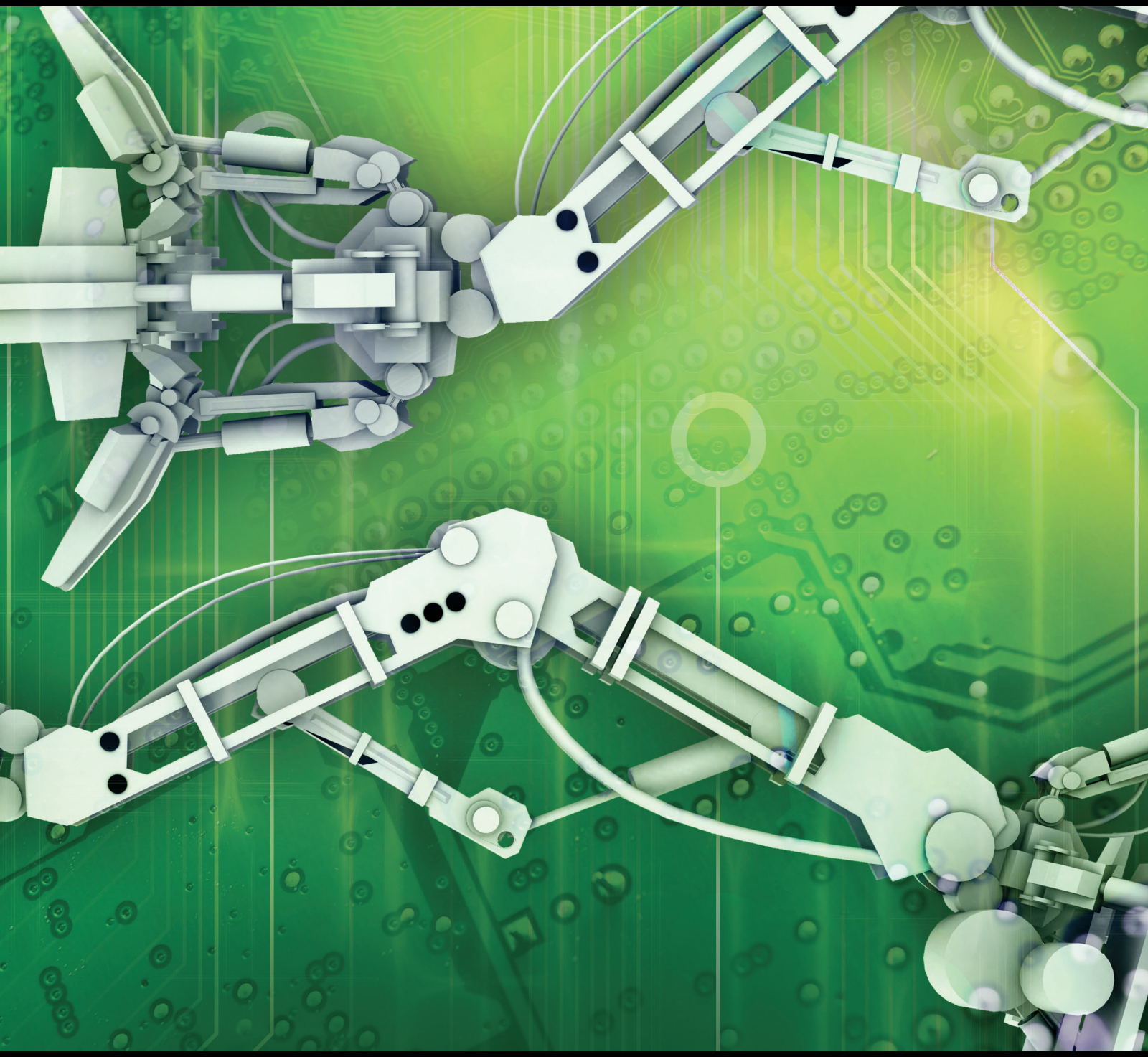
Journal of Robotics

Human-Robot Interaction

Lead Guest Editor: Yunyi Jia
Guest Editors: Biao Zhang, Miao Li, Brady King, and Ali Meghdari



Human-Robot Interaction

Journal of Robotics

Human-Robot Interaction

Lead Guest Editor: Yunyi Jia
Guest Editors: Biao Zhang, Miao Li, Brady King, and Ali Meghdari

Editorial Board

Contents

Hindawi
Journal of Robotics
Volume 2018, Article ID 3879547, 2 pages
https://doi.org/10.1155/2018/3879547

Editorial

Human-Robot Interaction

Yunyi Jia,[1] Biao Zhang,[2] Miao Li,[3] Brady King,[4] and Ali Meghdari[5]

[1] *Clemson University, USA*
[2] *ABB U.S. Corporate Research Center, USA*
[3] *Wuhan University and Cobot Technology, China*
[4] *Wayne State University, USA*
[5] *Sharif University of Technology, Iran*

Correspondence should be addressed to Yunyi Jia; yunyij@clemson.edu

Received 30 August 2018; Accepted 30 August 2018; Published 1 October 2018

Human-robot interaction plays an essentially important role in deployment of robotics systems in our daily life such as manufacturing, medicine, and domestic services. Traditional robotic systems, especially industrial robots, are mostly caged and isolated from humans to perform simple and repetitive tasks in well-structured environments. To expand the application scopes of robotics systems, i.e., to bring robots out of cages, we have to investigate various human-robot interaction technologies from robot designs, sensing, and controls to human-robot interfaces, to ensure the safety and efficiency of human-robot collaboration. In recent years, in academia and industry, human-robot interaction has attracted a significant number of attentions. Many collaborative robots have been developed and deployed in real applications such as assembly, warehouses, and home services. Some new human-robot interaction models and algorithms have also been developed to resolve the emerging issues in human-robot collaboration.

This special issue contains original research articles to address problems in both conventional and emerging human-robot interaction fields.

The paper "A Control Architecture of Robot-Assisted Intervention for Children with Autism Spectrum Disorders" by Y. Feng et al. presents a robot-assisted control architecture, referred to as CARAI, to improve the autonomy of the robots in interacting with children with autism (ASD). The CARAI has been developed based on a famous cognitive architecture called Adaptive Character of Thought-Rational (ACT-R) and some traditional intervention protocols for children with autism (DTT and DIR/Floortime). Following the perception-cognition-action model, the CARAI comprises several modules and submodules with special functions. Besides the presented details of the proposed control architecture, the authors have tested the performance of the CARAI on two participants with ASD using a NAO humanoid robot. Their robot-assisted training session was divided into the four following phases: initialization, arousing the child's interest, training, and finishing session. Even with the small number of their participants, the authors mentioned that using the CARAI can reduce the burden on clinical psychologists.

The paper "Hobbit: Providing Fall Detection and Prevention for the Elderly in the Real World" by M. Bajones et al. presents the second prototypical implementation of the Hobbit robot, a socially assistive service robot. It is designed especially for fall detection and prevention, providing various tasks, such as picking up objects from the floor, patrolling through the fat, and employing reminder functionalities, and it could support multimodal interaction for different impairment levels. The robot did autonomous operation of 371 days during field trials in Austria, Greece, and Sweden while interacting with 18 elderly users (aged 75 years and older) over multiple weeks. It shows that Hobbit's adaptive approach towards the user increasingly eased the interaction between the users and Hobbit. Lessons learned from the studies are also provided regarding the need for adaptive behavior coordination, support during emergency situations, and clear communication of robotic actions and their consequences.

The paper "Allocating Multiple Types of Tasks to Heterogeneous Agents Based on the Theory of Comparative Advantage" by T. Morisawa et al. presents a method to allocate multiple tasks with uncertainty to heterogeneous robots using

the theory of comparative advantage to maximize the benefit of specialization in human-robot teams. Simulation and experiments show that the method is effective in reducing the total task-execution time and dealing with uncertainty in task-execution time, uncertainty in the increasing number of tasks during task-execution, and uncertainty agents who are disobedient to allocation orders, compared with existing methods.

The paper "Hands-Free Maneuvers of Robotic Vehicles via Human Intentions Understanding Using Wearable Sensing" by W. Wang et al. presents wearable-sensing-based hands-free maneuver intention understanding approach to assist the human to naturally operate a robotic vehicle without physical contact. It is based on wearable electromyography (EMG) sensors and inertial measurement unit (IMU) to recognize the human maneuver intentions and then transfer the intentions to the controls of a robotic vehicle. Experimental results on a robotic vehicle illustrate the effectiveness of the proposed approach. It provides a new way for humans to interact with future autonomous vehicles without steering wheels and throttle and brake pedals.

The paper "Older Adults' Perceptions of Supporting Factors of Trust in a Robot Care Provider" by R. E. Stuck and W. A. Rogers studies what older adults would need to trust robot care providers in home-care context. It explores what older adults, who currently receive assistance from caregivers, perceive as supporting trust in robot care providers within four common home-care tasks: bathing, transferring, medication assistance, and household tasks. The results demonstrate that the older adult-robot care provider context has unique dimensions related to trust that should be considered when designing robots for home-care tasks.

The paper "Stabilization of Teleoperation Systems with Communication Delays: An IMC Approach" by Y. Li investigates an IMC-based control design for linear teleoperation system with communication delays. It is shown that the stability with the IMC approach is guaranteed delay-independently and the passivity assumption for external forces is removed for the proposed design of teleoperation systems. Simulations on a single-DOF linear teleoperation system show that the stability is guaranteed when the designed controller is applied and satisfying tracking performance can be achieved if the parameters are chosen suitably.

Conflicts of Interest

The editors declare that they have no conflicts of interest regarding the publication of this special issue.

Yunyi Jia
Biao Zhang
Miao Li
Brady King
Ali Meghdari

Hindawi
Journal of Robotics
Volume 2018, Article ID 3246708, 12 pages
https://doi.org/10.1155/2018/3246708

Research Article

A Control Architecture of Robot-Assisted Intervention for Children with Autism Spectrum Disorders

Yongli Feng, Qingxuan Jia, and Wei Wei

School of Automation, Beijing University of Posts and Telecommunications, No. 10 Xitucheng Road, Haidian District, Beijing 100876, China

Correspondence should be addressed to Yongli Feng; fengyongli@bupt.edu.cn

Received 1 November 2017; Revised 23 April 2018; Accepted 4 June 2018; Published 2 July 2018

Academic Editor: Ali Meghdari

Robot-assisted intervention has been successfully applied to the education and training of children with autism spectrum disorders. However, it is necessary to increase the autonomy of the robot to reduce the burden on the human therapists. This paper focuses on proposing a robotic architecture to improve the autonomy of the robot in the course of the interaction between the robot and the child with autism. Following the model of perception-cognition-action, the architecture also incorporates some of the concepts of traditional autism intervention approach and the human cognitive model. The details of the robotic architecture are described in this paper, and in the end, a typical scenario is used to verify the proposed method.

1. Introduction

Autism, or Autism Spectrum Disorder (ASD), describes a broad range of developmental disorders whose main symptoms include impairment in social communication and restricted or repetitive patterns of behavior, interests, or activities [1]. Previous studies reveal that behavioral intervention is one of the major approaches to stimulate children with ASD to reduce their symptoms and improve their abilities of social interaction [2]. In the field of ASD intervention, some of the major challenges are to maintain motivation of the children, while long-term and repetitive therapies require therapists to spend a lot of time and energy. To address these challenges, the novel techniques and devices have been studied to ensure effective intervention of ASD while reducing the workload of therapeutic professionals [3, 4].

In these technologies, Socially Assistive Robotics (SAR) is considered as support tool for autism therapy through social interaction [5]. In the current studies, these robots have shown high efficiency in the intervention in autism, and the social skills of children with ASD have been positively improved [6, 7]. The approach of robot intervention for ASD is expected to obtain a better assist to traditional intervention procedure. In many systems, the robot is controlled remotely by the operator to make appropriate responses. This control method limits the long-term, large-scale use of robots in ASD interventions. In the field of ASD intervention, robots should be positioned as support tools for the human therapists rather than as alternatives. During the intervention, robots require collaborating with people who lack knowledge of ASD intervention or robotic. In order to achieve this goal, it is a major trend that to develop autonomous robots to interact with children with ASD in the course of intervention sessions. In the field of ASD intervention, the robot could play the role of human therapists, and the function of the robot is to stimulate and encourage the social skills of children with ASD (as show in Figure 1).

In the unstructured environment, it is a complex process to realize autonomous interaction between the robot and the child. In order to improve the autonomy of the robot in the intervention in autism therapy, the appropriate control architecture design is an indispensable part. In particular, a well-designed robotic architecture is an essential part to adjust the robot's action by interpreting interaction signals reliably [8]. The main purpose of this paper is to present a control architecture that enables the robot to intervene in autism therapy with higher autonomy. The remainder of this paper is organized as follows: Section 2 provides an

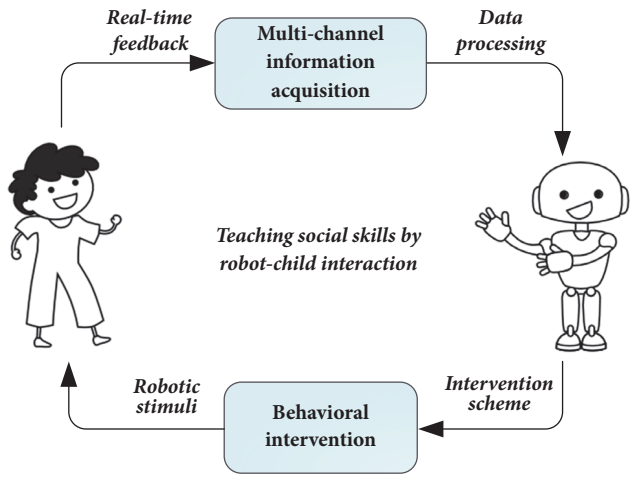


Figure 1: A basic overview of the robot application for autism intervention.

overview of related work; Section 3 presents the detail of the control architecture of the robot in each part and explains the intervention process of the robot for autism therapy; Section 4 describes the experiment to validate proposed architecture; in Section 5, we conclude our study and present future work.

2. Related and Previous Work

At present, the pathogenesis of autism is not clear and the early intervention is an effective means to relieve symptoms of children with ASD to promote their skills. In this section, we will introduce the traditional methods of intervention and the application of robots for autism therapy.

2.1. Traditional Methods of Autism Intervention. With years of development, researchers have presented various methods and models to help children with ASD, for example, Denver Model, Comprehensive Programs, TECCH Program, Applied Behavioral Analysis, and DIR/Floortime. Among these methods, Applied Behavioral Analysis (ABA) and DIR/Floortime are widely used and accepted. In the following sections, we will introduce the two methods, respectively.

(i) Applied Behavioral Analysis for Autism. Applied Behavior Analysis (ABA) which is based on the principles of learning and motivation is a general term for behavior modification [9]. ABA therapy is usually defined as a systematic approach to improve people's social behavior based on the mixture of psychological and educational techniques. Over the past few decades, the intervention methods based on the ABA principle have been applied to the behavior and learning of children with special needs. Particularly, in the intervention of children with ASD, ABA therapy is one of the most effective means of intervention for children with ASD [10].

In the course of intervention of autism, Discrete Trial Teaching (DTT) is a concrete implementation method based on principle of ABA therapy [11]. DTT was developed by psychologists Ivar Lovaas in the 1970s and its core elements include instruction, individual response, auxiliary, reinforcement, and pause [9]. In practical execution, DTT includes the following main contents. Firstly, the target task is decomposed into a series of smaller or mutually independent steps in a certain manner and sequence. Subsequently, each small step is trained and educated by the appropriate reinforcement method. Through this process, children with autism can master all the steps and fulfill the task independently. The ultimate goal of DTT teaching for children with ASD is to allow them to apply the knowledge and skills in other situations. DTT is a highly structured teaching model and this type of teaching is generally one-on-one intervention of children with ASD. The basic process of DTT is shown in Figure 2.

(ii) The DIR/Floortime. The Developmental, Individual-difference, and Relationship-based (DIR) mode is an outstanding developmental approach for autism intervention. The mode of DIR was developed by Stanley Greenspan and its core is Floortime [12].

Different from the ABA method, DIR/Floortime emphasizes children's emotional experience, imagination training, and interpersonal interaction. According to children with ASD's characteristics and stages of development, the ladder of capability development is set up which consists of six milestones. These milestones include (1) attention and interest, (2) engagement and intimate relationship, (3) two-way communication, (4) continuous problem solving, (5) creative thinking, and (6) abstract and logical thinking [13]. Based on specific developmental stages of children with ASD, adopting the different strategies will achieve better effect of intervention. For children with autism, the time and place of DIR/Floortime intervention are flexible, and intervener can use this method in drawing rooms, bedrooms, schools, or training institutions at any time [14]. The intervention process of DIR/Floortime for autism can be summarized as shown in Figure 3.

2.2. Application of Robots in ASD Intervention. Researchers have done a lot of studies on the use of robots in the intervention of children with autism. The results of these studies demonstrate that it is an effective way to use the robot in autism intervention.

In the course of intervention of children with autism, robots play a role of complementary therapy. In previous studies, researchers always use robots to assist human therapists for mediated interaction in tasks of action imitation, joint attention, turn talking, and so on [15]. These tasks can improve the social skills of children with ASD and help them integrate into society. Nevertheless, in the current approaches, almost all robots which are usually controlled by human operators remotely lack autonomy. In this mode, the operators need specialized knowledge of autism intervention and robots operation which is unsustainable for use of robots in long-term and large scale. Therefore, it is necessary to make robots have a certain degree of autonomy. In order to achieve this goal, the research of suitable control architecture of robots for intervention of children with autism requires developing preferentially.

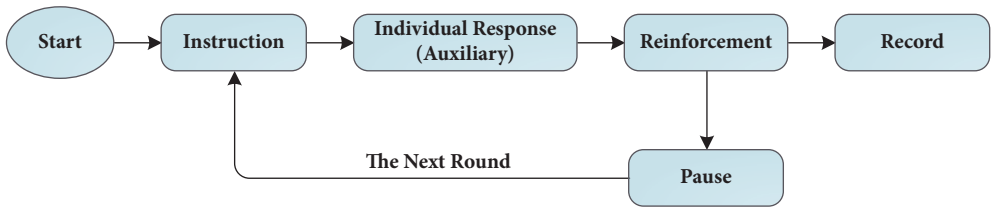


Figure 2: The basic process of DTT for children with ASD.

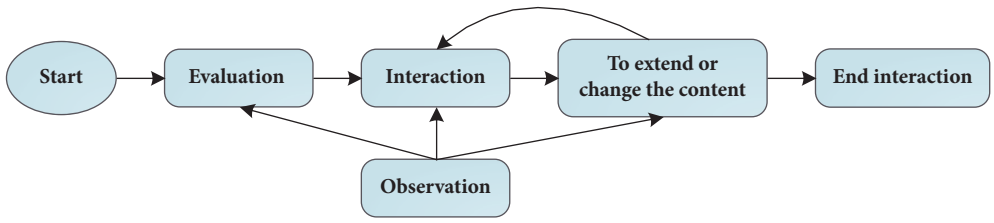


Figure 3: The basic process of DIR/Floortime for children with ASD.

At present, the researches of robots' control architectures for autism intervention mainly focus on the control of robots, and rarely take into account the traditional methods of intervention. Feil-Seifer and Mataric [16] proposed a kind of behavior-based control architecture which is named B^3IA. The B^3IA is composed of sensor and interpretation module, activity history module, behavior network, and effector module. In the task of playing video games, Wainer et al. [17] designed the control architecture of detection-planning-action, which makes the robot complete the task with a certain degree of autonomy. Sang-Seok et al. [18] developed control architecture based on four modules including human perception, interaction manager, user input, and robot effector. In their study, the DTT protocol was used. In addition, Gonzalez et al. [19] proposed a three layer planning architecture to carry out a rehabilitation therapy for patients with physical impairments. Pour A G et al. [20] proposed human-robot facial expression reciprocal interaction platform. The reciprocal interaction is composed of two main phases: nonstructured and structured interaction modes. In this platform, the imitation task of facial expression between the robot and the children with autism is realized. In their study, the traditional rehabilitation procedure was considered, which gives us some inspiration.

The intervention of autism therapy has its particularity. It is a promising research direction to integrate the ideas of traditional approaches of intervention into the control architecture design of robot. In this paper, we carried out the exploratory study.

3. The Design of Control Architecture for the Robot in Autism Intervention

3.1. The Feasible Procedure of the Robot for Autism Intervention. In autism intervention, it is necessary to improve the autonomy of the robot which can reduce the workload of the human (e.g., therapists, educators, and parents). Furthermore, people who lack professional knowledge of autism intervention or robotics can use robots to achieve their aims. In this way, the scope of use of the robot can be expanded, and the robot can play better roles for autism intervention. In order to achieve this goal, it is necessary to design the control architecture for robot based on traditional methods of autism intervention.

As mentioned in the preceding section, ABA and DIR/Floortime are two traditional methods for autism's early intervention commonly. DTT is the specific method of ABA program in autism therapy. This method has the advantages of structured process and easy to apply and has been used by robots in some studies for autism intervention [21]. Although DTT is very effective in the early intervention for children with ASD, quite a few scholars criticize that this method is hidebound and mechanical and is not conducive to the development of children with ASD [13]. Compared to DTT, DIR/Floortime attaches great importance to the developments, individual differences, and relationships of autism children. It advocates the intervention into the child's daily life, according to the child's development stages. Nevertheless, for the robot in autism intervention, this method requires the robot has high-level ability of natural interaction, but the existing technology cannot support that.

Therefore, as shown in Figure 4, we proposed a feasible procedure of the robot for autism intervention to improve the autonomy of the robot.

In the course of autism intervention, the robot awakes children's interest by dancing, singing, dialogue, and so on. In this way, children can focus their attention on the robot which is the basis for efficient interaction. Simultaneously, the robot collects the environmental information and evaluates the behavior of children with ASD. The content of assessment includes engagement, the stage of development of child which refers to the method of DIR/Floortime, requirement analysis of the child, and the evaluation of task feedback. And afterward, the robot assign tasks based on the results of evaluation and the tasks include DTT teaching and other ones (e.g., storytelling, singing, and dancing). Following this,

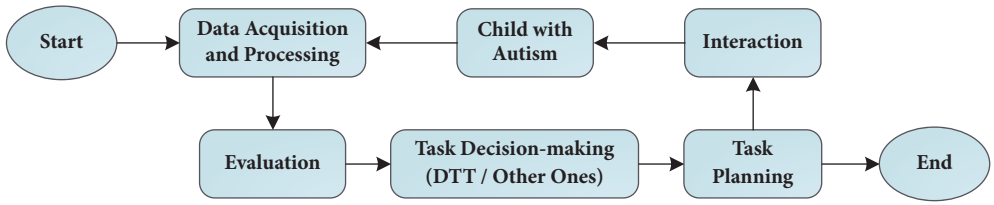


Figure 4: The flowchart of the robot intervention for children with autism.

the robot decomposes the task which has been decided and planning to perform. Finally, the robot interacts with the child or else ends the interaction.

In the process of interaction between robots and children with ASD, robots play the role of human therapists. Therefore, the cognitive mechanism of human should be considered in the design of robotic architecture. Among cognitive architectures, ACT-R (adaptive character of thought rational) has been studied for a long time and has good evaluation. ACT-R system is a hybrid cognitive architecture, which consists of two parts: symbolic system and subsymbolic system. ACT-R is a general theory of cognition and provides a framework for information processing [22]. The system of ACT-R is composed of several different modules. The production module connects other modules into a whole through buffers. In this framework, the symbolic system is driven by production system and the buffers of different modules are operated through the production rules. Besides, the subsymbolic system runs in the external structure of the ACT-R, and it controls the operation of symbolic system through a series of mathematical methods. One of the important features of ACT-R which are different from other similar theories is to apply a large number of experimental information directly to the research work. Therefore, some ideas of ACT-R were used in our study.

In the next section, we will propose the control architecture of the robot for autism intervention based on ACT-R and the flowchart which we have presented in this section.

3.2. The Control Architecture of the Robot for Autism Intervention. In order to improve the autonomy of the robot in the intervention of children with autism, we designed the control architecture of the robot for autism intervention (CARAI), which is shown in Figure 5. Following the perception-cognition-action model, the CARAI comprises several modules and submodules with special functions which are represented by rectangles. In the architecture, the arrows express the direction of information transmission and the dependency between modules. How each module works is described as follows.

3.2.1. Perception Module. The perception module is an interface that the robot obtains environment information and maps the information to the internal representation. In our study, the perception module is divided into two submodules, data acquisition module and data processing module. Among them, in the data acquisition module, the robot collects the data through sensors and transfers them to the data processing module. Besides, the data processing task is carried out in three steps. Firstly, according to the needs of the interaction task, the data processing module obtains the instruction from upper process of CARAI through production rules; then, the data processing module transfers the focus of the attention to the corresponding position according to the instruction, obtains the detailed information of the object, and carries on the data processing; finally, the data processing module transmits the results to the high-level module. Some general algorithms are applied to this module. For example, the robot locates the child with ASD through HOG-Linear SVM and detects the face of the child based on Haar feature. The library based on Deep Neural Network (DNN) is used for natural language processing.

3.2.2. Intention Module. Goal making is a very important process in human-robot interaction. Because the ability of the robot is always limited, the robot should revolve around its purpose when accepting input and processing and making output. In the CARAI, we use intention module to store the goals and aim to generate therapy plans for children with autism. In addition, the goal buffer is used as an interface to implement the interaction between the intention module and the robot core processing process. In the goal buffer, the goal can be created, temporarily stored, and modified. When the robot interacts with the child, a goal can be decomposed into subgoals, which are managed in a stack way.

As shown in Figure 6, the ultimate goal for the robot to achieve is G_0, which is the initial state of the goal stack. However, in order to achieve the goal G_0, some subgoals $G_1 \sim G_m$ need to be completed. Therefore, these subgoals are pushed into goal stack. In this way, the goal G_m is at the top of the goal stack and is popped to execute firstly. During the robot's execution of the current goal, the new goal may be created. At this point, the new goal will be pushed onto the top of the goal stack. This process is looped until the ultimate goal is completed.

3.2.3. Memory Module. The function and running rule of memory module are similar to the declarative module in ACT-R. In this module, the knowledge of intervention therapy for autism is stored. The knowledge, which is converted into production rules, comes from the experienced therapists and is filtrated according to the characteristics of the robot intervention. During the intervention, the central processing system of the CARAI retrieves the rules from memory module in real time and updates the knowledge (e.g., modify, remove, or add rule). In addition, the information of users (e.g., names, genders, and symptoms), robot's behavior set, and task information are also stored in this module.

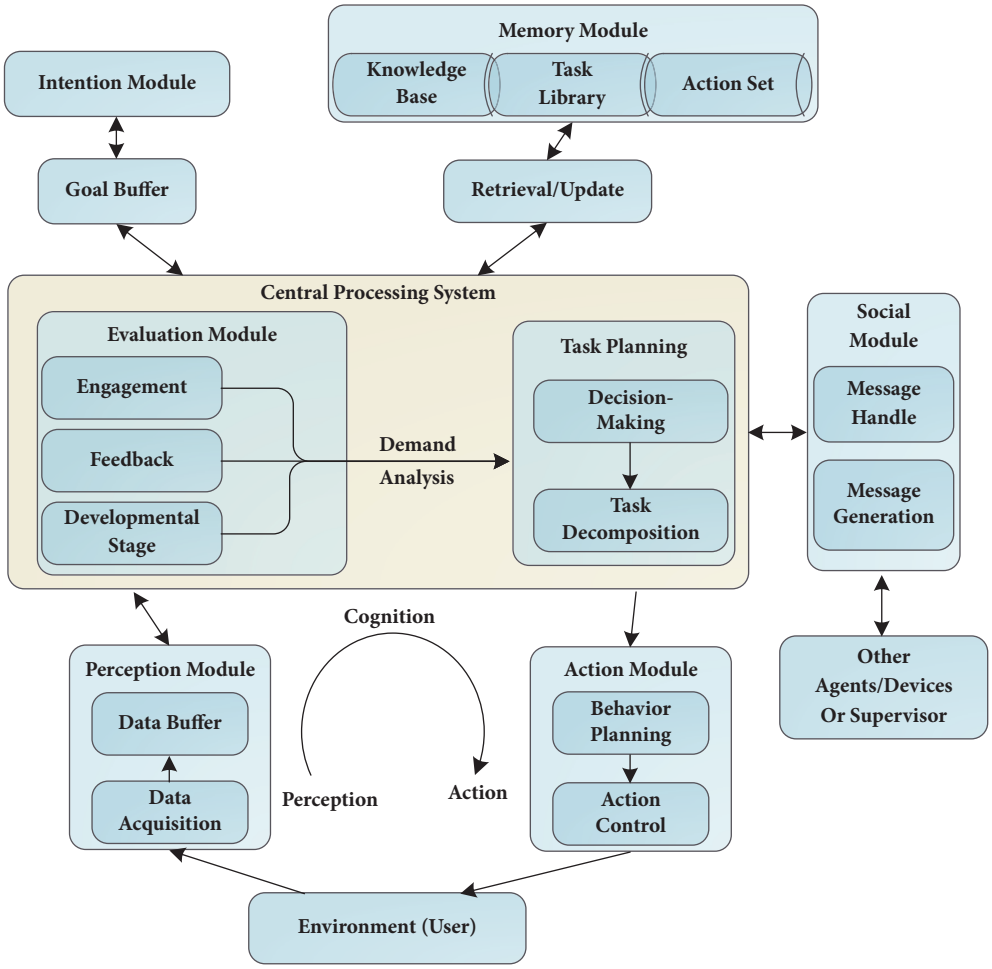


Figure 5: The control architecture of the robot for autism intervention (CARAI).

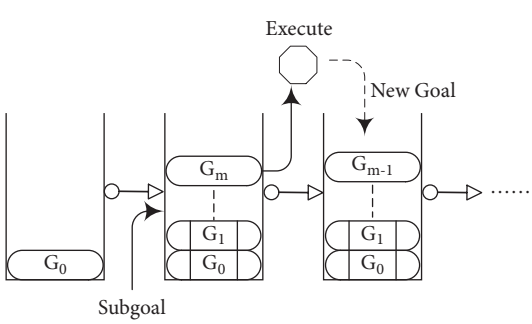


Figure 6: The schematic diagram of goal management.

Production rules can generally be expressed as "$P \leftarrow Q$". In this expression, Q represents a set of preconditions; P denotes several conclusions or actions. Its meaning is "if the premise Q is satisfied, the conclusion P (or action P should be performed) can be introduced". The knowledge represented by a production rule is an ordered set of productions. The syntax can be represented by (Backus Normal Form) as follows: ⟨symbol⟩::= ⟨name of rule⟩: IF "Q" THEN "P". In this study, two of the robot production rules are shown as follows:

⟨Rule 1⟩::=⟨*visual_location*⟩: IF *visual_goal* | *visual_state* | *location_state* THEN *move-attention*;

⟨Rule 2⟩::=⟨*action_leftarm*⟩: IF "*action_goal* | *action_state* | *leftarm_state*" THEN "*joint_angle_1* | *joint_angle_2* | *joint_angle_3* | *joint_angle_4*";

3.2.4. Evaluation Module. The evaluation module appraisals the state or situational context using data received from perception module. The evaluation module appraisals the state of the child based on several features and variables. In the CARAI, we used a parallel mechanism to evaluate the user's state. The evaluation module contains three submodules: engagement recognition, feedback appraisal, and assessment of developmental stage. Among them, the engagement recognition module mainly assesses the user's degree of participation in the interaction task currently; the feedback appraisal module is used to evaluate the completion of the interaction object for the current task; in the development stage module, the development of children with ASD is divided into several levels, and the level of the

Table 1: The description of the task.

Event	Content		
The difficulty of the task	Level 1	Level 2	Level 3
Task overview	Imitates a single arm of the robot	Imitates both arms of the robot at the same time	Ask child to imitate and answer questions
Score	1	3	5

user is determined by his performance in the human-robot interaction. The evaluation results of these modules will serve as the basis for goal setting and task planning of the system.

In the evaluation module, the engagement evaluation is the important step for using the robot to interact with the children with ASD. The evaluation results of the engagement can reflect the degree of acceptance of intervention tasks by children with ASD. In order to classify the degree of participation of the child, we developed an engagement evaluation model based on dynamic Bayesian networks and domain experts' knowledge. The inputs (evidence variables) of the model are child's features which are face orientation, interpersonal distance, and acoustic state. The outputs (query variables) of the model are the state of the child when he/she interacts with the robot. The expression of engagement evaluation is shown as

$$\begin{aligned} \boldsymbol{P}\left(S^t \mid \boldsymbol{e}^t\right) &= k_1 \boldsymbol{P}\left(S^{t-1} \mid \boldsymbol{e}^{t-1}\right) \boldsymbol{P}\left(S^t \mid S^{t-1}\right) \\ &\quad \circ \sum_{i=1}^{3} \left(P\left(H_i^t \mid S^t\right) \boldsymbol{P}\left(H_i^t \mid \boldsymbol{e}^t\right)\right) \\ \boldsymbol{P}\left(H_i^t \mid \boldsymbol{e}^t\right) &= k_2 \boldsymbol{P}\left(H_i^{t-1} \mid \boldsymbol{e}^{t-1}\right) \boldsymbol{P}\left(H_i^t \mid H_i^{t-1}\right) \\ &\quad \circ \left(\boldsymbol{P}\left(e_{i1}^t \mid H_i^t\right) \circ \boldsymbol{P}\left(e_{i2}^t \mid H_i^t\right)\right) \\ & \qquad i = 1, 2, 3 \end{aligned} \tag{1}$$

where k_1 and k_2 are normalization factors. Under the influence of the evidence variables $\boldsymbol{e}^t$, $\boldsymbol{P}(S^t \mid \boldsymbol{e}^t)$ denotes the probability value set of query variables, and $\boldsymbol{P}(H_i^t \mid \boldsymbol{e}^t)$ represents the calculated values of hidden variables in time t. Transition relations between two adjacent time slices are represented by 3-order confused matrices, which are $\boldsymbol{P}(S^t \mid S^{t-1})$ and $\boldsymbol{P}(H_i^t \mid H_i^{t-1})$. The symbol "$\circ$" indicates the dot product between matrices. Detailed content of engagement evaluation can be found in [23].

The feedback evaluation can measure whether the child's response to the robot is correct. For imitation task, we use "PyOpenPose" to evaluate the posture of the child. PyOpenPose is an implementation of OpenPose (an algorithm for human posture recognition) based on Python. In the application, the key points of the human body are first detected. Then, based on the coordinates of these points, a threshold is set to evaluate the child's feedback.

The evaluation result of developmental stage is the important basis for robot decision-making. In our application, we divided the development of children with ASD into three levels which include focused attention, two-way communication, and continuous interaction. During the interaction, the robot asks the child to complete the tasks with different difficulty which is assigned different score. For example, the robot raises a hand to ask the child to imitate, or the robot raises a hand, asking the child to answer which hand it is. The description of the task is shown in Table 1. When the children with ASD complete the tasks, the robot evaluates their developmental stages by the addition and subtraction of the score.

3.2.5. Task Planning Module. The process of task planning is divided into two stages: decision-making and task decomposition. In decision-making, the system fully integrates information which is from evaluation module, memory module, intention module, and social module. The learning mechanism and selection mechanism are also formulated in this step. In the task decomposition, the target task which is set in the previous step is decomposed into simple primitive tasks based on the robot's ability. In this way, these primitive tasks can be performed through the robot's actuators directly.

During the interaction between robots and children with ASD, the role of the supervisor is indispensable [24]. Therefore, we considered the role of the supervisor in the decision-making of the robot and achieved the purpose through the method of interactive reinforcement learning which can be defined by

$$a_t \longleftarrow \arg\max_{a \in \mathbf{A}(s)} \left((1-\beta) \times Q(s,a) + \beta \times E(s,a)\right) \tag{2}$$

where a_t is the result of decision which expresses the robot's action. $\boldsymbol{A}(s)$ represents the action set in state s. $Q(s,a)$ is the value of Q-learning and $E(s,a)$ is the result of supervisor's reinforcement. The symbol β represents the confidence level for supervisor's reinforcement. $Q(s,a)$ can be obtained by (3) which is the expression of Q-learning and the $E(s,a)$ can be received through prior agreement.

$$\begin{aligned} Q(s,a) &\leftarrow Q(s,a) \\ &\quad + \alpha\left(r + \gamma \max_{a'} Q\left(s', a'\right) - Q(s,a)\right) \end{aligned} \tag{3}$$

where $0 \leq \alpha \leq 1$ is the learning rate, which defines the extent of new information covering old information. $0 \leq \gamma \leq 1$ is the discount factor and reflects the importance of future rewards in the learning process. r represents the reward value of executing action a at the state s. s' and a' denote the state of the next step and the action to be performed. The detailed derivation process of the algorithm will be discussed in another paper.

In the CARAI, the task decomposition is achieved through hierarchical task network. The simple primitive tasks are comprised of the basic tasks that the robots can accomplish, like the joints of robot rotating to the specific angles, robot voice output, setting the LED colour of the robot eyes, and so on.

3.2.6. Action Module. When the task planning is finished, the CARAI translates the primitive tasks into the robot's behavior through the action module. First, the action sequence of the robot is formulated by the behavior planning module, and then the movements of the actuators are controlled by the action control module.

3.2.7. Social Module. In the therapeutic task, we expect that the robot could infer and understand the intentions of the child and take appropriate behavior to meet the child's individual needs. Usually, the capabilities of a robot are limited. In intervention schemes, sometimes, the robot needs to use other agents (e.g., glowing ball which can be controlled by programming) or sensors to achieve the intervention goals. Besides, it is unrealistic that the robot is fully automated which means the robot can adapt to any event during the intervention in unstructured environments. Therefore, in our study, while the robot interacts autonomously with the child, it needs to accept and prioritize the special instruction which given by the supervisor (the therapist, the teacher, or parents). In other words, when the robot's behavior does not correspond to the interactive content, the supervisor should be able to command the robot to adjust its behavior via special instruction. In order to achieve the above targets, we design the social module in the CARAI. The social module includes two submodules: one module is the message handling and the other is message generation. Through the social module, the robot can interact with other agents, devices or supervisors for information and data.

3.3. Intervention Process of the Robot. In this section, we will describe the robot intervention process based on the robotic architecture which is proposed in the previous section.

In the robot-assisted behavioral intervention for children with ASD, the overall process can be divided into two steps. As shown in Figure 7, the first step is to develop intervention plan and the second step is to execute the plan.

The intervention procedure starts with the individual information of the interactive object. Based on the evaluation result, the robot develops an initial scheme. This process is accomplished by the intention module of robotic architecture. The robot updates the intervention plan according to the environmental information along with the interaction.

The execution of the intervention plan includes three parts: real-time evaluation, decision support, and robot execute. Among them, the real-time evaluation is realized by evaluation module of the robotic architecture. The decision support function of the robot is achieved by task planning module of the robotic architecture. The function of robot execution belongs to the basic planning of robots which can be realized by action module of robotic architecture. At this stage, the robot converts the decision result into the sequence of instructions which can be executed directly, including the angle of the robot joints, voice, and LEDs control.

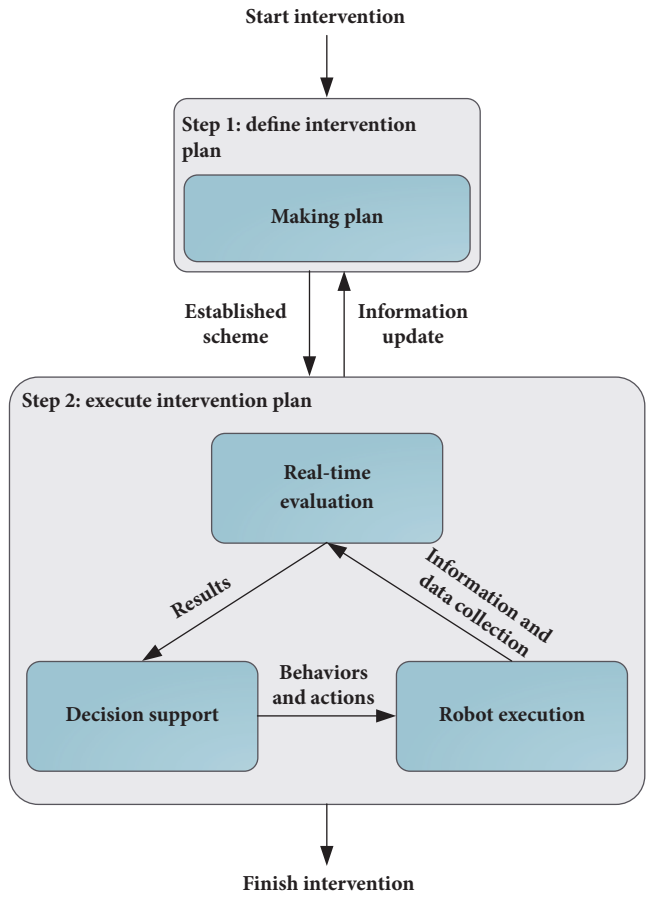


Figure 7: Steps of robot-assist behavioral intervention.

