Edge Computing based Human-Robot Cognitive Fusion: A Medical Case Study in the Autism Spectrum Disorder Therapy

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Abstract

In recent years, edge computing has served as a paradigm that enables many future technologies like AI, Robotics, IoT, and high-speed wireless sensor networks (like 5G) by connecting cloud computing facilities and services to the end users. Especially in medical and healthcare applications, it provides remote patient monitoring and increases voluminous multimedia. From the robotics angle, robot-assisted therapy (RAT) is an active-assistive robotic technology in rehabilitation robotics, attracting many researchers to study and benefit people with disability like autism spectrum disorder (ASD) children. However, the main challenge of RAT is that the model capable of detecting the affective states of ASD people exists and can recall individual preferences. Moreover, involving expert diagnosis and recommendations to guide robots in updating the therapy approach to adapt to different statuses and scenarios is a crucial part of the ASD therapy process. This paper proposes the architecture of edge cognitive computing by combining human experts and assisted robots collaborating in the same framework to help ASD patients with long-term support. By integrating the real-time computing and analysis of a new cognitive robotic model for ASD therapy, the proposed architecture can achieve a seamless remote diagnosis, round-the-clock symptom monitoring, emergency warning, therapy alteration, and advanced assistance.

Introduction

Edge Computing offers the full computation or part of the computation that can process the data at the edge network, which enables low latency, faster response, and more comprehensive data analysis (Khan et al. 2019). The connected devices can provide services in AI, robotics, autonomous driving, smart cities, healthcare, medical diagnosis, smart grids, multimedia, and security through the edge network. As one of the significant components of the smart city, the field of smart healthcare emerges from the need to improve the management of the healthcare sector, better utilize its resources, and reduce its cost while main-

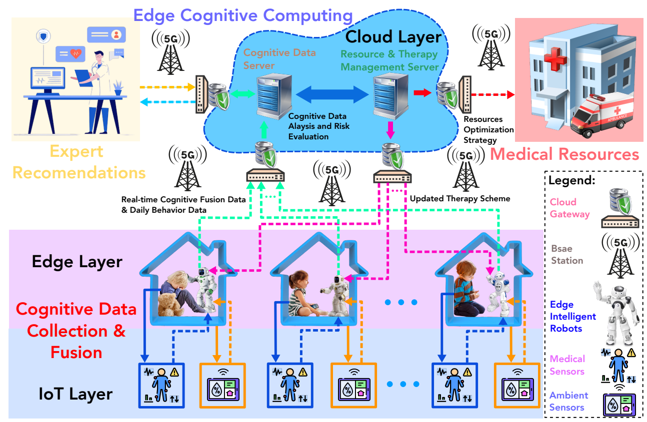

Figure 1: The illustration of the proposed architecture of cognitive computing based on Human-Robot cognitive fusion.

taining or even enhancing its quality level (Oueida et al. 2018). Traditional smart healthcare systems can be divided into three layers: the collection layer (gathering the sensing data from patients), the transmission layer (sending the data to the base station through the intelligent terminal), and the analysis layer (analyzing the data in the cloud data center), which lack of real-time monitor, emergency service, and comprehensive disease analysis, high communication latency, inflexible network resource deployment, etc (Chen et al. 2018). Although the recent 5G network can support edge computing–based healthcare systems, several challenges still hinder its application and benefits to the entire human community, such as large-scale healthcare, big data management, and patient information privacy (Hartmann, Hashmi, and Imran 2022).

Especially when integrating AI and robotics technology, future medical and healthcare applications will involve vast amounts of real-time clinical data computation and analysis. Moreover, combining human experts' feedback based on real-time results from intelligent terminals is also critical for the future of medical systems and smart healthcare, which can provide professional recommendations, personalized services, and corresponding accurate medical treatment measures. Taking robot-assisted therapy (RAT) for autism

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spectrum disorder (ASD)[1] as an example, it is essential to enable RAT to adapt to individual unique and changing needs. (Clabaugh et al. 2019) formalized personalization as a hierarchical human-robot learning framework consisting of five controllers mediated by a meta-controller that utilized reinforcement learning to personalize instruction challenge levels and robot feedback based on each user's unique learning patterns. To some extent, although it achieves long-term in-home deployments with children with ASD, it is hard to clarify the role of human experts in the therapy section and further improve their social skills in the real world. Therefore, the quality of the machine-to-machine communication and the human-robot interaction data fusion is the pre-condition for providing efficient and effective medical service, which can improve patient care experience and increase flexibility and adaptability from a business perspective (Wan, Gu, and Ni 2020).

