repetitive behaviors typically perform inflexible and special actions like repeating hopping and walking on tiptoe. Meanwhile, they may commonly play with toys in one particular way, require items in a fixed position, walk through the same route, only eat a little food after a long time, etc. Although the ICD is widely used in a clinical situations, the health level of individuals cannot be covered, which is essential for people with ASD.

To provide a comprehensive profile of an individual's functioning level, the World Health Organization (WHO) developed the International Classification of Functioning (ICF), which focused on the health condition, body functions (physiological functions of body systems) and body structures (anatomical parts of the body), activities (execution

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of a task) and participation (involvement in life situations), environmental factors (physical, social, and attitudinal environment), and personal factors (features intrinsic to the individual) [9], [10]. ICF's descriptions of functional categories allow for a common language, which can be applied by professionals from various disciplines, researchers, clinicians, teachers, and healthcare authorities, to facilitate effective communication in the context of assessment, treatment, and health policy issues [11]. The WHO issued the International Classification of Functioning, Disability, and Health-Children and Youth (ICF-CY) on the basis of ICF with a broader category code to describe the function of the Children and adolescents [12]. As a dynamic and personalized evaluation system, ICF-CY can clearly present the individualized and differentiated characteristics among autistic children through coding. However, the ICF-CY have over 1400 categories classifying the individual's functioning, which is too extensive to be applied in daily clinical practice. To make the ICF-CY practical, the ICF Core Sets for ASD was researched by selecting the most relevant categories. At present, the core combination of research certification still needs validation of validity and reliability.

The ICF and ICD are actually complementary with different emphasizes. ICF focuses on evaluating the individual's function in a particular aspect, while ICD focuses on the patient's behavioral manifestations and symptoms. The ICD is taken as the diagnostic criteria in clinical, which could determine whether the child has autism. ICF is employed for evaluating and improving the function, and ASD is not considered a disease.

The current clinical diagnosis and intervention of autism ultimately boils down to the assessment of symptoms or function. In the process of clinical assessment, the physicians observe and record whether the children lack social interaction, joint attention, communication, and mental or behavioral flexibility combining some assessment criteria and scales, such as Autism Diagnostic Interview-revised (ADI-R) and Autism Diagnostic Observation Schedule (ADOS) [13], [14], which are considered to be the most standard tool in autism diagnosis. Compared to other assessment scales, they set a more comprehensive range of ages, expose more psychometric data, and better meet DSM and ICD standards. However, the accuracy of clinical evaluation is only about 80%. Accurate diagnosis requires an extensive clinical experience. For the intervention, no matter based on which criteria, special education and intervention training are the main methods for autism rehabilitation at home and abroad, for there is no effective drugs or armaria to relieve ASD symptoms currently. The intervention needs parents and therapists to implement a one-to-one training program for each child with ASD. Actually, there are not enough therapists for the massive number of people with ASD, and the enormous economic and physical pressures of the intervention severely affect families and society. Although the medical and health conditions in big cities are much better, the doctors suggest nearby treatment as the intervention is a long-term process. There are many difficulties and demands to be solved in the current clinical diagnosis and intervention. The major problems are as follows.

A. *Comprehensive Assessment Is Difficult*

Children with ASD have a wide range of activities, which have high uncertainty and varying degrees of behavioral performance. Besides, it is insufficient to assess the core features associated with alterations in cognitive and emotional functioning, high rates of psychiatric comorbidity, difficulties with forming and maintaining relationships, and poor adaptive skills solely by the categorical diagnosis [10]. It is difficult to fully and instantly gather their performance by the doctors.

B. *Assessment Consistency Is Poor*

Because some of the manifestations of typically developing children (TD) are on a large scale, there are no certain criteria to distinguish the ASD from the normal children. Language developmental delay, Neurodevelopmental retardation, attention deficit hyperactivity disorder (ADHD), etc., can be easily confused with ASD for some similar performance. Meanwhile, the subjective and unquantifiable process also accounts for the problem. The diagnostic results given by different doctors always have some differences. Only a few experienced doctors could make fairly accurate judgments due to the lack of measurable and quantitative indicators.

C. *Professional Ability Is Demanding*

According to incomplete statistics, the number of professional doctors who are able to meet the diagnostic qualifications for ASD is only a few hundred in China, while there is a great number of potential children with ASD. The workload and pressure to finish an assessment are heavy, which takes 60–120 min. To make a correct diagnosis or intervention, plenty of experience needs to be gathered, and it usually takes 3–5 years to train a doctor. Thus, training enough professional therapists becomes tough work to achieve.

D. *Sample of Effective Interventions Is Small*

As a result of the above reasons, the current diagnosis of autism is late, missing the optimal time for intervention. Intervention for autism is a long-term or even lifelong task, and the number of rehabilitation professionals is relatively small. Many institutions want to train parents to make family interventions more effective, but the skills learnt by the parents are limited.

In order to solve or alleviate this problem, many studies have been trying new techniques in auxiliary diagnosis and interventions for ASD in the past few decades. The progress of science and technology makes it possible to diagnose and intervene ASD earlier and more effectively. In addition, the advantage of using engineering techniques to promote intervention is that each course of external stimulation is standard and controllable. It not only ensures consistency across the course of intervention but also can focus on a particular symptom or function. Even trained professionals struggle to do this [4]. These studies can be divided into two categories: one is to identify people with autism using different types of data and artificial intelligence algorithms. The presence or absence of the manifestations involved in ICD is of particular concern;

the other focuses on grading or evaluating some specific functions of autistic patients, which is in accordance with the ICF. Since most techniques capture only part of the patient's characteristics, those relevant studies are based on ICF, which can be used to grade recovery.

This review focuses on engineering technologies employed in the diagnosis and intervention for ASD based on ICD or ICF. The remainder of this review is organized as follows: Section II investigates the diagnosis of ASD based on electroencephalography (EEG), magnetic resonance imaging (MRI), wearable systems, and computer vision systems, respectively; Section III summarizes advanced intervention technologies, including humanoid robotics, transcranial direct-current stimulation (tDCS) and repetitive transcranial magnetic stimulation (rTMS), and virtual reality (VR); Section IV demonstrates several pieces of research using multisensor data fusion strategies. The challenges and development of the existing technologies are discussed in Section V, and this article is concluded in Section VI.

