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METHODS

CBASH: A CareBot-Assisted Smart Home System Architecture to Support Aging-in-Place

ZEQIANG ZHU[1], (Student Member, IEEE), YAN FU[1,2], WEIMING SHEN[1], (Fellow, IEEE), ALEX MIHAILIDIS[2,3,4], SHUN LIU[1], WENSHUANG ZHOU[1], AND ZHAOHUI HUANG[1]

[1]School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China
[2]U of T–HUST Collaborative Center for Robotics and Elderly Care, University of Toronto, Toronto, ON M5G 2A2, Canada
[3]KITE—Toronto Rehabilitation Institute, University Health Network, Toronto, ON M5G 1L7, Canada
[4]Department of Occupational Science and Occupational Therapy, University of Toronto, Toronto, ON M5S 0A1, Canada

Corresponding author: Yan Fu (laura_fy@mail.hust.edu.cn)

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ABSTRACT Powered by IoT technologies, smart home systems effectively support aging-in-place. However, they have some limitations in comprehensive event perception and timely appropriate action. Homecare robot systems have been proven to be effective in homecare task executions but still have significant technological challenges. To address this problem, this paper proposes a smart home system architecture integrating a mobile robot with better event perception and task execution performance. To support the proposed system architecture, an ontology of the smart home is built to address the data heterogeneity issue. Then an event perception method is built upon multi-data integration. To perform complex tasks, this work implements an improved genetic algorithm for task planning. Finally, simulations and physical experiments are conducted to validate the feasibility of the proposed system architecture.

INDEX TERMS Smart home, sensors, service robot, homecare robot, aging-in-place.

I. INTRODUCTION

Research has shown that the global aging population (over 65 years old) will reach 1.6 billion by 2050 and 3.1 billion by 2100 [1]. The huge aging population is a very challenging problem, especially in developed regions such as the United States, Canada, and Europe [2]. Most elderly prefer to stay at home rather than in a nursing facility [3]. Independent living is quite a big challenge for the elderly, especially those with geriatric diseases and mobility problems [4]. The ''aging-in-place'' strategy based on the smart home is quite a promising solution to address this problem, attracting attention from both academic and practical fields [5].

The smart home performs three main functions in the ''aging-in-place'' context: 1) monitoring living environment quality for the elderly, 2) monitoring activities of daily living (ADL) of the elderly, including fall detection, 3) long-term health monitoring of the elderly, among which the early diagnosis and intervention of geriatric diseases are quite beneficial [6], [7], [8]. However, those smart home systems primarily focused on monitoring functions are pretty weak in everyday manipulation tasks [9]. For example, when a person falls, the system can only recognize the fall and notify the first-aid personnel rather than taking more proactive actions like conversation and further investigations.

To remedy this situation, a robot with good mobility and interaction capability should be an essential agent in the smart home. However, there are some significant technological challenges [10], for example:

- To couple the robot into the smart home to sense states beyond its onboard sensors' perception range.
- To recognize the complex or vaguer tasks by the system.
- To plan complex tasks in quick response to emergencies.

This paper proposes a smart home system architecture called CareBot-Assisted Smart Home (CBASH) to cope with these challenges. In CBASH, a self-developed robot called CareBot is the primary sensing and actuation equipment responsible for event sensing and task execution. At the same time, a central data servo makes task decisions based on the integrated

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data from the embedded sensor networks, smart devices, and CareBot within the smart home. This paper makes the following contributions:

1) An adaptive and scalable system architecture is designed by integrating a robot into the smart home. This system architecture can improve event perception and task execution abilities in smart home environments.
2) An ontology of CBASH is proposed to address the data heterogeneity issue, and a task rule base is therefore built to support the event sensing and task planning.
3) A task planning method is presented with a focus on implementing complete tasks in quick response to emergencies under the constraints of robot charging.

The rest of this paper is organized as follows: Section II reviews the related work. Section III describes the proposed system design, including hardware design, software design, ontology, event perception, and task planning. Section IV presents the system implementation. Section V concludes the paper and discusses future research directions.

II. RELATED WORK

A. DEVELOPMENT OF A SMART HOME SYSTEM FOR THE ELDERLY

With the advantages of data collection, processing and automated operations in home systems, growing applications and related research are observed in the ''aging-in-place'' field. Helal et al. [11] designed the Gator Tech Smart House system at the University of Florida to perceive the daily activities of the elderly to detect emergencies like falls. Moutacalli et al. [12] presented an intelligent activity recognition system to recognize the elderly's daily activities to analyze chronic diseases of the elderly. Matsui [13] proposed a method to collect sensor data using a home energy management system (HEMS), which can adjust the indoor environment. Wood et al. [14] designed a system called AlarmNet to monitor the environment's safety and supervise chronic diseases, such as medical data collection and medicine-taking reminders. Jaouhari et al. [15] developed a method that provides sensor-based healthcare and energy management services to improve residents' overall quality of life.

The above studies have made great contributions to ''aging-in-place'' but were mainly focused on monitoring. Tasks requiring constant interactions between robots and the elders and physical manipulations cannot be fulfilled entirely solely on the smart home.

B. INTEGRATING ROBOT INTO SMART HOME

To implement the services of complex activities, many researchers have integrated service robots into smart homes to provide comprehensive services for the elderly [16]. Yu and Chen [17] designed a smart home monitoring system in which a robot performs tasks at programmed commands at the emergency identified by the smart home. Li et al. [18] proposed a multi-sensor fusion framework for a smart home social robot to operate household appliances. Sarkar [19] developed a smart home care system with a robot named''NurseBot,'' supervising the medicine-taking of the elderly. Although the robots in these systems can provide some services, they d ot have specific perception capabilities to offer active and personalized services. To complete more comprehensive tasks, the sensation and reasoning capabilities of robots should be integrated into smart home systems [20].

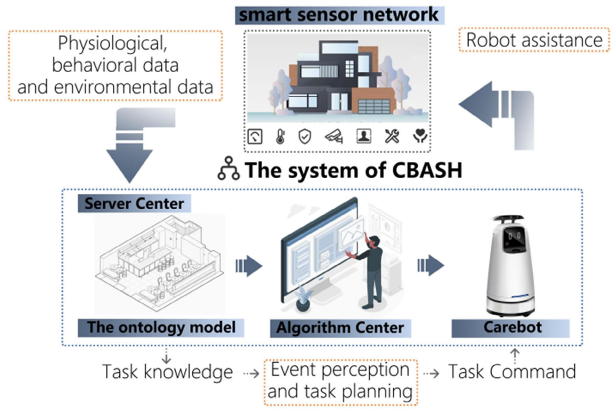

FIGURE 1. CBASH system overview.