4. Experimental Scenarios

4.1. The Robot Platform. We prepared the robot platform NAO to support our study, as shown in Figure 8. The NAO robot is a humanoid robot, it has an appealing appearance and is easy to be accepted by children. In previous studies, the NAO robot has been successfully applied to training tasks for children with ASD and achieved ideal results [25–28]. With the height of 574 mm and the weight of 5.4 kg, the NAO robot integrates various sensors (i.e., video cameras, microphones, inertial unit, tactile sensors, and joint position sensors) and actuators (i.e., loudspeakers, joint motors, and LEDs). Therefore, the NAO robot can collect environmental information and interact with people conveniently. The supported programming languages of the NAO robot include Python, C++, Java, and JavaScript. Based on this, we can be flexible for program development. In the experiment, we developed the application based on Python SDK of the NAO robot.

4.2. Interaction Session Design. In the study, we designed a scenario where the robot guided the child with ASD to imitate

Table 2: Overview and explanation of the basic event.

Phase	Basic event	Explanation
Initialization	Detect child	The robot detects the child and adjusts its position and poses for the child
	Identify child	The robot identifies the child and loads the data, including name, gender, stage of development, preference, etc.
	Greet child	The robot greets the child with body movement and speech
Arousing child's interest	Play audio	The robot plays music or other sounds, such as birds singing
	Dancing	The robot performs the dance
	Dialogue	The robot tries to talk to the child
	Body movement	The robot swings its limbs and head
	Facial expression	The robot attracts the child through changes in the eyes' LEDs
Training	Introduce training	The robot gives an explanation of what will to be done
	Correct mistake	If the child makes a wrong action, the robot will point out the mistake and ask the child to do it again. If the child fails three times, this action will be abandoned
	Pause session	The robot makes a short break for the child
	Claim attention	If the child is distracted, the robot reminds him to focus attention
	Guidance	The robot guides the child to imitate its action by language. For example, the robot says, "raise your right hand."
	Adjust the degree of tasks	When the child imitates correctly or mistakenly three times, the robot will adjust the difficulty level of the next action
	Encourage the child	When the child completes the task correctly, the robot praises him; when the child completes the task incorrectly, the robot encourages him
Finishing session	Say goodbye	The robot says goodbye to the child
	Update file	The robot updates the child's information and stores them in the database

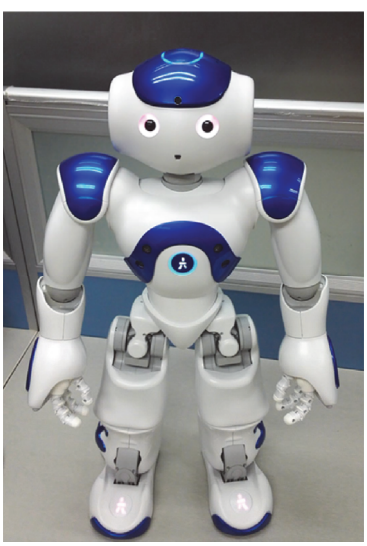


Figure 8: The NAO robot.

its action in the session. The training session was divided into four phases: initialization, arousing child's interest, training, and finishing session. In Figure 9, the rectangular box is used to represent each phase, where the basic events are indicated in a brace. The explanations of basic events are shown in Table 2.

4.3. Results. A 4-year-old boy and a 6-year-old girl were invited to participate in our study, which were supported by their parents. Figures 10 and 12 show sequences of the interaction between the robot and the child A and the child B, respectively. The session was divided into five rounds, and each round lasted 3 minutes. When the robot output the action, it waits for the child to perform the task for 5 seconds. The degree of difficulty of action imitation was divided into 3 training levels, and the reaction of the robot was counted. In each round, the distribution rate of the training levels and the robot's reaction on children's performance are shown in Figures 11 and 13. Figures 11(a) and 13(a) show the proportion of the feedback that the robot outputs when the child performs a task of imitation, including encouragement, praise, and claim attention. Figures 11(b) and 13(b) show the proportion of three different difficult movements output by the robot in each round. These percentages are obtained by dividing the number of corresponding items by the total number.

Figure 11 shows the distribution of training levels and robot's feedback when the robot interacted with the child A. For the training levels, the difficulty of the robot's action increases gradually from level 1 to level 3. According to Figure 11, different legends are used to distinguish the distribution of the robot's feedback and training levels in each round. In round 1, the robot asked the child to imitate the actions with a higher proportion (64.3%) of level 1, and the feedback of the robot consisted of encouragement (38.3%), praise (43.2%), and claim attention (18.5%). In round 2,

Table 3: The times of the supervisor intervenes during interaction.

Event	Content				
Rounds	Round 1	Round 2	Round 3	Round 4	Round 5
Total A	25	26	24	25	25
Times A	2	3	4	3	4
Total B	26	24	24	24	25
Times B	3	4	3	5	3

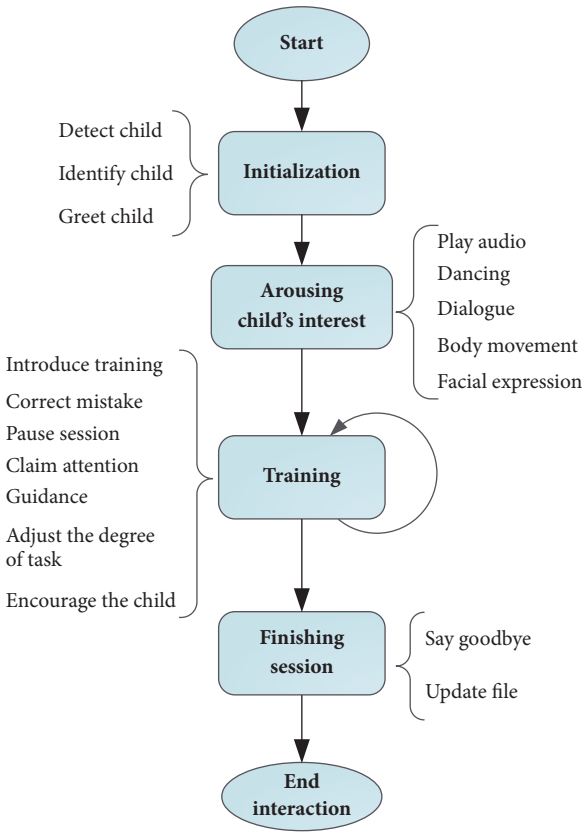


Figure 9: Phases of the interaction session.

the difficulty in training level was improved. According to Figure 11(b), the proportion of training of level 1 decreased while the proportion of training of level 2 and level 3 increased. In this round, more praises (57.5%) were given by the robot. With the child skilled in the task, the robot guided the child more to imitate actions of level 3 in round 3. However, in this round, the child did not perform well, so the robot gave more reaction of encouragement, and the robot reduced the difficulty of training level in round 4. In round 5, the child was tired of the imitation task, and the robot had to spend more time asking the child to keep his attention.

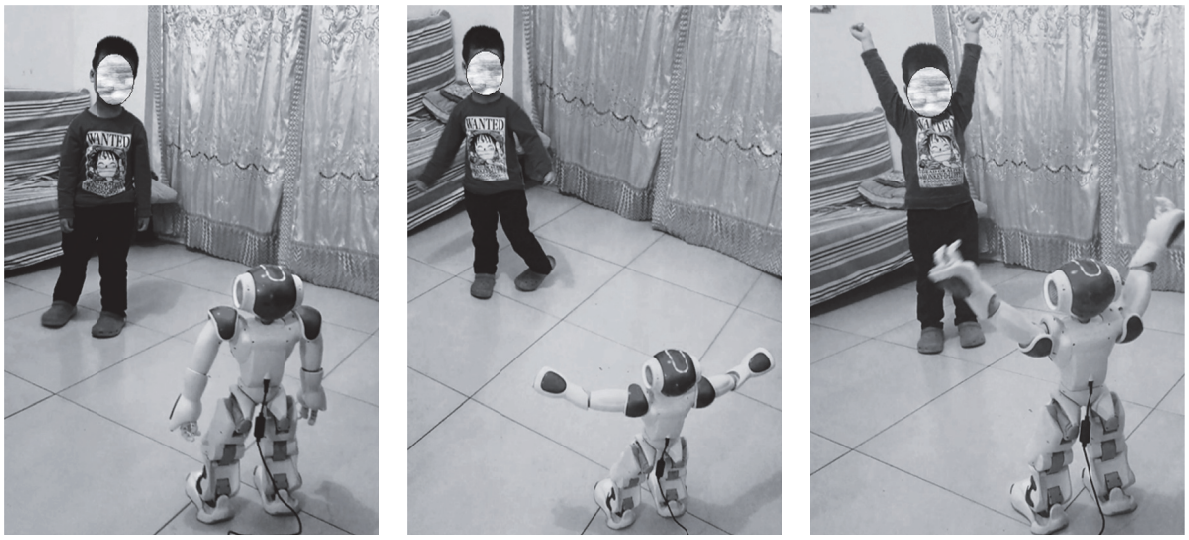
Similar to Figure 11, Figure 13 shows the distribution of training levels and robot's feedback when the robot interacted with the child B. Compared with the child A, the child B has the stronger ability of imitation. Therefore, the robot performed higher-level actions during the interaction. As shown in Figure 13(b), the proportion of training of level 2 and level 3 steadily increased, while the proportion of training of level 1 was decreased from round 1 to round 5. However, during the interaction, the child B showed the state of inattention. Therefore, compared with the interaction with the child A, the robot's feedback showed a higher proportion of claim attention (as shown in Figure 13(a)).

In the experiment, the robot can adjust its action according to the change of interaction environment and quickly meet the individual needs of the interactive object under the guidance of the supervisor. Sometimes, the robot's perception and cognition of the environment were not accurate, and the robot's behavior output was not reasonable. At this time, it is necessary for the supervisor to intervene in the interactive process to ensure the smooth progress of the task. This process is implemented through social module of the control architecture. The Table 3 shows how many times the supervisor gives the suggestion to the robot during interaction.

As shown in Table 3, total A represents the total number of imitative actions that the robot outputs in each round when it interacts with child A. Times A indicates that when the robot interacts with the child A, the number of the supervisor gives advice. Total B and times B indicate the same meaning when the robot interacts with the child B. During the interaction, when the supervisor thinks the robot's decision is inappropriate, he will intervene in the robot's decision through language. The robot adjusts its output through its decision-making algorithm (based on interactive reinforcement learning). In the experiment, the overall rate of intervention of the supervisor on the decision-making of the robot is about 14%. Through analysis, it is found that the error rate of the robot feedback evaluation to children is the main factor that influences the robot to make inappropriate decisions. Therefore, in the future research, the supervisor's intervention in the robot-child interaction process can be reduced by improving the robustness of the related algorithm.

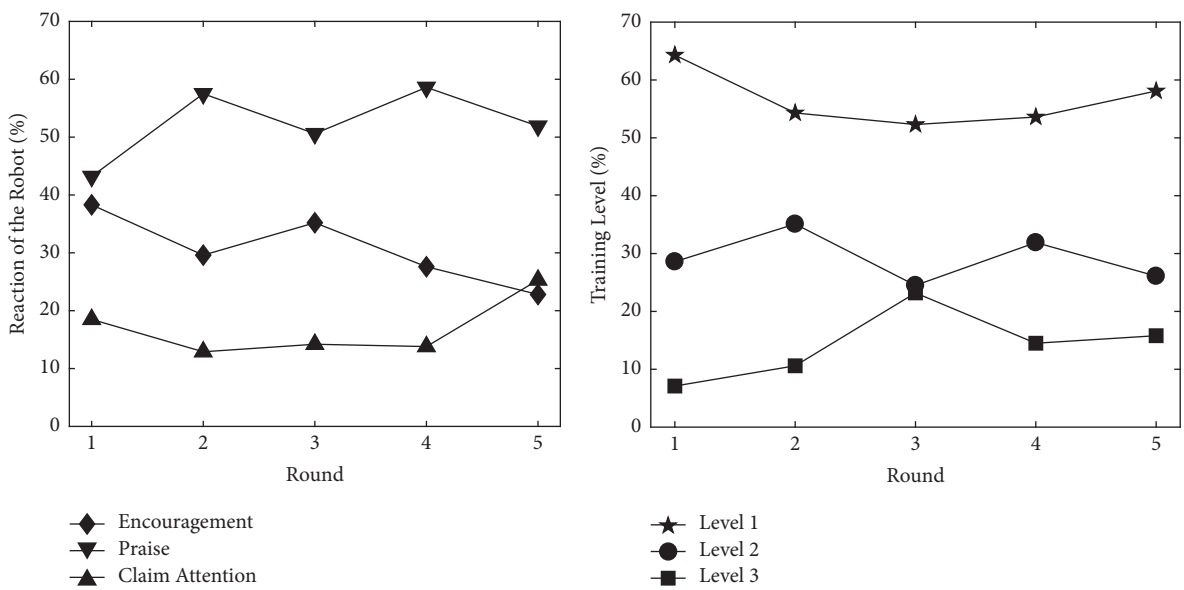
5. Conclusion

Robot-assisted intervention is an effective way to facilitate social skills for children with ASD. In this study, we proposed a control architecture to improve the autonomy of the robot, when the robot is used in the intervention of children with ASD. Following the perception-cognition-action model, the architecture is designed based on some ideas of traditional intervention (DTT and DIR/Floortime) and ACT-R. In the paper, the operating mechanism and some algorithms of the proposed architecture are described in detail. Finally, through



(a) (b) (c)

Figure 10: The robot is interacting with the child A.



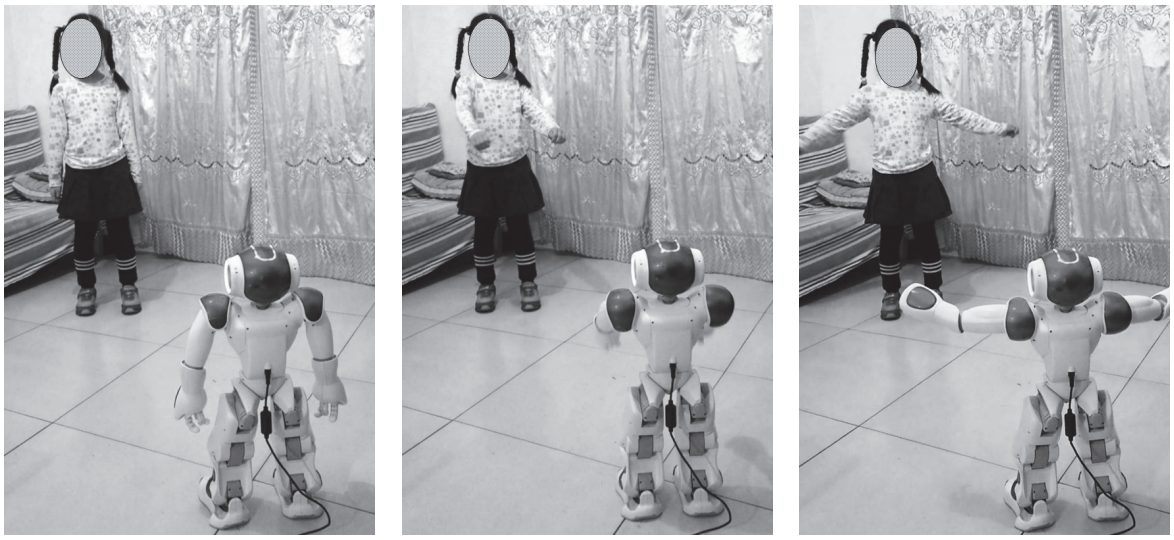
(a) (b)

Figure 11: The distribution rate of training levels and the robot's feedback for the child A in the session.

experimental verification, the proposed control architecture can improve the autonomy of the robot in the intervention of children with ASD and reduce the burden on supervisors.

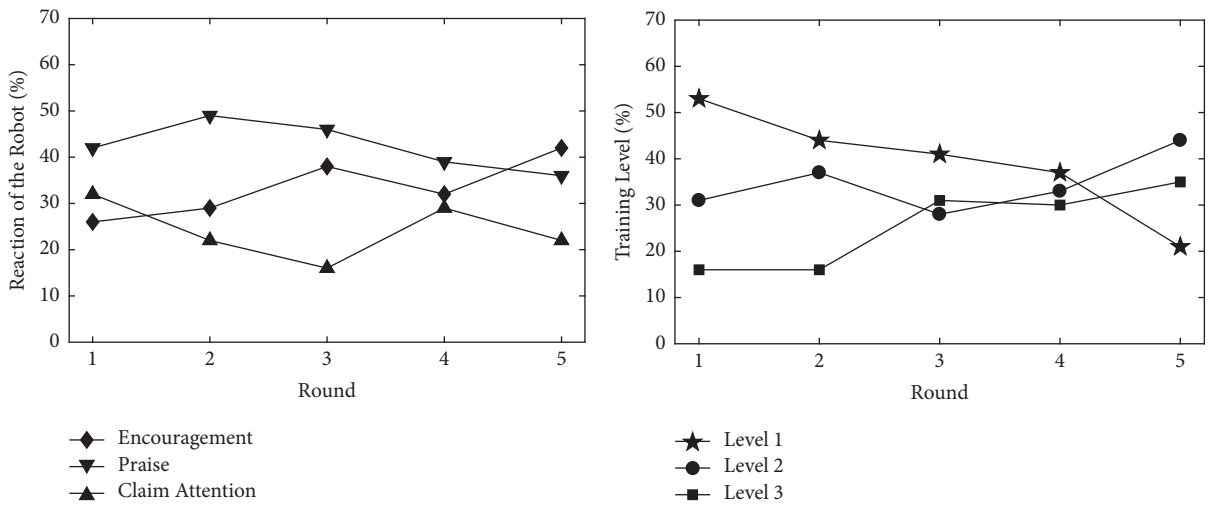
It should be noted that some limitations of this study still exist. For example, two children participated in the validation in this study. However, children with ASD have large individual differences and there are many situations in the intervention sessions. Therefore, more participants are needed to verify the advantages and disadvantages of the architecture. In addition, only one robot platform (NAO robot) was used in our study, and the application of some algorithms was limited. Moreover, the tasks of robot intervention for children with ASD need to be further enriched.

In a near future, we are planning to work in three aspects: (1) according to the characteristics of interactive objects, the collection, analysis, and interpretation of sensory information are carried out and improve the robustness of the robot by perfecting existing algorithms; (2) we will design interactive tasks which suitable for robot expression based on experience of traditional intervention; (3) we will expand the scope of clinical application, which can help us improve the study and make our study more meaningful.



(a) (b) (c)

Figure 12: The robot is interacting with the child B.



(a) (b)

Figure 13: The distribution rate of training levels and the robot's feedback for the child B in the session.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The research presented in this paper is supported in part by the National Natural Science Foundation of China (61573066 and 61327806).

References

[1] J.-J. Cabibihan, H. Javed, M. Ang Jr., and S. M. Aljunied, "Why Robots? A Survey on the Roles and Benefits of Social Robots in the Therapy of Children with Autism," *International Journal of Social Robotics*, vol. 5, no. 4, pp. 593–618, 2013.

[2] B. Ingersoll, "Brief report: Effect of a focused imitation intervention on social functioning in children with autism," *Journal of Autism and Developmental Disorders*, vol. 42, no. 8, pp. 1768–1773, 2012.

[3] S. Boucenna, A. Narzisi, E. Tilmont et al., "Interactive Technologies for Autistic Children: A Review," *Cognitive Computation*, vol. 6, no. 4, pp. 722–740, 2014.

[4] L. Escobedo, C. Ibarra, J. Hernandez, M. Alvelais, and M. Tentori, "Smart objects to support the discrimination training of children with autism," *Personal and Ubiquitous Computing*, vol. 18, no. 6, pp. 1485–1497, 2014.

[5] A. Peca, M. Coeckelbergh, R. Simut et al., "Robot Enhanced Therapy for Children with Autism Disorders: Measuring Ethical

Acceptability," *IEEE Technology and Society Magazine*, vol. 35, no. 2, pp. 54–66, 2016.

[6] C. A. G. J. Huijnen, M. A. S. Lexis, and L. P. de Witte, "Matching Robot KASPAR to Autism Spectrum Disorder (ASD) Therapy and Educational Goals," *International Journal of Social Robotics*, vol. 8, no. 4, pp. 445–455, 2016.

[7] P. Pennisi, A. Tonacci, G. Tartarisco et al., "Autism and social robotics: A systematic review," *Autism Research*, vol. 9, no. 2, pp. 165–183, 2016.

[8] B. Scassellati, H. Admoni, and M. Matarić, "Robots for use in autism research," *Annual Review of Biomedical Engineering*, vol. 14, no. 1, pp. 275–294, 2012.

[9] R. P. Hastings, "Behavioral adjustment of siblings of children with autism engaged in applied behavior analysis early intervention programs: The moderating role of social support," *Journal of Autism and Developmental Disorders*, vol. 33, no. 2, pp. 141–150, 2003.

[10] J. Virués-Ortega, "Applied behavior analytic intervention for autism in early childhood: meta-analysis, meta-regression and dose-response meta-analysis of multiple outcomes," *Clinical Psychology Review*, vol. 30, no. 4, pp. 387–399, 2010.

[11] M. W. Steege, F. Charles Mace, L. Perry, and H. Longenecker, "Applied behavior analysis: Beyond discrete trial teaching," *Psychology in the Schools*, vol. 44, no. 1, pp. 91–99, 2007.

[12] S. I. Greenspan and S. Wieder, "A Functional Developmental Approach to Autism Spectrum Disorders," *Research and Practice for Persons with Severe Disabilities*, vol. 24, no. 3, pp. 147–161, 1999.

[13] C. M. Corsello, "Early intervention in autism," *Infants & Young Children*, vol. 18, no. 2, pp. 74–85, 2005.

[14] S.-T. Liao, Y.-S. Hwang, Y.-J. Chen, P. Lee, S.-J. Chen, and L.-Y. Lin, "Home-based DIR/Floortime™ intervention program for preschool children with autism spectrum disorders: Preliminary findings," *Physical & Occupational Therapy in Geriatrics*, vol. 34, no. 4, pp. 356–367, 2014.

[15] S. Thill, C. A. Pop, T. Belpaeme, T. Ziemke, and B. Vanderborght, "Robot-Assisted Therapy for Autism Spectrum Disorders with (Partially) Autonomous Control: Challenges and Outlook," *Paladyn, Journal of Behavioral Robotics*, vol. 3, no. 4, pp. 209–217, 2012.

[16] D. Feil-Seifer and M. J. Matarić, "B3IA: A control architecture for autonomous robot-assisted behavior intervention for children with autism spectrum disorders," in *Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN*, pp. 328–333, deu, August 2008.

[17] J. Wainer, B. Robins, F. Amirabdollahian, and K. Dautenhahn, "Using the humanoid robot KASPAR to autonomously play triadic games and facilitate collaborative play among children with autism," *IEEE Transactions on Autonomous Mental Development*, vol. 6, no. 3, pp. 183–199, 2014.

[18] S.-S. Yun, H. Kim, J. Choi, and S.-K. Park, "A robot-assisted behavioral intervention system for children with autism spectrum disorders," *Robotics and Autonomous Systems*, vol. 76, pp. 58–67, 2016.

[19] J. C. González, J. C. Pulido, and F. Fernández, "A three-layer planning architecture for the autonomous control of rehabilitation therapies based on social robots," *Cognitive Systems Research*, vol. 43, pp. 232–249, 2017.

[20] A. Ghorbandaei Pour, A. Taheri, M. Alemi, and A. Meghdari, "Human–Robot Facial Expression Reciprocal Interaction Platform: Case Studies on Children with Autism," *International Journal of Social Robotics*, vol. 10, no. 2, pp. 179–198, 2018.

[21] M. Salvador, A. S. Marsh, A. Gutierrez, and M. H. Mahoor, "Development of an ABA Autism Intervention Delivered by a Humanoid Robot," in *Proceedings of the International Conference on Social Robotics*, vol. 9979, pp. 551–560, Springer International Publishing.

[22] G. Trafton, L. Hiatt, A. Harrison, F. Tanborello, S. Khemlani, and A. Schultz, "ACT-R/E: an embodied cognitive architecture for human-robot interaction," *Journal of Human-Robot Interaction*, vol. 2, no. 1, pp. 30–55, 2013.

[23] Y. Feng, Q. Jia, M. Chu, and W. Wei, "Engagement Evaluation for Autism Intervention by Robots Based on Dynamic Bayesian Network and Expert Elicitation," *IEEE Access*, vol. 5, pp. 19494–19504, 2017.

[24] P. G. Esteban, P. Baxter, T. Belpaeme et al., "How to Build a Supervised Autonomous System for Robot-Enhanced Therapy for Children with Autism Spectrum Disorder," *Paladyn, Journal of Behavioral Robotics*, vol. 8, no. 1, pp. 18–38, 2017.

[25] S. Shamsuddin, H. Yussof, L. I. Ismail, S. Mohamed, F. A. Hanapiah, and N. I. Zahari, "Humanoid robot NAO interacting with autistic children of moderately impaired intelligence to augment communication skills," *Procedia Engineering*, vol. 41, no. 2012, pp. 1533–1538, 2012.

[26] L. I. Ismail, S. Shamsudin, H. Yussof, F. A. Hanapiah, and N. I. Zahari, "Robot-based Intervention Program for autistic children with Humanoid Robot NAO: Initial response in stereotyped behavior," *Procedia Engineering*, vol. 41, no. 41, pp. 1441–1447, 2012.

[27] A. Tapus, A. Peca, A. Aly et al., "Children with autism social engagement in interaction with Nao, an imitative robot: A series of single case experiments," *Interaction Studies*, vol. 13, no. 3, pp. 315–347, 2012.

[28] M. A. Miskam, M. A. C. Hamid, H. Yussof, S. Shamsuddin, N. A. Malik, and S. N. Basir, "Study on social interaction between children with autism and humanoid robot NAO," *Applied Mechanics and Materials*, vol. 393, pp. 573–578, 2013.

Hindawi
Journal of Robotics
Volume 2018, Article ID 1754657, 20 pages
https://doi.org/10.1155/2018/1754657

Research Article

Hobbit: Providing Fall Detection and Prevention for the Elderly in the Real World

Markus Bajones,[1] David Fischinger,[1] Astrid Weiss,[1] Daniel Wolf,[1] Markus Vincze,[1] Paloma de la Puente,[2] Tobias Körtner,[3] Markus Weninger,[3] Konstantinos Papoutsakis,[4] Damien Michel,[4] Ammar Qammaz,[4] Paschalis Panteleris,[4] Michalis Foukarakis,[4] Ilia Adami,[4] Danai Ioannidi,[4] Asterios Leonidis,[4] Margherita Antona,[4] Antonis Argyros,[4] Peter Mayer,[5] Paul Panek,[5] Håkan Eftring,[6] and Susanne Frennert[6]

[1]*Automation and Control Institute (ACIN), TU Wien, Vienna, Austria*
[2]*Universidad Politécnica de Madrid, Madrid, Spain*
[3]*Akademie für Altersforschung am Haus der Barmherzigkeit, Vienna, Austria*
[4]*Institute of Computer Science, FORTH, Heraklion, Greece*
[5]*Institute for Design and Assessment of Technology, TU Wien, Vienna, Austria*
[6]*Department of Design Sciences, Lund University, Lund, Sweden*

Correspondence should be addressed to Markus Bajones; markus.bajones@tuwien.ac.at

Received 10 November 2017; Revised 13 February 2018; Accepted 19 March 2018; Published 3 June 2018

Academic Editor: Brady King

We present the robot developed within the Hobbit project, a socially assistive service robot aiming at the challenge of enabling prolonged independent living of elderly people in their own homes. We present the second prototype (Hobbit PT2) in terms of hardware and functionality improvements following first user studies. Our main contribution lies within the description of all components developed within the Hobbit project, leading to autonomous operation of 371 days during field trials in Austria, Greece, and Sweden. In these field trials, we studied how 18 elderly users (aged 75 years and older) lived with the autonomously interacting service robot over multiple weeks. To the best of our knowledge, this is the first time a multifunctional, low-cost service robot equipped with a manipulator was studied and evaluated for several weeks under real-world conditions. We show that Hobbit's adaptive approach towards the user increasingly eased the interaction between the users and Hobbit. We provide lessons learned regarding the need for adaptive behavior coordination, support during emergency situations, and clear communication of robotic actions and their consequences for fellow researchers who are developing an autonomous, low-cost service robot designed to interact with their users in domestic contexts. Our trials show the necessity to move out into actual user homes, as only there can we encounter issues such as misinterpretation of actions during unscripted human-robot interaction.

1. Introduction

While socially assistive robots are considered to be potentially useful for society, they can provide the highest value to older adults and homebound people. As reported in [1], future robot companions are expected to be

(1) strong machines that can take over burdensome tasks for the user,

(2) graceful and soft machines that will move smoothly and express immediate responses to their users,

(3) sentient machines that offer multimodal communication channels and are context-aware and trustable.

More and more companies and research teams present service robots with the aim of assisting older adults (e.g., Giraff (http://www.giraff.org), Care-O-Bot (http://www.care-o-bot.de), and Kompai (https://kompai.com)) with services such as entertainment, medicine reminders, and video telephony. Requirement studies on needs and expectations of older adults towards socially assistive robots [2] indicate that they expect them to help with household chores (e.g.,

cleaning the kitchen, bath, and toilet), lifting heavy objects, reaching for and picking up objects, delivering objects, and so forth. However, most of these tasks cannot satisfyingly be performed by state-of-the-art robotic platforms; hardly any companion robot fulfills the requirements mentioned above and only very few robots entered private homes of older adults so far. One of the biggest challenges is offering sufficient useful and social functionalities in an autonomous and safe manner to achieve the ultimate goal of prolonging independent living at home. The ability of a robot to interact autonomously with a human requires sophisticated cognitive abilities including perception, navigation, decision-making, and learning. However, research on planners and cognitive architectures still faces the challenge of enabling flexibility and adaptation towards different users, situations, and environments while simultaneously being safe and robust. To our conviction, for successful long-term human-robot interaction with people in their private homes, robotic behavior needs to be above all safe, stable, and predictable. During our field trials, this became increasingly evident, as the users failed to understand the robot's behavior during some interaction scenarios.

In this article, we present the Hobbit PT2 platform, referred to in the remainder of this article as Hobbit. A former version of Hobbit has been presented in detail in [3]. Hobbit is a socially assistive robot that offers useful personal and social functionalities to enable independent living at home for seniors. To the best of our knowledge, the Hobbit trials mark the first time a social service robot offering multifunctional services was placed in users' homes, operated autonomously and whose usage was not restricted by a schedule or any other means. The main contribution of this paper is twofold. First, we give a description of the hardware that is based on improvements derived from the first user trials on the previous version of Hobbit. Second, we describe the implemented functionality and its integration into the behavior coordination system. The building blocks of the behavior coordination system are based on a set of hierarchical state-machines implemented using the SMACH framework [4]. Each behavior was built upon simpler building blocks, each responsible for one specific task (e.g., speech and text output, arm movements, and navigation) to add up to the complex functionalities presented in Sections 3.3 and 4. Finally, we present the lessons learned from the field trials in order to support fellow researchers in their developments of autonomous service robots for the domestic environment. We evaluated Hobbit during 371 days of field trials with five platforms with older adults in their private homes in Austria, Greece, and Sweden. However, details on the field trials will be published elsewhere.

The paper proceeds as follows. Section 2 reflects on relevant related work on behavior coordination for social service robots and on studies of such robots outside of the laboratory environment. In Section 3, we give an overview on the project vision for Hobbit and its historical development up to the Hobbit PT2 platform, followed by a detailed description of its hardware and interaction modalities. Section 4 presents the behavior coordination system. We outline how we developed the interaction scenarios and transferred them into an implementable behavior concept. Section 5 presents an overview on the field trials. Lessons learned from the development and testing of Hobbit and a summary and conclusions are provided in Sections 6 and 7.

2. Related Work

Moving towards autonomous service robots, behavior coordination systems constitute an important building block to fulfill the requirements of action planning, safe task execution, and integration of human-robot interaction. HAMMER from Demiris and Khadhouri [5] is built upon the concept of using multiple forward/backward control loops, which can be used to predict the outcome of an action and compare this against the actual result of the action. Through this design, it is possible to choose the action with the highest probability of reaching the desired outcome, which has successfully been used in a collaboratively controlled wheelchair system [6], in order to correct the user's input to avoid an erroneous situation. Cashmore et al. [7] introduced ROSPlan, a framework that uses a temporal planning strategy for planning and dispatching robotic actions. Depending on the needs, a cost function can be optimized for planning in a certain manner (e.g., time- or energy-optimized). However, the constructed plan is up until now only available as a sequence of executed actions and observed events, but no direct focus is put on the human, besides modeling the user as means to acquire some event (e.g., moving an object from one location to another). Mansouri and Pecora [8] incorporate temporal and spatial reasoning in a robot tasked with pick and place in environments suited for users. In the context of ALIAS, Goetze et al. [9] designed their *dialogue manager* for the tasks of emergency call, a game, e-ticket event booking, and the navigation as state-machines. However, there are still significant research challenges regarding how to incorporate humans into the planning stages and decide when the robot needs to adapt to the user instead of staying with the planned task.

Most of those behavior coordination and planning systems treat the human as an essential part of the system [6] (e.g., for command input) and rely on the user to execute actions planned by the coordination system [10]. Such systems only work under the precondition that the robot will execute a given task for the user independently of the user input [8]. A crucial aspect, however, to successfully integrate a multifunctional service robot into a domestic environment is that it needs not only to react to user commands but also to proactively offer interaction and adapt to user needs (e.g., the user wanting a break from the robot or a proactive suggestion for an activity they could perform together). Our proposed solution is based on state-machines, which reflect turn-taking in the interaction, providing adaptations within certain states (e.g., voice dialogues) or situations (e.g., user approach). We integrated the possibility not only to handle robot-driven actions on a purely scheduled basis but also to adapt this scheduling and actions based on the user's commands.

2.1. State of the Art: Robotic Platforms. According to a study conducted by Georgia Tech's Healthcare Robotics Lab, people

with motor impairment drop items on average 5.5 times a day. Their small tele-operated Dusty (http://pwp.gatech.edu/hrl/project_dusty/) robots are developed for that purpose: picking up objects from the floor, which they achieve with a scoop-like manipulator. Cody, a robotic nurse assistant, can autonomously perform bed (sponge) baths. Current work focuses on GATSBII (http://www.robotics.gatech.edu), a willow Garage PR2, as a generic aid for older adults at home. The Care-O-Bot research platforms developed at the Fraunhofer Institute (IPA) are designed as general purpose robotic butlers, with a repertoire from fetching items to detecting emergency situations, such as a fallen person. Also from Fraunhofer is Mobina (https://www.ipa.fraunhofer.de/de/referenzprojekte/MobiNa.html), a small (vacuum-sized) robot specifically performing fallen person detection and video calls in emergency. Carnegie Mellon University's HERB (https://personalrobotics.ri.cmu.edu/) is another general-purpose robotic butler. It serves as the main research platform at the Personal Robotics Lab, which is part of the Quality of Life Technology (QoLT) Center. KAIST in Korea has been developing their Intelligent Sweet Home (ISH) smart home technology including intelligent wheelchairs, intelligent beds, and robotic hoists [11]. Their system also employs the bimanual mobile robot Joy to act as an intermediary between these systems and the end user. Robotdalen (http://www.robotdalen.se), a Swedish public-private consortium, has funded the development of needed robotic products such as Bestic (http://www.camanio.com/en/products/bestic/), an eating device for those who cannot feed themselves; Giraff, a remote-controlled mobile robot with a camera and monitor providing remote assistance and security; or TrainiTest, a rehabilitation robot that measures and evaluates the capacity of muscles and then sets the resistance in the robot to adapt to the users' individual training needs. Remote presence robots have recently turned up in a variety of forms, from simple Skype video chats on a mobility platform (Double Robotics (https://www.doublerobotics.com/)) to serious medical assistance remote presence robots such as those provided by the partnership between iRobot and InTouch Health (https://www.intouchhealth.com/about/press-room/2012/InTouch-Health-and-iRobot-to-Unveil-the-RP-VITA-Telemedicine-Robot.html), Giraff, and VGo Communications' postop pediatric at-home robots (http://www.vgocom.com/) for communication with parents, nurses, doctors, and patients.

Another class of robots aims more specifically at well-being of older adults. The recently completed FP7 project M obiserv (https://cordis.europa.eu/project/rcn/93537_en.html) aimed to develop solutions to support independent living of older adults as long as possible, in their home or in various degrees of institutionalization, with a focus on health, nutrition, well-being, and safety. These solutions encompass smart clothes for monitoring vital signs, a smart home environment to monitor behavioral patterns (e.g., eating) and detect dangerous events, and a companion robot. The robot's main role is to generally activate, stimulate, and offer structure during the day. It also reminds its user of meals, medication, and appointments and encourages social contacts via video calls. The US NSF is currently running the Socially Assistive Robotics project (https://www.nsf.gov/awardsearch/showAward?AWD_ID=1139078) with partners Yale, University of Southern California, MIT, Stanford, Tufts, and Willow Garage. Their focus is on robots that encourage social, emotional, and cognitive growth in children, including those with social or cognitive deficits. The elder care robot Sil-Bot (http://www.roboticstoday.com/robots/sil-bot) developed at the Center for Intelligent Robotics (CIR) in Korea is devised mainly as an entertainment robot to offer interactive games that have been codeveloped with Seoul National University Medical Center specifically to help prevent Alzheimer's disease and dementia. Sil-Bot is meant to be a companion that helps encourage an active, healthy body and mind. Its short flipper-like arms do not allow for actual manipulation. Another public-private partnership is the EC-funded CompanionAble project (http://www.companionable.net/), which created a robotic assistant for the elderly called Hector. The project integrates Hector to work collaboratively with a smart home and remote control center to provide the most comprehensive and cost-efficient support for older people living at home.

Hoaloha Robotics (http://www.hoaloharobotics.com/) in the United States are planning to bring their elder care robot to market soon. Based on a fairly standard mobile platform offering safety and entertainment, they focus on an application framework that will provide integration of discrete technological solutions like biometric devices, remote doctor visits, monitoring and emergency call services, medication dispensers, online services, and the increasing number of other products and applications already emerging for the assistive care market. Japan started a national initiative in 2013 to foster development of nursing care robots and to spread their use. The program supports 24 companies in developing and marketing their elderly care technologies, such as the 40 cm tall PALRO conversation robot (https://palro.jp/) that offers recreation services by playing games, singing, and dancing together with residents of a care facility. Another example is the helper robot by Toyota, which is mostly remotely controlled from a tablet PC. Going specifically beyond entertainment capabilities, Waseda University's Twendy One (http://www.twendyone.com) is a sophisticated bimanual robot that provides human safety assistance, dexterous manipulation, and human-friendly communication. It can also support a human to lift themselves from a bed or chair. Going even further, the RIBA-II robot (http://rtc.nagoya.riken.jp/RIBA/index-e.html) by RIKEN-TRI Collaboration Center for Human-Interactive Robot Research (RTC) can lift patients of up to 80 kg from a bed to a wheelchair and back. The Pepper robot (https://www.ald.softbankrobotics.com/en/robots/pepper) from Softbank Robotics (Aldebaran) is used in a growing number of projects focusing on human-robot interaction scenarios. Some ADL (activities of daily living) tasks are directly addressed by walking aids, for example [12], and cognitive manipulation training, for example, using exoskeletons [13, 14].