II. Diagnosis and Classification of ASD Based on Engineering Technology

A. Overview

It is true that the children with ASD are accompanied by abnormal symptoms in neurological activations, speech, face, body gestures, and physiological response. Correspondingly, different sensing modes are investigated, such as MRI, EEG, audio, video, accelerometry, electrocardiograph (ECG), etc., to render the characteristics of the ASD. Research on EEG has focused on differences in brain development in people with autism, some of which also use it to distinguish ASD. Most of the studies using MRI classify autism by the differences in brain structure. Research related to wearable systems mainly evaluates certain functions of children with autism, in line with ICF. Research based on computer vision systems has focused more on the symptoms of autism, relying on some of the characteristics presented in ICD. The sensors, systems, features, and results associated with these studies are reviewed.

B. Electroencephalography

It is known that ASD is a developmental disorder of the brain, so numerous studies focus on the difference of brain electrophysiological information between ASD and typical developed (TD) children using EEG. EEG is an electrophysiological monitoring method to record the electrical activity of the brain. It is a popular signal to explore specific manifestations of ASD due to its low-cost and mobility. Bosl *et al.* [15] used nonlinear features extracted from EEG signals as input to statistical learning methods to predict whether the infants were ASD or not from three months of age. These subjects included low-risk children and high-risk children who had an older sibling with ASD. The result showed that there were significant differences in some nonlinear measurements such as Sample entropy and Detrended Fluctuation Analysis between ASD and TD. Junxia *et al.* [16] collected the resting-state EEG data of 351 children from 3 to 9 years (80 children with ASD, 271 TD children). The relative power spectrum of EEG was calculated by Pwelch' method. The results showed that the relative power in the alpha band between ASD and TD are different. Alturki *et al.* [17] explored the effects of different features, logarithmic variance, energy, entropy, and logarithmic BP (LBP) extracting by common spatial pattern (CSP), and various machine learning methods on the classification of autism in the King Abdulaziz University data set (for ASD). The results showed that CSP-LBP-KNN provided the best performance with an average classification accuracy of approximately 98.46%. Haendel *et al.* [18] studied the changes of functional neural connectivity (EEG coherence) of adolescents with ASD before and after the Program for the Education and Enrichment of Relational Skills intervention. The results showed that positive changes were found in the EEG coherence, linked to the increased social activities and skills. Whitford *et al.* [19] synchronously recorded the EEG and structural MRI of the same subjects. The result showed that the curve of slow-wave brain electrical power and cortical gray matter density decrease was approximately parallel as the age grows. Billeci *et al.* [20] explored the neural correlations of responding and initiating joint attention (RJA and IJA) in high-functioning children with ASD. An integrated EEG/eye-tracking system simultaneously gathered the EEG and eye movement data at the same sampling rate – 500 Hz. The results showed that the overlapping and specialized neural circuitries was linked to both RJA and IJA, and the brain activity and connectivity changed after the six months' intervention. These studies showed that EEG might serve as a physiological marker for evaluating the effectiveness of autism interventions over time.

Except for the exploration of specificity, EEG was a potential signal to recognize emotions for ASD. Many machine learning algorithms were used to classify the emotions of ASD, such as the support vector machine (SVM), linear discriminant analysis, k-nearest neighbor, naive Bayes random forest, and deep-learning classification algorithms. Petrantonakis and Hadjileontiadis [21] proposed a filtering procedure, hybrid adaptive filtering (HAF), based on genetic algorithms. The features were extracted by the higher order crossings (HOCs) analysis. Vijayan [22] extracted the features by statistical measures, such as the Shannon Entropy and higher order auto-regressive model to distinguish different emotions. In [23], the features were selected by a balanced one-way ANOVA after calculating the Hjorth parameters (activity, mobility, and complexity) [24]. The deep learning algorithm got better results for ASD recognition with the emotions, including happy, angry, sad, and scared emotions.

Although EEG analysis is an objective evaluation of brain development for children with autism, it cannot provide sufficient proof for clinical diagnosis. Distinguishing the ASD from the TD in a certain group, including only ASD and TD children, is achievable as it is just a binary task. The EEG could be used to analyze the differences in brain development between autistic and TD children over time. It is a promising method to detect long-term development features of autism, which is helpful for the early diagnosis of ASD as a reference.

C. Magnetic Resonance Imaging

MRI is a medical imaging technique used in radiology, which plays a pretty important role in diagnosis and research for both health and disease. It is also studied in the early diagnosis of ASD. Akshoomoff *et al.* [25] first proposed six neuroanatomical predictors (cerebellar white and gray matter volumes, area of the anterior and posterior cerebellar vermis, and cerebral white and gray matter volumes) for discriminant function analysis to classify ASD from TD. The study successfully predicted ASD from the typical controls, 52 boys with a provisional diagnosis of autism and 15 typically developing TD, with 95.8% accuracy. It proved the feasibility of employing imaging indicators to aid clinical diagnosis in preliminary. Xiao *et al.* [26] put forward a diagnostic model generated by MRI-derived brain features in toddlers with ASD aged from 2 to 3 years old. The result revealed that thickness-based classification outperformed the volume-based classification and surface area-based classification. The classification based on the cortical thickness of regions with the top 20 highest importance obtained the best accuracy and specificity. Hazlett *et al.* [27] showed that cortical surface area hyper expansion between 6 and 12 months of age precedes brain volume overgrowth observed between 12 and 24 months in the 15 high-risk infants who were diagnosed with autism at 24 months. Meanwhile, the accuracy of prediction and diagnosis of autism in individual high-risk children at 24 months achieved a positive predictive value of 81% and sensitivity of 88%. These findings demonstrated that early brain changes occurred during the period in which autistic behaviors were first emerging.

Many data processing and Web-based learning methods have been developed to distinguish autism. Mostafa *et al.* [28] designed a brain network using the 264 regions-based parcellation scheme from a brain fMRI to diagnose ASD. 264 raw brain features by the 264 eigenvalues of the Laplacian matrix of the brain network and another three features by network centralities were defined. The classification accuracy obtained by employing the designed features reaches 77.7% on the autism brain imaging data exchange (ABIDE) database, a worldwide real-world multisite functional and structural brain imaging data aggregation. To address intersite heterogeneity of the multisite data, Wang *et al.* [29] proposed a multisite adaption framework via low-rank representation decomposition for ASD identification based on fMRI with an accuracy rate of 71.88%. Noriega [30] used the resting-state fMRI to identify the functional connectivity differences between individuals in three groups: 1) ASD with severe stereotypical behaviors; 2) ASD with mild issues; and 3) the TD. Three processing methods were employed. The results showed that both overconnectivity and under-connectivity in the autistic brain found, while the connectivity is no uniform rule of expression in different regions. Huang *et al.* [31] proposed a graph-based classification model based on the deep belief network to identify ASD in the ABIDE database. The remarkable connectivity features were selected, and the accuracy rate is up to 76.4%.