From the cognitive computing perspective, (Chen et al. 2018) introduces the Edge-Cognitive-Computing-based (ECC-based) smart healthcare system, which can monitor and analyze users' physical health using cognitive computing and solve the problems of inflexible network resource deployment. (Yvanoff-Frenchin et al. 2020) develops a multi-language robot interface based on edge computing, helping evaluate seniors' mental health by interacting through questions. However, from the edge intelligent devices (like robots) angle (Groshev et al. 2023), there are still several open questions in RAT for healthcare, such as what the best roles for robots are in therapy, how to develop a general approach to integrate robots into interventions adapting various patients' needs and recognize their status, and who among individuals with the specific symptoms are best suited for this approach, especially in RAT for ASD (Diehl et al. 2012).

From the system design perspective, edging computing involves complex and heterogeneous architecture, which makes it hard to build a general framework for every edging computing application ultimately (Krishnasamy, Varrette, and Mucciardi 2020). Particularly, smart healthcare systems are dynamic, flexible, and complex systems with unpredictable behaviors and need to organize resources and personalize diverse services efficiently (Oueida et al. 2018).

In order to address those challenges, this paper proposes the architecture of the edge computing by combining human experts and assisted robots collaborating in the same framework to help ASD patients with long-term support. By integrating the real-time computing and analysis of a new cognitive robotic model for ASD therapy based on cognitive-behavior therapy (CBT) (Beck 2020) with the proposed architecture, it can achieve a seamless remote diagnosis, round-the-clock symptom monitoring, emergency warning, therapy alteration, and advanced assistance. Fig. 1 outlines the proposed architecture of edge cognitive computing and we list the main contributions of this research as follow:

- We introduce the edge intelligent robot integrating cognitive data from patients and related ambient information by building the corresponding network architecture to achieve timely human expert recommendations and real-time medical resource optimization strategies;
- We design four stages of robot-assisted therapy (RAT) based on cognitive models of humor development to help ASD patients gradually master different levels of social and communication skills.

[1]ASD is a developmental disability caused by differences in the brain, which affects the patients' normal interactions, such as learning, moving, communicating, and paying attention.

Background and Preliminaries

This section briefly reviews the *edge computing* and *cognitive robotics*, and provide a brief background to the *cognitive-behavior therapy* (CBT). When describing a specific method, we use the notations and relative definitions from the corresponding papers.

Edge Computing

In recent years, edge computing has served as a critical enabler for lots of future technologies like 5G, the Internet of Things (IoT), augmented reality, and cooperative multi-agent/robot systems (such as vehicle-to-vehicle communications by connecting cloud computing facilities and services to end users), which brings the service and utilities of cloud computing closer to the end user and is characterized by fast processing and quick application response time (Khan et al. 2019). Specifically, in order to address the high latency between cloud servers and end-user devices in different scenarios, edge computing tackles them by bringing the processing to the edge of the network (like 5G) and building the corresponding edge computing models, such as Cloudlets (Shaukat et al. 2016), Fog computing (Bao et al. 2017), and Mobile Edge computing (Ahmed and Rehmani 2017), solving cloud computing issues.

Furthermore, with widely implemented deep learning (DL) models, including computer vision and natural language processing, in current end devices (like smart phone, mobile robot, and IoT devices), analyzing their generated data in real-time is essential for system performance and user experience. Therefore, edge computing, where a fine mesh of compute nodes are placed close to end devices, is a viable way to meet the high computation and low-latency requirements of DL on edge devices and also provides additional benefits in terms of privacy, bandwidth efficiency, and scalability (Chen and Ran 2019). As the representative technique of artificial intelligence (AI), integrating DL into edge computing frameworks can build an intelligent edge for dynamic, adaptive edge maintenance and management, improving the edge intelligent agents' capabilities and extending their range of applications essentially (Wang et al. 2020).