The short overview indicates that individually many ADL tasks are approached. However, they all require different types

of robots. The goal of grasping objects from the floor, while at the same time keeping the robot affordable, has led us to design and build the custom Hobbit platform. Moreover, the robot should offer everyday life suitable tasks in a socially interactive manner to be sustainably used by the older adults.

3. The Hobbit Robot

Hobbit is able to provide a number of safety and entertainment functions with low-cost components. The ability to provide many functions with sometimes contradictory requirements for the hardware design creates a demanding challenge on its own. To the best of our knowledge, we are the first to present a robot that operates in users' homes in a fully autonomous fashion for a duration of 21 days per user, while providing an extensive set of functionalities like manipulation of objects with an included arm.

3.1. General Vision. The motivation for Hobbit's development was to create a low-cost, social robot to enable older adults to independently live longer in their own homes. One reason for the elderly to move into care facilities is the risk of falling and eventually inflicted injuries. To reduce this risk, the "must-haves" for the Hobbit robot are *emergency detection* (the robot patrolling autonomously through the flat after three hours without any user activity and checking if the user is well and did not suffer a fall), *emergency handling* (automatic calls to relatives or emergency services), and *fall prevention* (searching and bringing known objects to the user and picking up objects from the floor pointed to by the user and a basic fitness program to enhance the user's overall fitness). Hobbit also provides a *safety check* feature that informs the user about possible risks in specific rooms (e.g., wet floor in the bathroom and slippery carpets on wooden floors) and explains how to reduce such risks.

In science fiction, social robots are often depicted as a butler, a fact that guides the expectations towards such robots. However, as state-of-the-art technology is not yet able to fulfill these expectations, Hobbit was designed to incorporate the Mutual Care interaction paradigm [15] to overcome the robot's downfalls by creating an emotional bond between the users and the robot. The *Mutual Care* concept envisioned that the user and the robot provide help in a reciprocal manner to each other, therefore creating an emotional bond between them, so that the robot not only provides useful assistance but also acts as a companion. The resulting system complexity based on the multifunctionality was considered as acceptable to fulfill the main criteria (*emergency detection and handling*, *fall prevention*, and *providing a feeling of safety*).

3.2. Mutual Care as Underlying Interaction Paradigm. The *Mutual Care* concept was implemented through two different social roles, one that enforces this concept and one that does not. Hobbit started in the Mutual Care-disabled mode during the field trials and changed after 11 days to the Mutual Care mode. The differences between these two modes or *social roles* of the robot were mainly in its dialogues, proactivity, and the proximity in which the robot would remain when the user stops interacting with the robot. In more detail, the main characteristics of the *Mutual Care* mode were the following: (1) return of favor: Hobbit asked if it could return the favor after situations where the user had helped Hobbit to carry out a task, (2) communication style: Hobbit used the user's name in the dialogue and was more human-like such as responding to a reward from the user by saying *You are welcome* instead of *Reward has been received*, (3) proactivity: Hobbit was more proactive and initiated interactions with the user, and (4) presence: Hobbit stayed in the room where the last interaction has taken place for at least 30 minutes instead of heading directly back to the charging station. In order to avoid potential biases, users were not told about the behavioral change of the robot beforehand.

3.3. Development Steps Leading to Hobbit. To gain insight into the needs of elderly living alone, we invited primary users (PU), aged 75 years and older and living alone, and secondary users (SU), who are in regular contact with the primary users, to workshops in Austria (8 PU and 10 SU) and Sweden (25 PU). A questionnaire survey with 113 PU in Austria, Greece, and Sweden and qualitative interviews with 38 PU and 18 SU were conducted. This iterative process [16] not only resulted in the user requirements but also influenced the design and material decisions, which were incorporated into the development of the Hobbit robots as seen in Figure 1. Based on these requirements and laboratory studies with the PT1 platform [17] with 49 users (Austria, Greece, and Sweden), the following main functionalities for Hobbit were selected:

(1) *Call Hobbit*: summon the robot to a position linked to battery-less call buttons

(2) Emergency: call relatives or an ambulance service. This can be triggered by the user from emergency buttons and gesture commands or by the robot during patrolling

(3) *Safety check*: guide the user through a list of common risk sources and provide information on how to reduce them

(4) *Pick up objects*: objects lying on the floor are picked up by the robot with no distinction between known or unknown objects

(5) *Learn and bring objects*: visual learning of user's objects to enable the robot to search and find them within the environment

(6) *Reminders*: deliver reminders for drinking water and appointments directly to the user

(7) *Transport objects*: reduce the physical stress on the user by placing objects on to the robot and letting it transport them to a commanded location

(8) *Go recharging*: autonomously, or by a user command, move to the charging station for recharging

(9) *Break*: put the robot on break when the user leaves the flat or when the user takes a nap

(10) *Fitness*: guided exercises that increase the overall fitness of the user

(a) (b) (c)

Figure 1: (a–c) First mock-ups designed by secondary users: the first (PT1) and second generation of Hobbit as used during the field trials.

(11) *Entertainment*: brain training games, e-books, and music

3.4. Robot Platform and Sensor Setup. The mobile platform of the Hobbit robot has been developed and built by MetraLabs (http://www.metralabs.com). It moves using a two-wheeled differential drive, mounted close to the front side in driving direction. For stability, an additional castor wheel is located close to the back. To fit all the built-in system components, the robot has a rectangular footprint with a width of 48 cm and a length of 55 cm. For safety reasons, a bumper sensor surrounds the base plate, protecting the hull and blocking the motors when being pressed. This ensures that the robot stops immediately if navigation fails and an obstacle is hit. An additional bumper sensor is mounted below the tablet PC, which provides the graphical user interface. During situations in which the user might not be able to reach the tablet PC (e.g. the person has fallen), a hardware emergency button is located on the bottom front side.

On its right side, the robot is equipped with a 6-DoF arm with a two-finger fin-ray gripper, such that objects lying on the floor can be picked up and placed in a tray on top of the robot's body. Furthermore, the arm can grasp a small turntable stored on the right side of the body, which is used to teach the robot unknown objects.

The robot's head, together with the neck joint with motors for pan and tilt movements, has been developed by Blue Danube Robotics (http://www.bluedanuberobotics.com). It contains two speakers for audio output, two Raspberry Pis with one display each for the eyes of the robot, a temperature sensor, and a RGB-D sensor. This sensor, referred to in the remainder of the paper as *head camera*, is used for obstacle avoidance, for object and gesture recognition, and—in conjunction with the temperature sensor—for user and fall detection. Similar to the previous prototype of the robot [3, 18], the visual sensor setup is completed by a second RGB-D sensor, mounted in the robot's body at a height of 35 cm facing forward. This sensor, referred to in the remainder of the paper as *bottom camera*, is used for localization, mapping, and user following. Figure 2 shows an overview of the Hobbit hardware; a more detailed explanation of the single components is given in the following sections.

3.4.1. Visual Perception System Using RGB-D Cameras. For the visual perception system, Hobbit is equipped with two Asus Xtion Pro RGB-D sensors. The head camera is mounted inside the head and used for obstacle avoidance, object learning and recognition, user detection, and gesture recognition and to detect objects to pick up. Since the head can perform pan and tilt movements, the viewing angle of this camera can be dynamically adapted to a particular task at hand. In contrast, the bottom camera, used for localization, mapping, and user following, is mounted at a fixed position at a height of 35 cm in the front of the robot's body, facing forward. This setup is a trade-off between the cost of the sensor setup (in terms of computational power and money) and the necessary data for safe usage and feature completeness, which we found to be most suitable for the variety of different tasks that require visual perception.

The cameras, which only cost a fraction of laser range sensors commonly used for navigation in robotics, offer a resolution of 640 × 480 pixels of RGB-D data and deliver useful data in a range of approximately 50 cm to 400 cm. Therefore, our system has to be able to cope with a blind spot in front of the robot. Furthermore, the quality of data acquired with the head camera from an observed object varies depending on the task. For example, in the learning task, an object that is placed on the robot's turntable is very close to the head camera, just above the lower range limit. In the pickup task, on the contrary, the object detection method needs to be able to detect objects at the upper range limit of the camera, where data points are already severely influenced by noise.

Because two of the main goals for the final system were affordability and robustness, we avoided incorporating additional cameras, for example, for visual servoing with the robot's hand. For further details and advantages of our sensor setup for navigation, we refer the reader to [18].

3.4.2. Head and Neck. Besides the head camera, the head contains an infrared camera for distance temperature measurement, two speakers for audio output, and two Raspberry Pis with displays showing the robot's eyes. Through its eyes,

Figure 2: Hardware setup of the Hobbit platform.

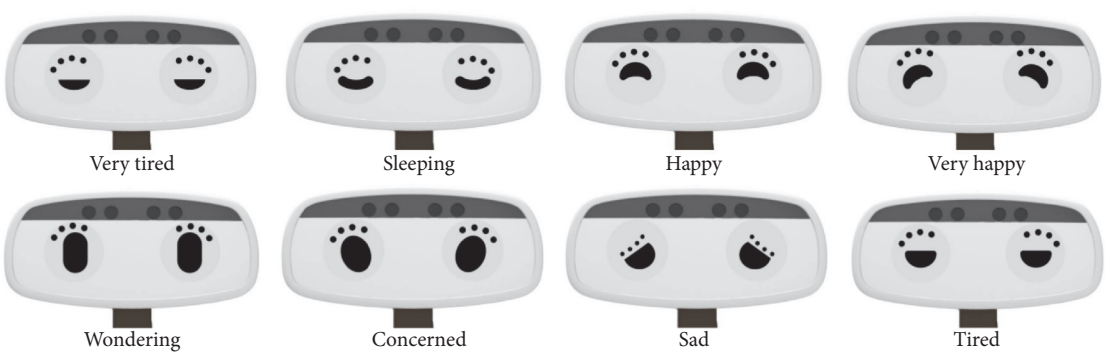


Figure 3: List of emotions shown by Hobbit's eyes.

the robot is able to communicate a set of different emotions to the user, which are shown in Figure 3. The neck joint contains two servo motors, controlling the horizontal and vertical movement of the head.

3.4.3. Arm and Gripper. To be able to pick up objects from the floor or to grab its built-in turntable, Hobbit is equipped with a 6-DoF IGUS arm and a two-finger fin-ray gripper. As a cost-effective solution, the arm joints are moved by stepper motors via Bowden cables; the used fin-ray gripper offers one DoF and is designed to allow form-adaptable grasps. While an additional DoF would increase flexibility and lower the need for accurate self-positioning to successfully grasp objects, for the sake of overall system robustness and low hardware costs, the 6-DoF version was the model of choice for the arm. The arm is not compliant; therefore, cautious behavior implementation with reduced velocities for unsupervised actions was required to minimize the risk of breakage.

4. Behavior Coordination

As Hobbit's goal directly called for an autonomous system running for several weeks, providing interactions on an irregular schedule and on-demand basis, the behavior coordination of the Hobbit robots was designed and implemented in a multistage development process. Based on the workshops with PU and SU and the user study with Hobbit PT1, elderly care specialists designed the specific scenarios. They designed detailed scripts for the 11 scenarios (see Section 3.3) the robot had to perform. Those 11 scenarios were subsequently planned in a flowchart-like fashion, which eased the transition from the design process to the implementation stage.

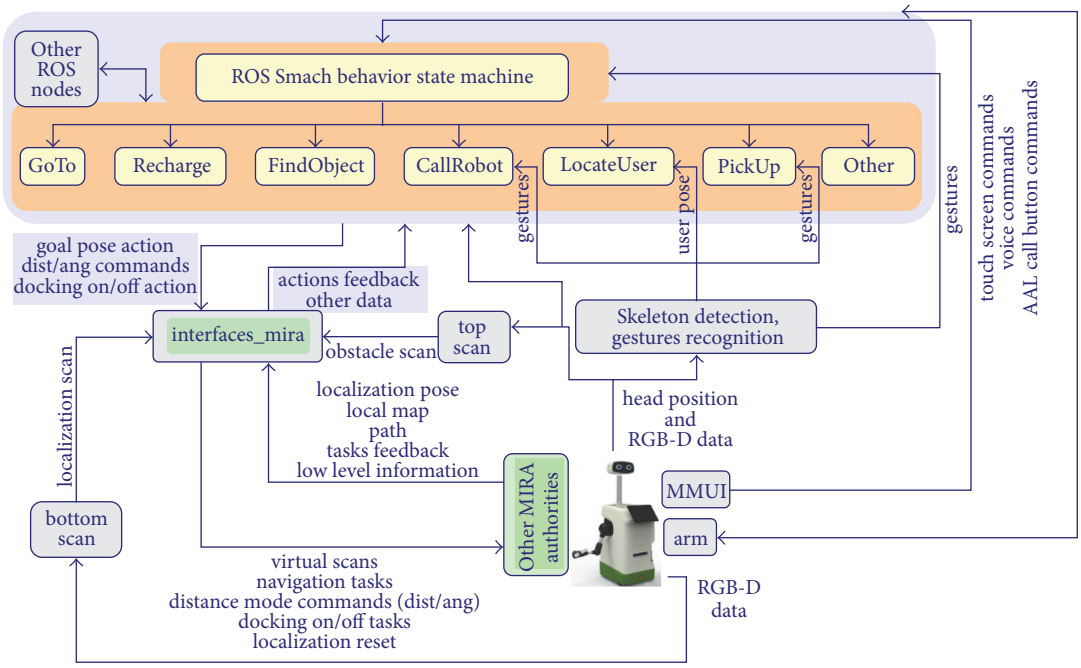


Figure 4: Hobbit behavior architecture.

In the following, we discuss the overall behavior coordination architecture and how the Mutual Care concept was implemented and go into detail of some of the building blocks necessary to construct the 11 scenarios. We further present the methods we developed to realize the goals of the project while respecting the limits set by the low-cost approach of our robots.

4.1. Behavior Coordination Architecture. Following the scenario descriptions, as defined by our specialists in elderly care, their implementation and the execution followed a script-based approach. A state-machine framework, SMACH (http://wiki.ros.org/smach), was therefore chosen to handle the behavior execution for all high-level codes.

An overview of the implemented architecture is shown in Figure 4. The top structure in this architecture is the PuppetMaster, which handles the decision-making outside of any scenario execution, where it can start, preempt, and restart any sub-state-machines. For this, it collects the input from those ROS nodes that handle gesture and speech recognition, text input via touchscreen, emergency detection (fallen and falling person detection, emergency button on the robot itself, and emergency gesture), and scheduled commands that need to be executed at a specific time of the day. The PuppetMaster delegates the actual scenario behavior execution to the sub-state-machines, which only rely on the input data needed for the current scenario. Each of these sub-state-machines corresponds to one of the scenarios designed to assist the users in their daily lives. As we needed to deal with many different commands with different execution priorities, it was necessary to ensure that every part of the execution of the state-machines can safely be interrupted without the risk of lingering in an undefined state. Particularly in situations when the arm of the robot was moving, it was necessary to be able to bring it into a position in which it would be safe to perform other tasks. The movement of the robot within the environment would have been unsafe if the arm would still stick out of the footprint of the robot itself. The priorities of the commands were defined with respect to the safety of the user, so that emergency situations can always preempt a possibly running state-machine, regardless of the state the system is currently in.

4.2. RGB-D Based Navigation in Home Environments. Autonomous navigation in user's homes, especially with low-cost RGB-D sensors, is a challenging aspect of care mobile robots. These RGB-D sensors pose additional challenges for safe navigation [18, 20–22]. The reduced field of view, the blind detection area, and the short maximum range of this kind of sensors provides limited information about the robot's surroundings. If the robot, for example, turns around in a narrow corridor, it might happen that the walls are already too close to be observed while turning, leading to increased localization uncertainty. In order to prevent such cases, we defined *no-go* areas around walls in narrow passages, preventing the robot from navigating too close to walls in the first place. For obstacle avoidance, the head is tilted down during navigation, so that the head camera partially compensates for the blind spot of the bottom camera. If obstacles are detected, they are remembered for a certain time in the robot's local map. However, a suitable trade-off had to be found for the decay rate. On one hand, the robot must be able to avoid persisting obstacles, but, on the other hand, it should not be blocked for too long when an obstacle in front of it (e.g., a walking person) is removed.

While localization methods generally assume that features of the environment can be detected, this assumption

Figure 5: Risky areas to be avoided. Obstacles like high shelves or stairs may not be perceived by Hobbit's sensor setup.

Figure 6: Examples of installed ramps to overcome door thresholds.

does not hold for the used RGB-D cameras with limited range and long corridors. In this situation, according to the detected features, the robot could be anywhere along the parallel walls, which can cause problems in cases where the robot should enter a room after driving along in such a corridor. When entering a room, it is especially important that the robot be correctly localized in the transversal direction to the doorway and that the doorway be approached from the front, so accurately driving through doors located on one side of a corridor is much more difficult than through doors located at the beginning or at the end of a corridor. In order to approach doors from the front, avoiding getting too close to the corner sides, a useful strategy for wide enough places is adding *no-go* areas at sides of a doorway entrance or at sharp corners. This way, it is possible to have safer navigation behavior in wide areas while keeping the ability to go through narrower areas. This provides more flexibility than methods with fixed security margins for the whole operational area.

No-go areas were also useful to avoid potentially dangerous and restricted areas and rooms. A few examples are shown in Figure 5. Areas with cables and thin obstacles on the floor and very narrow rooms (usually kitchens), where a nonholonomic robot as Hobbit cannot maneuver, were also avoided. However, it is worth noting that *no-go* areas are only useful as long as overall localization is precise enough. Other challenging situations were caused by thresholds and bumps on the floor and carpets. To overcome thresholds, we tested commercial and homemade ramps (Figure 6). After testing different configurations and finding proper incline limits, the robot was usually able to pass thresholds. Problems with standard planning methods, for example, when a new plan caused the robot to turn while driving on a ramp, were observed. A situation-dependent direct motion control instead of a plan-based approach can reduce the risk during such situations.

In order to facilitate the tasks to be carried out in the home environment, the concept of using rooms and labeled places inside the rooms (locations) was applied. The rooms are manually defined, such that spatial ambiguity is not a problem. Also, the geometry of the defined rooms does not have to be very precise with respect to the map, as long as the rooms contain all the places of interest that the user wants to label. Places are learned by tele-operating the robot to specific locations and the subsequent association of places to rooms operates automatically, based on the crossing number algorithm to detect whether a point lies inside a generic polygon [23]. Figure 7 shows several examples of rooms and places defined in the user trials for different tasks.

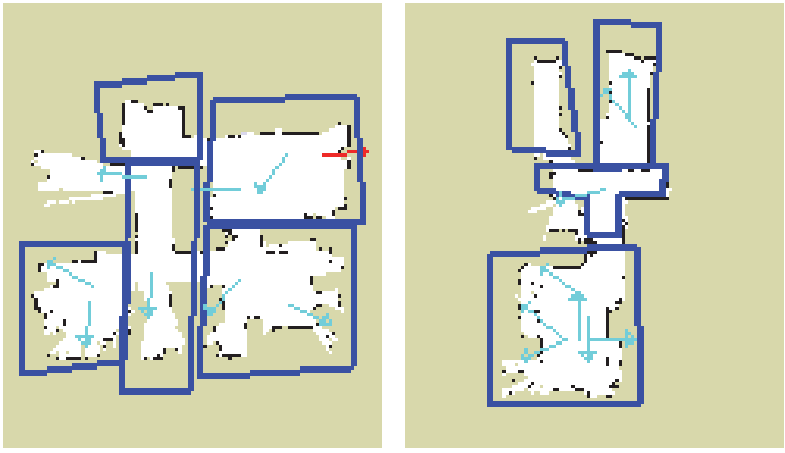


Figure 7: Rooms and places defined in two real apartments in Vienna.

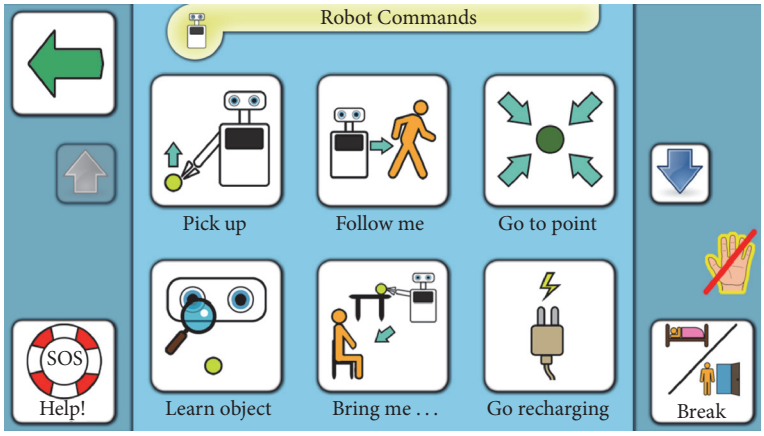


Figure 8: GUI of Hobbit showing one of the menu pages for robot commands. The strike-through hand on the right side indicates that the gesture input modality is disabled currently. A similar indicator was used for the speech input.

4.3. Multimodal Interaction Between the User and the Robot. The Hobbit robot deploys an improved version of the multimodal user interface (MMUI) used on Hobbit PT1. Generally speaking, the MMUI is a framework containing the following main building blocks: a Graphical User Interface (GUI) with touch, Automatic Speech Recognition (ASR), Text to Speech (TTS), and Gesture Recognition Interface (GRI). The MMUI provides emergency call features, web services (e.g., weather, news, RSS feed, and social media), control of robotic functions, and entertainment features. Compared to PT1, the graphical design of the GUI (Figure 8) was modified to better meet the user's needs. Graphical indicators on the GUI for showing current availability of GRI and ASR were iteratively improved.

During PT1 trials, we found that most of the users did not use the option of extending the MMUI to a comfortable ergonomic position for them. Therefore the mounting of the touchscreen was changed to a fixed position on Hobbit. Additionally, while the PT1 robot approached the user from the front, the Hobbit robot approaches the user from the right or left side while seated, which is more positively experienced by the user [24]. This offers the additional advantage that the robot is close enough for the user to interact via the touchscreen, while at the same time does not invade the personal space of the user (limiting her/his movement space or restricting other activities such as watching TV). Hobbit makes use of the MMUI to combine the advantages of the various user interaction modalities [25]. The touchscreen has strengths such as intuitiveness, reliability, and flexibility for multiple users in different sitting positions but requires a rather narrow distance between user and robot (Figure 9). ASR allows a larger distance and can also be used when no free hands are available, but it has the disadvantage of being influenced by the ambient noise level, which may reduce recognition performance significantly. GRI allows a wider distance between the robot and user and also works in noisy environments, but it only succeeds when the user is in the field of view of the robot. The interaction with Hobbit always depends on the distance between the user and Hobbit. It can be done through a wireless call button (far from other rooms), ASR and GRI (2 m to 3 m), and touchscreen (arm length, see Figure 9).

The ASR of Hobbit is speaker-independent, continuous, and available in four languages: English, German, Swedish,

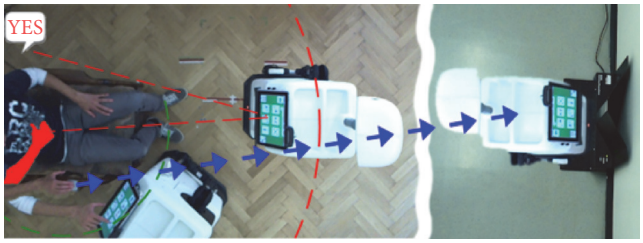


Figure 9: Different interaction distances between user and Hobbit seen from a ceiling camera. Short range: touch; middle range: speech and gesture; long range: wireless call button.

and Greek. Contemporary ASR systems work well for different applications, as long as the microphone is not moved far from the speaker's mouth. The latter case is called distant or far-field ASR and shows a significant drop in performance, which is mainly due to three different types of distortion [26]: (a) background noise, (b) echo and reverberation, and (c) other types of distortions, for example, room modes or the orientation of the speaker's head. For distant ASR, currently no off-the-shelf solution exists, but acceptable error rates can be achieved for distances up to 3 m by careful tuning of the audio components and the ASR engine [27]. An interface to a cloud based calendar was introduced, allowing PU and SU of Hobbit to access and partly to also edit events and reminders.

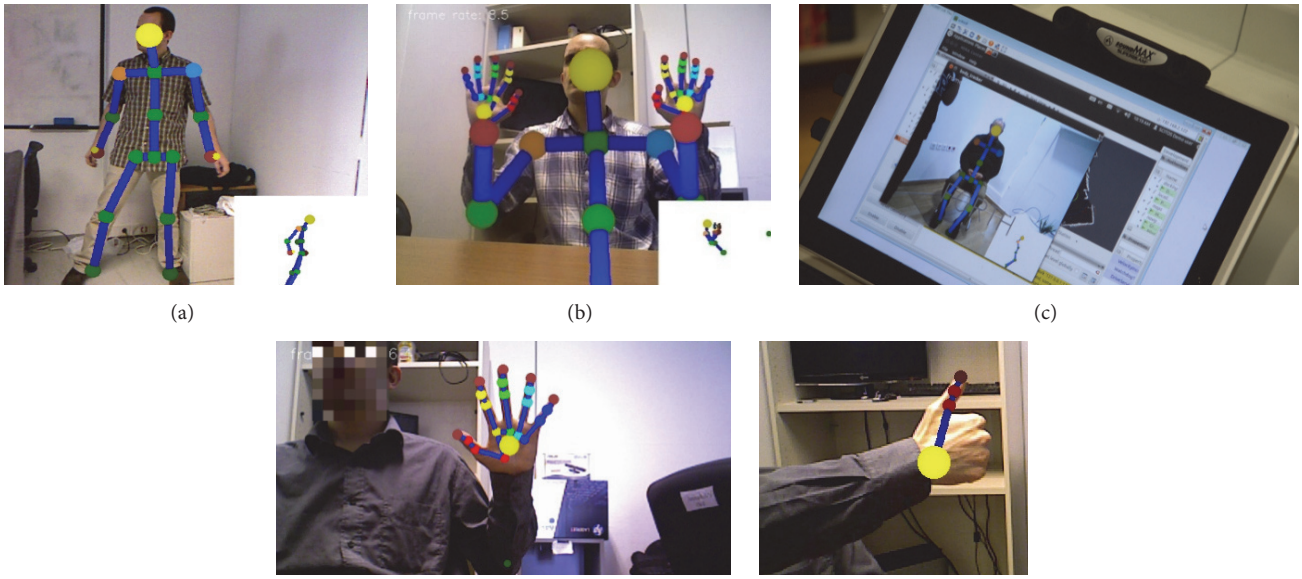
Despite the known difficulties with speech recognition in the far field and the local dialects of the users, the ASR of Hobbit worked as expected. The ASR was activated all over the Hobbit user trials, but the performance rate was commented on by users as necessary to be improved. The same was observed for the GRI. Eventually, the touchscreen as input modality was used most often by the majority of users, followed by speech and gesture. Touch was used more than twice as often as it was the case with ASR. Additionally, many users did not wait until the robot had completed its own speech output before starting to give a speech command which reduced the recognition rate. Considering these lessons learned, the aims for future work on the ASR are twofold: improving the performance of the ASR and providing better indication when the MMUI is listening to spoken commands and when it is not. The aspect of using two different variants for text messages from the robot to the user was taken over from Hobbit PT1. Based on other researches, it can be concluded that using different text variants does have an influence, for example, by increasing users' impression of interacting with a (more) vivid system. Some users demanded additional ASR commands, for example, *right, left, forward, reverse*, and *stop* in addition to *come closer*, as they would like to position (move) the robot with the help of voice commands or a remote control.

4.4. Person Detection and Tracking. To serve as building block for components like activity recognition [28] and natural human-robot communication [19, 29] as well as specialized functions like the fitness application [30], we developed a human body detection and tracking solution. Person detection and tracking in home environments is a challenging problem because of its high dimensionality and the appearance variability of the tracked person. A challenging aspect of the problem in Hobbit-related scenarios is that elderly users spend a considerable amount of time sitting in various types of chairs or couches. Therefore, human detection and tracking should consider human body figures that do not stand out from their background. On the contrary, they may interact with cluttered scenes, exhibiting severe partial occlusions. Additionally, the method needs to be capable of detecting a user's body while standing or walking based on frontal, back, or side views.

The adopted solution [31] enables 3D part-based, full/upper body detection and tracking of multiple humans based on the depth data acquired by the RGB-D sensor. The 3D positions and orientations for all joints of the skeletal model (full or upper body) relative to the depth sensor are computed for each time stamp. A conventional face detection algorithm [32] is also integrated using the color data stream of the sensor to facilitate human detection in case the face of the user is visible by the sensor. The proposed method has a number of beneficial properties that are summarized as follows: (1) performs accurate markerless 3D tracking of the human body that requires no training data, (2) requires simple inexpensive sensory apparatus (RGB-D camera), (3) exhibits robustness in a number of challenging conditions (illumination changes, environment clutter, camera motion, etc.), (4) has a high tolerance with respect to variations in human body dimensions, clothing, and so forth, (5) performs automatic human detection and automatic tracking initialization, thus recovering easily from possible tracking failures, (6) handles self-occlusions among body parts or occlusions due to obstacles/furniture and so forth, and (7) achieves real-time performance on a conventional computer. Indicative results of the method are illustrated in Figure 10.

4.5. Gesture Recognition. A vision-based gestural interface was developed to enrich the multimodal user interface of Hobbit in addition to speech and touch modalities. This enables natural interaction between the user and the robot by recognizing a predefined set of gestures performed by the user using her/his hands and arms. Gestures can be of varying complexity and their recognition is also affected by the scene context, actions that are performed in the foreground or the background at the same time, and by preceding and/or following actions. Moreover, gestures are often culture-specific, providing additional evidence to substantiate the interesting as well as challenging nature of the problem.

For Hobbit, existing upper body gestures/postures as used on PT1 had to be replaced with more intuitive hand/finger-based gestures that can be performed more easily by elderly users while sitting or standing. We redesigned the gestural vocabulary for Hobbit that now consists of six hand gestures that convey messages of fundamental importance in the context of human-robot dialogue. Aiming at natural, easy-to-memorize means of interaction, users have identified gestures consisting of both static and dynamic hand configurations that involve different scales of observation (from arms to fingers) and exhibit intrinsic ambiguities. Recognition needs to be performed in continuous video streams containing



(a) (b) (c) (d) (e)

Figure 10: Qualitative results of the 3D skeletal model-based person detection and tracking method. (a) Full model of a standing user. (b) Upper body (including hands and fingers) of a sitting user. (c) Full model of a sitting user. ((d) and (e)) Hand and finger detection supporting the gesture recognition framework (see Section 4.5).

other irrelevant actions. All the above need to be achieved by analyzing information acquired by a possibly moving RGB-D camera in cluttered environments with considerable light variations.

The proposed framework for gesture recognition [19, 29] consists of a complete system that detects and tracks arms, hands, and fingers and performs spatiotemporal segmentation and recognition of the set of predefined gestures, based on data acquired by the head camera of the robot. Thus, the gesture recognition component is integrated with the human detection and tracking module (see Section 4.4). At a higher level, hand posture models are defined and serve as building blocks to recognize gestures based on the temporal evolution of the detected postures. The 3D detection and tracking of hands and fingers relies on depth data acquired by the head camera of Hobbit, geometrical primitives, and minimum spanning tree features of the observed structure of the scene in order to classify foreground and background and further discriminate between hand and nonhand structures in the foreground. Upon detection of the hand (palm and fingers), the trajectories of their 3D positions across time are analyzed to achieve recognition of hand postures and gestures (Table 1). The last column describes the assignment of the chosen physical movements to robot commands. The performance of the developed method has been tested not only by users acquainted with technology but also by elderly users [19] (see Figure 11). Those tests formed a very good basis for fine-tuning several algorithmic details towards delivering a robust and efficient hand gesture recognition component. The performance of the final component was tested during field trials achieving high performance according to the evaluation results.

4.6. Fall Detection. According to the assessed user needs and the results of PT1 laboratory studies [17], a top-priority and prominent functionality of Hobbit regards fall prevention and fall detection. We hereby describe a relevant vision-based component that enables a patrolling robot to (a) perform fall detection and (b) detect a user lying on the floor. We focused mostly on the second scenario, as observing a user falling in the field of view of an autonomous assistive robot is of very low probability. The proposed vision-based emergency detection mechanism consists of three modes, each of which initiates an emergency handling routine upon successful recognition of the emergency situation:

(1) Detection of a falling user in case the fall occurs while the body is observable by the head camera of the robot

(2) Detection of a fallen user who is lying on the floor while the robot is navigating/patrolling

(3) Recognition of the emergency (help) gesture that can be performed by a sitting or standing user via the gesture recognition interface of Hobbit (see Figure 11, middle)

The methodology for (1) regards a simple classifier trained on the statistics of the 3D position and velocity of the observed human body joints acquired by the person detection and tracking component. For (2), once the general assumption, the fact that the human's head is above the rest of the body, does no longer hold true, an alternative, simple, yet effective approach to the problem has been adopted. This capitalizes on calibrated depth and thermal visual data acquired from two different sensors that are available on the head of Hobbit. More specifically, depth data from both cameras of the robot

Table 1: Set of hand/arm postures/gestures considered for the gestural interface of Hobbit.

User command	Upper body gesture/posture	Robot command	Related scenarios/tasks
Yes	Thumb up-palm closed	Positive response to confirmation dialogues. YES gesture	All (1 m to 2 m distance to robot)
No	Close palm, waving with index finger up	Negative response to confirmation dialogues	All (1 m to 2 m distance to robot)
Come closer	Bend the elbow of one arm repeatedly towards the platform and the body	Reposition the platform closer to the sitting user	All (1 m to 2 m distance to robot)
Cancel task	Both open palms towards the robot	Terminate an on-going robot behavior/task	All
Pointing	Extend one arm and point in 3D space towards an object (lying on the floor)	Detect and grasp the object of interest towards the pointing 3D direction	Pick up an (unknown) object from the floor
Reward	Open palm facing towards the robot and circular movement (at least one complete circle is needed)	Rewards the robot for an accomplished action/task	Approach the user
Emergency	Cross hands pose (normal-range interaction)	Emergency detection, initiated by the user	Emergency detection

Figure 11: Snapshots of Hobbit users performing gestures during lab trials. The recognition results are superimposed as text and a circle on the images indicating the location and the name of the recognized gesture (taken from [19]).

(head and base) are acquired and analyzed while observing the floor area in front of the robot. Figure 12 illustrates sample results of the fallen user detection component. In Figure 12(a), the upper part illustrates the color frame captured by the head camera of the robot that is titled down towards the floor, while navigating. In the bottom image, the viewpoint of the bottom camera is illustrated, after the estimation of the 3D floor plane has been performed.

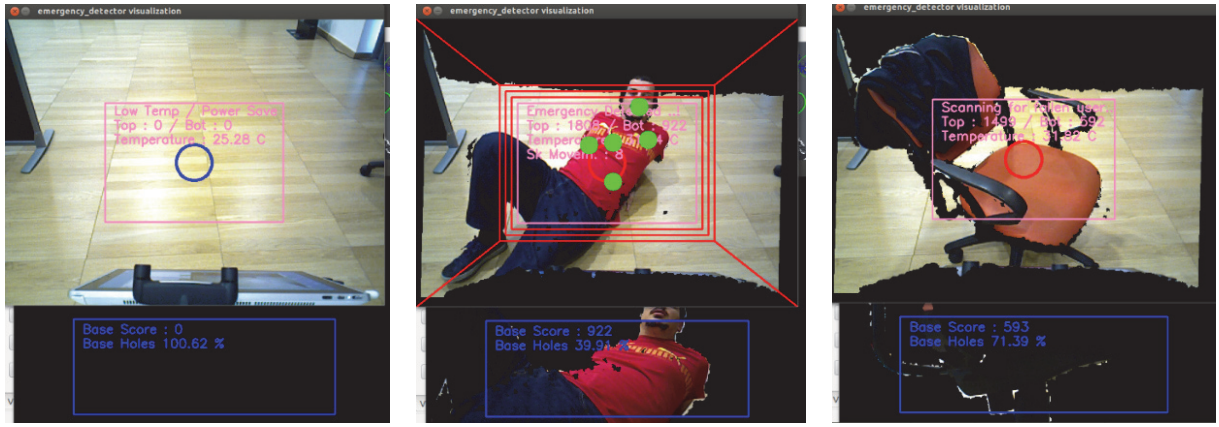
The methodology for vision-based emergency detection of case (3) refers to successful recognition of the emergency "Help me," based on the gesture and posture recognition module, as described in Section 4.5. The developed component is constantly running in the background within the robot's behavior coordination framework, while the robot is active during all robot tasks, except from object detection and recognition tasks.

4.7. Approaching the User. Specific behavior coordination was developed so that the robot could approach the user in a more flexible and effective way compared to standard existing methods. Using fixed predefined positions can be sufficient in certain scenarios, but it often presents limitations in real-world conditions [22]. The approach we developed incorporates user detection and interaction (Section 4.4), remembered obstacles and discrete motion for coming closer to the user with better, and adaptive positioning.

First, a safe position to move to is obtained from the local map and the robot moves there. Secondly, the user communicates to the robot whether it should move even closer or not in any of the three available modes (speech, touch, or gesture). Finally, the robot moves closer by a fixed distance of 0.15 m for a maximum of three times if the user wishes. This gives the users more control over final distance adjustments. A more detailed description of this novel approach will be published elsewhere.

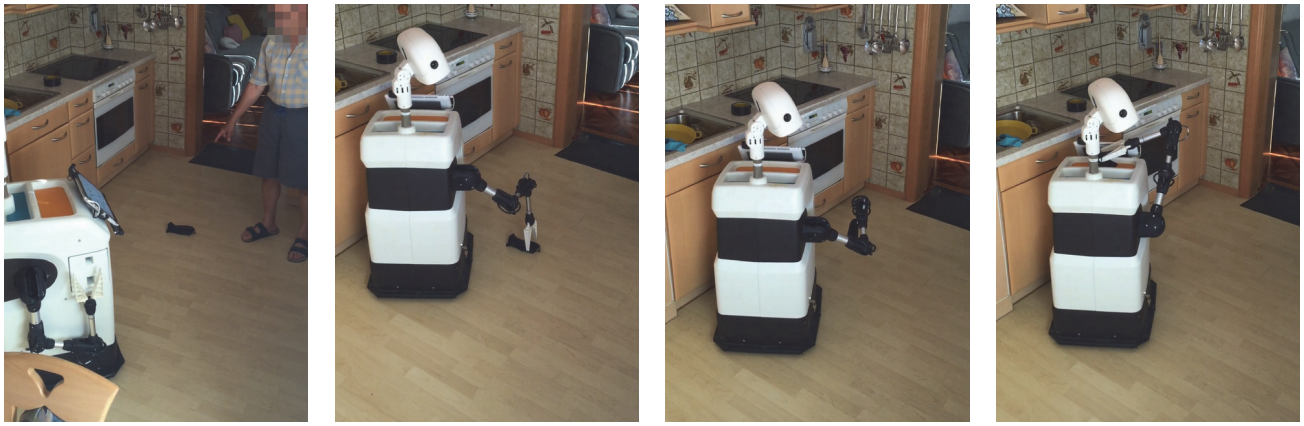
4.8. User Following. As the head camera is not available for observing the full body of a user during navigation (obstacle detection), we designed a new approach [33] to localize a user by observing its lower body part, mainly the legs, based on RGB-D sensory data acquired by the bottom camera of the platform.

The proposed method is able to track moving objects such as humans, estimate camera ego-motion, and perform map construction based on visual input provided by a single RGB-D camera that is rigidly attached to a moving platform. The moving objects in the environment are assumed to move on a planar floor. The first step is to segment the static background from the moving foreground by selecting a small number of points of interest whose 3D positions are estimated directly from the sensory information. The camera motion is computed by fitting those points to a progressively built model of the environment. A 3D point may not match the current version of the map either because it is a noise contaminated observation or because it belongs to a moving object or because it belongs to a structure



(a) (b) (c)

Figure 12: Vision-based emergency detection of a fallen user lying on the floor. The upper and lower middle images show the captured frame from the head and bottom cameras, respectively. The green dots mark a found skeleton within the search area (green and blue rectangles). (a–c) No human, no detection; person lying on the floor, correct detection; volumetric data from the head's depth and temperature sensor are in conflict with the volumetric date provided by the bottom depth sensor.