Several researchers have made some explorations. Do et al. [21] proposed a robot-integrated smart home (RiSH) system to detect and respond to the elderly falls through the fusion of service robots, intelligent wearable devices, and smart homes. Wilson et al. [22] developed a Robot Activity Support (RAS) system, which builds an error detection model to increase the robot's automatic perception ability. Tenorth and Beetz [23] proposed a knowledge processing system called KnowRob to reason about simple events and help robots understand abstract instructions. Zhang et al. [24] explored a system architecture, which explores a robot service mechanism based on system cooperation to assist the robot in actively discovering and providing the service task. Abate et al. [25] presented a semantic trust model to integrate different contextual information, which can couple the robot to the smart home. Harman et al. [10] proposed a continual planning framework, which can incorporate sensing and actuation capabilities into a robot's state estimation, task planning, and execution. As mentioned above, robots have a certain level of proactive perception ability but are relatively simple and cannot conduct multi-task planning, especially rapid response in emergencies. Thus, this paper proposes a system architecture to empower robots to percept various types of events and make an instant and appropriate response by task planning.

III. PROPOSED SYSTEM DESIGN

This section presents the system architecture named CareBot Assisted Smart Home (CBASH), as shown in Fig.1. The system comprises three main parts: a smart sensor network, a service center, and a CareBot. The three components will

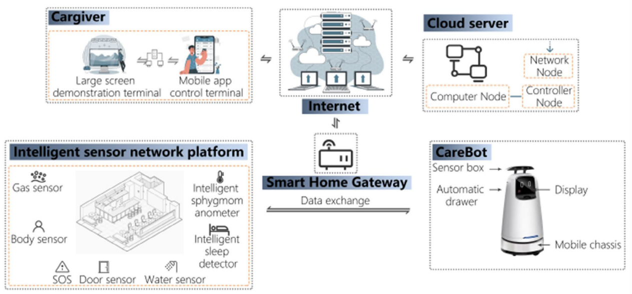

FIGURE 2. Hardware architecture.

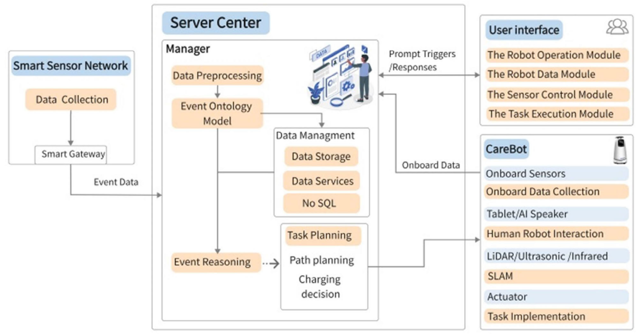

FIGURE 3. CBASH system architecture.

work independently or collaboratively in implementing event detection, task planning, and service provision. Firstly, the data from all resources, including smart sensor networks, robots, and wearable devices, are preprocessed to filter out time-out, duplicate and wrong data. Secondly, the Jena inference engine reasons the tasks according to the rule base established by historical and real-time information. Thirdly, event perception and task planning are fulfilled based on a series of optimization algorithms with the goal of the shortest response time to the emergency. Finally, CareBot performs the corresponding tasks according to the generated task sequence and the path. Specifically, the proposed system established unified hardware and software interfaces, allowing flexible adding of new services, application and components with minimum impact on existing system functionality.

A. HARDWARE DESIGN

The hardware design of CBASH is presented in Fig. 2. The cloud server connects the smart home, CareBot, and remote caregiving resources to optimize the service provision, especially empowering CareBot to tackle more complex service demands.

CareBot is equipped with various sensors and manipulators, including a mobile chassis, a configurable sensor module, a video call system, an AI chat system, and a smart logistics module. The mobile chassis is equipped with LiDAR (Light Detection and Ranging), IMU (Inertial Measurement Unit), and ultrasonic sensor for positioning, navigation, and path planning. The sensor module integrates different kinds of sensors, including a camera, a fire sensor, and a gas sensor. The sensors in this module are configured with rules of modularization and expandability. They can be easily reduced or added at the demand of future applications. The sensor module is designed within a compact box with three degrees of freedom, i.e., up and down, pitching, and left and right. The data from those sensors, as one source of event perception, will be processed and integrated at the center service with information from other sources. The video call and AI chat systems on CareBot have a voice module and a display module responsible for human-robot interactions and spiritual accompanying of the elderly. The smart logistics module is designed within the CareBot body, holding and managing important daily activities. The current version of CareBot has sphygmomanometers and an intelligent pill box in the automatic drawer to assist the elderly in measuring blood pressure and taking medicine on time. When the system needs to perform this task, the robot moves to the position of the elderly, and the robot drawer automatically pops up the smart medicine box. The robot then prompts the elderly to take medicine by voice, and the smart medicine box detects the elderly's medication status.

The intelligent sensor network platform comprises various sensors deployed in the home environment to collect behavioral, physiological, and environmental data. The behavioral sensors include depth cameras, door sensors, and human body sensors to record daily behaviors and detect falls of the elderly. The physiological sensors, including an intelligent sleep detector, sphygmomanometer, glucometers, and smart weight scales, are used for ADL detection. The environmental sensors include a temperature-humidity sensor, water sensor, gas sensor, and fire sensor used to monitor the home environment conditions. In addition, the SOS button and smartwatch are used to detect falls and call for help.

A home gateway is a personal computer to serve as a local hub for data collection and processing [26]. It is responsible for the data transmission between the server, the sensor network, and the CareBot. The controller node manages the databases, authentication, message queue, and networking in the cloud server. The computer node hosts hypervisors and client services. User interfaces are designed both for smartphones and computers.