Cognitive Robotics

Cognitive robotics studies the mechanisms, architectures, and constraints that allow lifelong and open-ended improvement of perceptual, reasoning, planning, social, knowledge acquisition, and decision-making skills in embodied machines (Merrick 2017). Since cognitive modeling uses symbolic coding schemes depicting the world, perception, ac-

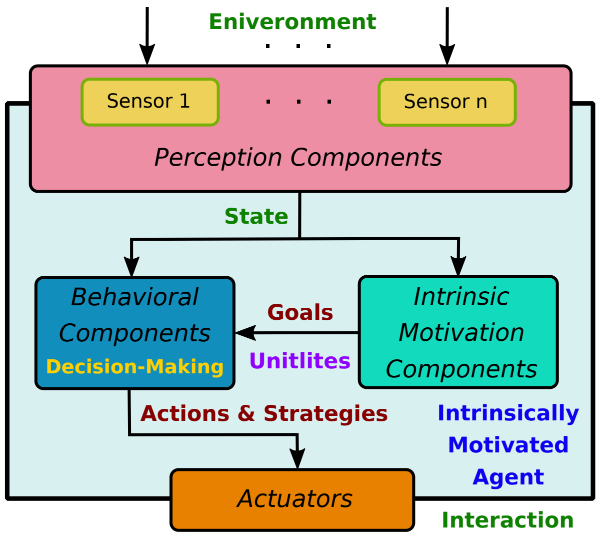

Figure 2: The illustration of the model for a generic intrinsically motivated agent.

tion, and symbolic representation become the core issues in cognitive robotics (Yang et al. 2019; Yang and Parasuraman 2020a, 2021). Related disciplines are not just artificial intelligence and robotics but also neuroscience, cognitive science, developmental psychology, sociology, and so on (Asada et al. 2009). Especially building a value system to mimic the "brain" of an AI agent mapping behavioral responses for sensed external phenomena is the core component of cognitive robotics, which is also an emerging and specialized sub-field in neurorobotics, robotics, and artificial cognitive systems research (Yang and Liu 2023). Fig. 2 presents a model for a generic intrinsically motivated agent in cognitive robotics (Merrick 2013).

Here, the value measures an agent's effort to expend to obtain a reward or avoid punishment (Yang and Parasuraman 2020b). It is not hard-wired for an AI agent, even a biological entity, and the specific value system achieved through experience reflects an agent's subjective evaluation of the sensory space (Yang and Parasuraman 2023a). And the value mechanisms usually have been defined as the *expected values*, particularly in uncertain environments. Moreover, the innate value reflects an agent's subjective evaluation of the sensory space, but the acquired value is shaped through experience during its development.

According to the development of cognitive robotics, the existing value systems can mainly be classified into three categories. *Neuroanatomical Systems* discuss the explainable biologically inspired value systems design from neuroanatomy and physiology perspectives (Sporns, Almássy, and Edelman 2000); *Neural Networks Systems* build more abstract models through mathematical approaches to mimic the agent's value systems; *Motivational Systems* consider the model that agents interact with environments to satisfy their innate values, and the typical mechanism is reinforcement learning (RL) (Yang and Parasuraman 2023b; Yang 2023).

Cognitive-Behavior Therapy

Cognitive behavioral therapy (CBT) is a type of psychotherapeutic treatment that helps people learn how to identify and change destructive or disturbing thought patterns that negatively influence their behavior and emotions (Hofmann et al. 2012). It is based on the *cognitive model* (Ellis 1962), which hypothesizes that people's emotions, behaviors, and physiology are influenced by their perception of events. In all forms of CBT that are derived from Beck's model (Beck 1964), treatment is based on a cognitive formulation, beliefs, and behavioral strategies that characterize a specific disorder (Alford, Beck, and Jones Jr 1997). Fig. 3 illustrates the relationship of behavior to automatic thoughts with the hierarchy of cognition (Beck 2020).

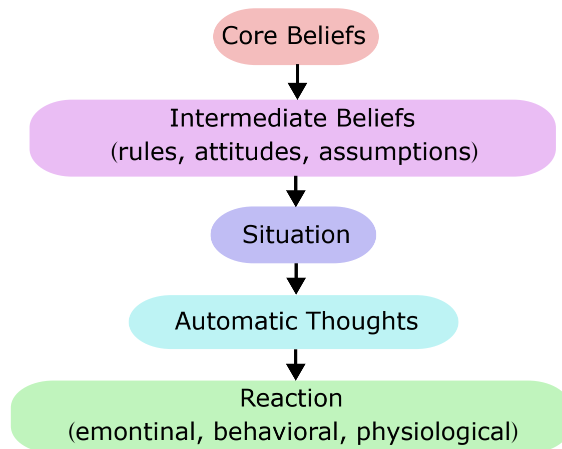

Figure 3: Illustration of the relationship of behavior to automatic thoughts with the hierarchy of cognition.