(a) (b) (c) (d)

Figure 13: (a–d) User points to an object on the floor and Hobbit drives to a point from where it can be picked up and moves the arm to a position to grasp it. The object is lifted and the check if grasp was successful is performed: the object is moved forward to check if something has changed at the previous position of the object on the floor. If successful, the object is placed on the tray on top of the robot.

attached to the static environment that is observed for the first time. A classification mechanism is used to perform this disambiguation. Additionally, the method estimates the camera (ego) motion and the motion of the tracked objects in a coordinate system that is attached to the static environment (robotic platform). In essence, our hypothesis is that a pair of segmented and tracked objects of specific size/width that move independently side-by-side at the same distance and direction in the field of view of a moving RGB-D camera correspond to user's legs being followed by the robot with high probability. The method provides the 3D position of user's legs with respect to the moving or static robotic platform. Other moving objects in the environment are filtered out or can be provided to an obstacle avoidance mechanism as moving obstacles, thus facilitating safe navigation of the robot.

4.9. Pick Up Objects from the Floor. To reduce the risk of falling, Hobbit was designed to be able to pick up unknown objects from the floor. Figure 13 shows the steps of the "Pick up object" task. The user starts the command and points at the object on the floor. If the pointing gesture is recognized, the robot navigates to a position from where it could observe the object. At this position, the robot looks at the approximate position of the object. Hobbit then makes fine adjustments to position itself at a location from where grasping is possible. If it is safe to grasp the object, the robot executes the arm trajectory and subsequently checks if the grasp was successful and will try to do so a second time if it was not.

Several autonomous mobile robots have been developed to fetch and deliver objects to people [34–38]. None of these publications evaluate their robot grasping from floor, and none evaluate the process of approaching an object and

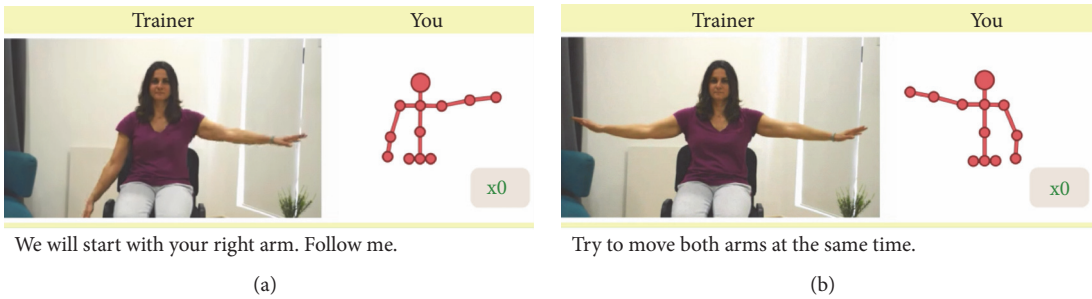


Figure 14: (a) Avatar mirroring the trainer's movement proved easier for users to follow. (b) Correction suggested by the system to the user.

grasping it as a combined action. Detection of the user and recognition of a pointing gesture were performed using the work presented in [19, 31]. Checks are performed to rule out unintentional or wrong pointing gestures and to enhance the accuracy of the detected pointing gesture.

A plausibility check tests if the pointing gesture is pointing towards the floor. To guarantee an exact position of the robot to bring the arm in a position where the gripper can approach the object in a straight line before closing, the accurate movement to the grasping position can be done as a relative movement to the object instead of using the global navigation. This is a crucial step as the region, in which the head camera is able to perceive objects and where the 6-DoF arm is able to perform a movement straight down to the floor without changing gripper orientation, is limited to $15 \times 10\,\text{cm}^2$. For calculating grasps, we use the method of Height Accumulated Features [39]. These features reduce the complexity of a perceived point cloud input, increase the value of given information, and hence enable the use of machine learning for grasp detection of unknown objects in cluttered and noncluttered scenes.

4.10. Fitness Application. The fitness application was introduced as a feature to the Hobbit robot after the PT1 trials and was made available during the PT2 trials for evaluation. The motivation behind this application comes from the fact that physical activity can have a significant positive impact on the maintenance or even on the improvement of motor skills, balance, and general physical well-being of elderly people, which in turn can lower the risk of falls in the long run. Based on feedback from the Community and Active Ageing Center of the municipality of Heraklion, Greece, the following requirements were produced. The exercises must (1) be easy to learn, (2) target different joints and muscles, (3) provide appropriate feedback to the user, (4) keep the user engaged while providing enough breaks, and (5) be designed to be performed from a seated position.

Based on these requirements and feedback from test users, we developed an application including three difficulty levels and seven different exercises. The user interface consisted of a split view of a video recording of the actual trainer performing each exercise on the left side and an avatar figure depicting the user's movement while executing the instructed exercise on the right side as shown in Figure 14. This side-to-side viewing setup allowed the user to compare his or her movements to those of the trainer. The bottom part of the interface was allocated for the instructions at the beginning of each exercise and also for any feedback and guidance to the user when needed. The design and development of the fitness application are described in more detail in [30]. The fitness application was explained to the participants of the trials by the facilitator at the initial introduction of the system during the installation day. The participants could access the application if desired at any time. Almost all users tried the fitness application at least once with some using it multiple times during the three-week evaluation period. From the comments received during the mid-term and end-of-trial interviews, it can be concluded that the overall concept of having the fitness program as a feature of the robot received positive marks by many of users as far as its usefulness and importance are concerned. However, most users who tried it out said that they would have liked it to be more challenging and to offer a larger variety of exercise routines with various challenging levels to choose from.

5. Field Trials

We conducted field trials in the households of 18 PU with 5 Hobbit robots in Austria, Greece, and Sweden. The trials lasted ~21 days for each household, resulting in a total of 371 days. During this time, the robots were placed in the homes of 18 older adults living on their own, where users could use and explore the robot on a 24/7 basis. Detailed results of the trials will be published elsewhere; preliminary results can be found in [40] (a first analysis only of the robot log data without any cross-analysis to the other data collected) and in [41] (a first overview on the methodological challenges faced during the field trails).

The trial sample consisted of 16 female and 2 male PU; their age ranged from 75 to 90 years ($M = 79.67$). All PU were living alone, either in flats (13 participants) or in houses. In adherence with inclusion criteria set by the research consortium, all participants had fallen in the last two years or were worried about falling and had moderate impairments in at least one of the areas of mobility, vision, and hearing. 15 PU had some form of multiple impairments. Furthermore, all participants had sufficient mental capacity to understand the project and give consent. In terms of technology experience, 50.0% of the PU stated that they were using a computer every day, 44.45% stated that they were never using a computer or used it less than once a week, and only one participant used a computer two to three times a week.

Before the actual trials, the PU were surveyed to make sure that they matched the criteria for inclusion and to discuss possible necessary changes to their home environments for the trials (e.g., removing carpets and covering mirrors). After an informed consent was signed, the robot was brought into the home and the technical setup took place. After this setup, a representative from the elderly care facility explained the study procedure and the robot functionalities to the PU in an individual open-ended manner. Afterwards, a manual was left within the household in case participants wanted to look up a functionality during the 21 days. All users experienced two behavioral roles of the robot. The robot was set to *device-mode* until day 11 when it was switched to *companion-mode* (i.e., Mutual Care). The real-world environment in which the field tests took place bears certain challenges, such as unforeseen changes in the environment and uncontrollable settings. Assessment by means of qualitative interviews and questionnaires took place at four stages of each trial: before trial, midterm, end of trial, and after trial (i.e., one week after the trial had ended). Moreover, log data was automatically recorded by the robot during the whole trial duration. The field trial methodology is comparable to similar studies (e.g. [42]).

The field trials revealed that several functions of the robot lack stability over time. Those technical issues certainly influenced the evaluation of the system because a reliable working technical system is a prerequisite for positive user experience. We tried to minimize potential negative feelings due to potential malfunctioning by informing our users that a prototype of a robot is a very complex technical system that might malfunction. Additionally, they were given the phone number of the facilitator who was available for them around the clock, 7 days per week, for immediate support. However, malfunctions certainly had an influence on subjects' answers during the assessments and may have attracted attention with the result that the subtle behavioral changes introduced by the switch from *device-mode* to *companion-mode* may have been shifted out of the attentional focus. Availability of commands was equally distributed across the two phases of *Mutual Care* as can be seen in Table 2. Please note that unavailability or malfunctioning of functions in one but not the other mode (unequal distribution of functionality) would have led to a bias within the evaluation. Table 2 gives an overview of the functional status across all PU during the field trials. It is based on the combination of (i) a check of the robot's features by the facilitator during the preassessment, midterm assessment, and end-of-trial assessments, (ii) protocols of the calls of the users because they had a problem with the robot, and (iii) analysis of the log data by technical partners.

The Hobbit field trials marked the first time an autonomous, multifunctional service robot, able to manipulate objects, was put into the domestic environment of older adults for a duration of multiple weeks. Our field trials provided insight into how the elderly used the Hobbit robot and which functionalities they deemed useful for themselves and how the robot influenced their daily life. Furthermore, we could show that it is in principal feasible to support elderly with a low-cost, autonomous service robot controlled by a rather simple behavior coordination system.

6. Lessons Learned

Based on all the insights gained from developing and testing Hobbit in the field, we can summarize the following recommendations for fellow researchers in the area of socially assistive robots for enabling independent living for older adults in domestic environments.

6.1. Robot Behavior Coordination. The developed behavior control based on a state-machine proved to be very useful and allowed us to implement many extensions in a short time. A close interconnection with the user was therefore helpful. In the following, we present our main lessons learned regarding the implementation of the robot behavior.

6.1.1. Transparency. Actions and their effects need to be communicated in a clear fashion so that the robot's presented functionality can be fully understood by the user. Users reported missing or nonworking functionality (e.g., reminders not being delivered to them and patrol not being executed). Most of these reported issues were caused by the fact that the users did not understand the technical interdependencies between robot functions. For example, if a command was not available due to a certain internal state of the robot, the user was not aware of this and did not understand the shown behavior of the robot. These functional relations need to be made explicit and stated more clearly to the users.

6.1.2. Legibility. The log data and conversations with participants revealed that the robot needs to communicate its intentions. For instance, when the robot proactively moved out of its charging station, the user was not always aware what was going to happen next. When they did not understand what the robot was doing, they canceled the robot's action, effectively stopping part of the robot's benefit to them. To work around this, a robot needs to clearly state the reason of its action and which goal it is trying to achieve when performing an autonomously started task.

6.1.3. Contradictory Commands. Log data presented an interesting effect while interacting with the touchscreen. When moving the hand towards the touchscreen on the robot, the gesture recognition system detected the movement of the hand as the *come closer* gesture, shortly followed by a command from the touch input on the GUI. We could replicate this behavior later on in our internal tests in the lab. A simple solution for such contradictions of commands is to simply wait for a short period of time (less than 0.2 seconds) before a gesture close to the robot is processed by the behavior coordination system to wait for a possibly following touch input.

6.1.4. Transparency of Task Interdependencies. The interviews revealed that the interdependencies between the tasks were not clear to the user; the best example was the learn-and-bring-object task. As described, for the bring-object task, the object first had to be learned so that it can be found in the apartment. However, this fact needs to be remembered by

Table 2: System reliability across 18 PU.

(a)

muc mode	Statistics	Call Hobbit	Come closer	Stop Hobbit	Emergency	Pick up object	Teach a new object	Bring object to user	Calendar reminders	Follow me	Move to location
Device	Days total	226	226	226	226	226	226	226	226	226	226
	Days of introduction	31	31	31	31	31	31	31	31	31	31
	Days switched off	55	55	55	55	55	55	55	55	55	55
	Days in use	140	140	140	140	140	140	140	140	140	140
	Days when feature was not working	14	13	13	19	84	12	79	49	105	15
	Days when feature was only partially working	23	20	22	44	47	116	62	83	13	32
Companion	Days total	148	148	148	148	148	148	148	148	148	148
	Days switched off	20	20	20	20	20	20	20	20	20	20
	Days in use	128	128	128	128	128	128	128	128	128	128
	Days when feature was not working	14	10	8	12	83	17	85	54	92	9
	Days when feature was only partially working	25	16	17	38	40	95	43	64	18	29
Device	Working over days in use	81.79%	83.57%	82.86%	70.71%	23.21%	50.00%	21.43%	35.36%	20.36%	77.86%
Companion	Working over days in use	79.30%	85.94%	87.11%	75.78%	19.53%	49.61%	16.80%	32.81%	21.09%	81.64%

(b)

muc mode	Statistics	Go recharge	Take a break	Telephone	Information	Surprise me	Entertainment audio	Entertainment games	Entertainment fitness	Reward
Device	Days in total	226	226	226	226	226	226	226	226	226
	Days of introduction	31	31	31	31	31	31	31	31	31
	Days feature was disabled	55	55	55	55	55	55	55	55	55
	Days of feature in use	140	140	140	140	140	140	140	140	140
	Days when feature was not working	19	16	19	11	11	11	23	20	11
	Days when feature was only partially working	20	6	22	9	23	7	20	27	6
Companion	Days in total	148	148	148	148	148	148	148	148	148
	Days feature was disabled	20	20	20	20	20	20	20	20	20
	Days of feature in use	128	128	128	128	128	128	128	128	128
	Days when feature was not working	10	8	22	8	8	7	26	19	14
	Days when feature was only partially working	33	9	16	7	23	8	11	23	7
Device	Working over days in use	79.29%	86.43%	78.57%	88.93%	83.93%	89.64%	76.43%	76.07%	90.00%
Companion	Working over days in use	79.30%	90.23%	76.56%	91.02%	84.77%	91.41%	75.39%	76.17%	86.33%

the user and as this is often not the case, users wanted to ask Hobbit to bring them an object even though it had not learned any objects before. In this specific case, the problem could be easily fixed by only offering the task "bring object" when an object was actually learned beforehand (e.g., the task could be greyed out in the MMUI).

6.1.5. Full Integration without External Programs. The handling of user input and output must be fully integrated with the rest of the robot's software architecture to be able to handle interruptions and continuations of interaction between the user and the robot. The user interface on the tablet computer (MMUI) incorporated multiple external programs (e.g., Flash games, speech recognition, and the fitness functionality). As those were not directly integrated, the behavior coordination was not aware about their current state, leading to multiple interaction issues with users. For example, a game would be exiting when a command with higher priority (e.g., emergency from fall detection) would start the emergency scenario. External programs need to be included in a way that makes it possible to suspend and resume their execution at any time.

6.1.6. Avoiding Loops. Reviewing the log data revealed that the behavior coordination system could be trapped in a loop without a way to continue the desired behavior execution. The behavior coordination needs to provide a fallback solution in case of a seemingly endless loop in any part of the behavior. The behavior coordination communicates with the MMUI in a way that does not provide immediate feedback over the same channels of communication. Due to timing issues, it occurred that a reply was lost between the communicating partners (i.e., the fact that the robot stopped speech output). From there on, the behavior coordination was in a state that should not be reached and was unable to continue program execution in the desired manner. Thus, the communication structures should always have a fallback solution to continue execution as well as the feedback data on the same channels to prevent such a stop in a scenario.

6.2. Human-Robot Interaction with the MMUI. The interaction with the user was based on a multimodal user interface that was perceived as easy to use during our field trials. While touch input turned out to be the most reliable modality, speech and gesture interaction was highly welcome. Many of the entertainment functions of the MMUI relied on Internet connectivity. Many users either were not interested in some UI features which therefore should be removed or asked for special configuration of the preferred features (e.g., selection of entertainment). The main way the user was able to communicate remotely with Hobbit was with the use of physical switches (call buttons) placed at several fixed places inside the house of the user. The user had to physically go to the designated switch spot and press the switch for the robot to approach her/him. A smartphone/tablet application could be developed to allow a better remote communication experience with the robot.

6.2.1. Internet Connectivity. Internet connectivity was not reliable depending on location and time. While in most countries Internet (line-based or mobile) coverage is no problem in general, local availability and quality vary significantly, which makes Internet-based services difficult to implement for technically unaware users. The integration of rich Internet-based content into the interaction therefore lacks usability in case of intermittent connectivity.

6.2.2. Graphical User Interface. The GUI could be personalized by the user for increased comfort during interaction. This, however, shows the need for localized content to be available. As the setup phase during the trials showed that PU are likely not aware what content is available, some (remote) support and knowledge from SU are necessary for the configuration of the user interface.

6.2.3. Speech Recognition. Field trials showed that speech recognition is still not working well for many users. Despite the overall acceptable recognition rate that varies largely from user to user and from language to language and that is based on the environment and distance, users often do not support the needs of current ASR technology for clearly expressed and separated commands in normal voice. The Sweet-Home project once more emphasizes the findings from the DiRHA 2 project that practical speech recognition for old people in the home environment is still a major challenge by itself [43]. However, our ASR provided a positively experienced natural input channel when used in a multimodal HRI, where the touchscreen with its GUI provides a reliably working base.

6.2.4. Smarthome Integration. The setup phase during the field trials showed that the integration into smarthome environments can be beneficial. Field trials showed that context awareness and adaptations highly impact the acceptance of the robot. Imagined features could be automatic on/off of the light or the stove or adjusting the proactively level of the robot based on the user's mood.

6.2.5. Remote End User Control. Reflecting on the field trial indicates that a potential valuable extension of the interaction modalities would be a remote control of the robot, for instance, on a smartphone enabling PU but also maybe SU to control the robot from outside the home. Potential useful scenarios could be to send the robot to the docking station or to patrol the flat and search for an object or the PU or the SU video calling the PU.

6.3. Implementation of Mutual Care Behavior. In the beginning of the trials, we implemented Mutual Care in such a fashion that in the companion mode the robot offers to return the favor after every interaction with the user. This was done in order to guarantee that the users would notice the difference between the modes during the interaction. The positive fact was that users noticed the changes. However, they were soon very annoyed by the robot. Consequently, we changed this implementation during the running trials. The return of favor frequency was reduced; it was no longer offered after the commands *Recharge batteries*, *Go to*, *Call*

button, and *Surprise*. Further feedback from the second and third Austrian and the second and third Swedish users led to further reduction of the return a favor frequency to offering it only after the following three commands:

(1) Pick up command (favor: Hobbit offers music: *I'd like to return the favor. I like music. Shall I play some music for you?*)

(2) Learn object command (favor: Hobbit offers to play a game (suitable because the user is already sitting down): *I'd like to return the favor. Do you want to play a game?*)

(3) Reward command (favor: Hobbit offers to surprise the user: *I'd like to return the favor. I like surprises. Do you want a surprise?*)

However, as the interviews showed, these behavioral changes were no longer recognized by the users. Similarly, the differences in proactivity and presence were not reflectively noticed by the users, but the changes in dialogue were noticed.

6.3.1. Help Situations. For the development of Mutual Care behavior in completely autonomous scenarios, which helping situations the robot can really identify in order to ask for help and how the robot can notice that it actively recovered through the help have to be considered.

6.3.2. Design of Neediness. In the interviews, PU reflected that they did not really recognize that the robot needed their input to continue its task. For Mutual Care, the *need of help* seems to be essential. For future version of the robot, how to design the *neediness* needs to be considered. This could be achieved with facial expressions, sounds, or movements. Also for behaviors such as presence and proactivity, the robot could say after an interaction: *"I would prefer staying with you in your room"* or proactivity (e.g., *"I would like to spend more time with you"* before offering an activity). This would give a better explanation of the robot's behavior to the user and an expected raise of acceptance.

7. Conclusions

In this article, we presented the second prototypical implementation of the Hobbit robot, a socially assistive service robot. We presented the main functionality it provided, as well as the behavior coordination that enabled autonomous interaction with the robot in real private homes. Hobbit is designed especially for fall detection and prevention, providing various tasks (e.g., picking up objects from the floor, patrolling through the flat, and employing reminder functionalities), and supports multimodal interaction for different impairment levels. We focused on the development of a service robot for older adults, which has the potential to promote aging in the home and to postpone the need to move to a care facility. Within the field trials, we reached the desirable long-term goal that a mobile service robot with manipulation capabilities enters real homes of older adults and showed its usefulness and potential to support independent living for elderly users.

To conclude, we believe that methods, results, and lessons learned presented in this article constitute valuable knowledge for fellow researchers in the field of assistive service robotics and serve as a stepping stone towards developing affordable care robots for the aging population.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This research has received funding from the European Community's Seventh Framework Programme (FP7/2007–2013) (Grant Agreement no. 288146, Hobbit).

References

[1] P. Dario, P. F. M. J. Verschure, T. Prescott et al., "Robot companions for citizens," *Procedia Computer Science*, vol. 7, pp. 47–51, 2011.

[2] J. M. Beer, C.-A. Smarr, T. L. Chen et al., "The domesticated robot: Design guidelines for assisting older adults to age in place," in *Proceedings of the 7th Annual ACM/IEEE International Conference on Human-Robot Interaction, (HRI '12)*, pp. 335–342, USA, March 2012.

[3] D. Fischinger, P. Einramhof, K. Papoutsakis et al., "Hobbit - The Mutual Care Robot," in *Assistance and Service Robotics in a Human Environment Workshop in conjunction with IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2013.

[4] J. Bohren, R. B. Rusu, E. G. Jones et al., "Towards autonomous robotic butlers: Lessons learned with the PR2," in *Proceedings of the 2011 IEEE International Conference on Robotics and Automation, (ICRA '11)*, pp. 5568–5575, China, May 2011.

[5] Y. Demiris and B. Khadhouri, "Hierarchical attentive multiple models for execution and recognition of actions," *Robotics and Autonomous Systems*, vol. 54, no. 5, pp. 361–369, 2006.

[6] T. Carlson and Y. Demiris, "Collaborative control for a robotic wheelchair: evaluation of performance, attention, and workload," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 42, no. 3, pp. 876–888, 2012.

[7] M. Cashmore, M. Fox, D. Long et al., "Rosplan: Planning in the robot operating system," in *Proceedings of the 25th International Conference on Automated Planning and Scheduling, (ICAPS '15)*, pp. 333–341, June 2015.

[8] M. Mansouri and F. Pecora, "More knowledge on the table: Planning with space, time and resources for robots," in *Proceedings of the 2014 IEEE International Conference on Robotics and Automation, (ICRA '14)*, pp. 647–654, China, June 2014.

[9] S. Goetze, S. Fischer, N. Moritz, J. E. Appell, and F. Wallhoff, "Multimodal Human-Machine Interaction for Service Robots in Home-Care Environments," in *Proceedings of the 1st Workshop on Speech and Multimodal Interaction in Assistive Environments*, 2012.

[10] H. S. Koppula, A. Jain, and A. Saxena, "Anticipatory planning for human-robot teams," *Springer Tracts in Advanced Robotics*, vol. 109, pp. 453–470, 2016.

[11] P. Kwang-Hyun and Z. Zenn Bien, "Intelligent sweet home for assisting the elderly and the handicapped," in *Independent Living for Persons with Disabilities and Elderly People: ICOST*, p. 151, 2003.

[12] T. Fukuda, P. Di, F. Chen et al., "Advanced service robotics for human assistance and support," in *Proceedings of the International Conference on Advanced Computer Science and Information Systems, (ICACSIS '11)*, pp. 25–30, December 2011.

[13] D.-J. Kim, R. Lovelett, and A. Behal, "An empirical study with simulated ADL tasks using a vision-guided assistive robot arm," in *Proceedings of the 2009 IEEE International Conference on Rehabilitation Robotics, (ICORR '09)*, pp. 504–509, Japan, June 2009.

[14] M. B. Hong, S. J. Kim, T. Um, and K. Kim, "KULEX: An ADL power-assistance demonstration," in *Proceedings of the 10th International Conference on Ubiquitous obots and Ambient Intelligence, (URAI '13)*, pp. 542–544, November 2013.

[15] L. Lammer, A. Huber, A. Weiss, and M. Vincze, "Mutual Care: How older adults react when they should help their care Robot," in *Proceedings of the 3rd international symposim on New Frontiers in Human-Robot interaction*, April 2014.

[16] T. Körtner, A. Schmid, D. Batko-Klein et al., "How social robots make older users really feel well - A method to assess users' concepts of a social robotic assistant," in *Proceedings of the International Conference on Social Robotics*, vol. 7621, pp. 138–147, Springer, 2012.

[17] D. Fischinger, P. Einramhof, K. Papoutsakis et al., "Hobbit, a care robot supporting independent living at home: First prototype and lessons learned," *Robotics and Autonomous Systems*, vol. 75, pp. 60–78, 2016.

[18] P. De La Puente, M. Bajones, P. Einramhof, D. Wolf, D. Fischinger, and M. Vincze, "RGB-D sensor setup for multiple tasks of home robots and experimental results," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, (IROS '14)*, pp. 2587–2594, USA, September 2014.

[19] D. Michel, K. Papoutsakis, and A. A. Argyros, "Gesture recognition supporting the interaction of humans with socially assistive robots," in *Advances in Visual Computing*, vol. 8887 of *Lecture Notes in Computer Science*, pp. 793–804, Springer International Publishing, Berlin, Germany, 2014.

[20] J. González-Jiménez, J. Ruiz-Sarmiento, and C. Galindo, "Improving 2D Reactive Navigators with Kinect," in *Proceeding of the 10th International Conference on Informatics in Control, Automation and Robotics (ICINCO '13)*, 2013.

[21] M. Jalobeanu, G. Shirakyan, G. Parent, H. Kikkeri, B. Peasley, and A. Feniello, "Reliable kinect-based navigation in large indoor environments," in *Proceedings of the 2015 IEEE International Conference on Robotics and Automation, (ICRA '15)*, pp. 495–502, USA, May 2015.

[22] P. De La Puente, M. Bajones, Reuther. C., D. Fischinger, Wolf. D., and M. Vincze, "Experiences with rgb-d based navigation in real home robotic trials," in *Austrian Robotics Workshop (ARW)*, 2016.

[23] M. Shimrat, "Algorithm 112: Position of point relative to polygon," *Communications of the ACM*, vol. 5, no. 8, p. 434, 1962.

[24] M. L. Walters, K. Dautenhahn, S. N. Woods, and K. L. Koay, "Robotic etiquette: Results from user studies involving a fetch and carry task," in *Proceedings of the HRI 2007: 2007 ACM/IEEE Conference on Human-Robot Interaction - Robot as Team Member*, pp. 317–324, USA, March 2007.

[25] P. Mayer, C. Beck, and P. Panek, "Examples of multimodal user interfaces for socially assistive robots in ambient assisted living environments," in *Proceedings of the 3rd IEEE International Conference on Cognitive Infocommunications, (CogInfoCom '12)*, pp. 401–406, Slovakia, December 2012.

[26] M. Wölfel and J. McDonough, *Distant Speech Recognition*, John Wiley & Sons, 2009.

[27] P. Panek and P. Mayer, "Challenges in adopting speech control for assistive robots," in *Ambient Assisted Living*, Advanced Technologies and Societal Change, pp. 3–14, Springer International Publishing, Berlin, Germany, 2015.

[28] D. I. Kosmopoulos, K. Papoutsakis, and A. A. Argyros, "Online segmentation and classification of modeled actions performed in the context of unmodeled ones," in *Proceedings of the 25th British Machine Vision Conference, (BMVC '14)*, pp. 1–12, September 2014.

[29] D. Michel and K. Papoutsakis, "Gesture Recognition Apparatuses," *Methods and Systems for Human-Machine Interaction*, 2016.

[30] M. Foukarakis, I. Adami, D. Ioannidi et al., "A robot-based application for physical exercise training," in *Proceedings of the 2nd International Conference on Information and Communication Technologies for Ageing Well and e-Health, (ICT4AWE '16)*, pp. 45–52, April 2016.

[31] D. Michel and A. Argyros, "Apparatuses, methods and systems for recovering a 3-dimensional skeletal model of the human body, 2016".

[32] P. Viola and M. J. Jones, "Robust real-time face detection," *International Journal of Computer Vision*, vol. 57, no. 2, pp. 137–154, 2004.

[33] P. Panteleris and A. A. Argyros, "Vision-based SLAM and moving objects tracking for the perceptual support of a smart walker platform," *Computer Vision-ECCV 2014 Workshops*, vol. 8927, pp. 407–423, 2014.

[34] A. Remazeilles, C. Leroux, and G. Chalubert, "SAM: A robotic butler for handicapped people," in *Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN*, pp. 315–321, Germany, August 2008.

[35] S. S. Srinivasa, D. Ferguson, C. J. Helfrich et al., "HERB: A home exploring robotic butler," *Autonomous Robots*, vol. 28, no. 1, pp. 5–20, 2010.

[36] B. Graf, U. Reiser, M. Hägele, K. Mauz, and P. Klein, "Robotic home assistant care-O-bot 3—product vision and innovation platform," in *Proceedings of the IEEE Workshop on Advanced Robotics and Its Social Impacts (ARSO '09)*, pp. 139–144, Tokyo, Japan, November 2009.

[37] D. Fischinger and M. Vincze, "Empty the basket - A shape based learning approach for grasping piles of unknown objects," in *Proceedings of the 25th IEEE/RSJ International Conference on Robotics and Intelligent Systems, (IROS '12)*, pp. 2051–2057, Portugal, October 2012.

[38] D. Fischinger and M. Vincze, "Shape based learning for grasping novel objects in cluttered scenes," in *Proceedings of the 10th IFAC Symposium on Robot Control, (SYROCO '12)*, pp. 787–792, Croatia, September 2012.

[39] D. Fischinger, A. Weiss, and M. Vincze, "Learning grasps with topographic features," *International Journal of Robotics Research*, vol. 34, no. 9, pp. 1167–1194, 2015.

[40] M. Bajones, A. Weiss, and M. Vincze, "Log data analysis of long-term household trials: Lessons learned and pitfalls. 2016. Workshop on Challenges and best practices to study HRI in natural interaction settings," in *Proceeding of the International Conference on Human-Robot Interaction*, 2016.

[41] J. Pripfl, T. Körtner, D. Batko-Klein et al., "Results of a real world trial with a mobile social service robot for older adults," in *Proceedings of the 11th Annual ACM/IEEE International*

Conference on Human-Robot Interaction, (HRI '16), pp. 497-498, IEEE Press, New Zealand, March 2016.

[42] F. Palumbo, D. La Rosa, E. Ferro et al., "Reliability and human factors in ambient assisted living environments," *Journal of Reliable Intelligent Environments*, vol. 3, no. 3, pp. 139–157, 2017.

[43] M. Vacher, F. Portet, A. Fleury, and N. Noury, "Development of audio sensing technology for ambient assisted living: Applications and challenges," *International Journal of E-Health and Medical Communications*, vol. 2, no. 1, pp. 35–54, 2011.

Hindawi
Journal of Robotics
Volume 2018, Article ID 1408796, 18 pages
https://doi.org/10.1155/2018/1408796

Research Article

Allocating Multiple Types of Tasks to Heterogeneous Agents Based on the Theory of Comparative Advantage

Toma Morisawa, Kotaro Hayashi, and Ikuo Mizuuchi

Department of Mechanical Systems Engineering, Tokyo University of Agriculture & Technology, 2-24-16 Nakacho, Koganei, Tokyo 184-8588, Japan

Correspondence should be addressed to Kotaro Hayashi; hayashik@cc.tuat.ac.jp

Received 10 November 2017; Revised 13 February 2018; Accepted 2 April 2018; Published 22 May 2018

Academic Editor: Yunyi Jia

We present a method to allocate multiple tasks with uncertainty to heterogeneous robots using the theory of comparative advantage: an economic theory that maximizes the benefit of specialization. In real applications, robots often must execute various tasks with uncertainty and future multirobot system will have to work effectively with people as a team. As an example, it may be necessary to explore an unknown environment while executing a main task with people, such as carrying, rescue, military, or construction. The proposed task allocation method is expected to reduce the total makespan (total length of task-execution time) compared with conventional methods in robotic exploration missions. We expect that our method is also effective in terms of calculation time compared with the time-extended allocation method (based on the solution of job-shop scheduling problems). We simulated carrying tasks and exploratory tasks, which include uncertainty conditions such as unknown work environments (2 tasks and 2 robots, multiple tasks and 2 robots, 2 robots and multiple tasks, and multiple tasks and multiple robots). In addition, we compared our method with full searching and methods that maximize the sum of efficiency in these simulations by several conditions: first, 2 tasks (carrying and exploring) in the four uncertain conditions (later time, new objects appearing, disobedient robots, and shorter carrying time) and second, many types of tasks to many types of robots in the three uncertain conditions (unknown carrying time, new objects appearing, and some reasonable agents). The proposed method is also effective in three terms: the task-execution time with an increasing number of objects, uncertain increase in the number of tasks during task execution, and uncertainty agents who are disobedient to allocation orders compared to full searching and methods that maximize the sum of efficiency. Additionally, we performed two real-world experiments with uncertainty.

1. Introduction

Research on a multirobot task allocation system and coordinating heterogeneous robots have become a hot topic of research in the field robotics. We propose a method of allocating multiple types of tasks to heterogeneous robots, based on the theory of comparative advantage [1], in order to minimize the makespan (the total length of task-execution time). The calculation time in the proposed method is negligibly short compared with the task-execution time, and it may also be effective for dynamic allocation (e.g., in an unknown real environment).

A key driving force of multirobot systems is their force of numbers. Multirobot systems are expected to improve the effectiveness of robotic systems in terms of the temporal efficiency [2]. Similar to humans, multiple robots work more effectively than a single robot, even those that do not have complex mechanisms or advanced intelligent control systems. Recent studies on decision-making of multirobot systems focus on two categories: allocation (centralized method for coordinating) and cooperation (decentralized method for coordinating). Yan et al. [3] valued the following two categories: the allocation that the central controller has a global view of the world, whereby the globally optimal plans can be produced, but it is not robust in relation to dynamic environments or failures in communications and other uncertainties and the cooperation can better respond to unknown or uncertain environments, but the solutions they reach are often suboptimal. In the real world, multirobot systems will be offered various tasks of the unknown and

uncertain environments. With the advancement of information and communication technology, it will require that multirobot systems for heterogeneous robots have various perception and capability by many vendors. Moreover, effective teamwork between groups of humans and robots is one of the goals in the fields of robotics and AI [4]. Multirobot systems must have a view of the environment including the humans. For example, in a rescue or industrial mission, humans and robots are required to work together. Our ultimate goal is allocating tasks to heterogeneous robots and humans, or the cooperating of heterogeneous robots with humans with minimum makespan and the real world. First of all, this study is focused on the allocation of tasks to heterogeneous robots in unknown environments by using the theory of comparative advantage: an economic theory that maximizes the benefit of specialization.

Conventional task allocation methods are categorized as static or dynamic allocation [5]. Static allocation gives the task assignments at the start until all the tasks are completed. Static allocation calculates the assignments to minimize the required time. This type of problem, in which the makespan is minimized, is called a job-shop scheduling problem [6]. The makespan refers to the total length of the schedule. However, the calculation time of static allocation increases exponentially as the number of tasks increases. In static allocation, the execution time of each task should be calculated and is perturbed by uncertainty. Dynamic allocation frequently conducts reallocation of static allocation [7] and requires more calculation time.

Dispatching methods to reduce the calculation time have been studied. In multirobot task allocation, the methods are instances of optimal assignment problems [8]. In the auction based method proposed by Gerkey and Matarić [9], the goal of the problem is to maximize the efficiency per task of allocation, where efficiency refers to the value per unit work of task-execution. However, maximizing the efficiency does not minimize the makespan in the case of allocating tasks to heterogeneous robots. For example, if a robot executes a task that another robot should do, the latter robot must execute yet another task that it is either not proficient at or is hard to execute. This type of loss is called opportunity cost [10]. We propose an allocation method based on the theory of comparative advantage, which reduces the opportunity cost and minimizes the makespan.

In this study, the allocation based on our method reduces the makespan compared with methods that maximize the sum of efficiency. We perform simulation experiments in environments with uncertainty and find that allocation based on the proposed method reduces the makespan under any uncertainty, compared with methods that maximize the sum of efficiency. In uncertain environments, the makespan with the proposed method was almost the same compared with frequent reallocation of static allocation. We also conduct a heterogeneous robots task-execution experiment and a human-robot collaborative experiment in the real environment. We propose task allocation methods for various tasks execution by heterogeneous multirobots. The proposed method is expected to be effective in real world experiments, because uncertainty can actually appear.

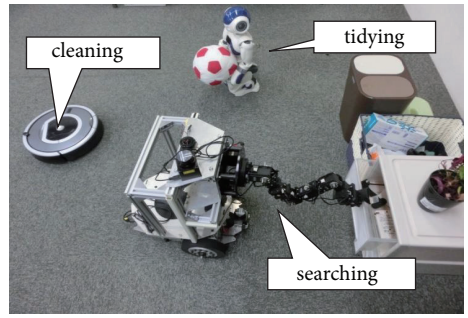


Figure 1: Task allocation to heterogeneous robots.

Currently, the area of the human-robot symbiosis is growing rapidly. As stated in the call of this special issue, assembly, warehouses, and home services need human-robot collaboration as soon as possible. Uncertainness of human is not only each individual difference but also effort input in human-robot collaboration. The definition of the theory of comparative advantage had to be extended to adapt to increases in the number of robots and tasks in the real world including humans.

2. Materials and Methods

2.1. Related Work. Because of the difficulties of constructing a single robot that has the required capability in real world, in recent literature, there are works on heterogeneous multirobot systems (e.g., in assembly of large-scale structures [2]). To allocate tasks to heterogeneous robots, each robot accomplishes its advantageous task, which increases the time performance [2, 11, 12]. How to optimally assign a set of robots to a set of tasks is well known as multirobot task allocation (MRTA) problem [13]. Liemhetcharat and Veloso [14] suggested that "the MRTA problem is categorized along three axes: single-task robots (ST) versus multitask robots (MT), single-robot tasks (SR) versus multirobot tasks (MR), and instantaneous assignment (IA) versus time-extended assignment (TA)." In the example shown in Figure 1, each robot accomplishes its advantageous task. Scheutz et al. [15] showed that swarms of high- and low-speed unmanned aerial vehicles exhibit higher performance than homogeneous swarms in locating and tracking chemical clouds. King et al. [16] performed experiments with a team consisting of rovers and blimps cooperatively executing two types of tasks. Zhang et al. [17] developed a fuzzy collaborative intelligence based algorithm to the collaboration of heterogeneous robots. In these studies, the types of robots are determined in advance, and each robot only executes its specific type of task. Ideally, task allocation methods should not depend on the types of robots, tasks, and environments. Many types of robots are expected to accomplish tasks flexibly as a team operating in any type of environment.

Under other circumstances, the problems of heterogeneous multirobot task allocation problems have been understood as instances of operations research, economics, scheduling, network flows, and combinatorial optimization

[5]. The allocating methods of these problems are categorized as either static allocation, in which tasks are allocated at the start until all the tasks are completed, or dynamic allocation, in which the next task is allocated to any robot as required. Gerkey and Matarić [5] have categorized task allocation problems in multirobot systems as instantaneous or time-extended assignment. Instantaneous assignment is similar to dynamic allocation, and time-extended assignment is similar to static allocation. Time-extended methods have been based on the scheduling algorithm [18]. However, it takes exponential time or longer for these methods to calculate the exact solution. In addition, static allocation is only initially efficient and will degrade over time [19]. We suppose that there are several types of uncertainty related to work in real environments. Especially in the human/multirobot collaboration, it is uncertain to predict a human's behavior such as in the following three cases:

(i) Uncertainty in task-execution time

(ii) Uncertainty increasing the number of tasks during task execution

(iii) Uncertainty agent who is disobedient to allocation orders

Dynamic allocation is a method that repeatedly allocates tasks dynamically during execution. There are many studies on rescheduling in job-shop scheduling problems in factories. In these works, jobs are added during execution [20], the processing speed is uncertain [7], efficiency under an uncertain environment based on the Intuitionistic Fuzzy Sets [21], slack-based techniques at low levels of uncertainty [22], and so forth. These methods are divided into two types: (1) all task assignments are given repeatedly until all the tasks are completed and (2) no planning for future allocations is performed. The latter is called a dispatching method (e.g., first in first out (FIFO) and shortest processing time (SPT) [18]). Allocations based on rescheduling all the tasks are thought to reduce the makespan, and allocations based on dispatching are thought to reduce the calculation time. The dispatching method is also used in CPU scheduling [23], where tasks (processes) are added successively. Compared with production scheduling in a factory [24], the makespan of multirobot task allocation is thought to be smaller. Computer performance may also be restricted in some multirobot task allocation problems. Therefore, dispatching methods have often been studied in multirobot task allocation (e.g., methods that maximize the sum of efficiency [9, 25–33]). These methods entail searching for the best combination of robots and tasks that maximize the sum of efficiency. In this case, efficiency is defined per robot per task, e.g., the inverse of the task-execution time for a robot to perform a task. These methods are based on the solution to the optimal assignment problem [8], the goal of which is to allocate tasks to robots to maximize the overall expected performance. However, allocation based on this method does not necessarily minimize the makespan. In allocation to heterogeneous agents, the opportunity cost can be added to the makespan [10]. Opportunity cost is a term used in economics, representing the value of an alternative forgone (unselected combination) to pursue a certain action. For example, consider that a robot executes a task that another robot should do, to maximize the sum of efficiency, and another robot executes a task for which it cannot minimize the makespan or that it cannot execute. If the former robot executes the task, the difference in task-execution times between the robots is added to the makespan as the opportunity cost. We focus on the makespan at the uncertainty and propose an allocating method based on the theory of comparative advantage, which is a framework to minimize makespan including the opportunity cost.