B. SOFTWARE DESIGN

This section presents the software design of CBASH, as shown in Fig. 3. To provide various kinds of elderly care services, CBASH is required to have a variety of functions based on the four physical modules: a smart sensor network, a server center, CareBot, and user interfaces. To reduce the requirements on computing resources and sensor configurations on CareBot, most data collection and processing, together with event reasoning and task planning, are conducted on the Server Center [27]. With the mobility advantage, CareBot can make up for the blind points of event

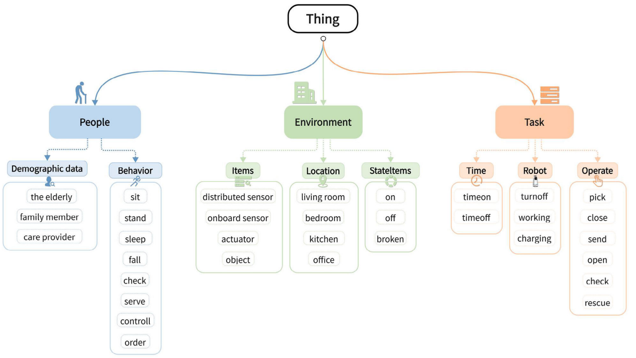

FIGURE 4. The ontology of CBASH.

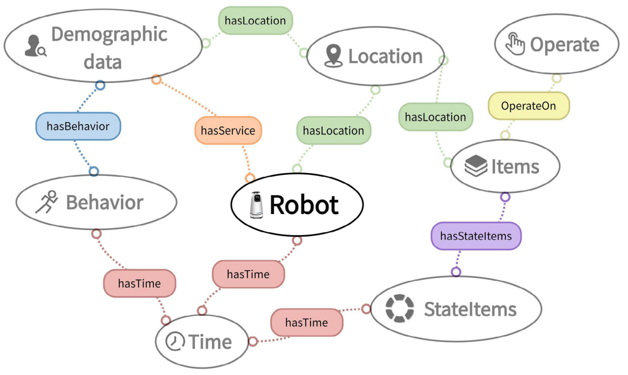

FIGURE 5. Relationship among main classes in CBASH.

observation while implementing most service tasks in the smart home environment.

The smart sensor network module collects event-related data from various sensors and transmits these data to the cloud server through the smart gateway. Raw data are preprocessed before the ontology deals with the data heterogeneity and generates the event knowledge. Still, the event reasoning and task planning are fulfilled in the server center. The outcomes of task planning will be transmitted to CareBot as direct commands on robot moving and manipulation. CareBot is an independent, smart device with event perception, path planning, and interaction functions. When the commands are output by the task planning on the server center, CareBot receives them and performs the tasks using SLAM [27], human-robot interaction, and task implementation functions.

In addition, user interfaces are designed to choose services, check the rooms and operate the robot remotely for the family members and care providers. It comprises service selection, robot operation, data reading, sensor control, and task execution.

C. PROPOSED ONTOLOGY

The system integrates various sensors and generates enormous heterogeneous data, affecting data processing efficiency. To address this problem, this study explores an ontology for CBASH and uses OWL (web ontology language) [29], [30] to build the CBASH ontology, which is richer in content than other studies [24].

As Fig. 4 shows, in the CBASH ontology, the smart home knowledge base is divided into three top-level classes: *people*, *environment,* and *task*.

For the *people* class, there are two subclasses: *demographic data* and *behavior*. The *demographic data* class is divided into the *elderly* class, *family member* class, and *care provider* class, which are used to store the demographic data. The *behavior* class is used to store the status information and is divided into *sit*, *stand*, *sleep*, *fall*, *check*, *serve*, *control,* and *order* classes.

For the *environment* class, there are three subclasses: *items*, *location,* and *stateitems*. The *Items* class represents the device's information and includes *distributed sensor*, *sensor, actuator*, and *object* class. The *location* class means the thing's location and has *living room*, *bedroom*, *kitchen*, and *office* classes. The *stateitems* class represents the state of the items and is divided into *on*, *off,* and *broken* classes.

For the *task* class, there are three subclasses: *time*, *robot*, and *operate*. The *time* class is used to store time information and includes *time on* and *time off*. The *robot* class is used to store the state of the robot and is divided into *turnoff*, *working,* and *charging*. The *operate* class is divided into *pick*, *close*, *send*, *open*, *check,* and *rescue* classes.

Furthermore, a knowledge representation should be set up to eliminate the heterogeneity of context information from all sources. In CBASH, a promising method is chosen to abstract the contextual knowledge, where classes are described in either the definition domain or the function range according to the different properties, as shown in Fig. 5. For example, in the description "an old man is in the bedroom," "an old man" belongs to the *demographic data* class and "bedroom" belongs to *location* class. Its property is *hasLocation*; the definition domain is the *demographic data* class, and the function range is the *location* class.

D. EVENT PERCEPTION

1) DATA PREPROCESSING

To reduce the system's burden in transporting, computing, and storing redundant and erroneous data, data preprocessing is conducted as the first step, as shown in Fig. 6. In data preprocessing, Sensor_Data = {Data_*ID*, Value, Time, Cycle_Time}

Data_ID: ID of each sensor used for data classification.

Value: the value of the sensor.

Time: the collection time of the data

Cycle_Time: the collection period of the data.

A table is designed to store the sensor data. When the new data is collected, its ID will be checked in the table. A unique ID will be created if no corresponding ID exists. CBASH will judge whether it is less than $T_{\text{Cycle\_Time\_max}}$. If it exceeds the maximum period $T_{\text{Cycle\_Time\_max}}$, CBASH identifies an error with this sensor and marks the sensor's ID. If it is less than $T_{\text{Cycle\_Time\_max}}$, the time of this data will be judged whether

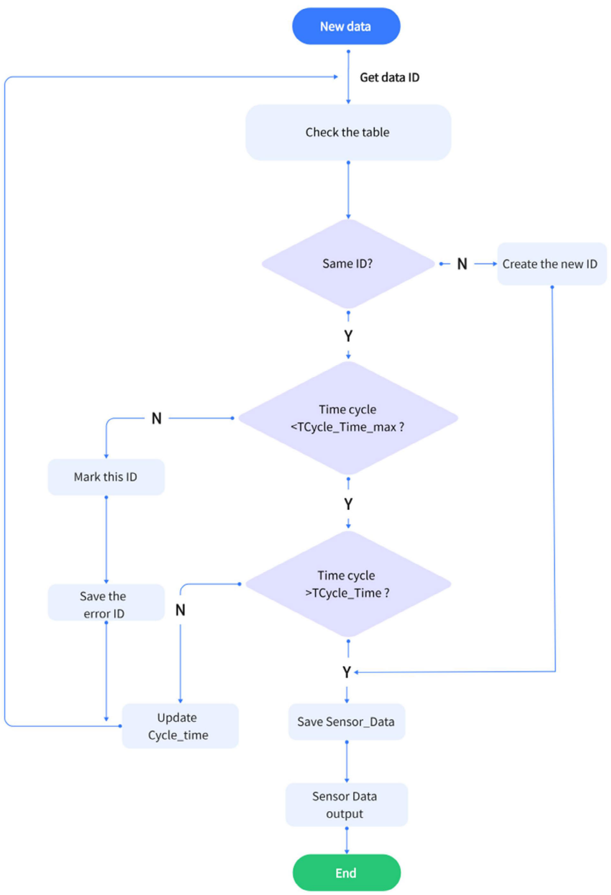

FIGURE 6. Data Preprocessing.