The spatial resolution of MRI can be very high, making it possible to tell autism from nonautism with great precision. However, ASDs have been classified into three different types:

Fig. 1. Wearable cameras in hat [32].

1) Autistic disorder or classic autism; 2) asperger disorder; and 3) pervasive developmental disorder. The specific brain structure is not very stable for all kinds of patients with ASD. In addition, MRI data acquisition requires a strict static state, which makes it difficult for young children to cooperate, so that it is impractical to screen or diagnose ASD.

D. Wearable Systems

The wearable system, comprising sensors nodes and a central computing unit, is a kind of portable and intelligent device that users can wear. It is widely used in both people's daily life and academic research, such as sports bracelet and surface electromyography signal acquisition. The exquisite wearable devices can not only gather and track various information from the body, such as movement parameters and physiological parameters, but also provide some critical application and feedback to the users like images and voices. Some research employed a variety of wearable systems, such as wearable cameras, wristband embedded with accelerometers, or galvanic skin response (GSR) sensors to analyze the behavior of patients with ASD. Noris *et al.* [32] developed a head-mounted eye-tracker that fixed two cameras and a mirror on a cap, as shown in Fig. 1. The cameras can record the images from the perspective of the patients, and the face of the user can be captured at the same time. Thus, the information from the face, like facial expression, gaze direction, could be recognized. The gaze of the child and the field of view in front of him were detected and recorded in natural interaction. It supports the phenomenon that the children with ASD pay more attention to the lower part of the vertical field and the lateral field of view than the typically developing children. Kaliouby *et al.* [33] described a wearable device that consists of a camera and other sensors. It is said that this system could record and analyze the facial expression and the head movements of the person with whom the wearer is interacting. This is a potential method to quantify the social-emotional information of the people with ASD.

The wristband designed with different sensors can obtain various physiological signals (e.g., GSR, surface Electromyography) and movement parameters, such as accelerated speed and directions [34], [35]. Goodwin *et al.* [36] detected the stereotypical motor

Fig. 2. Tool boxes with interchangeable lids [35].

movements of ASD by utilizing accelerometers and pattern recognition software automatically. The acceleration data were collected by use of Massachusetts Institute of Technology Environmental Sensors (MITes). The results show that about 82%–97% of hand-flapping and body-rocking motions can be correctly recognized with this wristband. Wedyan and Al-Jumaily [35] analyzed the fine motor and object manipulation skills to distinguish high-risk subjects from the low-risk subjects. The task asked the infants to insert a proper object into a box with interchangeable lids, as shown in Fig. 2. In this research, two wired sensors are worn on the wrists of the infants and a wireless Bluetooth sensor is fixed in manipulated objects. The mean classification accuracy was 71.9% based on SVM and 72.5% for extreme learning machine (ELM). Though the results are not bad, this task does not accord with classic evaluation criteria. Except for motion analysis, the physiological signals were researched as well. Krupa *et al.* [34] predicted the emotional states of the children with autism by analyzing the GSR and heart rate variability (HRV) when the subjects were given periodic stimuli. A wearable wristband embedded with noninvasive GSR sensors and a pulse sensor was developed to collect the data. It reached an overall accuracy of 93.33% to distinguish emoting states from the neutral state and a mean accuracy of 90% to separate happiness from involvement. However, the ability to differentiate ASD from TD is low.

The wearable devices can record the information dig from children with ASD. It can quantify some behaviors of the children with ASD even though it can only reflect one aspect. Thus, it is one sided and cannot be used as a basis for diagnosis. In addition, the wearable device may not be accepted by children, especially young children so that no studies have been done recently.

E. Computer Vision Systems

Computer vision systems use cameras and computers instead of human eyes to identify, track, and measure the target. They are considered as a noncontact and convenient way to get the behavior's information of human, making it possible to assess the autistic children's behaviors. Duda *et al.* [37] and Kosmicki *et al.* [38] designed a mobile application as a screening tool named Cognoa Screener. Unlike regular screening tool such as Modified Checklist for Autism in Toddlers (M-CHAT) [39], it requires the parents to provide four satisfactory videos except for the 15 multiple-choice questions, which are related to the behavior of the child. This method first adopts the videos to remotely screen the ASD using some machine learning algorithms, making the screening more accurate and convenient. It was verified that the average accuracy of this method could reach 71% in screening the child with from 18 to 72 months, which the adaptive range is vast compared to the traditional-scale screening [40]. However, this tool still relies on manual diagnosis, during which the trained medical students need to classify the videos by assessing the symptoms of the child. Besides, the accuracy does not stand out in the small intervals. For example, the M-CHAT still has the highest accuracy when the child is 18–30 month [41]. Even so, it is commendable because it is the first to combine screening for autism with a remote visual system. The directions of eye gaze needs to be considered as the essential point since autistic people have severe social deficits, especially attention deficit. The eye tracking and gaze estimation are regarded as significant clues to assess ASD [16], [42]. Yaneva *et al.* [43] distinguished adult participants with and without ASD by analyzing the eye movements while they look for information within Web pages. Their results showed that the proposed method could detect the adults with ASD automatically with around 74% accuracy. Hashemi *et al.* [44] employed mobile applications with video stimulation to elicit and analyze children's behaviors based on iPad. Through facial feature points, head posture estimation, and other algorithms, the response to name-call, engagement, and emotional reactions were recorded. The results showed that this method can assist in the behavioral analysis of autism.

Except for the mobile platform, many other computer vision-based studies in autism diagnosis have received a lot of attention in recent years. de Belen *et al.* [45] summarized a review article about the investigation of ASD based on the computer vision from 2009 to 2019, in which the equipment and the subjects were detailed. To its credit, this review combed through data sets from the various autism studies available. There have been several preliminary studies using noncontact visual systems to aid early diagnosis of autism. Liu *et al.* [46] and Wang *et al.* [47] proposed a computer vision system containing RGB cameras and depth cameras to capture and analyze the behaviors of the children in two separate diagnostic scenarios, response to name and response to instruction as showed in Fig. 3. The gaze estimation and object recognition were integrated to quantify the child's behavior. The result showed that this method could effectively assess the characteristic behavior of children and has great application prospect in the early screening process of autism in the future.