2.2. Task Allocation Based on the Theory of Comparative Advantage

2.2.1. Theory of Comparative Advantage. To increase the efficiency of tasks executed by heterogeneous robots through task allocation, we focus on "comparative advantage." Comparative advantage is an economic theory referring to the ability of any given economic actor to decrease the total economic cost. According to this theory, an appropriate allocation of tasks among robots is more efficient than each robot executing all tasks. We adapt this theory to the ability of robots and reduce the cost of multirobot decision.

Let e be the efficiency (the productivity per unit labor input) when the robot i executes task m. It is possible to compare the comparative advantage of robot i with robot j by

$$\frac{{}^{i}e_m}{{}^{i}e_n} > \frac{{}^{j}e_m}{{}^{j}e_n}. \tag{1}$$

If robot j has the comparative advantage in task n compared with robot i,

$$\frac{{}^{i}e_n}{{}^{i}e_m} < \frac{{}^{j}e_n}{{}^{j}e_m}. \tag{2}$$

We define ${}^{i}p_m$ as the "comparative advantage between robots" and ${}^{i}q_m$ as the "degree of comparative advantage between tasks":

$$\begin{aligned} {}^{i}p_m &= \frac{{}^{i}e_m}{{}^{j}e_m}, \\ {}^{i}q_m &= \frac{{}^{i}e_m}{{}^{i}e_n}. \end{aligned} \tag{3}$$

Each comparative advantage between each robot with each task becomes an index to allocate tasks. If robot i is inferior to robot j (${}^{i}e_m < {}^{i}e_m$) for task m and has the comparative advantage (see (1)), we should allocate robot i to task m. The total productivity of task m is given by

$$S_m = \sum_{i=1} {}^{i}e_m \, {}^{i}w_m, \quad \left(\sum_{i=1} {}^{i}w_m = 1\right), \tag{4}$$

where ${}^{i}w_m$ is the working ratio (the labor input rate), which is the cost of robot i completing task m per the total cost of robot i. The Pareto front (Figure 2) gives a solution to fix the value of

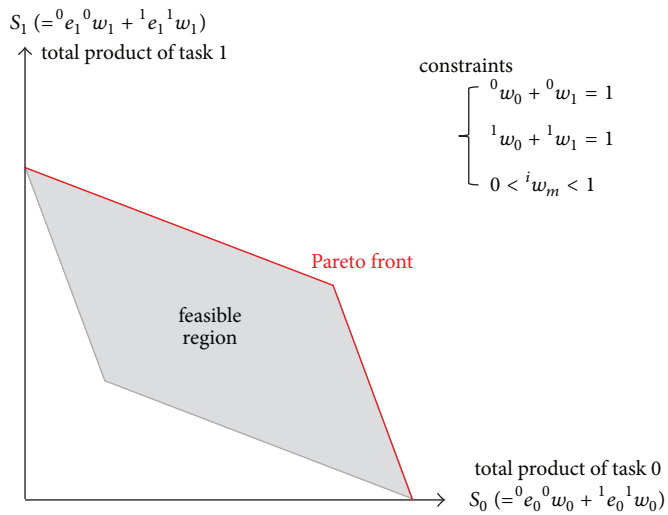


Figure 2: Pareto front.

efficiency ${}^ie_m$

	task 0	task 1
Robot 0	4	1
Robot 1	10	4

working ratio ${}^iw_m$

	task 0	task 1
Robot 0	1	0
Robot 1	${}^1w_0$	${}^1w_1$

or

${}^0w_0$	${}^0w_1$
0	1

Figure 3: Example of an optimal allocation on the Pareto front.

efficiency ${}^ie_m$

	task 0	task 1	task 2
Robot 0	1	2	3
Robot 1	4	5	6

degree of comparative advantage between robots ${}^ie_m/{}^je_m$

	task 0	task 1	task 2
Robot 0	1/4	2/5	6/3
Robot 1	4/1	5/2	3/6

working ratio ${}^iw_m$

	task 0	task 1	task 2	total
Robot 0	0	0	1	1
Robot 1	${}^1w_0$	${}^1w_1$	${}^1w_2$	1

or

0	${}^0w_1$	${}^0w_2$
${}^1w_0$	${}^1w_1$	0

or

${}^0w_0$	${}^0w_1$	${}^0w_2$
1	0	0

Figure 4: Comparative advantage with multiple tasks and two agents.

the working ratio. In this theory, to obtain the solution of the Pareto front (${}^iw_m = 1$), a robot with a comparative advantage (Figure 3) must specialize in a task. We define the cost of robot completing the task as the makespan.

For example, when two robots are allocated to two tasks by the Pareto front (Figure 1), robot 0 executes task 0 and robot 1 executes task 1 at first. Throughout the execution time, one robot is perfectly specialized in one task. The other robot first executes its comparatively advantageous task and subsequently executes the other task. When two robots are allocated to multiple tasks by the Pareto front, each robot performs the tasks in order of their comparative advantages. By the Pareto front, one can argue that maximizing the sum of efficiencies is inefficient. For example, Figure 4 shows a set of robots and tasks. According to the Pareto front, robot 0 executes the tasks in the order $(2, 1, 0)$ and robot 1 executes the tasks in the order $(0, 1, 2)$. By maximizing the sum of efficiency, if robot 0 executes any task after finishing task 2, it would not be an optimum allocation by the Pareto front.

2.2.2. Comparative Advantage with Multiple Agents and Multiple Tasks. The theory of comparative advantage can be

efficiency ${}^{i}e_m$

	task 0	task 1
Robot 0	1	4
Robot 1	2	5
Robot 2	3	6

working ratio ${}^{i}w_m$

	task 0	task 1
Robot 0	${}^{0}w_0$	${}^{0}w_1$
Robot 1	1	0
Robot 2	1	0

or

0	1
${}^{1}w_0$	${}^{1}w_1$
1	0

or

0	1
0	1
${}^{2}w_0$	${}^{2}w_1$

Figure 5: Comparative advantage with two tasks and multiple agents.

extended to allocation among multiple robots or multiple tasks [34]. Figure 4 shows an example of the allocation of two robots to multiple tasks. In Figure 4, tasks are arranged from the left in ascending order of ${}^{i}p_m$ of robot 0. The tasks are always arranged in descending order of ${}^{i}p_m$ of robot 1. Neither robot should perform tasks that have less ${}^{i}p_m$ than a benchmark task. We can choose any task as the benchmark task. If the benchmark is task 1, then robot 0 should first execute task 2 and robot 1 should first execute task 0 in the example in Figure 4. Figure 5 shows that each robot performs a task that has a larger ${}^{i}q_m$ than a benchmark agent. We can choose any agent as the benchmark agent.

In cases of multiple robots and multiple tasks, it will be complex to solve the problem. No general method for describing all the Pareto fronts has been established yet. In economics, several methods have been used to apply the theory of comparative advantage to cases of multiple agents and multiple commodities. There are methods of finding the solutions on the Pareto front or methods in which the number of agents or commodities is restricted [35–37]. In this study, we use a method proposed by Tian [37]. In the following, ${}^{i}r_m$ is the efficiency of robot i to execute task m (${}^{i}e_m$) divided by the sum of efficiency per task and robot:

$$ {}^{i}r_m = \frac{{}^{i}e_m}{\sum_k {}^{k}e_m \sum_l {}^{i}e_l}. \tag{5} $$

Robot i is allocated to task m for which r is maximum. Next, among the combinations of other robots and tasks, the robot and task combination that maximizes r is selected. This procedure is repeated for all the robots. A detailed allocation flowchart is given in Figure 6.

2.2.3. Optimal Assignment Problem. The optimal assignment problem [8] is a well-known problem in operations research. In this problem, M robots, N tasks, and nonnegative efficiencies that predict each robot's performance for each task are given. The goal is to assign tasks to robots to maximize the overall expected performance. In the task allocation problem, the goal is to find the appropriate ${}^{m}\alpha_n$ such that the sum of efficiency is maximized:

$$ \underset{\alpha}{\operatorname{argmax}} \left(\sum_{m=1}^{M} \sum_{n=1}^{N} {}^{m}e_n \, {}^{m}\alpha_n \right), \tag{6} $$

where e represents the task performance per time and ${}^{m}\alpha_n$ must be either 0 or 1; if robot m executes task n, then ${}^{m}\alpha_n = 1$.

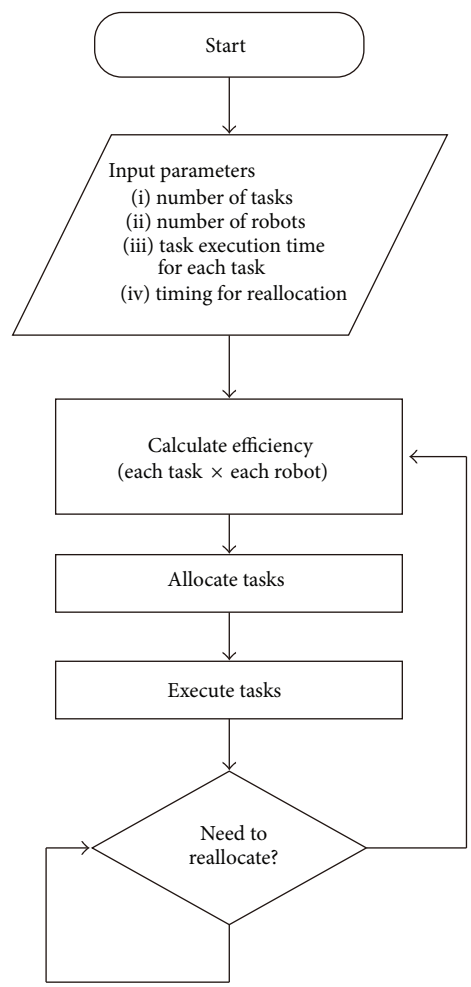


Figure 6: Allocation flowchart.

This is a method of instantaneous assignment which requires frequently solving the problem. It costs $O(MN^2)$ time using the Hungarian method [38]. However, maximizing the sum of efficiency does not always minimize the makespan. For example, in a case where each robot executes each different task (Table 1), robot 0 executes task 1 and robot 1 executes task 0 to maximize the sum of efficiency. Then, the total products are $S_0 = 1$ and $S_1 = 10$, where the solution is not on the Pareto front. In other instances, if robot 1 is specialized in task 1 and the working ratios of robots 0 and 1 are ${}^{1}w_0 = 0.25$ and ${}^{1}w_1 = 0.75$, respectively, the total products of task 0 are $S_0 = 1$ and $S_1 = 11.5$, where the solution is on the Pareto front.

Table 1: Example in which maximizing sum of efficiency does not minimize makespan.

	task 0	task 1
Robot 0	4	10
Robot 1	1	4

We can regard this multirobot task allocation problem as an extension of the traveling salesman problem (TSP) [39]. General TSPs with multiple agents are called multiagent traveling salesman problems [40], vehicle routing problems [41], or job-shop scheduling problems [6]. These problems are NP-hard [42]; they cannot be solved in polynomial time [43, 44]. Instead of listing all the orders (as in the full searching method), there are other methods to decrease the amount of calculation, e.g., by using dynamic programming of time computational quantity $O(2^N N^2)$ and the branch-and-cut algorithm [45]. General algorism, such as NN (Neural Network) [46] or ACO (Ant Colony Optimization) [47, 48], based approximate solutions are also given. In the study to solve vehicle routing problem, it is well known that the method clusters the area by the number of agents and calculates each shortest path [49]. Approximation algorithms and heuristics are, therefore, developed for these problems [48, 50, 51]. However, they require exponential time or longer to calculate the exact solution.

In the uncertain real environment, our proposed method should be able to solve large-scale problems with a large number of robots, tasks, people, animals, and so on. Our method should also be able to compare with different algorithms and the trajectories of robots. There are many things to clarify if our proposed method is feasible or not. But first and foremost, we think the full searching method is plausible to compare with the proposed method.

In this paper, we compare our method with existing methods and show the effectiveness of our method on situations: 2 task and 2 robots (Section 3.1), multiple tasks and 2 robots (Section 3.2), 2 robots and multiple tasks (Section 3.3), and multiple tasks and multiple robots (Section 3.4). As the reason for this, an optimal solution can be calculated for task allocation to the 2 robots situation, to the extent the number of tasks is not large. If our method in these situations is more effective than existing methods for the number of tasks that is more than a certain value, at least, the method has possibilities to solve large task allocation to multiple robots.

3. Task Allocation Method to Specific Problems

3.1. Allocating Two Types of Tasks to Two Types of Robots. To verify the effectiveness of the proposed method, we first simulate allocating two types of tasks to two types of robots (Figure 7). In this study, our purpose is to shorten the makespan of executing tasks in an unknown environment. Tasks in an unknown environment are divided into two main tasks: exploration and other tasks. We choose the carrying task as the basic other task in a field that consists of 20 × 20 areas. We define these two types of tasks as follows:

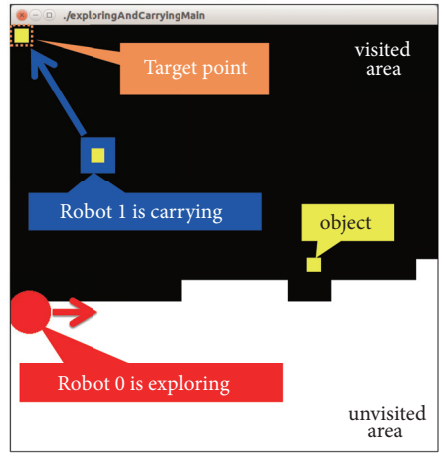


Figure 7: Simulation: two types of tasks by two types of robots. The field consists of 20 × 20 areas. The red circle and blue square represent the robots, the yellow squares represent objects to be carried, the white shading represents unvisited area, and the black shading represents visited area.

Table 2: Moving speeds of each robot.

	Not carrying (v_i)	Carrying ($v_{\mathrm{obj}(i)}$)
Agent 0	0.33	0.10
Agent 1	1.00	0.033

(i) Carrying task: carrying objects to a target point (Figure 7, dashed square). This task is finished once the robots have carried all the objects to the target point.

(ii) Exploring task: exploration of the unknown areas for mapping and discovering objects. Robots do not know where the objects are initially. Unknown areas, indicated by white, turn into known areas, indicated by black, when robots pass through the areas. This task is finished once the robots have passed through all the areas.

The two types of robots explore unknown areas and carry discovered objects. Table 2 shows the differences between the two types of robots. Here, v_i is the moving velocity when robot i does not carry any object, and $v_{\mathrm{obj}(i)}$ is the moving velocity when robot i carries an object. We define the efficiency (performance per unit work) of the carrying task, e_{car}. In this simulation, the efficiency is the inverse of the time taken for the robot to carry the nearest object to the target point:

$$^{i}e_{\mathrm{car}} = \left(\frac{l_0}{v_i} + \frac{l_1}{v_{\mathrm{obj}(i)}} \right)^{-1}, \tag{7}$$

where l_0 is the distance from the robot to the object and l_1 is the distance from the object to the target point. We also define

Table 3: Moving velocity.

	Not carrying	Carrying
Robot 0	0.4	0.1
Robot 1	1.0	0.4

the efficiency of the exploring task, e_{exp}. In this situation, it refers to the inverse of the time taken for the robot to go to the nearest unknown area:

$$^{i}e_{\text{exp}} = \left(\frac{l_2}{v_i}\right)^{-1}, \tag{8}$$

where l_2 is the distance from the robot to the nearest unknown area. In this simulation, the robots are allocated to tasks in the following situations: when one robot finishes carrying an object or exploring an area, when both robots try to carry the same object, and when the comparative advantages of the robots switch. If the allocated task is changed, while a robot is carrying an object, the robot leaves the object.

3.1.1. Comparison with Conventional Method. In this section, we compare the proposed method with conventional methods, i.e., maximizing the sum of efficiency [9] and exploring first method. In maximizing the sum of efficiency, new task is allocated to a robot which has best efficiency of the task as follows: the robot velocities are listed in Table 3. We defined the efficiency of exploring as the not-carrying velocity. We investigated the following three allocation methods:

(i) Proposed method: the theory of comparative advantage (Pareto front).

(ii) Maximizing the sum of efficiency: each robot executes each different task; if $^{0}e_0 + {}^{1}e_1$ is more than $^{0}e_1 + {}^{1}e_0$, then robot 0 executes task 0.

(iii) Exploring first method: both robots execute the exploring task at first and then execute the carrying task after the exploring task is finished.

We simulate three conditions of the number of objects (4, 8, 16). Under the proposed method, robot 0 executed the exploring task and robot 1 executed the carrying task. By maximizing the sum of efficiency, each robot executed opposite tasks. Figure 8 shows the results. Allocation based on our method minimized the makespan of the three types of allocation methods under all conditions.

3.2. Allocating Multiple Types of Tasks in Unknown Environment to Two Types of Robots. In unknown environments, robots have to execute many tasks which are manifold and uncertain. We propose a task allocation method based on the theory of comparative advantage in the case where there are multiple tasks in unknown environments. This allocation method is expected to minimize the makespan by executing in order of the comparative advantage between robots. There are many studies about situations consisting of multiple tasks (e.g., restaurants [52] and disaster mitigation [53]). We feature

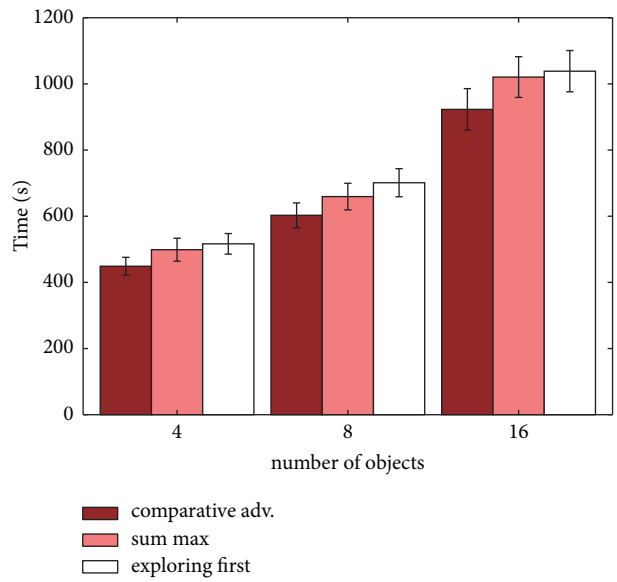


Figure 8: Results of proposed and conventional methods.

carrying multiple types of objects tasks as multiple types of tasks. We compare our method with the basic allocation method that gives all the task assignments of the entire period (we refer to this method as the full searching method). We also simulate allocation in unknown environments with possible accidents: later, adding, unreasonable, and speed-up.

3.2.1. Method to Allocate Tasks of Carrying Multiple Types of Objects. As noted above, we simulated the single-type carrying task allocated to heterogeneous robots by the Pareto front. We evaluate the Pareto front for allocation tasks of carrying multiple types of objects to heterogeneous robots. We define the efficiency of the carrying task $^{i}e_m$ as the time taken for the robot to carry the objects.

$$^{i}e_m = \left(\frac{l_0}{v_i} + \frac{l_1}{v_{\text{obj}(i,m)}}\right)^{-1}, \tag{9}$$

where $v_{\text{obj}(i,m)}$ is the moving velocity when robot i is carrying object m. The carrying velocity $v_{\text{obj}(i,m)}$ depends on the carried object. The comparative advantage between robots is determined by $^{i}e_m/^{j}e_m$ in (3). When any robot finishes carrying an object, both robots redetermine the carrying objects.

We compare the Pareto front with an allocation method based on the full searching of carrying orders. The full searching method calculates the task-execution times of all the carrying orders in the case of M robots and N objects and calculates an order of minimal time. The number of possible combinations is

$$\frac{(N+M-1)!}{(M-1)!}. \tag{10}$$

3.2.2. Setting of Simulation with Possible Accidents. We did a simulation to evaluate the proposed method by comparing

Table 4: Moving velocity.

	Not carry	Carry (0)	Carry (1)	⋯
Robot 0	1.0	0.10	0.11	⋯
Robot 1	1.0	0.20	0.21	⋯

The numbers in brackets represent the object IDs.

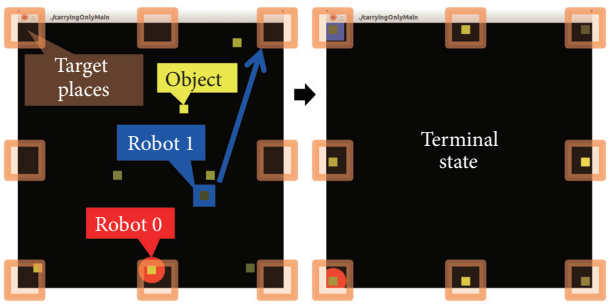


Figure 9: Simulation: heterogeneous robots and multiple carrying tasks.

it with the full searching method. Table 4 shows the moving velocities for types of robots and types of carrying objects. The field in the simulator consists of 20 × 20 areas (Figure 9). At first, the robots are in the center of the field, and the objects are in random positions. The robots know the positions of all the objects in the known area. The target place that each object should be carried to is different. Each robot carries an object that maximizes the comparative advantage between robots.

3.2.3. Conditions. We set simulation conditions defining unexpected events that may occur, including the following conditions:

(i) Later condition: the time required for a robot to carry is later than predicted.

(ii) Adding condition: new objects appear.

(iii) Unreasonable condition: some robots are disobedient to allocation orders.

(iv) Speed-up condition: the time to reach object positions is shorter than the carrying time.

We hypothesize that the proposed method based on the theory of comparative advantage performs better under these conditions than the full searching methods. In the proposed method, robots execute tasks that are given high priority according to the execution time difference among robots. Thus, the remaining tasks have shorter execution time difference among robots. If unexpected events occur, our method can avoid the situation in which an inappropriate robot executes a task and increases the total task-execution time.

Later Condition. This condition is the situation in which it takes more time to carry objects than predicted. For example, such situations occur when a robot carries an object that needs an unknown time to carry, accidents occur, and so

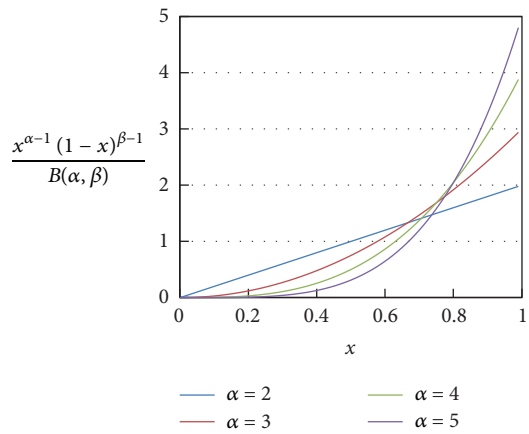


Figure 10: Beta distribution ($\beta = 1$).

forth. We simulated the delay by multiplying the estimated carrying velocity $v_{\text{obj}(i,m)}$ by noise x:

$$v_{\text{objreal}(i,m)} = x v_{\text{obj}(i,m)} \quad (0 < x < 1), \tag{11}$$

where $v_{\text{obj}(i,m)}$ is determined by the allocation and $v_{\text{objreal}(i,m)}$ is the carrying velocity when robots actually carry objects. We define noise x as a random number drawn on a beta distribution.

$$\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \quad (0 \le x \le 1), \tag{12}$$

where x represents a random variable and $B(\alpha, \beta)$ is a beta function. At $x = 1$, the time is the same as predicted. At $x = 1/2$, it takes twice as much time as predicted. x is defined for each combination of robots and objects. The parameter α controls the noise variance. If the value α is smaller, the noise variance increases. Figure 10 shows a plot of the beta distribution with $\beta = 1$.

We simulated two types of full searching methods: (1) full searching (static), in which the robots carry objects in the order that is decided at first and (2) full searching (dynamic), in which the robots redetermine the order every time a robot finishes carrying an object. We ran simulations to compare the proposed method and the two types of full searching methods for certain patterns of α.

Adding Condition. This condition is the situation in which the number of objects increases. At first, there are seven objects, and some objects are added later. Table 5 lists the carrying velocity and time of added objects. The robots redetermine executing tasks in all the methods every time a robot finishes carrying an object, or an object is added.

Unreasonable Condition. This condition is the situation in which some robots are unreasonable agents (UAs). A human or agent is often disobedient to allocation orders because they are in an inaccessible place, they think of a new way, or for other reasons. In these situations, it is necessary to reallocate tasks for the shortest execution time that the other agents are not executing. The full searching method redetermines the

Table 5: Carrying velocity of added objects.

Appearing time [s]	1st	2nd	3rd	4th
	100	200	300	400
Robot 0	0.11	0.19	0.13	0.17
Robot 1	0.21	0.29	0.23	0.27

Initial objects in Table 4.

Table 6: Moving velocity (object ID in brackets).

	Not carry	Carry (0)	Carry (1)	⋯
	v_i	$v_{\mathrm{obj}(i,0)}$	$v_{\mathrm{obj}(i,1)}$	⋯
Robot 0	0.6	0.010	0.011	⋯
Robot 1	1.0	0.020	0.021	⋯

Table 7: Moving velocity of added objects.

Appearing time [s]	1st	2nd	3rd	4th
	1000	1500	2000	2500
Robot 0	0.011	0.019	0.013	0.017
Robot 1	0.021	0.029	0.023	0.027

order for the robots every time an agent finishes a task. In this simulation, Robot 1 is a UA and the robot velocities are given in Table 4.

Speed-Up Condition. In this condition, the carrying velocities (Table 6) are increased to 1/10 of the velocities in previous experiments (Table 4). The time to move is also shorter than the carrying time. In addition, to evaluate this condition, we combined it with adding a condition. The carrying velocity and time when objects are added are shown in Table 7.

Comparing with Allocation Method of Full Searching of Carrying Orders. The calculation complexity of the proposed method is $O(MN)$. Figure 11 shows the average task-execution and calculation time for 100 experiments, where there are initially 7, 8, 9, or 10 objects in random places. The task-execution time for the proposed method is slightly longer than that of the full searching method. However, the calculation time in full searching increases exponentially with an increasing number of objects. From this result, if the executing time of the proposed method is slightly longer than the full searching method, it means that the proposed method has a shorter makespan than the full searching method. Our proposed method is effective for the task allocation to multiple robots in uncertain environment. The calculation time in the proposed method is negligibly short compared with the task-execution time: only 0.51 s for an experiment with 10 objects. Our hardware platform was a ThinkPad T530 with a Core i7-3520M processor, 16 GB memory, and HDD running Ubuntu 14.04.

Maximize the Sum of Efficiency. We also compared our method with methods that maximize the sum of efficiency. Table 4 lists the robot velocities. Figure 12 shows the experimental results of 100 time simulations. There were significant

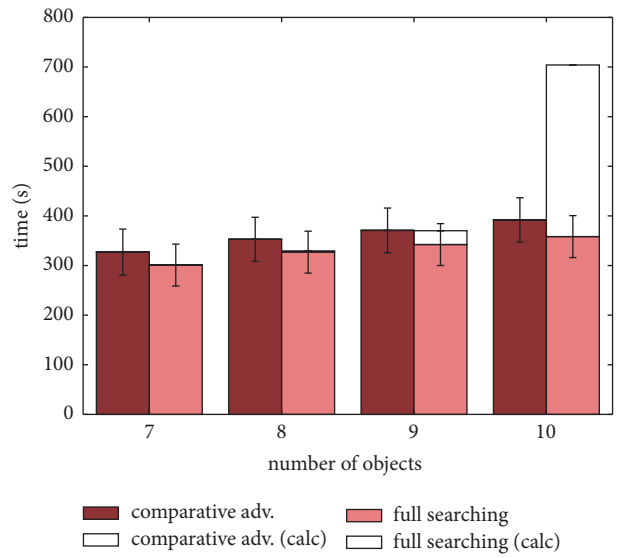


Figure 11: Makespan and calculation time in 100 simulations. There are 7, 8, 9, and 10 objects.

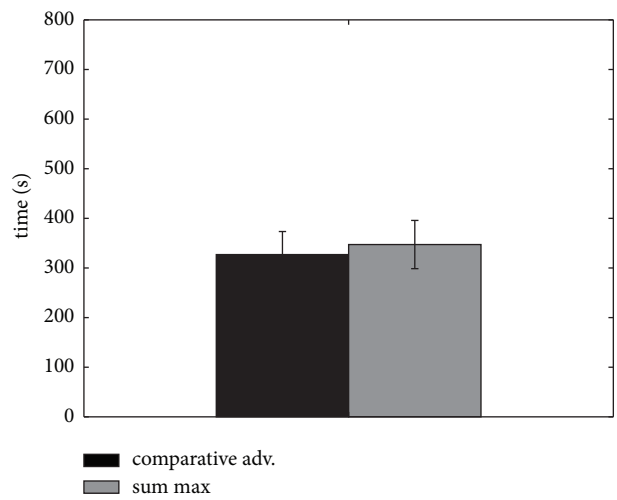


Figure 12: Makespan in 100 simulations.

differences: $t(99) = 9.08$; $p <: 05$. This is similar to the results in Section 3.1.

3.2.4. Results of Simulations with Possible Accidents

Results: Later Condition. Figure 13 shows the results. Compared with the full searching (static) method, the allocation based on our method reduced the makespan when the noise variance is large (e.g., $\alpha = 3$). Compared with full searching (dynamic) method, the Bonferroni method shows no significant difference between the methods for noises $\alpha = 5, 4, 3$, except for a significant difference between the method that maximizes the sum of efficiency with the full searching method at $\alpha = 5$ ($p < .01$). In the full searching (dynamic) method, the calculation time should be treated as idle time whenever the robots begin working.

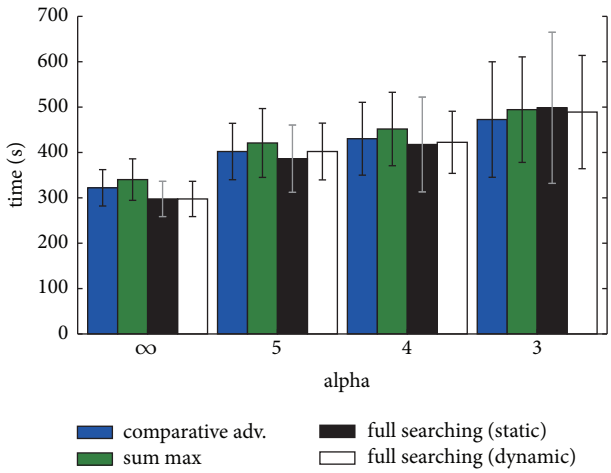


Figure 13: Makespan in the later condition.

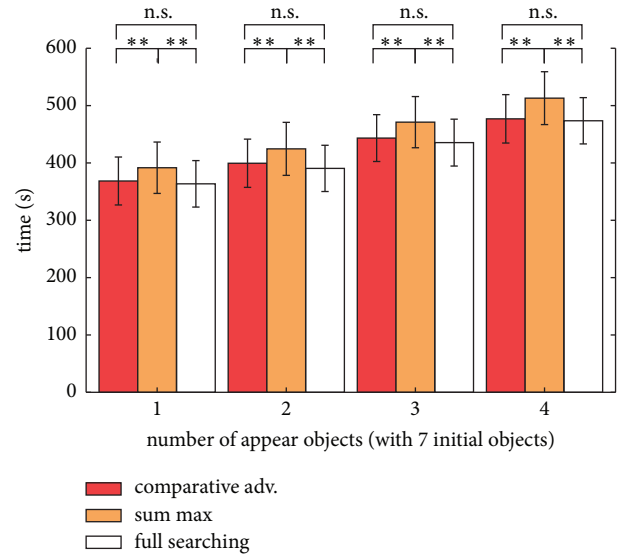


Figure 14: Makespan in the adding condition. $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

The substantial task-execution time includes the working and calculating time. Our method shortens the substantial task-execution time compared to that in the full searching (dynamic) method, depending on the number of carrying objects. Compared with methods that maximize the sum of efficiency, the allocation based on the proposed method reduces the makespan.

Results: Adding Condition. Figure 14 shows the experimental results. There are no obvious differences depending on the number of added objects. We confirmed that allocation based on the proposed method reduces the makespan compared with the methods that maximize the sum of efficiency. The Bonferroni method shows a significant difference between the proposed method and the methods that maximize the sum of efficiency under all conditions. However, the Bonferroni method shows no significant difference between the proposed method and the full searching method under all conditions.

Results: Unreasonable Condition. Figure 15 shows the results. There are significant differences. The proposed method minimizes the makespan of the three methods, in comparison with the full searching method. The UA does not execute an allocated task. In these simulations, the UAs execute the shortest-makespan task of the tasks that other agents are not executing. In the full searching method, the task order for the robots is redetermined every time an agent completes a task. Robot 1 in Table 4 is a UA. Figure 15 shows the results. There are no significant differences.

Each cell in Tables 8 and 9 shows the method that reduced the makespan. The bars (-) in the tables indicate that the t-test shows no significant difference between the methods. As a result, in cases with a UA, the proposed method is more effective than the full searching method. In certain cases without a UA, the proposed method is as effective as the full searching method.

Results: Speed-Up Condition. We think the proposed method is more effective than the full searching method in cases

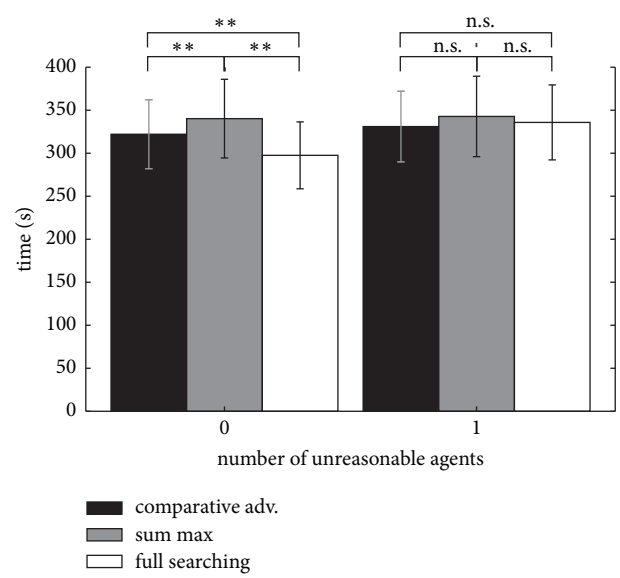


Figure 15: Makespan in the unreasonable condition. $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

where the differences in efficiency are smaller. Figure 16 shows the results for which the number of objects increases during the task execution. The allocation based on the proposed method reduces the makespan compared with the full searching method. The proposed method gives priority to the tasks whose carrying time differences are large. Therefore,

Table 8: Comparison between proposed method and full searching (with no unreasonable agents).

	$\alpha = \infty$	$\alpha = 5$	$\alpha = 4$	$\alpha = 3$
$n_{add} = 0$	full searching**	-	full searching^{+}	-
$n_{add} = 1$	full searching*	-	-	-
$n_{add} = 2$	full searching**	-	-	-
$n_{add} = 3$	full searching^{+}	-	-	-
$n_{add} = 4$	-	-	-	-

$^{+}p < .1$, $^{*}p < .05$, and $^{**}p < .01$; DOF = 199.

Table 9: Comparison between proposed method and full searching (with an unreasonable agent).

	$\alpha = \infty$	$\alpha = 5$	$\alpha = 4$	$\alpha = 3$
$n_{add} = 0$	proposed**	-	-	-
$n_{add} = 1$	proposed**	proposed*	proposed^{+}	-
$n_{add} = 2$	proposed**	proposed**	-	proposed*
$n_{add} = 3$	proposed**	proposed*	proposed**	-
$n_{add} = 4$	proposed**	proposed*	-	-

($^{+}p < .1$, $^{*}p < .05$, $^{**}p < .01$; DOF = 199).

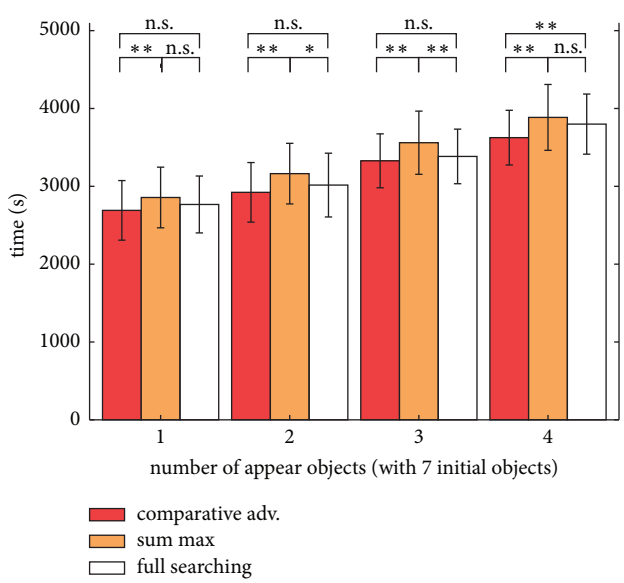


Figure 16: Makespan in the speed-up condition. (1/10 carrying speed condition). $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

the opportunity cost, which is the difference in carrying times between robots, is unlikely to increase when compared with the full searching method. The efficiency of each task has less differences depending on the robot position, because the carrying time does not depend on it. The proposed method considers only the instantaneous robot position.

Table 10: Moving velocity (object ID in brackets).

	Not carrying	Carrying
Robot 0	0.2	0.1
Robot 1	0.3	0.08
Robot 2	0.4	0.06
Robot 3	0.5	0.04

3.3. Allocating Two Tasks to Many Types of Robots

3.3.1. Limitation of Allocating Method. We think the Pareto front can shorten the makespan of many robots executing two tasks (exploring and carrying). In this theory, we must nominate a benchmark robot to determine how many robots should be allocated to each task (exploring or carrying) and the benchmark robot is the only one that executes both tasks. For the adjustment to many robots, the following steps are added to the allocation method based on the theory of comparative advantage. To decide a benchmark robot, we performed a simulation.

(1) Nominate a benchmark robot in some way.

(2) Allocate one task to robots that have a comparatively greater degree of advantage than the benchmark robot, according to (3).

(3) Allocate the other task to the other robots.

The whole-period Pareto front has a limitation for allocating tasks to many types of robots. When one task is finished first, every agent will be executing the other task. This means that there are robots that execute both tasks and the whole-period Pareto front is unadaptable to this situation. The whole-period Pareto front can be adapted to the situation in which each robot executes a single task. Hence, to allocate two tasks to many types of robots, it is unadaptable to shorten the overall makespan. However, we think that the particular makespan (e.g., until one task is finished) will be shortened by the whole-period Pareto front. We propose a new method to shorten the overall makespan through the simulation results.

3.3.2. Simulation: Allocate a Carrying and an Exploring Task to Many Types of Robots. We performed simulation experiments to allocate a carrying and an exploring task to four types of robots by the theory of comparative advantage (Figure 17). We set the moving velocities of four robots as the comparative advantage (Table 10), and (8) gives the efficiency of the robots for each task. We performed the following steps to simulate allocation.

(1) Determine a benchmark robot in number order of robots (decide how many robots to allocate the exploring task).

(2) Allocate exploring task to robots that have a comparatively greater degree of advantage than the benchmark robot.