$$
\begin{array}{l}
Body: Demographic\ data(B,D) \wedge Behavior(B,B) \wedge Location(B,L) \wedge \\
Time(B,T) \wedge hasBehavior(B,D,B,B) \wedge hasTime(B,D,B,T) \\
\wedge hasLocation(B,D,B,L) \\
Head: OperateOn(H,O,H,I) \wedge hasService(H,R,H,I)
\end{array}
$$

FIGURE 7. The rule of the behavior information.

it is more significant than T_{Cycle_Time}. If yes, the data will be output; if not, these duplicate data will be discarded.

2) CONSTRUCTION OF SWRL RULE BASE

In addition to an ontology, CBASH requires specific rules based on perception events in dynamic and complex smart home environments. SWRL language is selected to construct the rule base [31]. Three SWRL rule bases are constructed: elderly behavior, environmental information, and task status.

Fig. 7 shows an example of the behavior information rule. The body part is the *demographic data* class, *behavior* class, *location* class, and *time* class. The object properties are *hasBehavior*, *hasTime*, and *hasLocation*. The head part contains the *operate* class, the *robot* class and the *items* class. The object properties are described as *operateOn* and *hasService*.

$$
\begin{array}{l}
Body: Demographic\ data(B,D) \wedge Items(B,I) \wedge Location(B,L) \wedge \\
Time(B,T) \wedge hasStateItems(B,D,B,S) \wedge hasTime(B,D,B,T) \\
\wedge hasLocation(B,D,B,L) \\
Head: OperateOn(H,O,H,I) \wedge hasService(H,R,H,I)
\end{array}
$$

FIGURE 8. The rule of the environmental information.

$$
\begin{array}{l}
Body: Robot(B,R) \wedge Items(B,I) \wedge Location(B,L) \wedge \\
Time(B,T) \wedge hasStateItems(B,R,B,S) \wedge hasTime(B,R,B,T) \\
\wedge hasLocation(B,R,B,L) \\
Head: OperateOn(H,O,H,I)
\end{array}
$$

FIGURE 9. The rule of the task status.

$$
\begin{array}{l}
Demographic\ data(Tony) \wedge Behavior(sit) \wedge Location(sofa) \wedge \\
Robot(ready) \wedge Time(B,T) \wedge hasBehavior(Tony,sit) \wedge \\
hasTime(sit,10:00) \wedge hasLocation(Tony,sofa) \\
\rightarrow Robot\_move(send\_sphygmomanometer)
\end{array}
$$

FIGURE 10. The rule of the example.

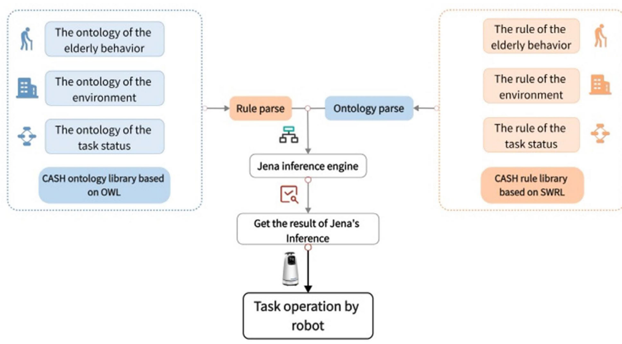

FIGURE 11. The task reasoning.

Fig. 8 shows an example of the environmental information rule. The body part is the demographic data class, items class, location class, and time class. The object properties are hasStateItems, hasTime, and hasLocation. The head part contains the operate class, the robot class and the items class. The object properties are described as OperateOn and hasService.

Fig. 9 shows an example of a task status rule. The body part is the *robot* class, *items* class, *location* class, and *time* class. The object properties are *hasStateItems*, *hasTime* and *hasLocation*. The head part contains the *operate* class, and the *items* class. The object property is *OperateOn*.

3) EVENT REASONING

Before event reasoning, rules to classify historical information should be generated. For example, when the elderly are ready for a blood pressure measurement on the sofa, the system will take the following rule to percept and perform the task of sending a sphygmomanometer, as shown in Fig. 10.

TABLE 1. Summary of notations.

O_i	Represents task i at level 1
O_j	Represents task j at level 2
O_z	Represents task z at level 3
k_i	The coefficient of level 1 task
k_j	The coefficient of level 3 task
k_z	The coefficient of level 3 task
C_{1i}	The completion time of task i at level 1
C_{2j}	The completion time of task j at level 2
C_{3z}	The completion time of task z at level 3
n_i	The number of level 1 task
n_j	The number of level 2 task
n_z	The number of level 3 task
p^s_{ijz}	The starting time of the task
p_{ijz}	The total time of the task
p^e_{ijz}	The ending time of the task
et^s_{ijz}	The starting time for the robot moving to the task
et_{ijz}	The total time for the robot moving to the task
et^e_{ijz}	The ending time for the robot moving to the task

Jena is used as the inference engine for event reasoning. Jena is an inference engine for the Semantic Web, with more efficient reasoning efficiency than Jess [32]. The reasoning process is shown in Fig. 11. Jena inference engine makes the inference and outputs the inference result as a command for the robot to execute.

E. TASK PLANNING

The tasks perceived by the perception module are continuous and cannot perform by CBASH. In addition, when multiple tasks are perceived, CBASH must perform them with a rule for saving time and resources. Therefore, task planning should be considered to perform tasks [33].

Suppose there are n service tasks to be executed by CareBot. Each service task has i subtasks, and each subtask has at least one operable device, which is a TSP problem [34].