Computer vision systems can capture the children's behaviors in multiple views and give quantitative characteristics, making evaluation process have objective indicators. Because of the low-cost and simple operation, computer vision systems hold great promise in the early screening and diagnosis of

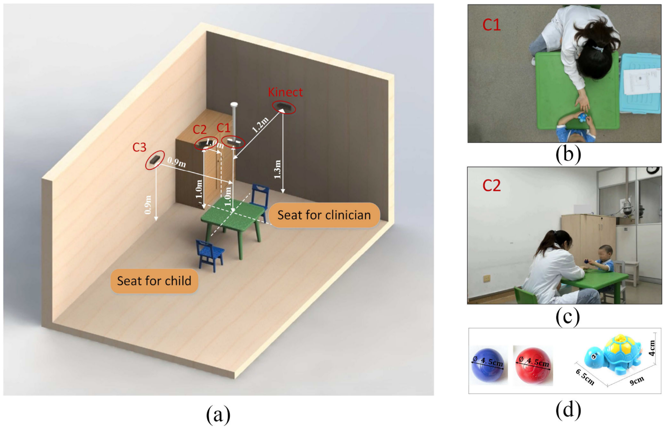

Fig. 3. Computer vision system in [46]. (a) 3-D representation of the designed experimental scene. Three RGB cameras: C1, C2, and C3 are located at the top, leftfront, and flank of the tabletop, respectively. The Kinect is hung on the wall toacquire the child's skeleton of the upper body, taking an angle of depression of 15°. (b) Top view snapshot of the experiment scenario by C1. (c) Leftfront view snapshot of the experiment scenario by C2. (d) Toys provided tochildren with annotated dimensions.

autism. However, it also has some limitations, that is, the effectiveness of relevant algorithms.

III. Treatment and Research of ASD Based on Engineering Technology

A. Overview

Intervention for autism aims to improve symptoms, such as social difficulties and stereotypical behavior, and to provide cognitive education and life skills training. There are two ways to improve symptoms: 1) from the outside in and 2) from the inside out. Outside-in refers to improving social behavior through repeated training in social situations. Inside-out refers to neural stimulation that can changes the structure of the brain network and reduces some of the symptoms. To reach the above objectives, some advanced technologies, such as humanoid robotics, TMS, tDCS, VR, etc., were studied to improve some of the individual's core functions and life skills. This section will provide a review of these related studies.

B. Humanoid Robotics

A large number [48]–[50] have suggested that autistic children are more willing to contact and interact with robots rather than humans. Because autistic children are emotionally stable in predictable environments, interacting with robots may be relatively safe and straightforward [51]. The robot-assisted therapy (RAT) is a kind of therapy that augments traditional human therapy and is considered a game-changer. In recent years, RAT with children who suffer from ASD has attracted much attention. This has opened up an area within robotics that promises to make a difference in the future of healthcare and education. RAT is used in many aspects of therapy, which include social or learning aspects [52], [53]. Several notable humanoid robots used for therapy make great success, such as NAO and Kaspar robots.

In 2004, Scassellati [54] proposed to use machine-assisted methods to obtain quantitative objective data utilizing sensor detection of the line of sight, object location tracking, and sound prosody analysis so as to assist professional doctors and clinical professionals in the diagnosis of autism. Although the concept of using sensors to obtain quantitative data has been proposed earlier, relevant research on children with ASD is still mainly to verify the advantages of the diagnosis and treatment process involving robots [55], [56].

AuRoRA is an earlier machine-assisted autistic child treatment research project at the University of Hertfordshire in the United Kingdom [53]. The main research direction of this project involves the employment of robots to strengthen interventions. Wainer *et al.* [57] used the humanoid robot KASPAR to conduct a series of interventional treatment studies. An intervention therapy games for imitation and turn-taking were designed. The Robot communicates with children with ASD through gestures, expressions and language. Another research also let autistic children play with KASPAR in [58]. In the experiment, each child played games with a human partner and KASPAR twice, that is to say, a total of four times. Different from the expected results, children with autism do not show much interest in playing games with KASPAR, and did not show more enthusiasm in the shape of the selection, and did not show the social behavior related to the game. However, after playing games with KASPAR, children are able to cooperate with human partners better.

To improve the physical contact of children with autism, the tactile sensors are mounted on the robot surface [59]. In human–computer interaction research of autism, it is suggested that the intervention should have the characteristics of the simple design and remarkable cooperation mechanism. More importantly, it is proposed that the interaction of robots should be structured, and the language should be intuitive and straightforward. There are many studies of imitative interventions using Nao [60]. This article [61] aimed to investigate whether children with autism show more social engagement when interacting with the Nao robot compared to a human partner in a motor imitation task. Kaboski *et al.* [62] at the University of Notre Dame used the humanoid robot NAO to intervene between autistic children and normal children to reduce the social anxiety of children with ASD. Zheng *et al.* [63] at Vanderbilt University in the United States designed an imitation training autonomous system for autistic children using the humanoid robot NAO and an additional Kinect sensor. The robot performs gestures for the child to imitate, and the actions of the autistic children are collected by the imaging sensors. The completion of the target action imitation is evaluated by a finite state machine and other algorithms. Yun *et al.* [64] in the Korean Academy of Science and Technology designed a three-way interactive behavioral intervention system for autistic children using the humanoid robot iRobiQ and CARO and additional Kinect sensors intending to eliminate insecurities in the social environment. The whole intervention process is based on the Discrete Trial Teaching criterion, which is trained for gaze contact and expression judgment. The robot first judges the scene through the sensor information, and then interacts according to the preset scene with corresponding interaction language or action. In addition to imitation training, there has been some research on joint attention training. Ali *et al.* [65] explored which kinds