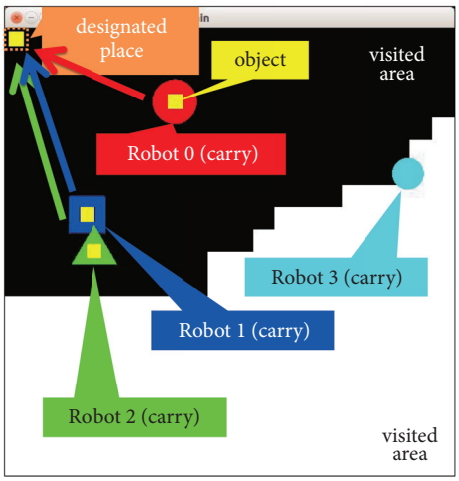


Figure 17: Simulation example: allocate the exploring and carrying tasks to four robots.

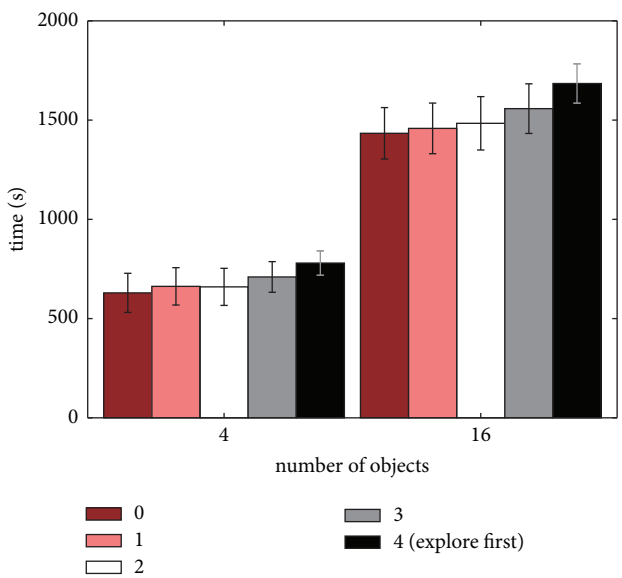


Figure 18: Results based on our method. The legend shows the benchmark agent id: minimal numbers of exploring agents.

(3) Allocate the carrying task to other robots in the order of the degree of comparative advantage.

(4) Allocate the exploring task to the remaining robots.

We simulated five robot conditions (benchmark robots are 1–4; exploring robots are 0–4) versus the object condition (number of objects are 4 or 16) on the instantaneous Pareto front. Figure 18 shows the results. In both object conditions, when the exploring robot was zero, the instantaneous Pareto front can shorten makespan the most. From these results, we can propose a method "explore until find." Under this method, if an object is found, it should be moved instantly. Accordingly, for few tasks, robots should give preference to other tasks over the exploring task. Thus, we propose a method in the case that there are many tasks in an unknown environment.

Table 11: Moving velocity.

	Not carry	Carry (0)	Carry (1)	⋯
	v_i	$v_{\mathrm{obj}(i,0)}$	$v_{\mathrm{obj}(i,1)}$	⋯
Robot 0	1.0	0.10	0.11	⋯
Robot 1	1.0	0.20	0.21	⋯
Robot 2	1.0	0.30	0.31	⋯
Robot 3	1.0	0.40	0.41	⋯

3.4. Allocating Many Types of Tasks to Many Types of Robots

3.4.1. Method. We propose a method to allocate many types of tasks to many types of robots, based on the theory of comparative advantage proposed by Tian [37]. The numbers of robots and objects are represented by M and N, respectively. Here, ${}^{i}r_m$ is the efficiency for robot i to execute task m (${}^{i}e_m$) divided by the sum of the efficiencies per task and per robot by (5). Robot i executes task m, for which r is maximum. Next, among the combinations of other robots and tasks, the combination for which r is maximum is selected. This procedure is repeated M times. In case of $M = 2$, the task selected by this method is always the same as the method of Section 3.1. Figure 19 shows an example of allocation based on this method. The red-colored values indicate the selected tasks.

3.4.2. Verification. We verify the proposed method to allocate carrying tasks to many robots by a simulation, as shown in Figure 20. The simulation settings used here are the same as those in Section 3.1. We employed the following conditions for verification.

(1) Robot condition: the robots have different comparative advantages. We set the moving velocities of four robots as the comparative advantage (Table 11).

(2) Environment condition: the system knows or does not know about the environment.

(3) Unreasonable condition: this is the same as in Section 3.2: task-execution time, added objects, and unreasonable agent.

We compare the proposed method with the full searching method and the method that maximizes the sum of efficiency. The full searching method in this section refers to the "dynamic full searching" method: robots are reallocated to each task every time a robot finishes carrying an object.

Figure 21 shows the makespan in these three methods in a known environment. Multiple comparisons with the Bonferroni methods show significant difference between these three methods. The method that maximizes the sum of efficiency is the highest in the known environment.

We show the following results of the conditions in an unknown environment.

Task-Execution Time. We performed simulation experiments in situations where it takes an unknown time to carry objects. Figures 22 and 23 show the experimental results. Multiple comparisons with the Bonferroni method revealed that there

efficiency ${}^{i}e_m$

	task 0	task 1	task 2	task 3	task 4
Robot 0	1	2	3	4	5
Robot 1	6	7	8	9	10
Robot 2	11	12	13	14	15
Robot 3	16	17	18	19	20

$\frac{{}^{i}e_m}{(\Sigma_i {}^{i}e_m)(\Sigma_m {}^{i}e_m)}$ $\times 10^{-3}$

1.96	3.51	4.76	5.80	6.67
4.41	4.61	4.76	4.89	5.00
4.98	4.86	4.76	4.68	4.62
5.23	4.97	4.76	4.59	4.44

red: selected tasks

Figure 19: Example of allocation based on the proposed method.

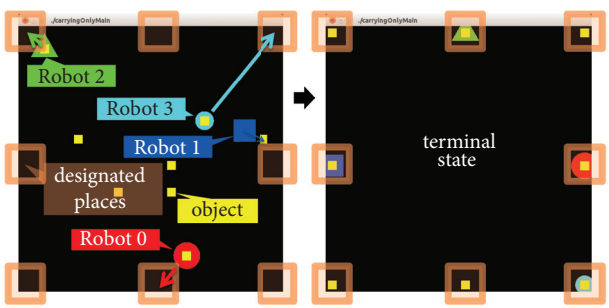


Figure 20: Simulation of carrying objects with four robots.

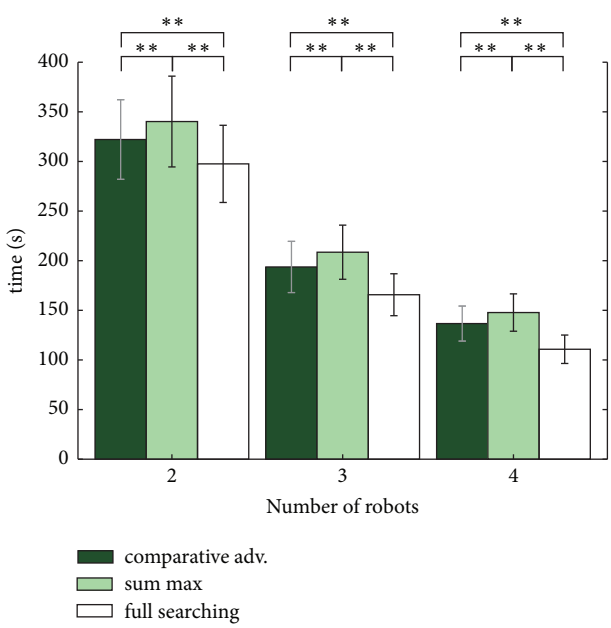


Figure 21: Makespan of some number of robots. $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

are significant differences ($p < .001$) except for $\alpha = 4$, comparative adv versus sum max (n.s.). Compared with methods that maximize the sum of efficiency, the proposed method reduces the makespan under any condition. Compared with the full searching method, the makespan ratio decreased with

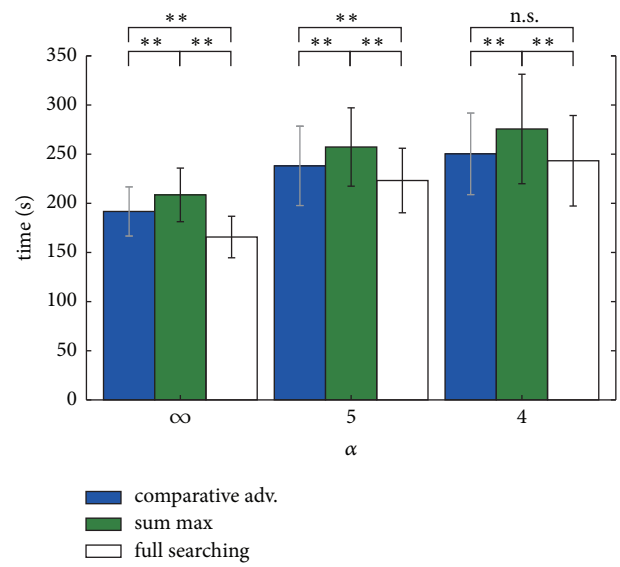


Figure 22: Makespan in situations where carrying objects can be late (three robots). $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

increasing uncertainty. The Bonferroni method shows no significant differences ($p = .05$ level for $\alpha = 4$).

Adding Objects. Figures 24 and 25 show the experimental results. Compared with the methods that maximize the sum of efficiency, the proposed method reduces the makespan under any condition. Compared with the full searching method, the makespan ratio decreased with increasing uncertainty. The Bonferroni method shows no significant differences ($p = .05$ level for $n_{\text{add}} = 2, 3$, or 4).

Unreasonable Robots. In this experiment, robots with large index numbers are unreasonable. For example, for two UAs and one reasonable agent (RA), robots 1 and 2 are unreasonable and robot 0 is reasonable. Figures 26 and 27 show the experimental results. Compared with the methods that maximize the sum of efficiency, the proposed method reduces the makespan under any condition. The Bonferroni method shows no significant differences ($p = .05$).

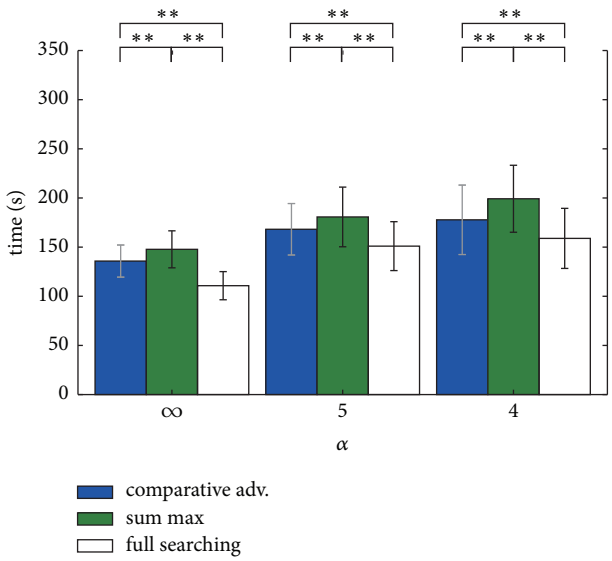


Figure 23: Makespan in situations where carrying objects can be late (four robots). $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

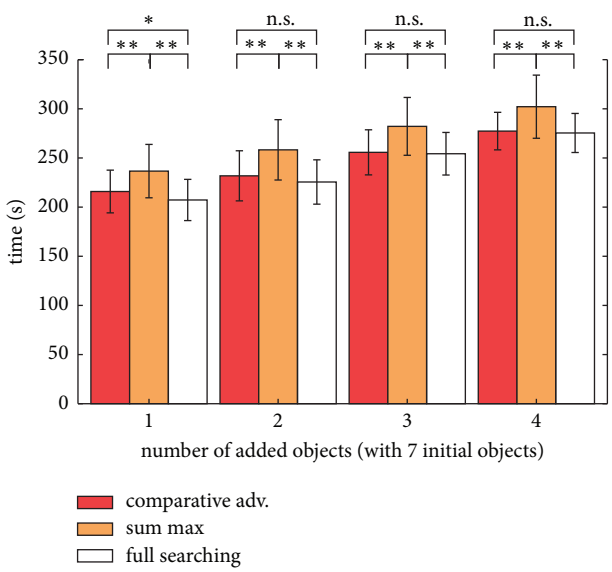


Figure 24: Makespan in situations where carrying objects are added later (three robots). $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

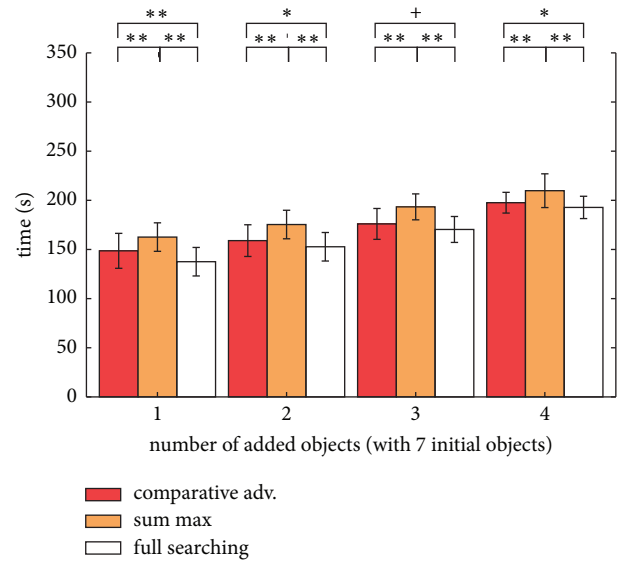


Figure 25: Makespan in situations where carrying objects are added later (four robots). $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

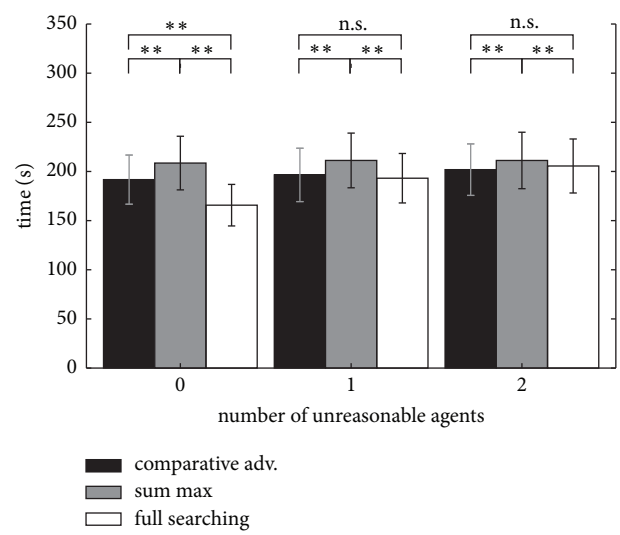


Figure 26: Makespan in situations where there is an unreasonable agent (three robots). $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

The task-execution time for the proposed method is slightly longer than that of the full searching method from Figures 22–27. However, the calculation time in full searching increases exponentially with an increasing number of objects. We expect that our method will become shorter than full searching with an increase in the number of agents.

These results are similar to those in Figure 8, where the allocation based on our method reduces the makespan under any condition compared with methods that maximize the sum of efficiency. Compared with the full searching method, the makespan ratio decreased with increasing uncertainty.

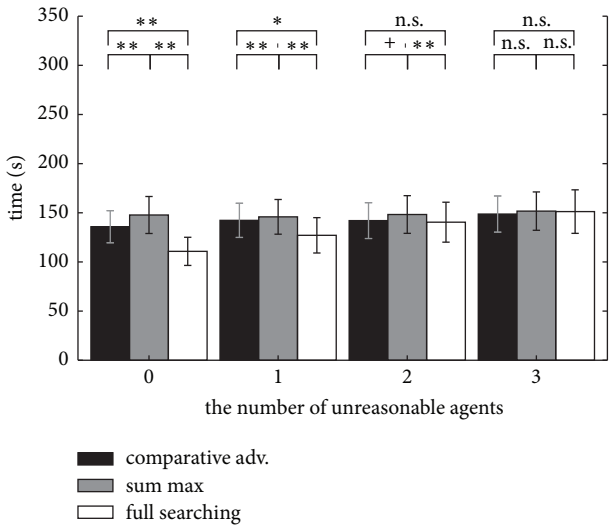


Figure 27: Makespan in situations where there is an unreasonable agent (four robots). $^{**}p < .01$, $^{*}p < .05$, and $^{+}p < .1$. A significant p value indicates that a significant difference in prescribing exists between the conditions. The lower p value indicates a strong significant difference. n.s. means no significant difference between the conditions.

Table 12: Moving ability of each robot.

	Proceeding	Rotating
Roomba	100 mm/s	100°/s
NAO	60 mm/s	60°/s

3.4.3. Experiments in the Real Environment. Additionally, beyond the simulations, we conducted an allocation experiment in a real environment. Figure 28 shows scenes of this experiment. We used two types of robots: a wheeled robot Roomba (iRobot) and a small humanoid NAO (Aldebaran Robotics). These robots can move forward or backward and rotate in their current position. Table 12 shows the speeds of the robots. The objects that should be carried and their features are as follows:

(i) Box: both robots can easily carry this object by pushing Roomba.

(ii) Ball on the wall: it is difficult for Roomba to push this object. Roomba cannot move the object to the target area directly, unless Roomba pushes it off the wall. Roomba needs to go around it and move it from behind. NAO can scrape objects from the wall using its hand, which costs approximately 5 s.

(iii) Table: it has four legs. Roomba is not wide enough to span the legs of the long side. Therefore, Roomba must alternately push the left and right legs in order to move the object. NAO has a comparative advantage to carry the table.

We calculated the carrying time using the moving path and moving speeds (Table 12). The robot controller gave a list of points as the moving path to the robots. Figure 28 shows the flow of the experiments. We regard the failure to carry as a factor of the delay of the carrying time. The proposed method is effective in allocating carrying tasks in an unknown environment as well as in the simulation.

Allocating Carrying Tasks to Wheeled Robot and Humanoid. Figure 28 shows scenes of experiments. (3) shows that Roomba failed to carry the box. If Roomba had not failed, Roomba would have carried the ball. We performed real-world experiments of allocating carrying tasks to real robots using the proposed method. We tried to confirm how our method works in the real world. As a result, the advantage of the proposed method will gradually reduce the differences between the execution times of remaining tasks.

Allocating Tasks to Robot and Human. We also conducted an experiment in which a robot and a human carry objects to confirm the effectiveness of the proposed method in allocation with an unreasonable agent. We used Roomba as the robot. Figure 29 shows the scene of this experiment, which included four types of objects (two boxes, a ball, and a table). Roomba is good at carrying the two boxes and is poor at carrying the table and ball. The human carries an object that the robot is not carrying. The results indicated that the human carried the table and ball, and the robot carried the two boxes. The robot saved carrying time for comparatively disadvantageous objects, thereby reducing the makespan. The robot executed comparatively advantageous tasks and prevented the UA from executing such tasks. The makespan would be reduced by the proposed method.

4. Discussion

4.1. Limitation

4.1.1. Computing Power. In this research, to allocate tasks to robots, we used the economic theory of comparative advantage as a method to reduce the total makespan. We compared the proposed method with conventional methods used in robotic exploration missions. These results have been enabled by the recent developments in computing power and the ability of robots. In the future, high computing power will reduce the total makespan, particularly the calculating time, and standardized robots that are able to execute multitasks will be developed. However, our method contributes to the efficiency of robots' labor output. Monofunctional robots can practically execute tasks other than their main task (e.g., cleaning task for the Roomba). Real robots can execute tasks that they should not or that their developers did not consider, but only at a low level (e.g., carrying task for the Roomba). In real environments, we cannot perceive everything that occurs. In such cases, our method can allocate the tasks to robots that include these low-level performances on a real-time basis according to the comparative advantage.

4.1.2. Simulation Setting. We conducted simulation in a field that is free (without obstacles) and small (20 × 20 grid), by robots without sensors and motions. Obstacles increase uncertainty and sensing capability relate closely to a robot's

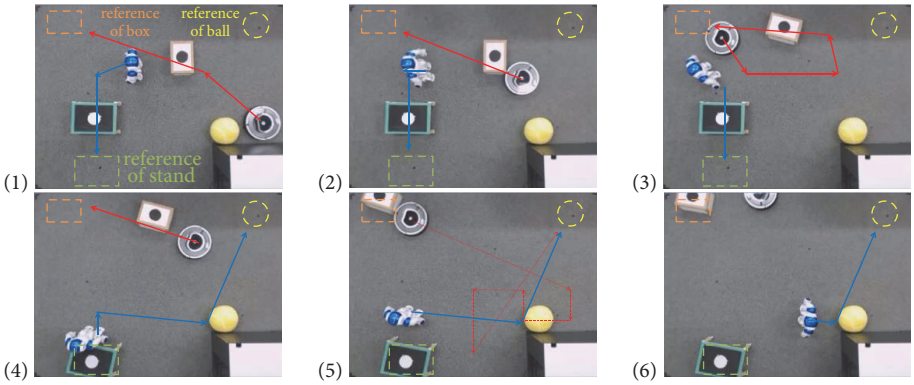


Figure 28: Experiment of real robots based on the proposed method. (1) Initial state. The robot decided the carrying object based on the list of carrying time. (2) Trying to move each object. (3) Roomba fails to carry the box and try to do again. (4) NAO finishes carrying the stand and begins to carry the ball. (5) Roomba finishes carrying the box. The method then determines which robot carries the ball, and NAO continues carrying the ball. (6) Roomba finished tidying, and NAO continues carrying the ball.

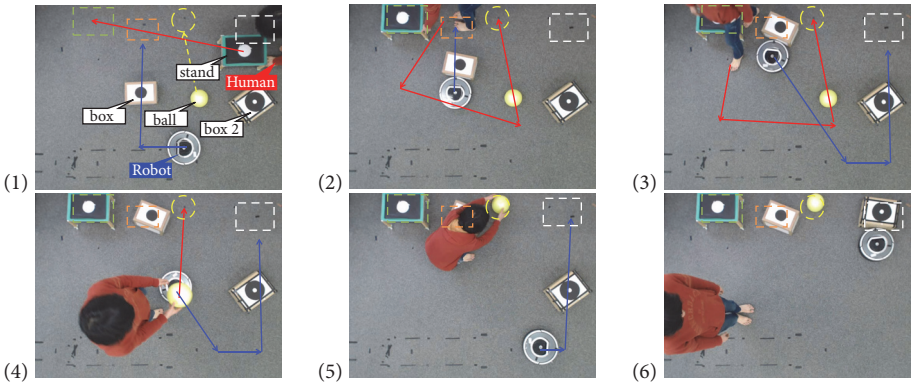


Figure 29: Experiment of the robot with a human.

performance. This study is a first step to investigate how to reduce the total makespan by using comparative advantage. We must unite the proposed method with existing algorithms of obstacle avoidance, exploration, and safe wandering. If it is possible to evaluate the performance of agents by real time, our method can be dynamically adaptive.

4.2. Future Work. There have been sparse improvements to the methods of allocating many tasks to many robots. We have a forward-looking approach in which the allocation of next tasks is preliminarily based on the theory of trade with the comparative advantage [54]. In the traveling salesman problem or the job-shop scheduling problem, there are many studies to reduce the calculation time. The proposed method should be applied to these studies and our method should be comparatively verified with them. In this study, one robot executes only one task (single-task robots). In the uncertain real environment, it is important to solve complex large-scale problems with a large number of robots, tasks, people, animals, and so on. Our method should also be able to be compared with different algorithms and the trajectories of robots. It is necessary to expand this to include the condition under which one robot executes certain tasks at the same time (multitask robots). In addition, the condition under which some robots execute one task at the same time should be considered. We supposed a centralized robot system in this study; thus, we should expand the proposed method to include the distributed autonomous systems.

This study investigated the allocation methods using simulations. We must comparatively verify these results in a real environment with other conventional methods such as market-based techniques inclusive of TraderBots [55, 56] and Hoplites [57]. The uncertainty instances with humans have numerous possible causes. Dealing with true "uncertainty" requires consideration of human-robot collaborations. Performance of a human is not certain quantitatively. Our method observes and calculates the performance of human and allocates tasks to robots with competence dynamically.

5. Conclusion

We investigated a method of using the theory of comparative advantage to allocate tasks to robots with uncertainty including humans. The proposed method is a dynamic sharing algorithm to allocate uncertainty tasks in an unknown

environment, assuming timely reallocation. First, we confirmed that the proposed method reduces the total makespan (the total task-execution time) compared with conventional methods used in robotic exploration missions. We expect that our method is also effective in terms of calculation time when compared with the time-extended allocation method. We simulated carrying tasks and exploring tasks, which include uncertainty conditions of the work in an unknown environment. The proposed method is also more effective in dealing with uncertainty in task-execution time, uncertainty in the increasing number of tasks during task-execution, and uncertainty agents who are disobedient to allocation orders, compared to existing methods (the sum of efficiency and full searching methods). Finally, through experiments in a real environment, we confirmed that the proposed method can reduce the makespan.

This paper makes several contributions to human-robot interaction. First, the effectiveness of a new economic theory was shown for heterogeneous robots. In robot-robot collaboration, it is important to execute tasks even if the robot has inferior ability to accomplish a task. Second, the theory was effective in the uncertain environments including a human. Human-robot collaboration is receiving a lot of attention. The reallocation corresponding to uncertainness of people is a critical issue.

Disclosure

The full text is not published; it was accepted and presented in ROBOMECH2015 conference [58].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

The authors would like to thank Editage (https://www.editage.jp) for English language editing.

References

[1] D. Ricardo, *Principles of Political Economy and Taxation*, John Murray, 1817.

[2] A. Farinelli, L. Iocchi, and D. Nardi, "Multirobot systems: A classification focused on coordination," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 34, no. 5, pp. 2015–2028, 2004.

[3] Z. Yan, N. Jouandeau, and A. A. Cherif, "A survey and analysis of multi-robot coordination," *International Journal of Advanced Robotic Systems*, vol. 10, article no. A399, 2013.

[4] B. Scassellati and B. Hayes, "Human-robot collaboration," *AI Matters*, vol. 1, no. 2, pp. 22-23, 2014.

[5] B. P. Gerkey and M. J. Matarić, "A formal analysis and taxonomy of task allocation in multi-robot systems," *International Journal of Robotics Research*, vol. 23, no. 9, pp. 939–954, 2004.

[6] R. L. Graham, "Bounds for certain multiprocessing anomalies," *Bell System Technical Journal*, vol. 45, no. 9, pp. 1563–1581, 1966.

[7] S. R. Lawrence and E. C. Sewell, "Heuristic, optimal, static, and dynamic schedules when processing times are uncertain," *Journal of Operations Management*, vol. 15, no. 1, pp. 71–82, 1997.

[8] D. Gale, *The Theory of Linear Economic Models*, McGraw-Hill Book Co, New York, NY, USA, 1960.

[9] B. P. Gerkey and M. J. Matarić, "Sold!: auction methods for multirobot coordination," *IEEE Transactions on Robotics and Automation*, vol. 18, no. 5, pp. 758–768, 2002.

[10] F. von Wieser and A. Ford Hinrichs, *Social Economics*, Adelphi, New York, NY, USA, 1927.

[11] L. E. Parker, "The effect of heterogeneity in teams of 100+ mobile robots," in *MultiRobot Systems Volume II: From Swarms to Intelligent Automata*, pp. 205–215, Kluwer, 2003.

[12] B. P. Gerkey, *Gerkey. on multi-robot task allocation [Ph.D. thesis]*, University of Southern California, 2003.

[13] A. Khamis, A. Hussein, and A. Elmogy, "Multi-robot task allocation: A review of the state-of-the-art," *Cooperative Robots and Sensor Networks*, vol. 604, Springer International Publishing, pp. 31–51, 2015.

[14] S. Liemhetcharat and M. Veloso, "Weighted synergy graphs for effective team formation with heterogeneous ad hoc agents," *Artificial Intelligence*, vol. 208, pp. 41–65, 2014.

[15] M. Scheutz, P. Schermerhorn, and P. Bauer, "The utility of heterogeneous swarms of simple UAVS with limited sensory capacity in detection and tracking tasks," in *Proceedings of the 2005 IEEE Swarm Intelligence Symposium, SIS 2005*, pp. 265–272, USA, June 2005.

[16] E. King, Y. Kuwata, M. Alighanbari, L. Bertuccelli, and J. How, "Coordination and control experiments on a multi-vehicle testbed," in *Proceedings of the 2004 American Control Conference (AAC)*, pp. 5315–5320, usa, July 2004.

[17] L. Zhang, H. Zhong, and S. Y. Nof, "Adaptive fuzzy collaborative task assignment for heterogeneous multirobot systems," *International Journal of Intelligent Systems*, vol. 30, no. 6, pp. 731–762, 2015.

[18] P. Brucker, *Scheduling Algorithms*, Springer, 2007.

[19] B. Gerkey and M. Mataric, "A framework for studying multi-robot task allocation," in *Proceedings of the In Proceedings of the Second International Naval Research Laboratory Workshop on Multi-Robot Systems*, 2003.

[20] R. T. Nelson, C. A. Holloway, and R. Mei-Lun Wong, "Centralized scheduling and priority implementation heuristics for a dynamic job shop model," *IIE Transactions*, vol. 9, no. 1, pp. 95–102, 1977.

[21] X. Zhang, Y. Deng, F. T. S. Chan, P. Xu, S. Mahadevan, and Y. Hu, "IFSJSP: a novel methodology for the Job-Shop Scheduling Problem based on intuitionistic fuzzy sets," *International Journal of Production Research*, vol. 51, no. 17, pp. 5100–5119, 2013.

[22] A. J. Davenport, G. Christophe, and J. Christopher Beck, "Slack-based Techniques for Robust Scheduling," in *Proceedings of the 6th European Conference on Planning ECP-01*, pp. 181–192, Toledo, Spain, 2001.

[23] J. Błażewicz, K. H. Ecker, E. Pesch, G. Schmidt, and J. Węglarz, *Scheduling Computer and Manufacturing Processes*, Springer, Berlin, Germany, 2nd edition, 2001.

[24] A. Edward, F. Silver David, and R. Peterson, *Inventory Management and Production Planning and Scheduling*, Wiley, 1998.

[25] B. B. Werger and M. J. Mataric', "Broadcast of local eligibility for multi-target observation," in *Distributed Autonomous Robotic Systems*, pp. 347–356, 2000.

[26] L. Vig and J. A. Adams, "Multi-robot coalition formation," *IEEE Transactions on Robotics*, vol. 22, no. 4, pp. 637–649, 2006.

[27] L. E. Parker and F. Tang, "Building multirobot coalitions through automated task solution synthesis," *Proceedings of the IEEE*, vol. 94, no. 7, pp. 1289–1304, 2006.

[28] L. Fanelli, A. Farinelli, L. Iocchi, D. Nardi, and G. P. Settembre, "Ontology-based coalition formation in heterogeneous MRS," in *Proceedings of the International Symposium on Practical Cognitive Agents and Robots, PCAR 2006*, pp. 105–116, Australia, November 2006.

[29] Y. Zhang and L. E. Parker, "Considering inter-task resource constraints in task allocation," *Autonomous Agents and Multi-Agent Systems*, vol. 26, no. 3, pp. 389–419, 2013.

[30] C.-H. Fua and S. S. Ge, "COBOS: Cooperative backoff adaptive scheme for multirobot task allocation," *IEEE Transactions on Robotics*, vol. 21, no. 6, pp. 1168–1178, 2005.

[31] R. Zlot, *An auction-based approach to complex task allocation for multirobot teams [PhD. thesis]*, Carnegie Mellon University, 2006.

[32] A. Gautam, J. K. Murthy, G. Kumar, S. P. A. Ram, B. Jha, and S. Mohan, "Cluster, Allocate, Cover: An Efficient Approach for Multi-robot Coverage," in *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*, pp. 197–203, Hong Kong, October 2015.

[33] D. Wu, G. Zeng, L. Meng, W. Zhou, and L. Li, "Gini coefficient-based task allocation for multi-robot systems with limited energy resources," *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 1, pp. 155–168, 2018.

[34] R. Dornbusch, S. Fischer, and P. A. Samuelson, "Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods," *American Economic Review*, vol. 67, no. 5, pp. 823–839, 1977.

[35] L. W. McKenzie, "Specialisation and efficiency in world production," *The Review of Economic Studies*, vol. 21, no. 3, pp. 165–180, 1954.

[36] R. W. Jones, "Comparative advantage and the theory of tariffs: A multi-country, multi-commodity model," *Review of Economic Studies*, vol. 28, no. 3, pp. 161–175, 1961.

[37] Y. Tian, "A New Idea about Ricardo's Comparative Advantage Theory on Condition of Multi-Commodity and Multi-Country," *International Journal of Business and Management*, vol. 3, no. 12, pp. 155–160, 2009.

[38] H. W. Kuhn, "The Hungarian method for the assignment problem," *Naval Research Logistics Quarterly*, vol. 2, pp. 83–97, 1955.

[39] M. M. Flood, "The traveling-salesman problem," *Operations Research*, vol. 4, pp. 61–75, 1956.

[40] T. Bektas, "The multiple traveling salesman problem: an overview of formulations and solution procedures," *Omega* , vol. 34, no. 3, pp. 209–219, 2006.

[41] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Management Science*, vol. 6, no. 1, pp. 80–91, 1959.

[42] C. H. Papadimitriou, *Computational Complexity*, Addison-Wesley, 1994.

[43] J. K. Lenstra and A. H. G. R. Kan, "Complexity of vehicle routing and scheduling problems," *Networks*, vol. 11, no. 2, pp. 221–227, 1981.

[44] M. R. Garey, D. S. Johnson, and R. Sethi, "The complexity of flowshop and jobshop scheduling," *Mathematics of Operations Research*, vol. 1, no. 2, pp. 117–129, 1976.

[45] A. H. Land and A. G. Doig, "An automatic method of solving discrete programming problems," *Econometrica*, vol. 28, pp. 497–520, 1960.

[46] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, no. 6088, pp. 533–536, 1986.

[47] M. Dorigo, *Optimization, learning and natural algorithms [Ph.D. thesis]*, Politecnico di Milano, Milano, Italy, 1992.

[48] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 53–66, 1997.

[49] J. Bramel and D. Simchi-Levi, "A location based heuristic for general routing problems," *Operations Research*, vol. 43, no. 4, pp. 649–660, 1995.

[50] G. Clarke and J. W. Wright, "Scheduling of vehicles from a central depot to a number of delivery points," *Operations Research*, vol. 12, no. 4, pp. 568–581, 1964.

[51] G. A. Croes, "A method for solving traveling-salesman problems," *Operations Research*, vol. 6, pp. 791–812, 1958.

[52] T. Van Der Zant and L. Iocchi, "Robocup@home: Adaptive benchmarking of robot bodies and minds," in *Proceedings of the International Conference on Simulation Modeling and Programming for Autonomous Robots*, vol. 7072, pp. 171–182, 2010.

[53] S. Tadokoro, H. Kitano, T. Takahashi et al., "RoboCup-Rescue project: a robotic approach to the disaster mitigation problem," in *Proceedings of the ICRA 2000: IEEE International Conference on Robotics and Automation*, pp. 4089–4094, April 2000.

[54] Y. Shiozawa, "Final resolution of the ricardian problem on international values," in *Proceedings of the International Conference on Structural Economic Dynamics*, 2012.

[55] R. Zlot, A. T. Stentz, M. B. Dias, and S. Thayer, "Multi-robot exploration controlled by a market economy," in *Proceedings of the 2002 IEEE International Conference on Robotics adn Automation*, pp. 3016–3023, usa, May 2002.

[56] R. Zlot and A. Stentz, "Market-based multirobot coordination for complex tasks," *International Journal of Robotics Research*, vol. 25, no. 1, pp. 73–101, 2006.

[57] N. Kalra, D. Ferguson, and A. Stentz, "Hoplites: A market-based framework for planned tight coordination in multirobot teams," in *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, pp. 1170–1177, Spain, April 2005.

[58] T. Morisawa and I. Mizuuchi, "2P1-V06 Allocating Multiple Tasks to Heterogeneous Robots Based on the Theory of Comparative Advantage," *The Proceedings of JSME annual Conference on Robotics and Mechatronics (Robomec)*, vol. 2015, no. 0, pp. _2P1-V06_1–_2P1-V06_4, 2015.

Hindawi
Journal of Robotics
Volume 2018, Article ID 4546094, 10 pages
https://doi.org/10.1155/2018/4546094

Research Article

Hands-Free Maneuvers of Robotic Vehicles via Human Intentions Understanding Using Wearable Sensing

Weitian Wang, Rui Li, Longxiang Guo, Z. Max Diekel, and Yunyi Jia

Department of Automotive Engineering, Clemson University, Greenville, SC 29607, USA

Correspondence should be addressed to Yunyi Jia; yunyij@clemson.edu

Received 11 November 2017; Accepted 6 February 2018; Published 17 April 2018

Academic Editor: L. Fortuna

Intelligent robotic vehicles are more and more fully automated, without steering wheels, gas/brake pedals, or gearshifts. However, allowing the human driver to step in and maneuver the robotic vehicle under specific driving requirements is a necessary issue that should be considered. To this end, we propose a wearable-sensing-based hands-free maneuver intention understanding approach to assist the human to naturally operate the robotic vehicle without physical contact. The human intentions are interpreted and modeled based on the fuzzy control using the forearm postures and muscle activities information detected by a wearable sensory system, which incorporates electromyography (EMG) sensors and inertial measurement unit (IMU). Based on the maneuver intention understanding model, the human can flexibly, intuitively, and conveniently control diverse vehicle maneuvers only using his intention expressions. This approach was implemented by a series of experiments in the practical situations on a lab-based 1/10 robotic vehicle research platform. Experimental results and evaluations demonstrated that, by taking advantage of the nonphysical contact and natural handleability of this approach, the robotic vehicle was successfully and effectively maneuvered to finish the driving tasks with considerable accuracy and robustness in human-robotic vehicle interaction.

1. Introduction

With the improvements of computational resources and manufacturing capacities, there is a rapid and steady development in intelligent robotic vehicles technology in recent decades [1, 2]. These robotic vehicles have numerous advantages over traditional vehicles to solve traffic problems such as traffic jams and traffic accident which are caused by the driver's error or negligence [3]. Besides, the intelligent robotic vehicles are more and more likely to eliminate gas/brake pedals, gearshifts, and steering wheels. Google has built a two-seater prototype intelligent vehicle sans the steering wheel or pedals. Even without vehicle controls available to the human driver, this prototype is able to safely maneuver around obstacles via the built-in sensors and the software system [4]. Besides, aiming at ride-hailing and ride-sharing fleets, Ford will build a fully autonomous robotic vehicle without a steering wheel or pedals by 2021 [5].

However, in the intelligent robotic vehicle driving process, the human driver or passenger usually has some specific driving requirements such as accelerating in a straight road, stopping for some emergencies, or turning in a temporary direction. Consequently, how to maneuver the driving modes according to the human special intentions is a necessary issue that should be considered in the vehicle design.

During the human-robotic vehicle interaction process, it is significant for the vehicle to understand the human intentions or behaviors in order to achieve different vehicle maneuvers. Several related works have been conducted in recent years.

By using human motions, the car's speed, and the distance between the car and the intersection, Ohashi et al. proposed a model using case-based learning to construct an experimental system for human driver's intentions understanding [6]. In [7], the research team recognized a set of continuous driver intentions by observing the easily accessible vehicles and environment signals such as pedals or global vehicle positions. Based on the playback system and machine learning, Oliver and Pentland presented a dynamical graphical framework to model and recognize driver's behaviors at a tactical level that focused on how contextual information impacted the driver's performance [8]. Researchers in [9] developed

a driver behavior recognition approach by characterizing and detecting driving maneuvers and then modeled and recognized the driver's behaviors in different situations. From the accessible vehicle onboard sensors, Berndt and Dietmayer investigated a method to infer the driver's intentions to leave the lane or other maneuvers. In this work they expected to help drivers predict trajectories or assess risks [10].

However, these recognition and understanding methods for human intentions are too complex to implement in practice. Additionally, we usually cannot get much recorded information from the vehicle embedded system since there are less traditional operation devices in the future robotic vehicles.