Among all n tasks, emergencies like falls and fires occur randomly but should be dealt with high priorities. Furthermore, a charging strategy is essential to ensure the execution of tasks, assuring CareBot has enough electricity to implement tasks when an emergency occurs.

1) MATHEMATICAL MODEL

According to the above description, to establish and descript the model, the following symbols and variables are introduced in Table 1.

2) OPTIMIZATION GOAL

In optimization problems, the optimization goal is usually the minimum completion time. However, in this situation, completing emergency tasks in a short time to ensure the safety of the elderly is essential. In addition, different tasks have different levels of significance. To address this problem, the accumulation of response time to an emergency is set as the main optimization goal. Task urgency is rated with three levels. This proposed system aims to calculate the sum of the completion times for all the tasks, multiplied by a different coefficient k, indicating the urgency level. Thus the task sequence is generated based on the shortest task period, while tasks with the highest urgency are solved as soon as possible, as shown in (1).

$$\begin{aligned} \min f = &\min(\max(C_{11} + \cdots + C_{1i} + \cdots + C_{1n_i}) * k_i \\ &+ \max(C_{21} + \cdots + C_{2j} + \cdots + C_{2n_j}) * k_j \\ &+ \max(C_{31} + \cdots + C_{3z} + \cdots + C_{3n_z}) * k_z) \end{aligned} \tag{1}$$

According to the above assumptions and the actual situation, the constraint conditions are as follows:

The robot can only perform one task at a time, as shown in (2).

$$\sum_{w=1}^{v} x_{ijw} \leq 1 \tag{2}$$

The ending time of the task is the sum of the starting time and the whole time of the task, as shown in (3).

$$p^e_{ijz} = p^s_{ijz} + p_{ijz} \tag{3}$$

The ending time for the robot moving to the task is the sum of the starting time and the whole time moving to the task, as shown in (4).

$$et^e_{ijz} = et^s_{ijz} + et_{ijz} \tag{4}$$

The ending time for the robot moving to the task cannot exceed the task's starting time, and the task's ending time cannot exceed the starting time for the robot moving to the next task, as shown in (5), and (6).

$$et^e_{ijz} \leq p^s_{ijz} \tag{5}$$

$$et^s_{i+1j+1z+1} \geq p^e_{ijz} \tag{6}$$

3) ALGORITHM

An improved genetic algorithm (IGA) is proposed based on the traditional genetic algorithm to address the problem [35]. The genetic Algorithm (GA) is a computational model that simulates the biological evolution process of natural selection and the Genetic mechanism of Darwin's biological evolution [36].

a: FITNES FUNCTION

When the fitness difference between different individuals in the population is slight, the ability of selection operation is weak, and the population evolution is slow, the algorithm is easy to fall into a local optimal. The dynamic linear calibration method is used to adjust the population fitness dynamically.

$$F = f^n_{\max} + \lambda \xi^n - f\xi \in (0.9, 0.99) \tag{7}$$

F is the fitness function. Field $f^n_{\max}$ is the maximum objective function of the n-generation individual, $\lambda\xi^n$ is the dynamic pressure regulation number of the n-generation individual. Because the population difference of the problem studied in this paper is modest in the experimental process, an initial value is set based on [37] and a value of 450 is obtained on experiments in our algorithm. f is the objective function.

b: SELECTION OPERATOR

The genetic algorithm has many selection operators, such as the tournament selection operator, roulette selection operator, and ranking method selection operator. The combination of the tournament selection operator and ranking method selection operator is used in CBASH. This process is repeated until the number of offspring generations reaches a predetermined termination condition. Suppose the population size is N. There will be offspring generations. Next, the ranking operator selection is used to select a parent for the crossover operator from the populations in the tournament selection operator. By using this combination of methods, the quality of selection is improved.

c: CROSSOVER OPERATOR

Position-based crossover (PBX) [38] operator is typical. Though this operator has excellent advantages, it sometimes slows down the algorithm. Therefore, an operator based on segmentation rules is proposed. A threshold value set is S. The threshold S is determined by analyzing the algorithm's results before improvement. When the desired path length exceeds the threshold S, PBX is used for crossover operations. In addition, the self-crossover (SX) operator is used. The convergence speed and stability of the algorithm are improved through the improvement. S is set to 1000 in CBASH.

Firstly, the PBX operator selects discontinuous intersections from parent one, then extracts the crossroads to the offspring. The remaining genes are filled sequentially by parent two from the second intersection, as shown in Fig. 12.

Then, there is SX, which is more accessible. Two positions are randomly selected on the parent generation, and a region is formed in the middle of the two positions. The regions' numbers are swapped left and right to get the child generation, as shown in Fig. 13.

d: MUTATION OPERATOR

A heuristic mutation operator is applied in the following steps:

Step1: Assume M=9 8 7 6 5 4 3 2 1

Step2: Pick three points at random, like 8, 3, 1, and swap them arbitrarily to get five different individuals, as listed below.

9 8 7 6 5 4 1 2 3
9 3 7 6 5 4 1 2 8
9 3 7 6 5 4 8 2 1
9 1 7 6 5 4 3 2 8
9 1 7 6 5 4 8 2 3

Step3: the one with the highest fitness is selected as the new individual from these individuals.

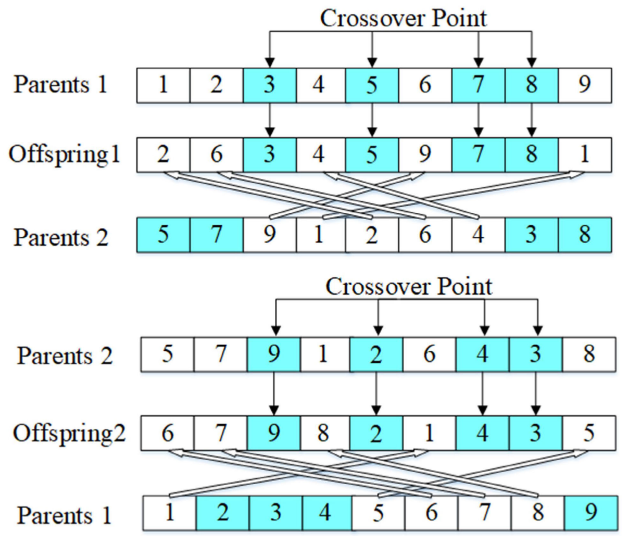

FIGURE 12. An example of PBX.