CBT involves a wide range of strategies to help people overcome negative patterns, such as identifying negative thoughts, practicing new social skills, SMART goal-setting, stress problem-solving, and self-monitoring (Beck 2020). It can be used as a short-term treatment to help individuals learn to focus on present thoughts and beliefs (symptoms like addiction, anger issues, anxiety, depression, etc.) and improve mental health conditions (like chronic pain, insomnia, stress management, etc.) (Hofmann et al. 2012).

Approach Overview

This section discusses the details of the proposed architecture of cognitive computing and cognitive models of the edge intelligent robot based on cognitive-behavior therapy (CBT) for ASD.

Cognitive Computing Architecture

To organize the medical resources and manage a real-time healthcare system, it is crucial to define cognitive computing modules in the network edge clearly and implement corresponding cognitive analysis of the users' physical health data and ambient information. It can lower latency and guarantee the delivery of reliable and latest patient information and analysis results to doctors or experts.

Our proposed edge cognitive computing architecture (Fig. 1) leverages information collection and recognition, data fusion and analysis, resource strategy optimization, human expert recommendations, and real-time therapy updating, providing high energy efficiency, low cost, and high user Quality of Experience (QoE).

Cloud Layer In the cloud layer, we consider two kinds of servers – *Cognitive Data Server* and *Resource and Therapy Management Server* – to analyze cognitive data, evaluate patients' risks, optimize resource strategies, and update therapy schemes. We introduce them as follow:

a. Cognitive Data Server

The server collects the cognitive fusion data from all edge intelligent robots, including users' physical signals and daily behavior data, and related internal network information such as the network type, service data flow, communication quality, and other dynamic environmental parameters. Moreover, according to users' priority level, the cognitive data server will distribute corresponding network and medical resources based on patients' risk evaluation. Furthermore, doctors or experts will receive the results of analyzed cognitive data and provide professional suggestions about the specific user case, such as updated prescriptions and medical instructions. Combining the surveillance cognitive information of users, the dynamic network resource information, and professional recommendations from experts provides the maximum edge computing resources to users based on their disease risk levels and significantly improves the QoE and healing probability.

b. Resource and Therapy Management Server

Through receiving the analysis results from the cognitive data server, this server will learn resources about edge cloud computing, network communication, and medicine. Then, it optimizes scheduling strategies and distributes corresponding resources in real-time. Moreover, the server sends the integrated resource data back to the cognitive data server, updating its database. Specifically, the server can achieve resource optimization and energy saving by implementing the computing unload, handover strategy, caching and delivery, and the corresponding intelligent algorithms (Chen et al. 2018), which can meet various heterogeneous application requirements.

Edge Layer Instead of constantly moving data to the cloud for computing operations, which accounts for the energy costs, in the edge layer, data can be mined and processed on edge devices and servers closer to the user (Bhargava and Ivanov 2017). Moreover, compared with traditional edge devices, we define a novel *edge intelligent robot* for medical applications and smart health care, which not only can collect and process data from users and the environment but also serve as the medical equipment or tool to cure patients.

Specifically, the edge intelligent robot needs to first integrate its perception data, such as voice, image, and video, with the data of medical sensors worn in patients and ambient sensors deployed in environments as a standard structure data flow uploading to the cloud layer through a high-speed sensor network like 5G. Furthermore, it executes the current or updated therapy scheme or instructions from the cloud layer to interact with patients, guiding them to fulfill the corresponding treatment. Moreover, it records all the interaction data and related medical parameters, sending them to the cloud layer for deeper analysis and human expert references.

More importantly, the edge intelligent robot can provide patients with 24-hour surveillance and care. If any emergency happens, it will inform the hospital or doctors through the network the first time and get the corresponding resources to tackle them, avoiding many human errors in traditional medical treatment.

IoT Layer The IoT layer contains various devices and sensors, which can be classified into medical and ambient categories. The medical sensors were worn by patients, monitoring their status and recording related health parameters. They mainly collect the real-time physiological data of the user, which include electrocardiography (ECG), electromyography (EMG), respiration, heartbeat, body temperature, systolic pressure, and blood oxygen saturation (SpO2). The physiological data will be uploaded to the nearby edge computing node (edge intelligent robot) at the same time.