Using the gesture to represent human intentions for the robotic vehicle maneuver is a practical and interesting work that attracts a lot of attention. Operating robotic vehicles via human gestures will help the human take his/her hands off the current operation habits to reduce the contributions of the negligence and error which may cause vehicle collisions [11]. Ionescu et al. developed efficient human-vehicle interaction through a smart and real-time depth camera operating in the near infrared spectrum. The acquired depth information was processed for the human gesture detection and recognition to interpret the driving intentions to control the vehicle [12]. Researchers in [13] established the communication by gestures between the human and an intelligent wheelchair through a webcam and sensors. By using an array of cameras which outputted information with an instantaneous state, Kramer and Underkoffler acquired the images of human gestures and then designed a controller that automatically extracted and detected the gesture from the gesture data for the vehicle maneuver [14]. In [15], to enable the human and the vehicle to communicate and work together, Fong et al. used sensor fusion and computer vision to recognize the remote environment and improve the situation awareness. Then they created easily used remote driving tools for the vehicles. Researchers in [16] employed a Leap Motion to detect the gesture data and extracted seven independent instructions for the autonomous vehicle maneuver.

Although there are several vision-based approaches, vision-based driving intention recognition and understanding highly depends on the working surroundings. Its performance is easily interfered by the complex and dynamic background such as the crowded urban settings. Furthermore, the vision system usually requires the human to be within some certain areas in order to capture the motion information, which significantly constrains the activities and working ranges of the humans.

Therefore, with the extensive development and employment of robotic vehicles, researchers expect that humans and vehicles could collaborate seamlessly in different driving situations. Developing a simply configured, naturally operable, and highly robust human intention understanding approach for human-robotic vehicle collaboration is a very necessary issue.

To this end, different from existing approaches of using vehicle built-in devices or vision systems, we propose a wearable-sensing-based maneuver intention understanding approach using a wearable sensory system [17–19] to assist the human in the maneuvering of robotic vehicle without physical contact. This interaction method does not restrain the human's hand to be physically involved in the driving task and can be applied in the complicated human-robotic vehicle interactions.

The major contributions of this work include the following: (1) We propose a natural wearable sensing solution to assist human drivers to maneuver robotic vehicles without traditional operation devices in specific driving situations, which is more robust than existing approaches. (2) We develop a driving intention understanding approach using fuzzy control and human motions information, including forearm postures and muscle activities, which are captured by the wearable sensory system.

2. System Framework

The system framework, which is designed for the human to use the wearable-sensing-based maneuver intention understanding approach to operate the robotic vehicle, is shown in Figure 1. This system contains three layers: the data layer, the decision layer, and the execution layer.

When the human intends to change the robotic vehicle's driving modes, his intentions expressed by forearm postures and muscle activities are detected and calculated via a wearable sensory system, as presented in Figure 2. After being collected, the expression information is preprocessed and fused together to output useful information in the data layer. Then the processed information, including the human hand's rotation angles and arm muscles electromyography (EMG) signals, is sent to the decision layer by means of wireless communication devices in real time.

After that, in the decision layer, the acquired information is further processed to generate intention instructions based on the intention understanding model. Simultaneously, the instruction outputs motivate the vehicle motion planning algorithms by calling the corresponding driving mode function. In order to ensure the vehicle to execute accurately, both intention instructions and algorithm outputs are utilized to make motion planning decisions.

In the execution layer, the vehicle driving commands are generated based on the decision layer outputs for the vehicle to plan motions in the real world workspace. Meanwhile, the vehicle execution states are sent back to the decision layer to alert the motion planning algorithms if the driving intention is accepted. The motion planning algorithms will output the decision again if the driving intention failed to be accepted.

3. Maneuver Intention Representation and Data Acquisition

3.1. Maneuver Intention Representation. The human maneuver intentions [20], including brake, turn, and acceleration, are pretty common in daily driving. These intentions can be reflected and represented by lots of manners, such as body movements and natural languages. Because there are no traditional manual operation devices in the future intelligent robotic vehicles, the normal driving manners are not available in these cases. In this research, in order to make it practical

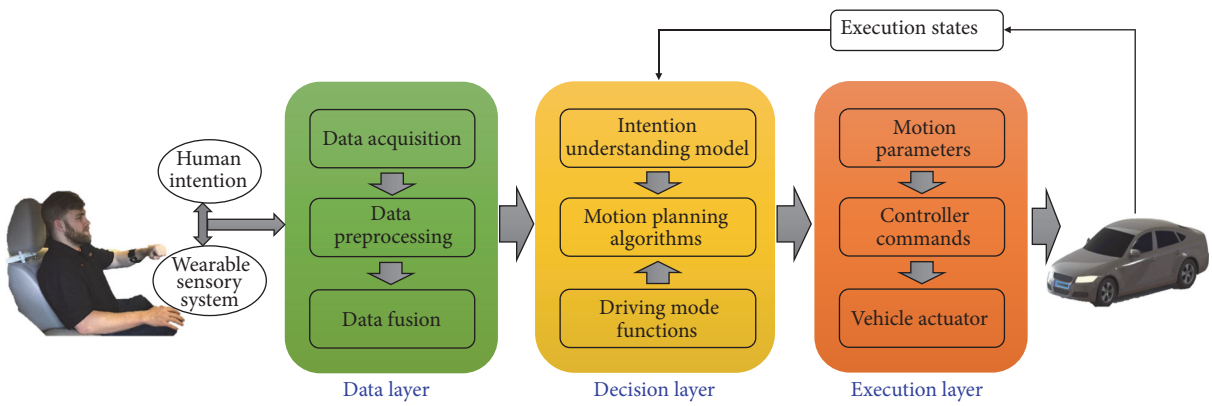


Figure 1: The framework of wearable-sensing-based driving intention understanding for the robotic vehicle maneuvers.

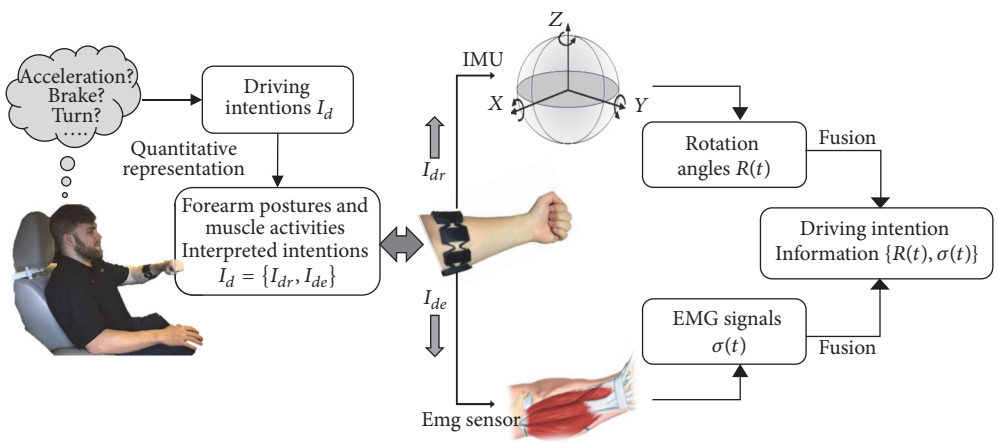


Figure 2: The driving intentions represented by the forearm postures and muscle activities information.

and natural, we utilize the human forearm postures and muscle activities to represent these maneuver intentions. As shown in Figure 2, the intention information usually contains forearm rotation angles and EMG signals. Therefore, the maneuver intentions can be described as

$$I_d = \{I_{dr}, I_{de}\}, \tag{1}$$

where I_{dr} denotes the maneuver intention interpreted by forearm rotations; I_{de} denotes the maneuver intention interpreted by EMG signals.

3.2. Wearable Sensory System. We employ a wearable sensory system for human-robotic vehicle interaction to acquire the human forearm postures and muscle activities information in the maneuver process. The sensory system that we choose is Myo [21], which can be worn at the driver's forearm and integrates with an inertial measurement unit (IMU) [22–24] and eight EMG sensors [25–27]. The IMU chip contains an onboard digital motion processor (DMP) and MPU-9150 module which consists of a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer. The detected information from the IMU and EMG sensors is preprocessed by a microcontroller unit (MCU) with a 32 bit ARM architecture 72 MHz Cortex M4 CPU core. All the raw and calculated data are made available through a first-in-first-out (FIFO) buffer that is read by the MCU over the communication bus. The Bluetooth Low Energy (BLE) module on the mainboard is used for external communication between Myo and the client controller [28].

The working principle of the information acquisition by this wearable sensory system is presented in Figure 2. The human forearm postures will be tracked and recorded by the IMU. This data includes acceleration and angular velocity information which can be fused to describe the forearm motions and rotation angles. When the human performs maneuver intentions, the electrical skeletal muscle activities from his forearm will be measured by the EMG sensors. This EMG information can be extracted to estimate human's finger motions such as wave-in, finger-spread, and fist.

3.3. Data Acquisition and Processing. When the human performs his maneuver intentions, as shown in Figure 2, his forearm postures can be quantified by the IMU outputs which contain the 3-axis acceleration information and the 3-axis angular velocity information about forearm motions. Furthermore, these data can be fused together into quaternions

$$q = [q_0, q_1, q_2, q_3]^T, \tag{2}$$

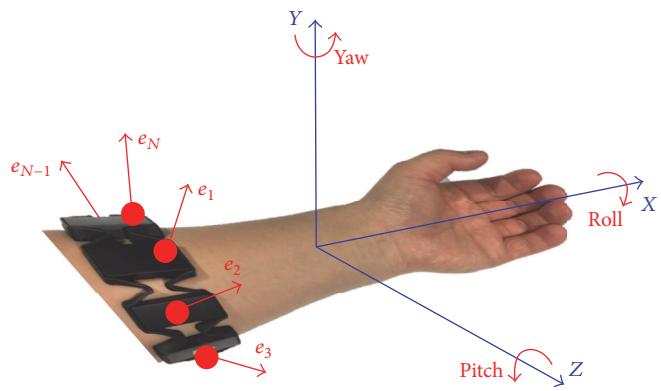


Figure 3: EMG signals and spatial rotations from the human driver's forearm.

where $|q|^2 = {q_0}^2 + {q_1}^2 + {q_2}^2 + {q_3}^2 = 1$. The sample frequency of the IMU is 50 Hz in our work.

In order to calculate the forearm postures, Euler angles [29] are utilized to parameterize the forearm spatial rotations in the 3D work space. The Roll-Pitch-Yaw Euler angles can be represented by

$$R(t) = [\phi(t), \theta(t), \psi(t)]^T, \tag{3}$$

where t denotes the IMU sampling time, ϕ is the Roll rotation about the x-axis, θ is the Yaw rotation about the y-axis, and ψ is the Pitch rotation about the z-axis. As presented in Figure 3, Euler angles are able to visually describe the forearm rotation movements in the hand-over process.

Moreover, the Euler angles are able to be calculated by the quaternions as

$$R = \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} \arctan \dfrac{2q_0q_1 + 2q_2q_3}{1 - 2q_1^2 - 2q_2^2} \\ \arcsin(2q_0q_2 - 2q_1q_3) \\ \arctan \dfrac{2q_1q_2 + 2q_0q_3}{1 - 2q_2^2 - 2q_3^2} \end{bmatrix}. \tag{4}$$

Therefore, the driver's intentions I_{dr} interpreted by the arm rotation in (1) can be represented as

$$I_{dr} = \{I_{dr}(x_r) \mid x_r \in R(t)\}. \tag{5}$$

Simultaneously, the human finger motions can be calculated based on the EMG signals which are collected from the human forearm's muscle activities. The EMG data acquired by the wearable sensory system can be described as

$$E(t) = [e_1(t), e_2(t), \ldots, e_n(t)]^T, \tag{6}$$

where t is the sampling time of the EMG sensor, $e(t)$ is the output of each EMG sensor, and n is the number of EMG channels on the wearable sensory system which is 8 in our work. We sample these EMG signals at a frequency of 200 Hz.

The raw EMG signal is a set of discrete points with positive and negative components. Along with the finger activities, the electric potentials generated by muscle cells have a distinct effect on the dispersion of the EMG signal. Therefore, to take advantage of the EMG data accurately, we adopt the standard deviation (SD) σ of the EMG data to extract the characteristics from the finger activities. The standard deviation could reflect the muscle activities observably. In the human-robotic vehicle interaction, the standard deviation can be calculated by

$$\sigma_i = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(e_i(k) - \frac{1}{K}\sum_{k=1}^{K} e_i(k)\right)^2}, \tag{7}$$

where $e_i(k)$, $k = 1, 2, \ldots, K$ is a set of EMG signals and K is the window size for determining the number of EMG data to be employed to calculate the stand derivation. We select $K = 150$ in this study.

Moreover, the maneuver intentions I_{de} interpreted by the finger motions in (1) can be represented by

$$I_{de} = \{I_{de}(x_e) \mid x_e \in \sigma(t)\}. \tag{8}$$

According to (5) and (8), the maneuver intention can be represented as

$$I_d = \{I_{dr}(x_r), I_{de}(x_e) \mid x_r \in R(t),\ x_e \in \sigma(t)\}. \tag{9}$$

From the above, it can be concluded that, during the robotic vehicle maneuver process, $R(t)$ and $\sigma(t)$ are dynamically programmed and updated via the human forearm postures and muscle activities. Therefore, the maneuver intentions I_d will be interpreted and updated in real time.

4. Maneuver Intention Understanding Using Fuzzy Control

In this section, based on the wearable sensing information and the maneuver intention representation, we build an intention understanding model using the fuzzy control.

4.1. Maneuver Intention Fuzzification. Before developing the fuzzy controller [30], we should define the fuzzy set and domain of discourse using the wearable sensing information, which contains forearm postures and muscle activities. In this

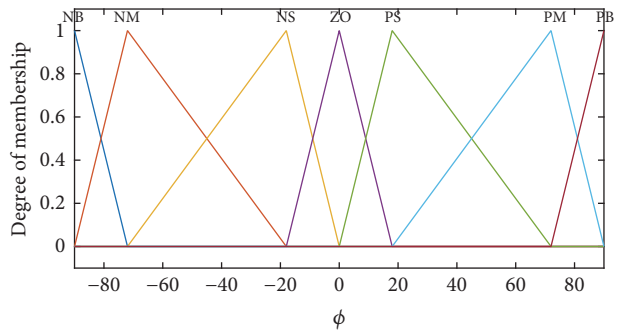


Figure 4: The membership function of the Roll angle ϕ.

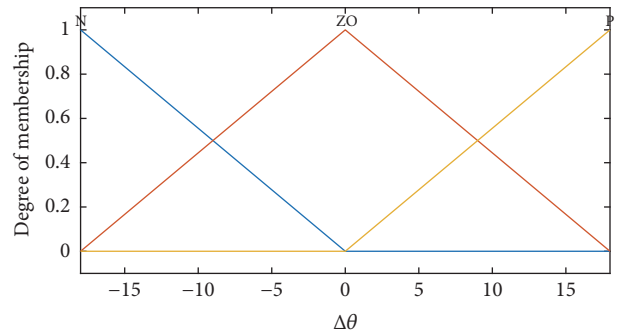


Figure 5: The membership function of the Yaw angle $\Delta\theta$.

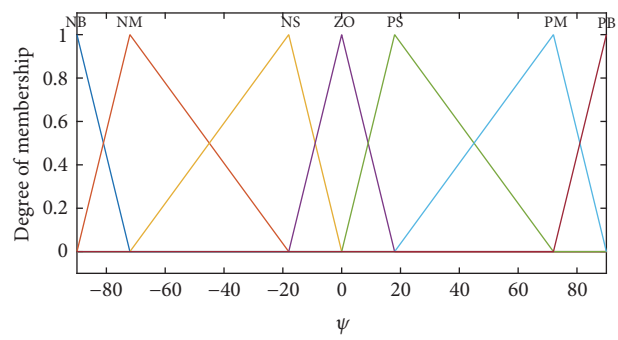


Figure 6: The membership function of the Pitch angle ψ.

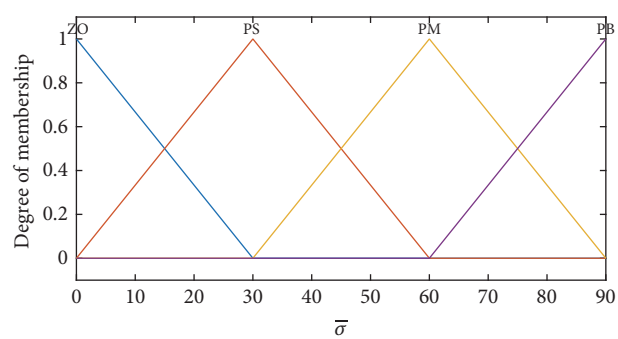


Figure 7: The membership function of the EMG signal $\overline{\sigma}$.

work, we find it is difficult to distinguish various intentions by directly employing the raw standard derivations of all EMG signals, while the average of them presents clear differences. Hence, we utilize $\overline{\sigma} = \sum_{i=1}^{8} \sigma_i/8$ to denote the muscle activities from the driving intention. Additionally, in order to distinguish steering modes in the robotic vehicle maneuver, we utilized $\Delta\theta = \theta(t+1) - \theta(t)$ to work as an input for the fuzzy controller. Therefore, combining the forearm rotation angles and EMG signals together, we deploy the fuzzy controller with four inputs $(\phi, \Delta\theta, \psi, \overline{\sigma})$ and one output (I_d).

Moreover, the fuzzy sets of the inputs and output are defined as follows:

(i) The Roll angle ϕ : {NB, NM, NS, ZO, PS, PM, PB}

(ii) The Yaw angle $\Delta\theta$: $\{N, \text{ZO}, P\}$

(iii) The Pitch angle ψ : {NB, NM, NS, ZO, PS, PM, PB}

(iv) The EMG signal $\overline{\sigma}$: {ZO, PS, PM, BD, PB}

(v) Driving intentions I_d : {AC, DC, ST, TL, TR, BD},

where "AC," "DC," "ST," "TL," "TR," and "BD" denote the maneuver intentions of "*Acceleration*," "*Deceleration*," "*Stop*," "*TurnLeft*," "*TurnRight*," and "*BackwardDriving*," respectively. Additionally, "NB," "NM," "NS," "ZO," "PS," "PM," and "PB" denote negative big, negative middle, negative small, zero, positive big, positive middle, positive small, and separately, which are employed to represent degree of membership in the maneuver intention understanding.

4.2. Membership Functions. According to the fused wearable sensing information and driving operations in the vehicle maneuver, we define the domains of discourse of the inputs and output as follows:

(i) The Roll angle ϕ : $[-90^\circ, 90^\circ]$

(ii) The Yaw angle $\Delta\theta$: $[-18^\circ, 18^\circ]$

(iii) The Pitch angle ψ : $[-90^\circ, 90^\circ]$

(iv) The EMG signal $\overline{\sigma}$: $[0, 90]$

(v) Driving intentions I_d : $\{-2, -1, 0, 1, 2, 3\}$.

In this study, we ask 5 subjects, who have different hands and muscular tensions when maneuvering the robotic vehicle, to detect the forearm rotation angles and EMG signals. Each subject performs 20 times for each maneuver intention. The triangular membership function [31] is employed for each input and output in the fuzzy controller. The membership functions we design are shown in Figures 4~8. It can be seen that, during the maneuver process, the degree of membership is varied with the domain of discourse of each input or output correspondingly.

4.3. Maneuver Intention Understanding. Since the fuzzy controller in this work is configured with four inputs and one output, the fuzzy rules cannot be presented by the traditional rule-table. However, we can use the "IF-THEN" statements [32] to describe the valid fuzzy rules we utilize in the robotic vehicle maneuver. As shown in Table 1, the "IF" parts are antecedents and the "THEN" parts are consequents.

For the maneuver intention understanding, we employ "AND" as the fuzzy operator in each rule and "OR" as the

Table 1: The valid fuzzy rules we utilize in the robotic vehicle maneuver.

IF	ϕ	ZO	ZO	ZO	ZO	ZO	PS, PM, PB
	$\Delta\theta$	N, ZO, P	N, ZO, P	N, ZO, P	P	N	N, ZO, P
	ψ	ZO	ZO	PS, PM, PB	ZO	ZO	ZO
	$\overline{\sigma}$	PM, PB	PS	ZO	ZO	ZO	ZO
THEN	I_d	AC	DC	ST	TL	TR	BD

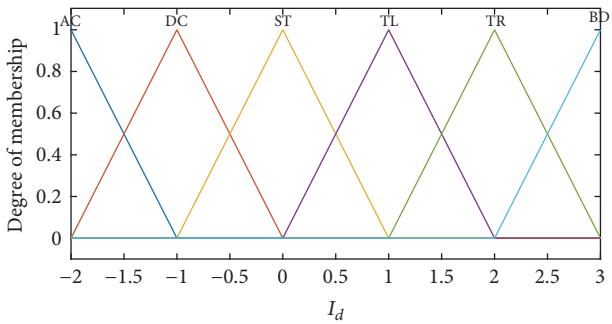


Figure 8: The membership function of the driving Intentions I_d.

fuzzy operator among different rules. As presented in Table 1, for the maneuver intention of "Acceleration," we utilize the aggregate degree of membership as its fuzzy decision, which can be calculated by

$$\begin{aligned}\mu(I_{\mathrm{AC}}) = &\left(\mathrm{ZO}_\phi \cap N_{\Delta\theta} \cap \mathrm{ZO}_\psi \cap \mathrm{PM}_{\overline{\sigma}}\right)\\ &\cup \left(\mathrm{ZO}_\phi \cap \mathrm{ZO}_{\Delta\theta} \cap \mathrm{ZO}_\psi \cap \mathrm{PM}_{\overline{\sigma}}\right)\\ &\cup \left(\mathrm{ZO}_\phi \cap P_{\Delta\theta} \cap \mathrm{ZO}_\psi \cap \mathrm{PM}_{\overline{\sigma}}\right)\\ &\cup \left(\mathrm{ZO}_\phi \cap N_{\Delta\theta} \cap \mathrm{ZO}_\psi \cap \mathrm{PB}_{\overline{\sigma}}\right)\\ &\cup \left(\mathrm{ZO}_\phi \cap \mathrm{ZO}_{\Delta\theta} \cap \mathrm{ZO}_\psi \cap \mathrm{PB}_{\overline{\sigma}}\right)\\ &\cup \left(\mathrm{ZO}_\phi \cap P_{\Delta\theta} \cap \mathrm{ZO}_\psi \cap \mathrm{PB}_{\overline{\sigma}}\right).\end{aligned} \tag{10}$$

Similarly, the fuzzy decisions of other maneuver intentions can be calculated based on Table 1. Afterwards, we employ the Middle of Maximum (MOM) [33] as the defuzzification approach to calculate the corresponding maneuver intention. Furthermore, the maneuver intention understanding result can be expressed as

$$I_d = \mathrm{round}\left[\arg\ \mathrm{mom}\ \mu(I_x)\right], \tag{11}$$

where $I_x \in \{\mathrm{AC}, \mathrm{DC}, \mathrm{ST}, \mathrm{TL}, \mathrm{TR}, \mathrm{BD}\}$, $\mu(I_x)$ denotes the outputted fuzzy decision, and "round" means that the output is rounded to the nearest integer.

Therefore, based on (11), the maneuver intention can be understood when the human operates the robotic vehicle under specific requirements.

5. Experimental Results and Analysis

5.1. Experimental Platform. The developed approach in this work is implemented on a lab research autonomous robotic vehicle of the 1/10-Scale Vehicle Research Platform (1/10-SVRP). The 1/10-SVRP consists of five 1/10-scale autonomous robotic vehicles, a human manual driving interface, and a 1/10-scale driving environment including an ultra-wideband based indoor GPS system, traffic lights, road signs, and various lane setups. As shown in Figure 9, the wearable sensory system described above is worn around human's arm during the human-robotic vehicle interaction. The sensory information detected by IMU and EMG sensors is sent to the control system in real time via a pair of Bluetooth devices. Once the controller generates new commands, these signals are sent to the vehicle motor drivers to plan the goal motions.

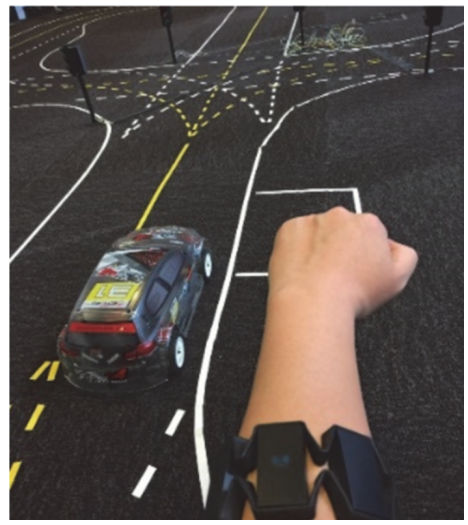


Figure 9: The human is employing the wearable sensing to maneuver the robotic vehicle on the 1/10-Scale Vehicle Research Platform.

In the robotic vehicle maneuver process, the velocity we employed for the robotic vehicle is expressed by

$$V(t) = k_\sigma \overline{\sigma(t)}, \tag{12}$$

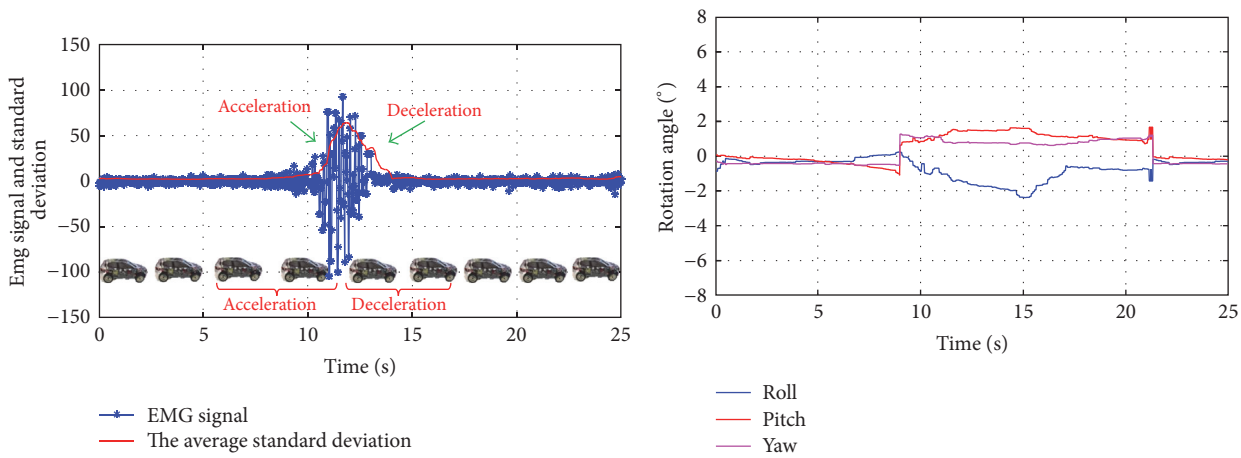
where k_σ is the EMG control factor; $\overline{\sigma(t)}$ is determined by the clench and release of the human fist.

The steering angles in the robotic vehicle turning operation are calculated with the following function:

$$\theta_T(t) = k_\theta \theta(t) + l_\theta, \tag{13}$$

where k_θ is the steering angle coefficient; l_θ works as the offset to adjust the initial angle.

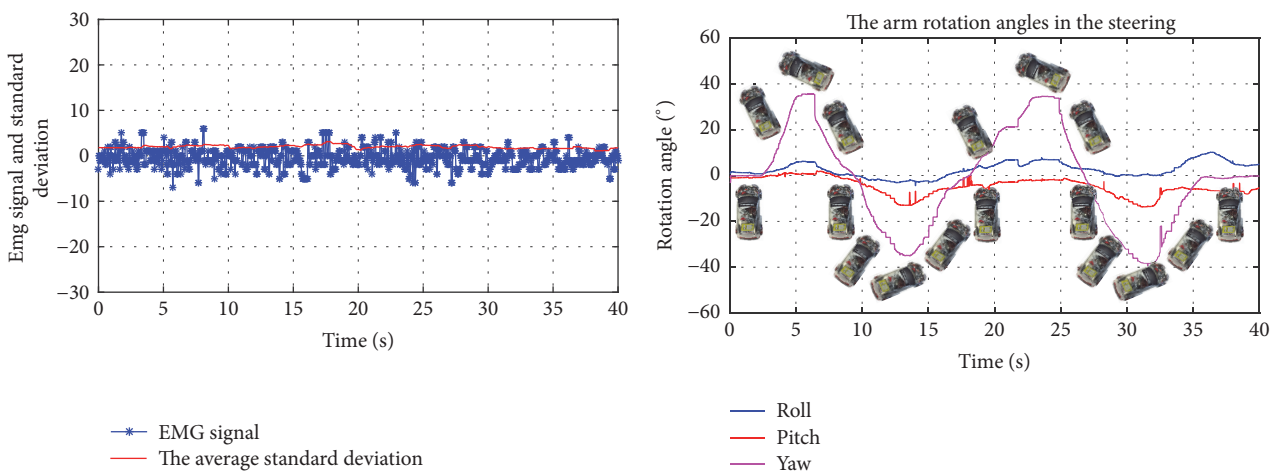
5.2. Maneuver Intention Understanding Verification. In this section, we test the maneuver intention understanding



(a) The vehicle movements along with the EMG signals

(b) The forearm rotation angles

Figure 10: The variation of the human EMG signals and rotation angles in the acceleration and deceleration operation.



(a) The EMG signals

(b) The vehicle movements along with the rotation angles

Figure 11: The variation of the human EMG signals and rotation angles in the steering operation.

approach via the forward (acceleration and deceleration) and steering (turning left and turning right) driving modes in practical situations and present the verification results.

5.2.1. Forward Driving. When the human expects the robotic vehicle to speed up or speed down in the forward driving, according to the fuzzy rules, he should present specific finger motions and keep the rotation angles constrained in the required intervals at the same time. As depicted in Figure 10, the human forearm rotations and finger activities properly meet the required rules. Meanwhile, the vehicle's movement procedure in Figure 10(a) shows that the vehicle is accelerated and decelerated correspondingly along with the variation of the EMG signals. Consequently, it can be seen that the maneuver intention understanding approach correctly follows the human intentions to execute the accelerating and decelerating driving.

5.2.2. Steering. When the human wants the robotic vehicle to turn left or right, in accordance with the steering rules of "TL" and "TR," he should control the Yaw angle properly and keep the Roll angle and Pitch angle in the designed constraints simultaneously. The rotation angles information and EMG signals are presented in Figure 11. It can be seen that the robotic vehicle properly performs the steering directions along with the variation of the rotation angles, which indicates that the proposed approach exactly understands the maneuver intentions in the steering operation.

5.3. Accuracy Evaluation. In this section, we conduct understanding accuracy evaluation and compare the results with the work in [16], which utilized a Leap Motion to acquire the human behaviors' information for the vehicle maneuver.

We employ the wearable sensory system to perform all designed maneuver intentions to operate the robotic

Table 2: Driving intentions understanding accuracy.

Driving intentions	Testing data	Successful	Failed	Recognition accuracy
AC	40	39	1	97.5%
DC	40	38	2	95%
ST	40	38	2	95%
TL	40	36	4	90%
TR	40	35	5	87.5%
BD	40	38	2	95%

Table 3: The comparison of our approach and the previous work.

Works	Interaction interface	Accuracy	SD-E
Our approach	Wearable sensor	93.33%	3.76
The work in [16]	Leap Motion	77.4%	4.52

vehicle without considering the fixed route. Each intention is operated 40 times based on the understanding model. The understanding accuracy results are presented in Table 2. It can be seen that the proposed understanding approach is able to effectively and sensitively identify all the maneuver intentions in the human-robotic vehicle interaction. However, for some intentions understanding such as "TR" and "TL," they present relatively fair accuracy than others. To solve it, we can design much better fuzzy rules through practical trials to improve the accuracy of these maneuver intentions' understanding.

In addition, the average understanding accuracy of this study is about 93.33% which is higher than the work in [16]. Furthermore, from [16] we can calculate that the standard deviation of all errors (SD-E) is about 4.52, which is higher than 3.76 in our work. Therefore, it can be concluded that our approach is more stable in the maneuver intentions understanding. The result comparisons are shown in Table 3.

5.4. Robustness Evaluation. Based on the research platform, we design two tasks to evaluate the robustness of the maneuver intention understanding model in some common driving scenes, such as driving straight on the lane, turning in the intersection, and turning for obstacle avoidance.

5.4.1. Lane Tracking. When the human maneuvers a robotic vehicle in the straight lane, the straightness of driving is very significant to the traffic. Meanwhile serpentine driving usually results in a fine or even a terrible accident. Therefore, the straight driving test is conducted based on the intention understanding model.

We ask 5 individuals with valid driving licenses and considerable driving experiences to maneuver the vehicle one by one for two loops. Each individual operates one straight driving process in each loop. Therefore, we can get 10 driving records from the experiment. As shown in Figure 12, the vehicle is driven forward from A to B.

According to the maneuver results, the occurrences of lane departure in the straight driving are shown in Figure 13. The numbers of lane departures of these ten driving records

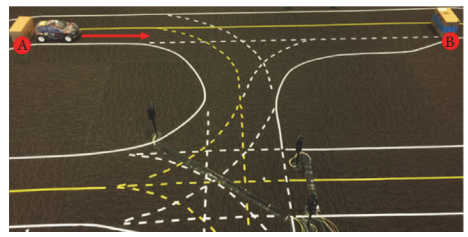


Figure 12: The lane tracking task.

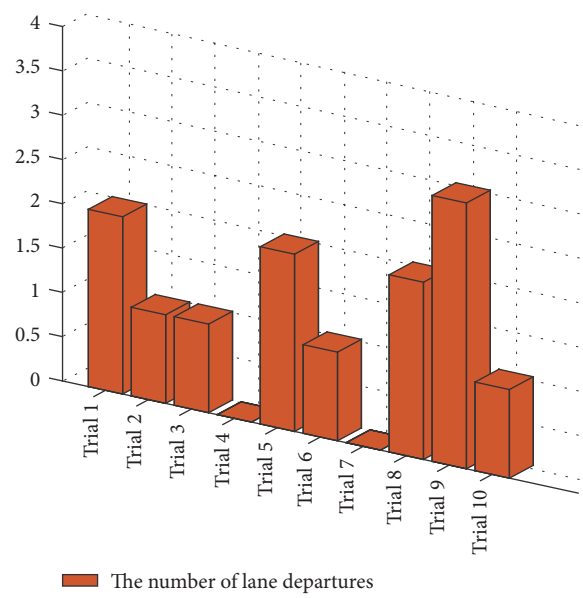


Figure 13: The times of lane departure of the two accelerating methods in the lane tracking task.

are "2," "1," "1," "0," "2," "1," "0," "1," "3," and "1," respectively. The average of the number of lane departures is 1.20, which suggests that the maneuver intention understanding approach presents a robust stability and adaptability for different individuals in the straight driving situations.

5.4.2. Obstacle Avoidance. To evaluate the performance of flexibility of the maneuver intention understanding model, some hybrid driving modes to avoid obstacles are allocated to the robotic vehicle in the second task. As presented in Figure 14, the vehicle is driven from A to B. During this process, the vehicle must cross the intersection and avoid colliding with obstacles on the road. The experiment is conducted using the same method by 5 different individuals as task 1.

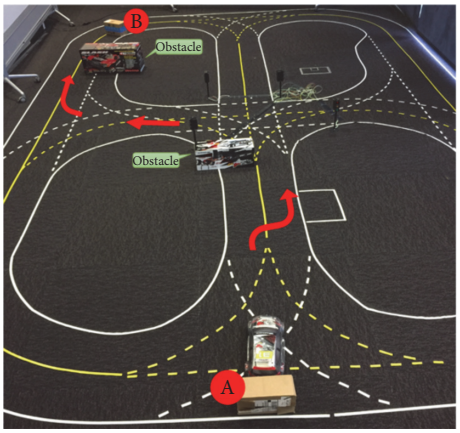


Figure 14: The obstacle avoidance task.

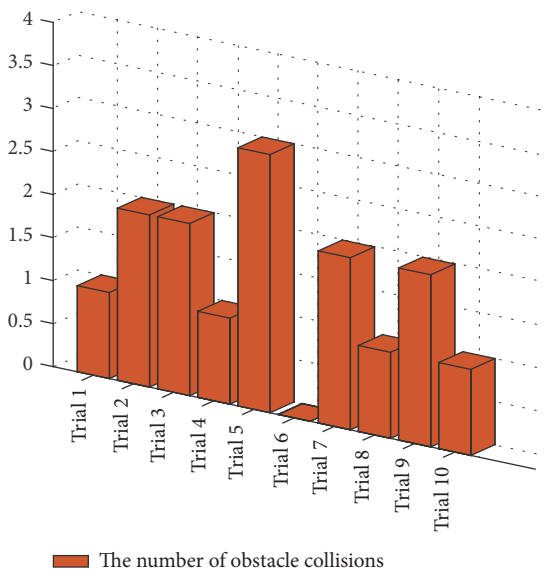


Figure 15: The times of obstacle collision of the two accelerating methods in the second task.

Based on the driving records, the numbers of obstacle collisions are "1," "2," "1," "1," "3," "0," "1," "3," "2," and "1," respectively. As shown in Figure 15, the average of the number of obstacle collisions is 1.50. From the results, it can be observed that the maneuver intention understanding approach presents a robust flexibility for the hybrid driving modes in the complex road setting. Comparing to task 1, the standard deviation of the numbers of obstacle collisions (0.97) is higher than that of the numbers of lane departures (0.92), which reveals that the intention understanding approach in hybrid driving modes shows a relatively fair robustness. One of the key reasons is that different fuzzy rules for the intentions present diverse understanding accuracies, in which some of them will impact the overall robustness. Additionally, it is easy for divers to feel nervous in the complicated driving surroundings which can result in obstacle collisions. However, these problems above could be overcome by optimizing fuzzy rules in the proposed approach and taking more practice for the human.

From the above, it is shown that the vehicle maneuvers are successfully and effectively performed by using the maneuver intention understanding approach. Notably, experimental results and evaluations of this approach demonstrate that by taking advantage of the natural wearable sensing information the human driver can maneuver the vehicle only using forearm postures and muscle activities in a much easier and more stable manner with considerable accuracy and robustness.

6. Conclusions

A novel and practical wearable-sensing-based maneuver intention understanding approach was proposed to assist the human driver to naturally operate the robotic vehicles without physical contact. The wearable sensory device can be naturally applied in the complicated human-vehicle interactions without restraining the human's hand to be physically involved in the driving task. First, when the human driver performed his maneuver intentions, the wearable sensory system information which included forearm postures and muscle activities was recorded and updated in real time. Additionally, after getting the parameterized intention information, we developed a maneuver intention understanding approach using the fuzzy control. Afterwards, based on the proposed approach, we conducted a set of experiments on our vehicle research platform. Experimental results and evaluations demonstrated that by taking advantage of the nonphysical contact and natural handleability of this approach the robotic vehicle was successfully and effectively maneuvered to accomplish the driving tasks with considerable accuracy and robustness in human-robotic vehicle interaction.

In human-vehicle interaction, the driver's unconscious gestures and involuntary movements may cause unstable detection and interpretation of the driver's intentions. Therefore, future works will be conducted on integrating multiple kinds of sensing information, such as human gaze information and natural language, as triggers to avoid the false-positive intention understanding. Additionally, with looking forward to extending the applications of our approach in more complicated situations, future works will also be conducted on integrating radar sensing information as the input of the fuzzy control to improve the intention understanding accuracy to avoid potential collisions.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Supplementary Materials

The demo we recorded for the experimental verification. *(Supplementary Materials)*

References

[1] D. L. Fisher, M. Lohrenz, D. Moore, E. D. Nadler, and J. K. Pollard, "Humans and Intelligent Vehicles: The Hope, the Help, and the Harm," *IEEE Transactions on Intelligent Vehicles*, vol. 1, no. 1, pp. 56–67, 2016.

[2] B. Paden, M. Cap, S. Z. Yong, D. Yershov, and E. Frazzoli, "A Survey of Motion Planning and Control Techniques for Self-Driving Urban Vehicles," *IEEE Transactions on Intelligent Vehicles*, vol. 1, no. 1, pp. 33–55, 2016.

[3] L. Li, W. Huang, Y. Liu, N. Zheng, and F. Wang, "Intelligence testing for autonomous vehicles: a new approach," *IEEE Transactions on Intelligent Vehicles*, vol. 1, no. 2, pp. 158–166, 2016.

[4] https://www.cnet.com/news/google-unveils-self-driving-car-sans-steering-wheel.

[5] http://www.theverge.com/2016/8/16/12504300/ford-autonomous-car-ride-sharing-2021.