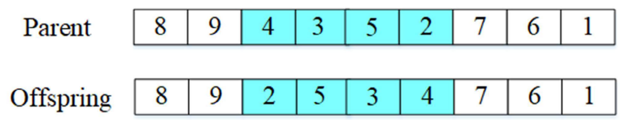

FIGURE 13. An example of SX.

e: ALGORITHM PROCESS

The proposed IGA is described as follows.

Step1: Input the location of each service task, and categorize all the tasks

Step2: Create an initial population, and set relevant parameters, including the task coefficient.

Step3: Dynamic linear calibration and calculation of individual fitness.

Step4: The tournament algorithm selects the next generation directly, and the ranking operator selects the parent of the crossover.

Step5: When the value is greater than the threshold N, use PBX; otherwise, use SX.

Step6: Heuristic mutation operation.

Step7: Determine whether the condition is satisfied. If yes, output the optimal solution; otherwise, return to Step 3.

The specific flow chart is shown in Fig. 14.

4) BATTERY CHARGING STRATEGY

Due to power limitations, the robot may need to charge many times during task implementation. If the battery is low, the robot must stop the task and returns to the charging pile. The robot cannot work while charging. A fixed threshold cannot be set for the robot recharging. One reason is that the robot

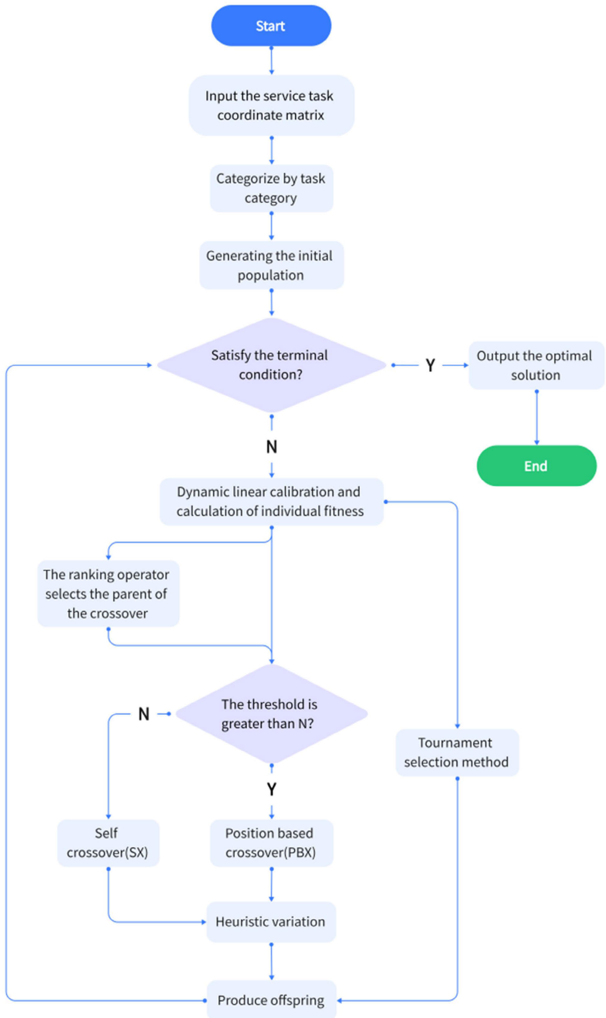

FIGURE 14. The IGA algorithm in CBASH.

may be far from the charging pile when the power reaches the fixed threshold level and cannot return to the charging pile within the rest of the power. The other reason is that the rest task can be completed within the power of the fixed threshold level, and there is no need for recharging during the tasks. Hence, an adaptable charging strategy is proposed to address the recharging requirements, as shown in Fig. 15

For every ten minutes, calculations on the power level of the robot at three different task statuses will be conducted to determine whether there is a recharging need. The first calculation is on the current power status (E1). The second is to judge the power (E2) required by the robot to move from the current position to the charging pile. The third is to compare the gap between the power needed for the next task (E3) plus E2 and E1.

IV. SYSTEM IMPLEMENTATION

To validate how CBASH supports daily elderly care activities in smart home, five types of tasks are fulfilled: emergency aid,

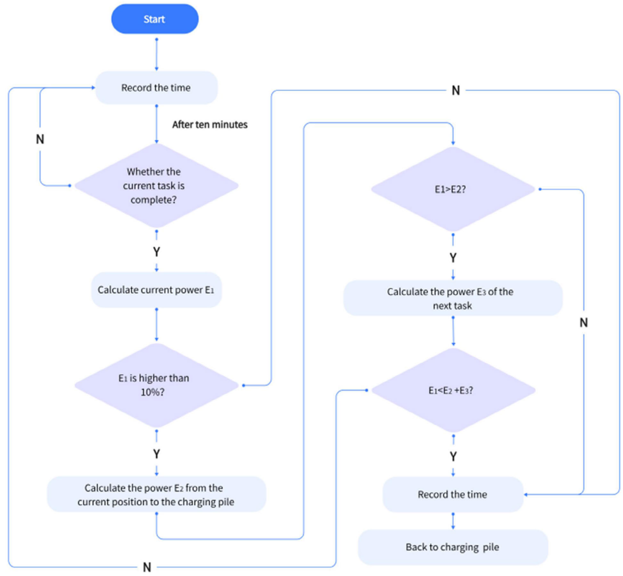

FIGURE 15. Charging strategy.

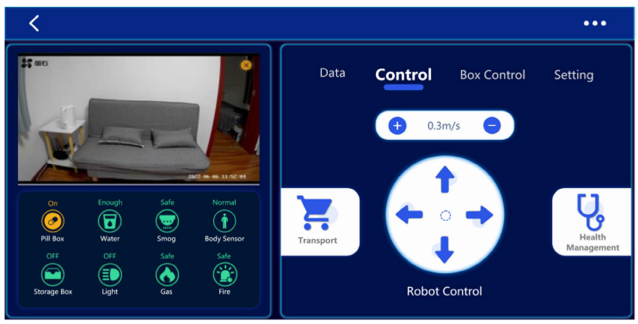

FIGURE 16. Family member interface.

health management, daily life assistance, emotional companionship, and security detection.