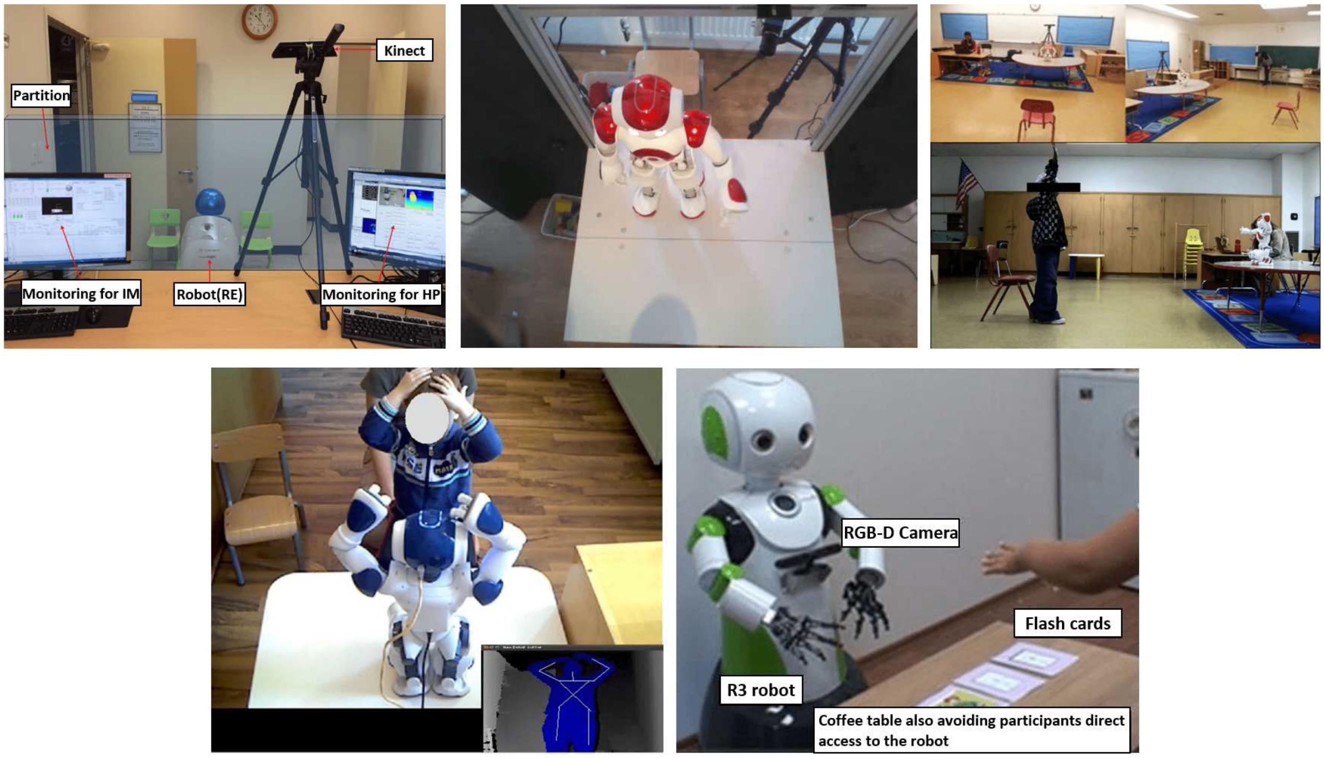

Fig. 4. System configuration for individual scenarios.

of stimuli: visual, auditory, and motion, are more effective for autism intervention using NAO robots. The joint attention and duration of eye contact were employed to assess the behavior of the ASD. The result showed all three types of stimulation were effective, but visual stimulation was the most effective. Mehmood *et al.* [66] used two NAO robots to study the attentional behavior difference of autistic children under different social stimuli, the same as [65]. However, the result showed that the speech could capture the children attention faster than the others. Cao *et al.* [67] compared the joint attention performance of ASD and TD when interacting with a humanoid robot, NAO, and a traditional human partner. The results showed both ASD and TD children performed better with the human partner than with the robot in response to JA tasks. Expect for the intervention, there have also been studies using robots in cognitive training. Research has shown that the inclusion of robots in autism education programs can increase children's engagement, focus, and communication [68].

Multiple visual systems were proposed to detect the behavior of the children interacting with a humanoid robot during the intervention [69], [70]. Face detection, landmark extraction, gaze estimation, head pose estimation, facial expression recognition, object recognition, and action recognition are integrated into a system, which was proved to be effective in analyzing children's behavior in a particular situation. Anzalone *et al.* [71] in the University of Paris combined the humanoid robot NAO with the Kinect-based perception system to observe the activity characteristics of autistic children during the joint attention scene. Messinger *et al.* [72] used image sensors to collect facial images and then used algorithms to judge expressions as a basis for evaluating autism patterns. Table I lists several cases of robot-assisted autism for different intervention models in recent years. It can be seen that combining robots with Kinect sensors can correspond to different autism intervention patterns as Fig. 4. Ognjen *et al.* [73] focused on the robot's perception of the emotional state and engagement of children with ASD. A deep learning method, called personalized perception of affect network (PPA-net), was proposed to make personalized assessments for children of different ages in different regions. Zheng *et al.* [74] focused on the single clinical scenarios, joint attention, to help the diagnosis and intervention by visual systems. The results show that it could provide a quantitative report that could help therapists to assess the ASD diagnosis or intervention consistently.

TABLE I
RESEARCH ON THE TREATMENT OF AUTISM WITH MACHINE-ASSISTED THERAPY IN RECENT YEARS

Research Group	Year	Robot	Objective
Wainer et al. [58]	2014	KASPAR	Turn-taking
Kaboski et al. [63]	2015	NAO	Turn-taking
Zheng et al. [64]	2015	NAO	Imitation
Yun et al. [65]	2016	iRobiQ	Turn-taking
Ognjen et al. [74]	2018	NAO	Affect and Engagement
Ali et al. [66]	2020	NAO	Joint attention
Mehmood et al. [67]	2020	NAO	Joint attention
Cao et al. [68]	2020	NAO	Joint attention
Arshad et al. [69]	2020	NAO	Cognitive abilities

The application of humanoid robots in the field of autism has to overcome three technical challenges: first, how to control the movement of the robot and what kind of stimuli is more effective [75]; second, how to obtain the input from the participant; and third, most of the robotic systems currently studied are open-loop, operated by either a precompiled program or remote manipulation [76]. Due to safety and cost considerations, social robots are still restricted to a small range in the field of autism, and the behavior of robots is relatively monotonous, such as only lifting their arms. Although it is essential to achieve language communication or gesture communication between robots and human, robots have still been very limited in this respect. Because if the speech recognition rate is required to be high, only simple script voice commands can be identified. Therefore, the identification of nonscript voice commands remains to be explored. In addition to speech, robots can also capture human facial expressions and human posture by a camera, so as to achieve human-machine interaction [4]. It is an excellent choice for applying humanoid robots to the autism therapy since they have simple social signals and can give predictable and specific feedback [60]. These new contactless visual systems have the potential to assess the ASD diagnosis and intervention based on a quantitative metrics.