On the other hand, the ambient sensors are in charge of the surveillance of patient treatment environments and reserving various ambient information, such as ambient temperature, humidity, air quality, atmospheric pressure, etc., for further medical analysis and reference. Moreover, these devices transmit data to the edge intelligent robot and exchange information with the cloud through the high-speed communication network.

Cognitive Models of the Edge Intelligent Robot

In this section, we take the treatment of autism spectrum disorder (ASD) as an example and propose robot-assisted therapy (RAT) based on cognitive models of humor development to help ASD patients gradually master different levels of social and communication skills.

Through above discussed edge cognitive computing network, the edge intelligent robot implements this therapy based on the results of cognitive data analysis and is guided by expert recommendations at each stage to cure the patients. We discuss more details as follow:

Humor Styles for Cognitive Distortions The type of humor reflects the cognitive development of people and the level of their social skills (Bernet 1993). Humor styles are potential mediators of the association between cognitive and interpersonal vulnerability factors and psychological dysfunction, distress, or poor interpersonal functioning (Rnic, Dozois, and Martin 2016). To some extent, by improving their sense of humor, ASD patients can gradually enhance their communication skills and enter the mutual socialization process with others (Southam 2005).

Based on what McGhee (McGhee and Pistolesi 1979) described, this research considers four stages of humor development in the whole CBT process. Using the assisted robot to design different funny scenarios and jokes treats ASD patients, especially the children, in their corresponding peri-

Table 1: Four Stages of Humor Development through RAT

Therapy Stage	**Cognitive Stage**	**Humor Style**	**RAT**	**Data Type**
Entry Level	Sensorimotor Stage	Incongruous Actions	Funny Behaviors	images
Basic Level	Sensorimotor Stage	Incongruous Events	Interesting Expression	Image, Voice
Middle Level	Preoperational Stage	Conceptual Incongruity	Knock-Knock Jokes	Image, Voice
Advanced Level	Concrete Operations	Multiple Meanings	Sarcastic Jokes	Image, Voice

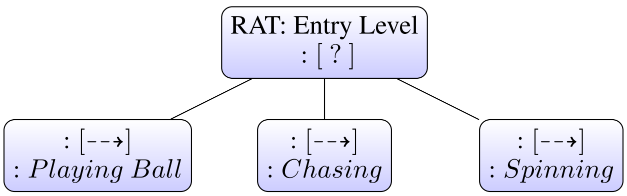

Figure 4: Entry Level: Assisted Robot's Behavior Trees

ods. Tab. 1 illustrates the four stages of human development through RAT in our research.

Behavior Tree based Humor Styles Representation According to the above discussion, we design four specific application cases representing them as behavior trees (BT) (Colledanchise and Ögren 2018) to improve patients' experience and enhance the effect of the RAT in different stages of ASD.

a. Entry Level: Funny Behaviors

Patients with less social skills enjoy interactions with familiar objects or games by creating something new or different out of them. Therefore, at the entry level, we design three scenarios (playing ball, chasing, and spinning) to let the assisted robot interact with patients, helping them develop interests and willingness to communicate and make new friends. Fig. 4 shows the three scenarios as the BT.

b. Basic Level

As patients develop interests and are not resistant to communicating with new partners, they become willing to use language and gestures for fun and to engage others. There may be some overlap between *Entry Level* and *Basic Level* in humor development, but the distinguishing feature of the *Basic Level* is that a "verbal statement alone creates the incongruity and leads to laughter" (McGhee and Pistolesi 1979).

At this point, humor becomes a significant part of social skill development. In order to help patients gain positive emotional reactions from their partners, we create a simple pretend game [2] – Aladdin and the Magic Lamp[3] – to let them play with the robot, adding social reinforcement to the fun. Fig. 5 illustrates an example of the Assisted Robot's Behavior Trees of "Aladdin and the Magic Lamp".

c. Middle Level

When patients master the above two levels of humor, their cognition will develop to Piaget's Preoperational Stage (Papalia, Olds, and Feldman 2007). Humor can be regarded as the intellectual play expressed through language (Freud 1960), and the production and appreciation of humor also change.