The drivers for the robot are developed on ROS (Robot Operating System) [39] in the Ubuntu environment on the Intel X86 minicomputer. A Micro Control Unit named STM32 is used for data acquisition and operation in the robot. STM32 communicates with X86 through serial ports to establish a data transmission channel. In addition, the robot communicates with the server remotely through TCP/IP.

The cloud computing server runs the Ubuntu16.04 operating system. A relational database is built based on MySQL Service 5.6 [40], and event perception and task planning are realized in Eclipse.

For data transmission, CAN bus, Zigbee, and RFID [41] are applied in an ARM-based gateway to collect and transmit data. 5G technology is used to send data to the server in the shortest time [42], [43].

The user interfaces based on Android and Web are designed for family members and care providers, as shown in Fig.16 and Fig.17. For family member users, the data checking module, robot control module, and equipment control

FIGURE 17. Care provider interface.

TABLE 2. Task importance leve.

Task number	Level	Task number	Level	Task number	Level
P1	3	P7	3	P13	2
P2	3	P8	3	P14	1
P3	3	P9	3	P15	1
P4	3	P10	3		
P5	3	P11	3		
P6	3	P12	3		

module are designed to remotely check the status of the elderly and indoor conditions and control CareBot. For care providers, the interface provides access to check data from sensors and interact with CareBot and other smart devices in the smart home.

We experimented with these five types of tasks to test the prototype system in our lab. According to the daily needs of the elderly, we set the following events for system response in the experiments of five tasks

Event 1: An older man named Tony watches TV on the sofa (P11) in the living room in the morning, and he needs to take medicine this morning.

Event 2: Water leakage occurred in the toilet (P12) and kitchen (P13), and the robot needs to check.

Event 3: The robot needs to check the smoke sensor alarm in the kitchen (P14) and the fire sensor alarm in the kitchen (P15).

Event 4: The robot needs to water the flowers in 5 positions, respectively P1, P2, P3, P4, and P5.

Event 5: The robot needs to clean five positions, respectively P1, P2, P3, P4, and P5.

In CBASH, the smart sensor network collects the data of these five types of events and transmits them to the service center through the smart gateway. Protégé 4.3 is used to create intelligent space ontology and realize the construction of an ontology library through MySQL Server 5.0. The Jena inference engine matches the data information with the rules in the rule base and identifies five events by event perception. The executable sequences of these five types of tasks are generated in the task planning module. This sequence includes the sequence in which the robot executes five events and the steps of each type of event. Since the current flow of all the events is fixed, this paper discusses the overall task sequence of the five types of events. Each of the five events is implemented by a certain number of tasks attributed to the robo's locations. The tasks are rated by the level of task emergency from 1 to 3, as shown in Table 2.

The corresponding locations of the above subtasks are as shown in Figure 18.

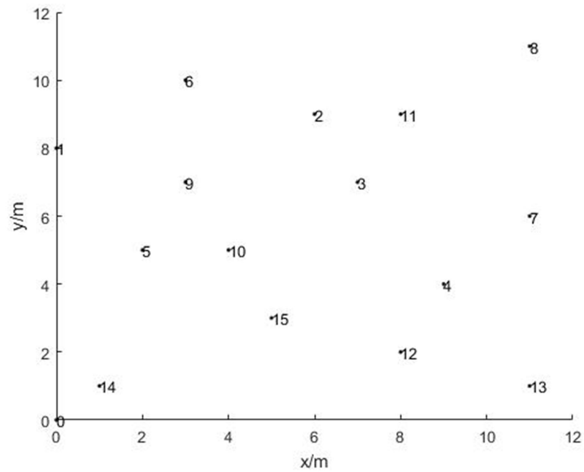

FIGURE 18. Task location.

TABLE 3. The parameters of IGA.

The number of urgent tasks	15	The mutation probability	0.05
The population number	500	The number of iterations	500
The crossover probability	0.8	The task importance coefficient $k_i / k_j / k_z$	1.00/1.05/1.09

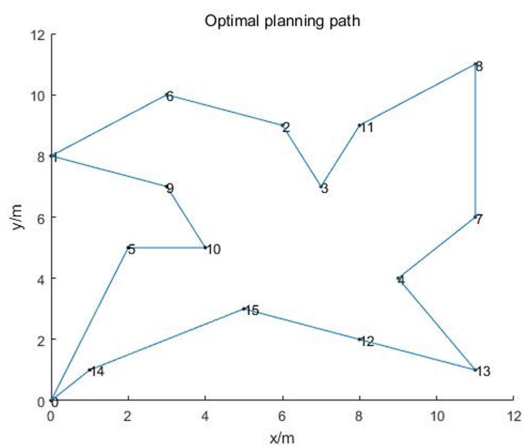

FIGURE 19. Task planning path by IGA.

TABLE 4. Compare the two algorithms.

Algorithm	The optimal path /s	The average path /s
IGA	1618	1636
AGA	1857	1902

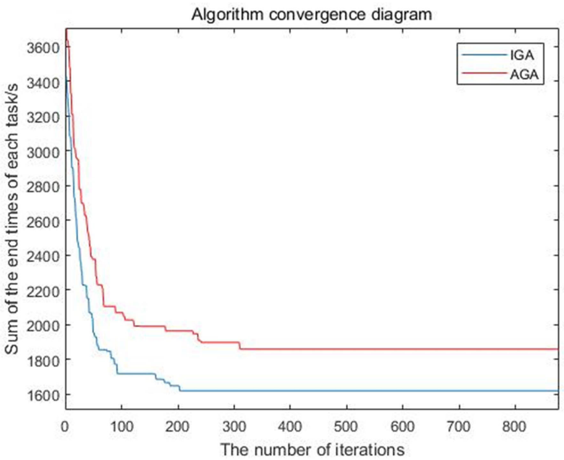

FIGURE 20. Iterative figure by IGA and AGA.

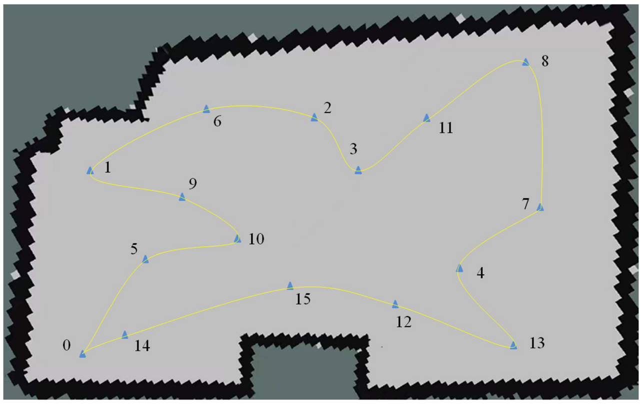

FIGURE 21. The real path in the lab.