C. Noninvasive Brain Stimulation Techniques

It is known that noninvasive brain stimulation techniques, including rTMS and tDCS, could alter brain activity in specific brain regions and mould plasticity at the network level [77], [78]. Thus, these two methods have been studied for the treatment of ASD naturally. Sokhadze *et al.* [79] demonstrated the potential therapeutic benefit of rTMS in autism to provide a means of altering neuronal plasticity through a presumed mechanism of enhanced cortical gamma oscillations. They further studied whether the inhibitory rTMS could benefit the executive function deficits. It was suggested that rTMS might also be a potential therapeutic tool for the treatment of ASD [80]. As mentioned, patients with ASD often show symptoms of autonomic nervous system functioning abnormalities such as faster heart rate with slight variation and increased tonic electrodermal activity. Wang *et al.* [81] studied the changes of electrocardiogram and skin conductance level (SCL) of the ASD after rTMS. Results showed that cardiac interval's variability increased, tonic SCL decreased, cardiac vagal control increased, and sympathetic arousal reduced. On the behavioral level, the tTMS could decrease irritability, hyperactivity, stereotype behavior, and compulsive behavior ratings. Barahona-Corrêa *et al.* [82] reviewed the studies investigating therapeutic use in ASD in detail. The study of Casanova *et al.* [83] showed that the low-frequency TMS therapy could improve multiple patient-oriented outcomes. These studies show the great promise of rTMS in improving the clinical symptoms of autism. However, the optimal stimulation parameters, including pulse frequency, stimulation intensity, the number of magnetic pulses delivered, and intersession interval, require a degree of individualization [84].

tDCS can increase or decrease neuronal excitability via the application of low-amplitude ($0.5 \sim 2$ mA) direct current. Giordano [85] first used the TDCS in the treatment for the patient with ASD. In the experiment, the cathode was positioned over the left dorsolateral prefrontal cortex (DLPFC), and the anode was placed over the contralateral deltoid with a direct current of 1.5 mA. The results showed there was a dramatic reduction in behavioural abnormalities for the patient. Amatachaya *et al.* [86] suggested that anodal TDCS over the F3 might be a potential clinical tool in autism through evaluating the childhood autism rating scale (CARS), autism treatment evaluation checklist (ATEC), and children's global assessment scale (CGAS) after anodal tDCS in individuals with autism.

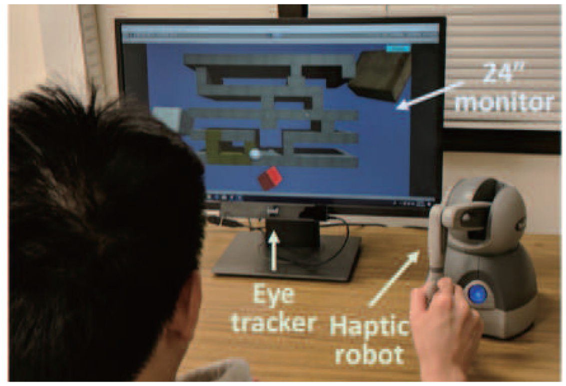

Fig. 5. Savr setup [94].

The rTMS and tDCS bring a new dimension to the treatment of ASD. Further research needs to be conducted to verify its effectiveness and pertinence. The region of function, optimal parameters, and effects need to be further determined in detail until they can be used in the clinic.

D. Virtual Reality

The one-on-one intervention training model requires a lot of repeated training for physicians and parents. However, the participation and training effect of the children with ASD are still variable. It is well known that virtual games are very attractive to children. Thus, in order to improve the engagement and training effect, some researchers began to develop virtual games for the intervention and evaluation of the autistic children using the VR technique [87]. Weilun *et al.* [88] developed an interactive quiz programme in which a virtual avatar was employed to pose questions. A Sumo wrestling game using robotics agent iRobot Create was designed to train motor skill. Results showed the virtual games motivate kids to participate in the learning process. The virtual games were also designed using VR technology, which could set the children in an immersive environment [89]. Nie *et al.* [90] proposed an immersive Computer-mediated Caregiver-Child Interaction (C3I) to train the initiation of joint attention (IJA) skill for the individuals with ASD. The caregivers, without additional workload or stress, were incorporated within the loop. The results show the feasibility of this method. Some games have been developed to train children's cognitive motor and social interaction abilities. Astro jumper [91] and avatar play can be played in a first-person or third-person mode [92]. Jyoti and Lahiri [93] developed a joint attention task platform, the VR-based JA task system (ViJAT), based on the visual reality, which could automatically adjust the prompt level for individuals with different functioning. The results showed that this system can estimate the skills level of the participants. Koirala *et al.* [94] designed a sensory assessment VR system (SAVR) to evaluate the visual and touch sensory processing differences between the ASD and TD through game playing. SAVR contained a centralized game and device controller, a gaze module, a touch module, a display module, and a data logging module as shown in Fig. 5. The evident difference was found in this group and the results strongly correlate to traditional questionnaire-the adult/adolescent sensory profile (AASP) results. Zhao *et al.* [95] designed a communication-enhancement collaborative virtual environment system, Hand-in-Hand, to help the children with ASD play a series of interactive games by using simple hand gestures. This system allows the participants to share information and discuss game strategies using gaze and voice-based communication, promoting natural communication and cooperation. The results are positive that the children with and without ASD are willing to accept this system. It has the potential to promote the communication and collaboration skills of children with ASD. Babu and Lahiri [96] proposed a multiplayer interaction platform using eye tracking for intervention to promote social reciprocity and interaction between individuals with ASD.

Although these studies are still in a primary stage and the ability trained by the virtual games to generalize in real life, it is believed that virtual games have great potential to train and educate children with ASD in some cases. However, the biggest challenge is how to make children with ASD learn practical skills from VR. Then, make sure it can be successfully applied in the real world. Games can be repeated, and mistakes can be made, but in reality, there can be a great danger.

IV. Multimodality Sensing Strategy for ASD Assessment

There is no single method for the diagnosis and intervention of autism, which requires comprehensive judgment and interaction based on the pathological manifestations of the person. Various kinds of information that can reflect the pattern of autism, including language, sight, expression, movement, and the physiological signal, can be collected and extracted through a multisensor sensory network. Multisensor data fusion technology is a new comprehensive multi-information processing. It makes full use of multisensor information resources of different time and space, and automatically analyzes, synthesizes, and dominates the multisensor information through computer technology under certain criteria in order to obtain the consistent interpretation of the measured object. Therefore, the system can achieve the required decision and estimation tasks and gain better performances than components.