In this intellectual linguistic play, the listener needs to understand the double meanings of words to find it humorous (Southam 2005). At this stage, making others laugh becomes the reward of social approval, which can drive patients to develop this social language skill. Knock-knock jokes and other ready-made jokes are popular at this level. Considering knock-knock jokes and other ready-made jokes are popular, we design the scenarios of knock-knock jokes to support patients interacting with the robot at this level (Fig. 6).

d. Advanced Level

In the cognitive stage of concrete operations (Papalia, Olds, and Feldman 2007), patients will improve mental operations to analyze multiple aspects of a situation and perform tasks at a higher level than they could in the preoperational stage. They need to understand the meanings of puns and other forms of more abstract humor and can use inductive and deductive reasoning and reversibility in thinking about the beginning, middle, and end points of a funny story or joke (Southam 2005). Teasing and sarcastic jokes are commonly used at this level. Fig. 7 illustrates two examples of assisted robot's BT of sarcastic jokes.

[2] It is a loosely structured form of play that generally includes role-play, object substitution, and nonliteral behavior (Fein 1981).

[3] Here, the assisted robot plays the Magic Lamp and the patient plays the Aladdin.

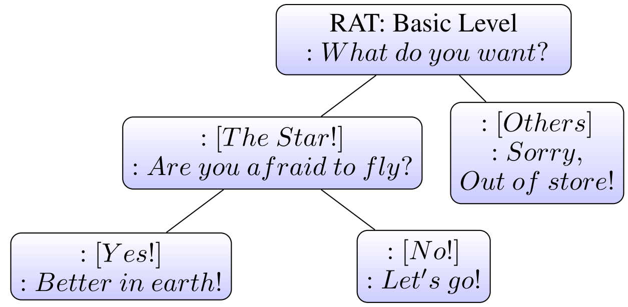

Figure 5: Entry Level: an Example of the Assisted Robot's Behavior Trees of "Aladdin and the Magic Lamp".

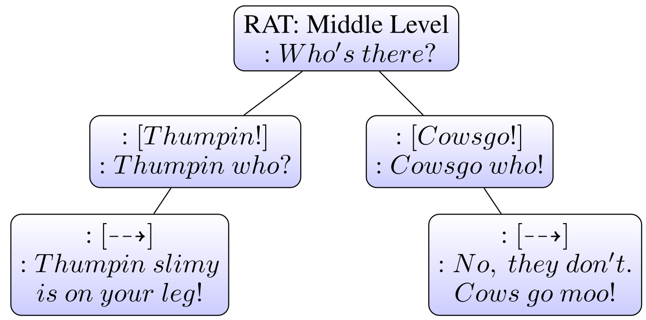

Figure 6: Middle Level: an Example of the Assisted Robot's Behavior Trees of the Knock knock joke.

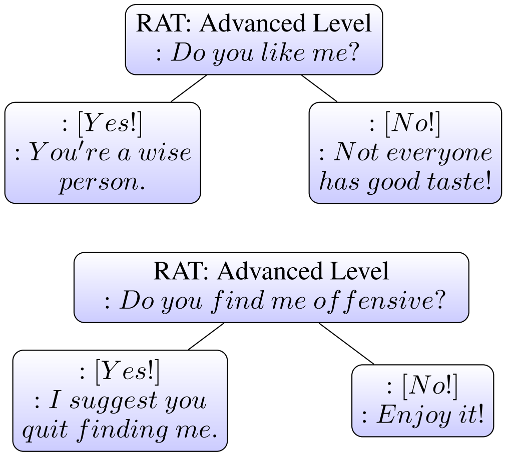

Figure 7: Advanced Level: Examples of Assisted Robot's Behavior Trees of the Sarcastic Jokes.

Conclusion and Future Works

This paper introduces a novel architecture of edge cognitive computing integrating human experts and edge intelligent robots collaborating in the same framework to form the next generation of medical and smart healthcare systems. It can achieve a seamless remote diagnosis, round-the-clock symptom monitoring, emergency warning, therapy alteration, and advanced assistance.

Furthermore, we proposes a cognitive robotic model based on cognitive-behavior therapy (CBT) for Autism Spectrum Disorder (ASD) with robot-assisted therapy (RAT). From the development of humor, we create four cognitive models through the assisted robot to help ASD patients boost their cognitive stages and master corresponding communication and social skills gradually, supporting ASD patients to reunite in our community.

For the next step, we want to implement our methods in real robots, such as Unitree Go2 and LoCoBot, and test them in the AWS wavelength framework. Furthermore, we want to apply the architecture in a real hospital medical system to test its robustness and effectiveness.

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