To address the task planning problem, an IGA algorithm is run to generate a path with a minimized sum of the completion time of all tasks. Simulations of path generation are conducted on MATLAB [44]. After specific trials, the following parameters are applied, as shown in Table 3.

As shown in Fig. 19, the optimized moving route of CareBot is:

$$0 \rightarrow 14 \rightarrow 15 \rightarrow 12 \rightarrow 13 \rightarrow 4 \rightarrow 7 \rightarrow 8 \rightarrow$$
$$11 \rightarrow 3 \rightarrow 2 \rightarrow 6 \rightarrow 1 \rightarrow 9 \rightarrow 10 \rightarrow 5 \rightarrow 0$$

Fig. 20 shows that the best result is 1618s with 203 iterations. To compare the result with the adaptive genetic algorithm, IGA performs better, as shown in Table 4.

At the same time, the adaptive genetic algorithm (AGA) addresses the same problem. The shortest sum of time is 1857s, and the number of iterations is 318. The result of IGA is better than AGA, as shown in Fig. 20. Fig. 21 presents the path of CareBot in the whole cycle of task implantation in the experimental context.

FIGURE 22. Examples of Task Implementations.

V. CONCLUSION AND FUTURE WORK

The applications of smart home and robotic technologies have received significant interests for their support to "Aging-in-place." This paper focuses on integrating robots into smart home systems and building a robot-smart home collaboration system. The system integrates the robot's mobility advantage with the smart home's perception ability for instant responses to emergencies. This paper takes the proposed system architecture as the main idea and then introduces the software and hardware of the system from the perspective of functions and gives an overview of the problems, including event perception and task planning that need to be solved in the framework. Finally, this paper explores the implementation of a complete task in a quick response to emergencies under the constraint of robot charging. The experiment results show that the proposed CareBot-Assisted Smart Home (CBASH) can perceive complex or ambiguous events and plan for homecare tasks with a quick response to emergencies. Future research can focus on improving the CBASH system's proactive perception based on training in realistic scenarios. At the same time, a deep reinforcement learning algorithm can be integrated into the CBASH system to improve the efficiency of task planning in response to emergencies.

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ZEQIANG ZHU (Student Member, IEEE) received the B.E. degree in mechanical engineering from the School of Mechatronics Engineering, China University of Geosciences, Wuhan, China, in 2020. He is currently pursuing the master's degree in industrial engineering with the School of Mechanical Science and Engineering, Huazhong University of Science and Technology (HUST), Wuhan. His research interests include smart homes, optimization algorithms, and production scheduling.

YAN FU received the Ph.D. degree from the Huazhong University of Science and Technology (HUST), China, in 2012. She is currently an Associate Professor with the School of Mechanical Engineering, HUST, and the Co-Director of the U of T–HUST Collaborative Center for Robotics and Eldercare, which focuses on the collaborations between China and Canada on AgeTech development and applications. She is also the Research Chair of the Hubei Engineering Research Center on Active Health Smart Equipment. She has authored many scientific articles on rehabilitation and assessment, disability support devices, and robots. Her current research interests include a multi-intervention system for neural degeneration, digital therapy, and human–robot interaction. She serves on the editorial board of *Frontiers in Aging Neuroscience* and *Frontiers in Neuroscience*.

WEIMING SHEN (Fellow, IEEE) received the bachelor's and master's degrees from Beijing Jiaotong University (formerly Northern Jiaotong University), Beijing, China, in 1983 and 1986, respectively, and the Ph.D. degree from the University of Technology of Compiègne, Compiègne, France, in 1996. He is currently a Professor with the Huazhong University of Science and Technology, Wuhan, China, and an Adjunct Professor with the University of Western Ontario, London, ON, Canada. His research interests include intelligent software agents, wireless sensor networks, the IoT, big data, and their applications in industry. He is a fellow of the Canadian Academy of Engineering and the Engineering Institute of Canada.

ALEX MIHAILIDIS received the Ph.D. degree from the University of Strathclyde, Glasgow, U.K., in 2002. He is the Scientific Director of the AGE-WELL Network of Centres of Excellence. He is a Professor with the Department of Occupational Science and Occupational Therapy (U of T) and in Biomedical Engineering (U of T), with a cross appointment in the Department of Computer Science (U of T). He is the Fellow of Rehabilitation Engineering and Assistive Technology Society of North America (RESNA) and a Fellow in the Canadian Academy of Health Science (CAHS). His main contributions are in the field of technology to support older adults and rehabilitation. He has published over 200 journal papers, conference papers, and abstracts in this field. His research interests include biomedical and biochemical engineering, computer science geriatrics, and occupational therapy.

SHUN LIU received the B.E. degree from the School of Mechanical Science and Engineering, Huazhong University of Science and Technology (HUST), Wuhan, China, in 2013. He is currently pursuing the graduate degree with the School of Mechanical Engineering, HUST. He was an Automotive Designer with the Automotive Engineering Research Institute, Guangzhou Automotive Group Company (GAEI), and Dongfeng Lantu Automotive Technology Company. His current research interests include developing and designing intelligent cockpits for vehicles and smart electronics in complex scenarios, including human–computer interaction, user experience, and emotional design of vehicles and products.

WENSHUANG ZHOU is currently pursuing the degree with the School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan, China. Her current research interests include an in-depth study of perceptual engineering and the application of the industrial Internet of Things.

ZHAOHUI HUANG is currently an Associate Professor with the Department of Industrial Design, School of Mechanical Engineering, Huazhong University of Science and Technology, and a Supervisor of master's students. She has long been engaged in the research of digital medical product design and system integration design. She is also the Director of the Industrial Design Innovation Center (Provincial Design Center), Huazhong University of Science and Technology. She is also the Director of the Industrial Design Branch, Chinese Mechanical Engineering Society; the Director of the Design Education Branch, Chinese Industrial Design Association; the Director of the Industrial Design Committee, Hubei Mechanical Engineering Society; and the Correspondence Evaluation Expert of the Development Center for Degree and Postgraduate Education of Ministry of Education.