Multisensor data fusion technology is especially suitable for the diagnosis and treatment of ASD due to its comprehensive coverage of time and space, high measurement dimension, and high credibility. Dang *et al.* [97] obtained movement and EEG vectors from HD Camera, Kinect, and MindWave to obtain motion and mental features, and then diagnosed ASD. Fig. 6 shows the position of the devices.

During the diagnosis process, the TV plays an interactive version of the story. When appropriate, it stops playing and continues to play after getting the child's interaction through high-definition camera, Kinect, and MindWave. Meanwhile, the motion and mental data detected by the devices will be recorded and analyzed by the computer. The Kinect and MindWave data are generated in units of one second. Kinect

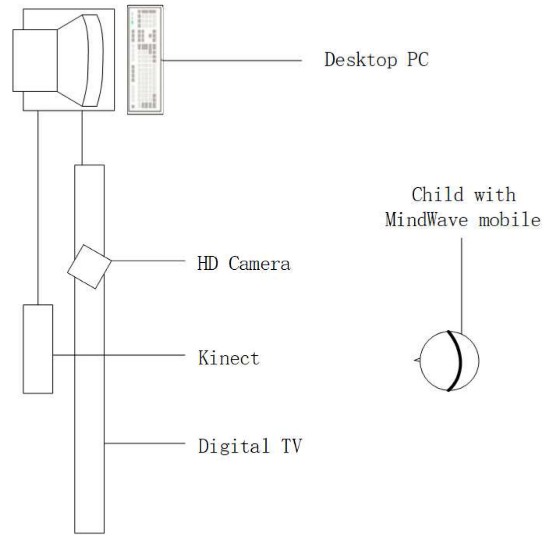

Fig. 6. Position of the devices include Desktop PC, HD Camera, Kinect, Digital TV, and MindWave mobile [97].

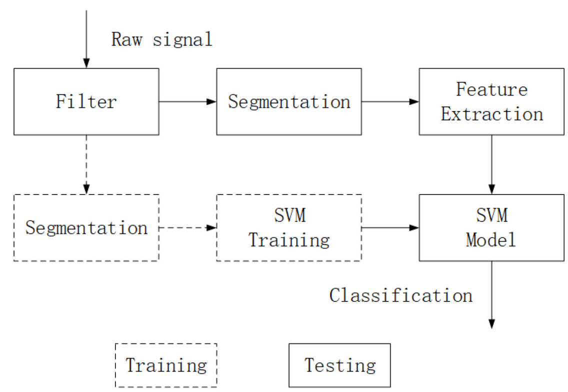

Fig. 7. Block diagram of the activities classification system for the system for the children with ASD [97].

divides each second into eight segments to produce motion features. It uses 14 land markers for skeleton description. It produces three characteristic vectors of mean differentiation of joint angle, median differentiation of joint angle, and standard deviation of the differentiation of joint angle for each land marker. That means Kinect produces 336 feature vectors every second. The signal generated by MindWave includes the power spectrum of the eight basic EEG signals used to characterize mental features. The classification requires three characteristics of mean differentiation of basic waves, median differentiation of basic waves, and standard deviation of the differentiation of basic waves. That means MindWave generates 24 feature vectors every second. Fig. 7 shows the process of data processing. First, the noise is removed from the skeleton and EEG. Next, the filtered signal is divided into fragments of constant size, and then motion features and EEG features are extracted from the segmentation signal for modeling, and finally classification. Dang *et al.* carried out four independent experiments on good movement, not good movement, positive engagement, and negative engagement, respectively, for five children, and obtained an accuracy of 96.2%, 93.3%, 94.06%, and 97.40%.

Hashemian and Pourghassem [98] established a system to record EEG signals for autistic and typical children during the processing of facial expression modes. They mapped their EEG signals to the feature space to reflect spatial, temporal, and spectral data and brain differences and also use a genetic algorithm to optimize the mapping process. The feature vectors corresponding to the three facial expressions of emotional modes are classified by the SVM. The decision-level data fusion was used for ASD diagnosis through the majority voting rule. Chien *et al.* [99] employed a smart tablet with a touch screen and an embedded inertial motion sensor to record the movement and posture of 37 ASD children and 45 normal children aged 3–6 years old. Experiments have shown that the accuracy of determining autism using this system is as high as 93%.

In addition to the diagnosis of ASD, multisensor fusion can also be used in the treatment of ASD [70]. Ichinose *et al.* [100] linked the electronic instrument Cyber Musical Instrument with Score (Cymis) to the game device Kinect to teach children with ASD to integrate visual and auditory senses, exercise, and body awareness to provide music therapy. It has been proven that the use of multisensor systems can accurately and efficiently diagnose and treat ASDs. However, it is a challenge to choose the suitable algorithm for effective data fusion for multisensor systems.

V. Challenges and Directions

A. Challenges

Most of the technologies are only at the preliminary stage and have not been widely used for clinical diagnosis and intervention. Moreover, some devices have to be worn on the body or restrict the children with ASD to a small area in an almost immovable posture. These severe conditions limit the practicability and generality of the application on account of the children's imparity and even rejection. In the face of clinical diagnosis and intervention needs: to obtain objective quantitative indicators, to reduce the requirements of artificial experience, and to improve the efficiency and accuracy of screening and diagnosis, there are still many problems and challenges with the existing technical approaches.

First, most of the methods only focus on a single symptom of ASD, which may distinguish ASD from TD in a particular group, but it will fail or encounter many problems in practice. For example, developmental delay and language impairment are two confusable disorders for ASD because some of the symptoms are similar. Second, the environments of some sensors are quite demanding if you want to get stable and reliable signals. The hyperactivity of children and the uncertainty of the general indoor environment can cause a great disturbance to the data. Third, a large amount of data is needed to make a data-driven diagnosis of autism. Still, the existing methods are difficult to generalize because they only involve small samples of local areas. Finally, in the experiments, the mapping of intervention objectives and results is not clear. It remains to be verified whether it can improve the function of children in real life.

There are mainly two challenges for the diagnosis and intervention using the engineering technologies.

1) *Unification and Standardization of Data Collection:* As children with ASD have a wide range of activities, their dynamic behaviors are challenging to capture. To find a unified and quantized standard, the data acquisition system needs to be stabilized and fixed at every age when using the same techniques. Until then can the collected data be shared and analyzed to obtain meaningful evaluation indicators. Small data size is a core bottleneck in machine learning algorithms, especially in the deep learning algorithm. So, enough uniform and normalized data play an important role in the study of ASD based on engineering technologies.
2) *Uniform Expression of Pathological Information Is Difficult:* Because the difference in behavioral manifestations among autistic patients is unpredictable, it seems complicated to distinguish behaviors and establish a unified standard. The pathological behavior feature recognition is complex, and it is necessary to adjust the threshold set by the pathological description according to different patients' conditions. Any new technology needs to be widely tested in healthy children first. Based on a large number of statistical data, the patient situation can be defined.

B. Directions

The new techniques for diagnosis and intervention will never be adopted in clinical situations until they are approved by most clinicians. Thus, new technology-based approaches to behavior analysis need to be studied with the participation of clinical experts. No matter which way to use for autism research, establishing the same experimental conditions and collection methods are beneficial to data sharing, which is very important for the study of autism from an engineering perspective.

1) Directions for Diagnosis: The directions for the diagnosis of ASD should be focused on addressing the clinical demands and problems that the existing technical methods.

a) Simplify assessment methodology: It is necessary to conduct the effective evaluation by the structured or semistructured experimental paradigm under the guidance of clinical experts based on the ICD and the ICF Core Set. Although the current accuracy of gaze estimation, behavior recognition, etc., based on noncontact visual sensing needs to be further improved, the joint analysis of multisensor data is still very promising research directions in the diagnosis for ASD.

b) Explore more specific pathological features for ASD: It is one of the critical steps to finding more specific pathological features to improve the diagnosis accuracy of ASD. The research based on nervous imaging and physiological signals such as EEG, NIR, ECG, etc., needs to be further explored. Once the true biomarker for ASD was found, the diagnosis of ASD could be proved to be objective.

c) Establish a standardized database: With the rapid development of artificial intelligence algorithms, data-driven intelligent diagnosis is a hot research direction. The premise is establishing a standardized database that means collecting a large amount of standard experimental data under the same paradigm and conditions whichever technique you choose. The data should be classified for different symptoms or functions of autism first and then classified according to different modes. The moment when a characteristic behavior occurs needs to be clearly marked in addition to label the data. The environment and interacting objects or people should also be concerned. More importantly, the performance of typically developing children should be collected in large numbers as a control group.

2) Directions for Intervention: In addition to some primary cognitive education, intervention should focus on improving children's health condition in daily life. Whether it works in real life is the most important indicator to evaluate the effectiveness of this approach. To improve the intervention of ASD, some noninvasive methods are promising.

a) Social robot: Although the intelligence and flexibility of current robots are far less than the level of the therapist, social robots can play an important role in some simple cognitive and life skills training repeatedly. Considering the interest of autistic children in robots, some skill training can be integrated into their interactions, which can significantly improve the effectiveness of the intervention conducting by the therapist. They can also develop some simple cognitive training and life skills repeatedly with the same standard and patience. More and more studies show that the humanoid robot works well in the imitation, joint attention, and turn-taking interaction, which are the three basic intervention treatment scenarios.

b) Noninvasive brain stimulation techniques: The current research on tDCS and rTMS is still in the early stages, and the treatment methods and their effects need further evaluation. Only through sufficient sample experiments and long-term prognosis tracking can the effect be evaluated effectively. The mapping of intervention objectives and results needs to be more evident. This is a deeper treatment model than behavioral intervention.

c) Virtual reality: Whether in an immersive or nonimmersive virtual environment, autistic children can learn skills and knowledge with interest. It is also proved that computer-based interventions could guide the development of social-emotional of autistic individuals [101]. Combined with some other sensors, the behaviors of the participant could be recorded and analyzed. But the ultimate goal of the skills learned in the virtual environment is to enable the child to adapt to the real social scene. Virtual training needs to be combined with manual training to provide its generalization ability.

VI. Conclusion

A growing number of studies have focused on the diagnosis and intervention of autism, and many engineering technologies are tried in this area. The assessment criteria ICD identifies the ASD by their impairments in social interaction and in communication, while ICF attempts to assess the ASD in a comprehensive way focused on the individual's health level of functioning. According to the two criteria, attention was paid to some of the symptoms or individual's functions. The early diagnosis of ASD can be diagnosed as early as six months of age in high-risk children with ASD using MRI, which is one of the earliest ways to distinguish the autistic children with relatively high accuracy. But, robust imaging features have not been identified, and the widespread screening is impractical for the high complexity operation and rigorous experimental environment. It is widely accepted that developmental disorders in children with ASD have specific manifestations in EEG data. Many studies have also found significant differences between autistic children and TD children in brain electrical signals with age grows. EEG is a promising way to find the characteristics of autistic children and a helpful tool in the intervention as a status monitoring signal. However, the EEG-based method for early diagnosis of ASD still has many challenges, such as the specificity of feature analysis and the convenience and universality of information collection. The wearable system for the diagnosis of ASD may be an outdated method for noncontact sensing technology, especially the rapid development of visual image processing. But the VR could be an effective intervention and education approach in an immersion or nonimmersion manner. Though tDCS and rTMS are the most advanced interventions, whether there are any other effects of these methods has not been studied except that they can improve the symptoms. It is a promising way to intervene and train autistic children through humanoid robots, but the intelligence and flexibility of robots need to be further improved. Meanwhile, it needs to be further researched whether there is any progress in communication between autistic children and people after training with robotic assistance. There are still many problems to be solved in the field of auxiliary diagnosis and intervention for autism. The combination of multisensor, multimode, and multiscene is the development trend of this field in the future. Computer vision systems can comprehensively analyze the children's behaviors and give quantitative evaluation, which has great application prospect in clinic. Although these advanced technologies are necessary for further study on ASD, a noninvasive, multiscenario, and easy-to-use approach, urgently needs to be developed to help the clinical diagnosis and intervention.

This review also had some limitations: on the one hand, only those autistic researches in terms of engineering perspectives were included while those clinical ones are not. On the other hand, the timelines of referred studies were not illustrated clearly. This review searched and organized the literature from an engineering perspective, focusing on techniques for diagnosing and intervening in autism. The pathogenesis of autism, such as genetic studies, was not covered. Nevertheless, as far as is known, this was the first comprehensive review focusing on the methods of diagnosis and intervention for autistic children from an engineering perspective.

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