[6] K. Ohashi, T. Yamaguchi, and I. Tamai, "Humane automotive system using driver intention recognition," in *Proceedings of the SICE Annual Conference 2004*, pp. 2363–2366, jpn, August 2004.

[7] H. Berndt, J. Emmert, and K. Dietmayer, "Continuous driver intention recognition with Hidden Markov Models," in *Proceedings of the 11th International IEEE Conference on Intelligent Transportation Systems, ITSC 2008*, pp. 1189–1194, China, December 2008.

[8] N. Oliver and A. P. Pentland, "Driver behavior recognition and prediction in a SmartCar," in *Proceedings of the Enhanced and Synthetic Vision 2000*, pp. 280–290, April 2000.

[9] N. Kuge, T. Yamamura, O. Shimoyama, and A. Liu, "A driver behavior recognition method based on a driver model framework," *SAE Technical Papers*, 2000.

[10] H. Berndt and K. Dietmayer, "Driver intention inference with vehicle onboard sensors," in *Proceedings of the 2009 IEEE International Conference on Vehicular Electronics and Safety, ICVES 2009*, pp. 102–107, India, November 2009.

[11] C. A. Pickering, K. J. Burnham, and M. J. Richardson, "A research study of hand gesture recognition technologies and applications for human vehicle interaction," in *Proceedings of the 3rd Institution of Engineering and Technology Conference*, Automotive Electronics, pp. 1–15, on, 2007.

[12] B. Ionescu, V. Suse, C. Gadea et al., "Using a NIR camera for car gesture control," *IEEE Latin America Transactions*, vol. 12, no. 3, pp. 520–523, 2014.

[13] S. P. Kang, G. Rodnay, M. Tordon, and J. Katupitiya, "A hand gesture based virtual interface for wheelchair control," in *Proceedings of the 2003 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM 2003*, pp. 778–783, Japan, July 2003.

[14] K. H. Kramer and J. S. Underkoffler, "Gesture-Based Control System For Vehicle Interfaces," in *Google Patents*, 2009.

[15] T. Fong, C. Thorpe, and C. Baur, "Advanced interfaces for vehicle teleoperation: Collaborative control, sensor fusion displays, and remote driving tools," *Autonomous Robots*, vol. 11, no. 1, pp. 77–85, 2001.

[16] U. E. Manawadu, M. Kamezaki, M. Ishikawa, T. Kawano, and S. Sugano, "A hand gesture based driver-vehicle interface to control lateral and longitudinal motions of an autonomous vehicle," in *Proceedings of the 2016 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2016*, pp. 1785–1790, Hungary, October 2016.

[17] A. Nag, S. C. Mukhopadhyay, and J. Kosel, "Wearable Flexible Sensors: A Review," *IEEE Sensors Journal*, vol. 17, no. 13, pp. 3949–3960, 2017.

[18] I. H. Lopez-Nava and A. Munoz-Melendez, "Wearable Inertial Sensors for Human Motion Analysis: A Review," *IEEE Sensors Journal*, vol. 16, no. 22, pp. 7821–7834, 2016.

[19] M. Janidarmian, A. Roshan Fekr, K. Radecka, and Z. Zilic, "Multi-Objective Hierarchical Classification Using Wearable Sensors in a Health Application," *IEEE Sensors Journal*, vol. 17, no. 5, pp. 1421–1433, 2017.

[20] S. Lefèvre, C. Laugier, and J. Ibañez-Guzmán, "Exploiting map information for driver intention estimation at road intersections," in *Proceedings of the 2011 IEEE Intelligent Vehicles Symposium, IV'11*, pp. 583–588, Germany, June 2011.

[21] https://www.myo.com/.

[22] G. Loianno, C. Brunner, G. McGrath, and V. Kumar, "Estimation, Control, and Planning for Aggressive Flight With a Small Quadrotor With a Single Camera and IMU," *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 404–411, 2017.

[23] H. Ahmed and M. Tahir, "Improving the Accuracy of Human Body Orientation Estimation With Wearable IMU Sensors," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 3, pp. 535–542, 2017.

[24] J. Wahlstrom, I. Skog, P. Handel, and A. Nehorai, "IMU-Based Smartphone-to-Vehicle Positioning," *IEEE Transactions on Intelligent Vehicles*, vol. 1, no. 2, pp. 139–147, 2016.

[25] N. D. Bunt, J. C. Moreno, P. Müller, T. Seel, and T. Schauer, "Online Monitoring of Muscle Activity During Walking for Bio-feedback and for Observing the Effects of Transcutaneous Electrical Stimulation," *Biosystems and Biorobotics*, vol. 15, pp. 705–709, 2017.

[26] S. H. Roy, G. De Luca, M. Cheng, A. Johansson, L. D. Gilmore, and C. J. De Luca, "Electro-mechanical stability of surface EMG sensors," *Medical & Biological Engineering & Computing*, vol. 45, pp. 447–457, 2007.

[27] C. J. De Luca, M. Kuznetsov, L. D. Gilmore, and S. H. Roy, "Inter-electrode spacing of surface EMG sensors: Reduction of crosstalk contamination during voluntary contractions," *Journal of Biomechanics*, vol. 45, no. 3, pp. 555–561, 2012.

[28] K. Nymoen, M. R. Haugen, and A. R. Jensenius, "Mumyo–evaluating and exploring the myo armband for musical interaction," 2015.

[29] J. Diebel, "Representing attitude: Euler angles, unit quaternions, and rotation vectors," *Matrix*, vol. 58, pp. 1–35, 2006.

[30] K. Tanaka and H. O. Wang, *Fuzzy control systems design and analysis: a linear matrix inequality approach*, John Wiley and Sons, 2004.

[31] J. S. Kim and K.-S. Whang, "A tolerance approach to the fuzzy goal programming problems with unbalanced triangular membership function," *European Journal of Operational Research*, vol. 107, no. 3, pp. 614–624, 1998.

[32] H. Ishibuchi, K. Nozaki, N. Yamamoto, and H. Tanaka, "Selecting fuzzy if-then rules for classification problems using genetic algorithms," *IEEE Transactions on Fuzzy Systems*, vol. 3, no. 3, pp. 260–270, 1995.

[33] H. Hellendoorn and C. Thomas, "Defuzzification in fuzzy controllers," *Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology*, vol. 1, no. 2, pp. 109–123, 1993.

Hindawi
Journal of Robotics
Volume 2018, Article ID 6519713, 11 pages
https://doi.org/10.1155/2018/6519713

Research Article

Older Adults' Perceptions of Supporting Factors of Trust in a Robot Care Provider

Rachel E. Stuck[1] **and Wendy A. Rogers**[2]

[1]*Georgia Institute of Technology, 654 Cherry St., Atlanta, GA 30332, USA*
[2]*University of Illinois Urbana-Champaign, 1206 South 4th St, Champaign, IL 61820, USA*

Correspondence should be addressed to Rachel E. Stuck; stuck.rachel@gatech.edu

Received 10 November 2017; Revised 2 February 2018; Accepted 15 February 2018; Published 1 April 2018

Academic Editor: Yunyi Jia

The older adult population is increasing worldwide, leading to an increased need for care providers. An insufficient number of professional caregivers will lead to a demand for robot care providers to mitigate this need. Trust is an essential element for older adults and robot care providers to work effectively. Trust is context dependent. Therefore, we need to understand what older adults would need to trust robot care providers, in this specific home-care context. This mixed methods study explored what older adults, who currently receive assistance from caregivers, perceive as supporting trust in robot care providers within four common home-care tasks: bathing, transferring, medication assistance, and household tasks. Older adults reported three main dimensions that support trust: professional skills, personal traits, and communication. Each of these had subthemes including those identified in prior human-robot trust literature such as ability, reliability, and safety. In addition, new dimensions perceived to impact trust emerged such as the robot's benevolence, the material of the robot, and the companionability of the robot. The results from this study demonstrate that the older adult-robot care provider context has unique dimensions related to trust that should be considered when designing robots for home-care tasks.

1. Introduction

The population of older adults is increasing worldwide at an advanced rate. A recent World Health Organization (WHO) report on aging emphasized the need to have tailored interventions for these aging populations, such as older adults with care providers [1]. As the number of older adults increases so will the demand for care providers and, with an insufficient number of humans to fill the demand, robots might help fulfill this need. Trust is essential for older adults to successfully interact with robot care providers, and we need an in-depth understanding about the factors that influence trust within this specific context of an older adult and robot care provider.

To gain an understanding of what factors might emerge, we first reviewed human-human trust research but found that it had not been specifically explored in the context of care providers. However, in general, key elements in human-human trust are the characteristics of the trustee, characteristics of the trustor [2], and the relationship [3]. For the perceived characteristics of the trustor, the ability, values, and benevolence all contributed to trust [2]. In the patient-nurse trust literature, there were several elements apart from ability, reliability, and other task specific characteristics that contributed to trust. Patients wanted to feel respected [4] and cared for, especially in situations where they felt vulnerable [5]. In addition, as trust developed, the communication between the nurse and patient became a key element in what influenced how the patient perceived the trustworthiness of the nurse [4]. These findings give insight into trust, but it is unclear if these factors will also emerge in the human-robot context.

Human-automation trust provided the basis for human-robot trust. Trust of automation is associated with use of that automation [6]. For example, if an operator trusts a system then they are more likely to use the system. This highlights the key need to understand and support trust for appropriate use of a system. Aspects that influence trust in automation include characteristics of the automation such as

the quality of the system feedback [7] and the reliability of the system [8]. For example, lack of reliability and failures of the system negatively impact trust [6]. However, the relationship between failures and trust is complicated and does not have a one-to-one ratio in lowering trust [6]. Characteristics of the operator also influence trust such as the operator's self-confidence [9] and their personality traits [10].

With the increase of robots in workplace and the home, research has also focused on trust specifically in robots. A model of trust was developed by Sanders et al. [11] that identified the main components that contribute to human-robot team trust. These included the characteristics of the person, the characteristics of the robot, the environmental characteristics, and the training and design implications. The person's characteristics included aspects such as personality, self-confidence, general attitude towards robots, and knowledge of the robot [11, 12]. The qualities of the robot included elements related to the robot's performance such as the reliability and predictability [11–13]. Other qualities included the proximity of the robot to the human, type of robot, and the appearance of the robot [12, 13]. The environmental characteristics included the type of task and communication [11]. Training and design implications demonstrate how these are influenced by both the human and the robot qualities and thereby influencing trust [11, 14]. A framework that identified key components of human-robot interaction with older adults also identified many of these components including the human characteristics (e.g., psychographics, abilities), robot characteristics (e.g., appearance, capabilities), tasks constraints (e.g., proximity, accuracy requirements), and context of the interaction (e.g., living environment, safety considerations) [15].

Research has also explored older adults' attitudes towards robots in the home. Smarr et al. [16] explored healthy, independent living older adults' acceptance of robots in the home as well as what tasks they preferred a robot to do. Older adults in this study were generally accepting of a robot, but they had preferences about the type of tasks they preferred a robot to perform [16]. The older adults preferred a robot over a human for tasks related to household chores, manipulating objects, or information management [16]. In another study, older adults' acceptance of robots in the home was confirmed as they reported that they would prefer to stay at home with a robot than have to go to a facility [13]. After exposure to an assistive robot, older adults not only reported higher perceptions of usefulness but also a greater willingness to have the robot assist with various tasks [17].

One study specifically focused on trust between older adults and home robots [18]. Reliability, precision, efficiency, and safety were the top descriptors used for a trustworthy robot [18]. However, this study was limited as it did not specifically assess the role of the task, a key component of trust, and also interviewed older adults who did not necessarily have any experience with receiving care.

A first step in exploring trust in the home-care context is to understand older adults' perceptions of robot care providers and what traits the older adults want the robot care provider to have to trust it. Perceptions influence technology acceptance such as the perceived benefits or concerns of using the technology [19]. In the human-human trust literature, the trustor's perceptions of the trustee influenced the decision to trust [2, 20]. In addition, studies have shown that an individual's perception of a robot influenced how they interacted with it [21]. Insight into what factors older adults perceive as necessary for them to trust a robot will allow us to support their development of trust and diminish acceptance issues that are related to perceptions of the robot being untrustworthy.

The focus of this paper is to explore what factors older adults who currently receive care identify as supporting trust in a robot care provider. In particular, the goal was to address these specific research questions:

(1) Do the dimensions of trust identified in the literature emerge in the older adult-robot care provider relationship?

(2) Do new dimensions of trust emerge in the older adult-robot care provider relationship?

This research is part of a larger project that explored trust in human care providers as well. For details about the rest of the project see [22].

2. Method

2.1. Participants. We interviewed 24 older adults (12 in independent living and 12 in assisted living) above the age of 65 (M = 81, SD = 7.13, age range 67–96) who received 4 or more days of care a week. On average, they received around 6 days of care with the caregiver staying around 1–3 hours each visit. Participants were recruited through outreach to local independent and assisted living communities. They were primarily females. They were diverse in ethnicity and education. Overall, participants reported that they had fair health. On average, the participants cognitive function was at a scoring on the Montreal Cognitive Assessment (MOCA) that represents mild cognitive impairment [26]; note that 5 participants were unable to complete cognitive assessment due to vision or physical impairment. Participants were on average moderately confident performing daily living tasks, but there was a lot of variability between participants and tasks. When asked about technology experience, the participants reported no usage to relatively low usage. For a detailed list of descriptors see Table 1.

2.2. Procedure. Prior to inclusion in the study, participants were screened in person or via telephone to ensure that they met the eligibility criteria which included passing the Wechsler Memory Scale III [27] to ensure that they would be able to follow along with the interview. All participants gave informed consent prior to participation in the study. Participants were then given several questionnaires before the interview (Table 2).

Following the questionnaires, a semistructured interview was administered to investigate the participants' perceptions of what factors support trust. The order of the interview questions was counterbalanced between discussions of the robot care provider and the human care provider to control

Table 1: Participant characteristics.

Factor	Measure	% of participants (n)
Ethnicity	Black/African American	29% (7)
	White/Caucasian	67% (16)
	Others	4% (1)
Education	Less than high school graduate	8% (2)
	High school graduate/GED	17% (4)
	Some or in-progress college/associates degree	71% (10)
	Bachelor's degree (BA, BS)	13% (3)
	Master's degree	13% (3)
	Doctoral degree	8% (2)
General health[a]	"In general, would you say your health is…"	M = 2.38 SD = 1.06
Montreal cognitive assessment[b] (n = 19)		M = 23.05 SD = 4.01
Days assistance received each week (n = 23)*		M = 6.05 SD = 1.53
Average length of caregiver stay[c]		M = 2.00 SD = 1.05
Technology usage[d]	"In the past year, how often have you used…"	M = 0.79 SD = 0.57
Self-efficacy for daily tasks[e]*	"How confident are you in performing…?"	M = 61.26 SD = 29.13

(a) 1 = poor, 2 = fair, 3 = good, 4 = very good, 5 = excellent; (b) score ≥ 26 = normal; (c) 1 = less than an hour, 2 = 1–3 hours, 3 = 4–6 hours, 4 = 6–12 hours, and 5 = 12–24 hours; (d) 0—not used; 1 = used once, 2 = used occasionally, and 3 = used frequently; (e) 1 = not at all confident and 10 = completely confident (summed across 10 questions; range is 10–100); *one participant did not wish to answer.

Table 2: Preinterview questionnaires.

Questionnaire title	Description of measured variables	Reference
(1) Demographic/health	General descriptive information about the health and hearing/vision/motor capabilities of the participants	Czaja et al. [23]
(2) Technology experience profile	Usage and experience with various types of technologies within the last year	Barg-Walkow et al. [24]
(3) Daily living self-efficacy scale	Level of confidence on various ADL and IADL tasks	Sanford et al. [25]
(4) Assistance level with daily tasks	Level of assistance with various ADL and IADL tasks, who assists them, and how often they receive help	Locally developed
(5) Formal caregiver experience	Information about experience with caregiver either personal or through assisted living	Locally developed
(6) Montreal cognitive assessment	General cognitive ability and level of cognitive impairment	Nasreddine et al. [26]

for carry over effects (the focus of the present paper is on the discussion of the robot care provider only). To gain a deeper insight and provide context, we explored what supported trust within 4 task scenarios: bathing, medication assistance, transfer, and household tasks (see Table 3). The scenarios were developed with the help of three subject matter experts (SMEs). We chose two activities of daily living (ADLs; bathing and transferring) and two instrumental activities of daily living (IADLs). These tasks were chosen because they are some of the most frequent tasks of formal care providers for older adults in their homes [28] and bathing was added upon recommendation by the SMEs.

Bathing was discussed first as it contains the greatest amount of vulnerability. Participants were asked in general what a robot care provider would need to be like for them to trust it with that task and what would cause them to not trust the robot. Bathing was discussed in-depth with specific questions about previously identified dimensions specifically from human-human (values and benevolence), human-robot literature (precision and predictability), and dimensions discussed in both (ability, reliability, appearance, and communication). For each of the following tasks, we asked general questions about how they would want a robot care provider to be to trust it to perform the task and what would negatively impact their trust.

After completing the interview, the participants completed several follow-up questionnaires (Table 4). They were then compensated $30.00 for their time and effort and debriefed about the purpose of the study. The interviews were audio recorded and then transcribed.

Table 3: Scenario descriptions for each task.

Imagine you have a new formal caregiver who is going to assist you with	
Bathing	This will include them helping you remove your clothes and physically helping you bathe
Medication assistance	This means they would help remind you to take medications at the appropriate time and perhaps bring the medication bottle to you
Transferring	This will include the caregiver helping you sit up, lifting you, and moving you to the wheelchair
Household tasks	These tasks will include helping plan and prepare meals and doing some light housework such as laundry, doing the dishes, or making the bed

Table 4: Postinterview questionnaires.

Questionnaire title	Description of measured variables	Reference
(1) Robot self-efficacy scale	Level of confidence operating a robot	Locally developed
(2) Robot familiarity and usage	Assessed familiarity and usage of various robots	Smarr et al. [16]
(3) Trust preference checklist	Preference of human versus robot care provider for various tasks	Olson [18]

3. Results and Discussion

3.1. Overview of Analysis. We asked participants about what they perceived as supporting trust in a robot care provider across four tasks. The goal was to understand in general what factors support trust in a robot care provider, so the data presented are collapsed across tasks. However, when there were differences across tasks, we highlight those differences.

One individual coder segmented all the interviews into units of analysis. A segment was defined as a section of responses that related to one specific task. The coding scheme was developed based on prior research on trust as well as themes that emerged from the interviews [29, 30]. The coding scheme categorizes the qualitative data to understand similar attitudes amongst participants. To identify emerging themes, four interviews were randomly selected and reviewed by two coders to discuss themes that emerged that did not fit into previously identified themes.

After development of the coding scheme, three independent rounds of intercoder agreement were conducted. For each round, using MAXQDA Version 12, Cohen's Kappa was calculated to ensure that coders were in agreement at a minimum threshold of 85% based on prior research that recommends between 80 and 90% as a minimum level of agreement [31]. For each round, if agreement was not met, coders met to discuss discrepancies and used this to inform the design of the coding scheme. For the final round, a reliability of 91.61% was met. Interviews were then divided between coders and independently coded.

To distinguish the most frequent factors for each overall theme, we used a threshold of 5% as a cutoff. There is no standardization for a cutoff, but previous qualitative research has used 5% as a method of reducing attention on categories that were not prominent across participants [32]. Excel was used to calculate frequencies and descriptive statistics for the questionnaires and response frequencies.

3.2. Robot Experiences and Attitudes. In general, participants had limited to no experience with robots (M = 1.25, SD = 0.59) based on a familiarity rating of 0: not sure what this is, 1: never heard about, seen, or used this robot, 2: have only heard about or seen this robot, 3: have used or operated this robot only occasionally, 4: have used or operated this robot frequently. Only 5 participants had ever used or operated a robot only occasionally (1: domestic robots, 3: entertainment robots, and 1: research robot).

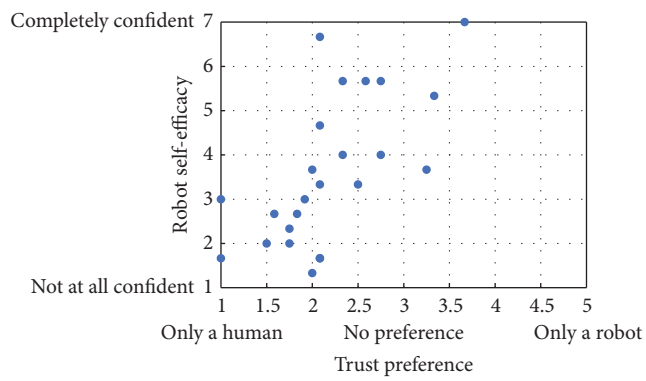


Figure 1: Relation of self-efficacy to trust preference.

We also assessed participants' self-efficacy (their belief in their ability to succeed) of being able to operate a robot in three situations (if there was no one around to tell them what to do, if they only had the robot manuals for reference, and if someone else showed them how to use it first). They rated on a scale of 1–7 how confident they were (1 = not at all confident, 7 = completely confident). In general participants had low to neutral self-efficacy in operating the robot (M = 3.61; SD = 1.67).

When asked if they would prefer to trust a robot or a human for a list of various home-care tasks, participants overall reported that they preferred to trust a human (M = 2.18; SD = 0.66; 1: only a human, 2: prefer a human, 3: no preference, 4: prefer a robot, and 5: only a robot).

Figure 1 illustrates the relationship between self-efficacy of operating a robot and trust preference. There was a positive

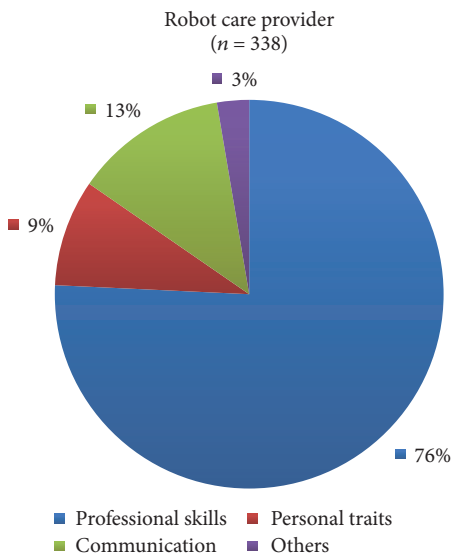


Figure 2: Trust factors across all tasks.

correlation ($r = .65$, $p < 0.01$) between self-efficacy and trust preference. Although this needs further exploration, perceived self-efficacy in operating a robot may make older adult users more open to trusting a robot to assist them. If this is the case, when providing robots for use by older adults, it would be important to design the robots so that they are easy to use and to train the older adults so that they feel confident in getting the robot to perform a task.

3.3. Trust Factors for Robot Care Providers. In the interviews, three main themes emerged as supporting trust in a robot care provider: professional skills, personal traits, and communication (see Figure 2). Overall, professional skills were the most frequently discussed factors that older adults perceived as supporting trust in a robot care provider. This factor was followed by communication and then personal traits. Personal traits may not have been discussed as frequently because of the participants' limited experience with robots.

Within each of these themes there were several factors from prior literature that emerged within this specific context. We will examine the details of these in the sections below.

3.3.1. Professional Skills. Within professional skills, the most frequently mentioned themes were general capability, precision, consistency of performance, safety, predictability, and gentleness (see Figure 3). A theme not previously identified in literature that emerged within this context was gentleness. Table 5 provides information on how we defined these themes, and an example quote from the interviews for the most frequently discussed themes in this category.

Within the tasks, there was some variability in the prevalence of each of these factors. For the task of bathing, 20% of participants reported wanting the robot care provider to have had prior experience with bathing, but this was not mentioned for other tasks. There were a few specific factors that seemed to be prevalent in tasks that involved touch (bathing and transfer). For example, safety and gentleness were mentioned most frequently for these two tasks. Contextual knowledge, which is defined as understanding the capabilities and sensitivities of the older adult, was also only mentioned for these two tasks. Thus, for tasks in which there is human-robot touch, there are other considerations to take into account. Particularly, older adults receiving care are commonly suffering from a chronic condition that may cause specific sensitivities that need special consideration in tasks where the robot is in contact with their body. One element that was unique for transferring was that older adults wanted to know that the robot was physically capable of lifting them, but physical capability was not mentioned as frequently for other tasks.

For medication assistance, 37.5% mentioned that the robot needed to be on time, whereas this was only mentioned once for bathing and once for household tasks. This provides another example of how, for specific tasks, there are key elements of the tasks that are more salient to the older adults than for other tasks. A key aspect of medication management is ensuring that medications are administered at the required time and this importance increases with the more medications that are being managed leading to the older adults want to be sure that the medication would be given at the appropriate time.

Previously identified themes such as general capability and reliability were also pertinent to the context of a robot care provider. Beyond these themes, there were factors that influenced the participants' perceptions related to trust such as the gentleness with which the task is performed or how safely it is performed. Some of these factors were more salient within specific tasks. When designing for specific tasks, first identify what the key components are for the user within this task and then designers should try to ensure that those expectations are met. For example, for tasks involving human-robot touch a primary goal might be that the robot is gentle and safe, but with medication assistance, the focus of design should be on ensuring the robot can deliver the medication at the appropriate time.

3.3.2. Personal Traits. For personal traits, the main factors that emerged were the material or texture of the robot, the general appearance of the robot, the compatibility of the robot, the congruence of the care provider values with the older adult's values, the benevolence and kindness of the robot, and how the robot was dressed. See Figure 4 for the frequency of factors mentioned in professional skills. See Table 6 for the list of definitions and example quotes for each of these themes.

We also asked the participants after discussing all four tasks what role benevolence played in them trusting a robot. 67% of the participants stated that benevolence would impact their trust in a robot care provider. For example, a participant responded "*that would play a lot of role. I would really trust him. If he's doing exactly what I want him to do*."

Benevolence only emerged without specifically inquiring about it within the task of bathing which suggests that when a task is personal and vulnerable, the need to feel cared for

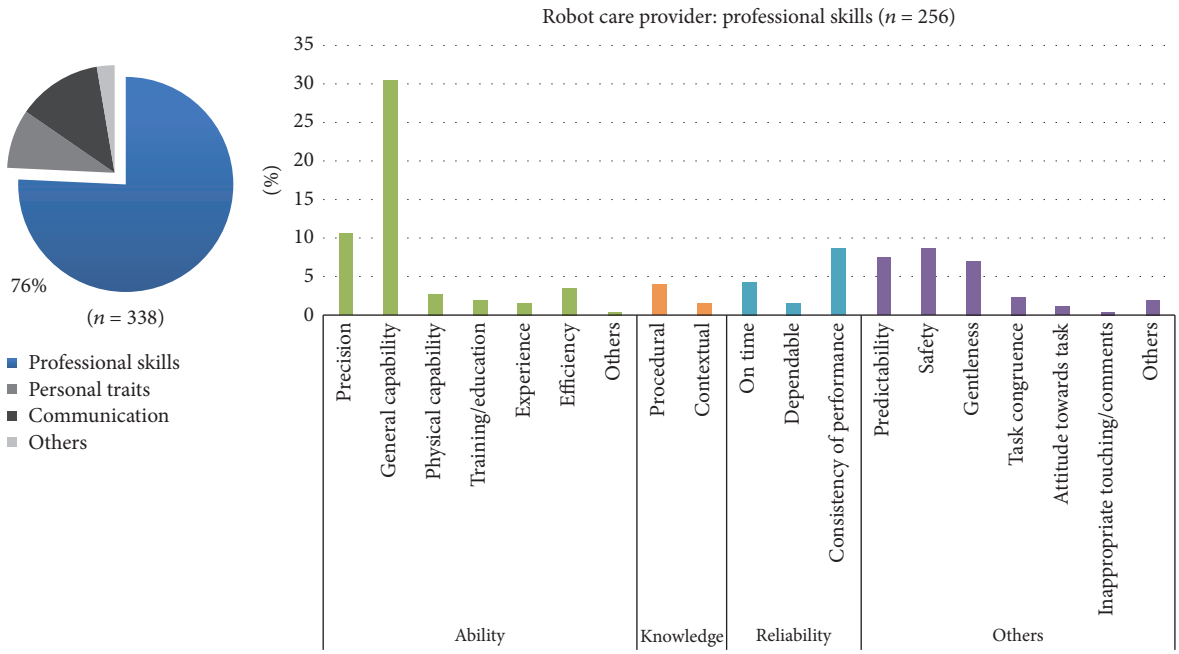


Figure 3: Professional skills.

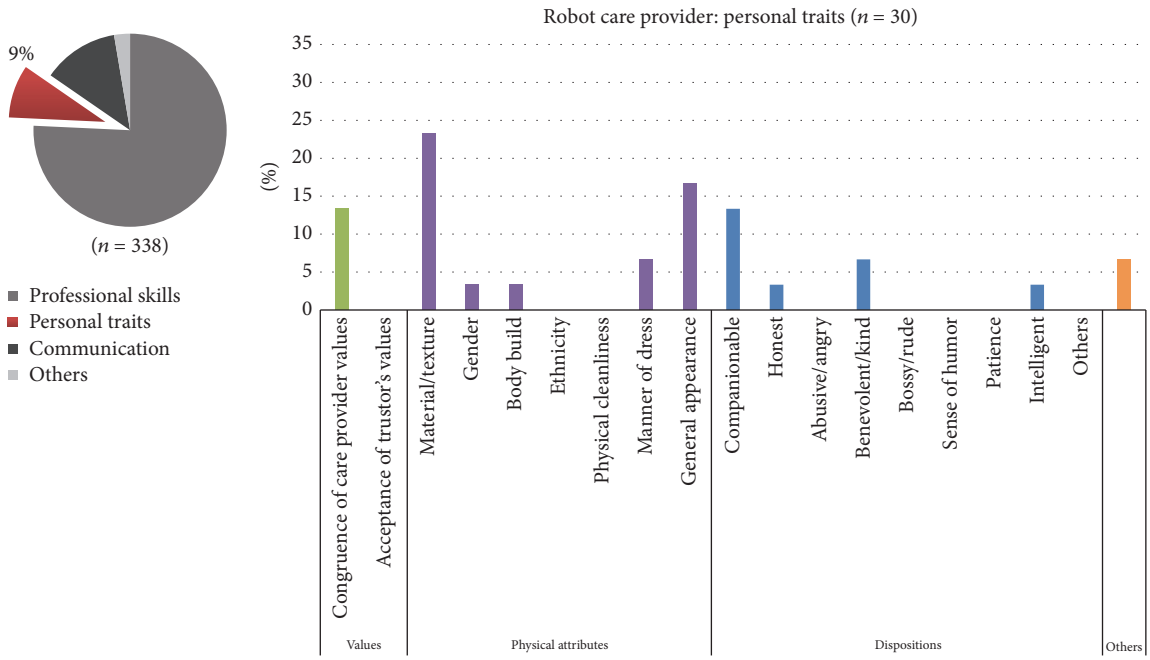


Figure 4: Personal traits.

is salient to the older adults. The only other personal trait that seemed to be impacted by task was the concern for the material and texture of the robot which was mentioned only in the tasks that involved human-robot touch like bathing and transferring. This highlights the need for comfort in tasks that involve physical interaction with the robot.

Themes related to personal traits go beyond just general appearance that was identified in human-robot literature before and demonstrate that several themes from human-human trust are also relevant to this context, such as the congruence of values and benevolence of the robot. There were also context-specific themes that emerged such as the material and texture of the robot that are a key element in human-robot tasks that involve touch. Older adults also wanted the robot to be companionable and to get along with them as well as their friends and family. All of these demonstrate that they want the robot to go beyond just performing tasks but also to provide them with a feeling of being cared for as well as something that they feel comfortable having others interact with.

Table 5: Professional skills: definitions and examples of factors.

Factor	Definition	Example quote
General capability	Is the robot able to perform that specific task	"*That it got the right bottles. Just if they're gonna just bring me the bottles, as long as they bring the right bottles, that's all I would require*"
Precision	Is the robot exact and accurate in their performance of the task; does it complete the task thoroughly	"*That (precision) is important to me. . .because I would want to feel that it is done right and I wouldn't be able to trust the robot if it's not done right*"
Consistency of performance	Is the robot consistent in their task performance	"*Well, some days a human would do it thoroughly and other days they wouldn't, so the robot would need to do it the same way every time*"
Safety	The task is performed with little to no potential to harm the older adult	"*if he dropped me or even if he hurt me while he was doing it. Now. . .I don't (know) if I would trust a robot*"
Predictability	The robot acts in a way that is consistent with the older adults' expectations	"*Yeah that (predictability) is really important. Much more important than that because you don't interact with a robot in the same way you do with a person, I don't think*"
Gentleness	The task is performed with little to no potential to harm the older adult	"*That they be gentle, and, because I have a lot of pain*"

Table 6: Personal traits: definitions and examples of factors.

Factor	Definition	Example quote
Material/texture	Is there a preference for the material or texture or temperature of the robot that would influence trust	"*Have warm hands. Definitely. I can only picture this metal concoction in my mind. I just can't conceive me going through that*"
General appearance	Is there any preference for the appearance of the care provider that would influence trust	"*You wouldn't want anything, just like you wouldn't want anything in your house ugly looking, you'd want something maybe streamlined. Like a car, whatever, like a wheelchair sometime(s) they make them- or cane people, they have colored ones. You'd want something that has a nice appearance to it*"
Companionable	Is the care provider friendly and sociable and likes people	"*That it would be friendly and be, I don't know how much personality they have. . . whatever is programed into him I guess. But . . . I would want him to get along with baby dog if it will*"
Congruence of care provider values	Do they have the same set of values as the older adult	"*I feel like that for me to trust him, he has to have good values like I do*"
Benevolence/kind	Are they a caring person/are they doing the task because they care about the older adult	", *I feel like that for me to trust him, he has to. . .really show me that he wants to help me*"
Manner of dress	Is the care provider dressed in a way suitable to the older adult; what they are actually wearing	"*If it's for me only, being dressed as a female in some variety . . . even if it is some pant suit*"

3.3.3. Communication. Communication has been previously identified as generally impacting trust, but not specifically how communication might be used to support trust. Within the interviews, three main communication themes emerged that older adults perceived as supporting trust: task specific communication, engaging and responsiveness in communication, and the robot able to both understand and communicate clearly with the older adult. See Figure 5 and Table 7 for more details.

These findings not only confirm that communication impacts trust, but it also deepens our knowledge of how it can impact trust by identifying exactly what type and manner of communication older adults perceive as supporting trust. For care tasks, it is not only important that the communication be used to prepare the older adult for what the robot is doing, but that the robot also demonstrates competency in being able to understand and produce appropriate responses. In addition, being able to understand the robot is key for older adults to have successful communication with the robot care provider.

3.3.4. Others. There were some other categories that did not fit into any of the major themes. However, these emerged primarily within the task of bathing. 20% of participants reported for bathing that they would need experience with the robot before they could trust it. In addition, seven participants explicitly stated that they would not trust the robot with bathing, but this was not mentioned frequently for all the tasks. There was one participant who stated for every task that they would not trust a robot.

4. Conclusion

Specialized interventions for specific groups of older adults are needed as this population continues to increase across

Table 7: Communication: definitions and examples of factors.

Factor	Definition	Example quote
Task specific	They explain what they are doing or about to do related to the task	*"Assuring me. . .that it could do the task that I have asked it to do, that it has done it before, give me a list of the places it has been used and how it turned out"*
Responsiveness/engagement	Answers questions; listens to what they are saying and responds appropriately	*"Answering questions and feedback as to how I feel"*
Communicates/understands clearly	Can the older adult understand them and does the robot understand the older adult	*"It would have to demonstrate that it understands its orders real well. Understands the orders and can recite them back to me or to someone who is with me"*

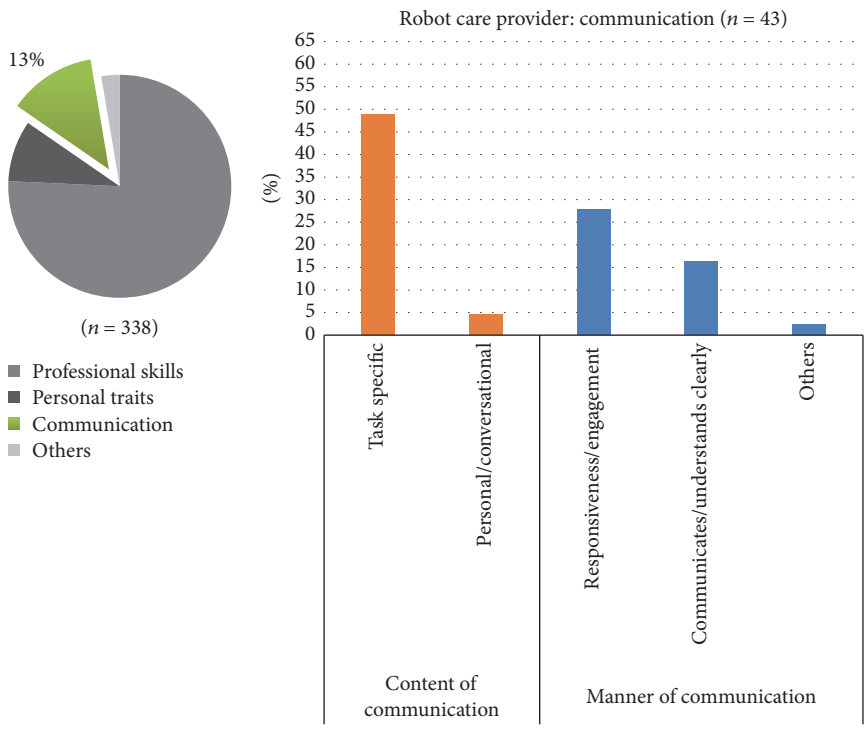


Figure 5: Communication.

the world. Robot care providers will be key in helping supply care for older adults and mitigating potential issues caused by decrease of human care providers. As trust is a key element in creating a successful relationship between an older adult and a robot care provider, this study explored what factors older adults perceived as supporting trust within home-care tasks.

The results from this study show that many previously identified themes from both human-human trust literature and human-robot literature emerge within this context. Themes from prior human-robot literature that were confirmed as supporting trust in this context were the capability to perform the task, precision, general appearance, reliability, predictability, and safety of the robot. Human-human themes were the knowledge, values, and benevolence of the robot.

There were also unique themes that emerged in this study including the material/texture, the gentleness, and the companionability of the robot care provider. We found support that communication is key to supporting trust. In addition, this study expands what we have previously understood about the role communication plays in supporting trust by identifying what components of communication can support trust such as the content of the communication being task specific, the responsiveness and engagement of the robot, and the ability of the robot to communicate and understand clearly

To provide better care and improve the lives of older adults, robot care providers should be designed to exemplify these factors and support trust. Although training can be used to mitigate some of these expectations, if the older adults do not perceive the robot as trustworthy then they will not accept or use the robot. We provide design recommendations in Table 8 based on our findings that might enhance the likelihood that older adults will trust a robot care provider.

For the professional skills of the robot, this study highlights that when designing robot as care providers, the robot's ability must go beyond the actual capability to perform the task. Robots caring for older adults must be able to adapt to the older adult's health conditions and specific sensitivities.

Table 8: Design recommendations for robot care providers.

Factors	Design recommendation
Professional skills	(i) Robots should be able to complete the task precisely, reliably, and in a way that the older adult expects (ii) As many of the older adults receiving care are suffering from various health conditions, it is important to that robots are able to be specialized for individuals for tasks such as transferring and bathing where certain areas might be more sensitive (iii) Design should ensure that appropriate pressure is applied for safety but still be gentle as to not incur harm on the older adult
Personal traits	(i) Need to be able to navigate the social environment in the home including family, friends, and pets of the older adult (ii) Able to demonstrate to older adult that tasks are being done for their well-being as primary motive (iii) Flexibility to demonstrate a set of values similar to each older adult (e.g., honesty, task values such as personal standards of cleanliness, or method in which task is performed) (iv) Material and temperature of robot for tasks that involve touch should be designed to be comfortable for older adult (e.g., not metal cold "hands" for bathing)
Communication	(i) Provide information while task is being performed to accurately describe the robots planned goals and steps for that task (ii) Create controls whether verbal or physical that allow the user to have clear input and output decisions so that they know the robot understood them and responds appropriately (iii) Ensure that user interface is usable by older adults (a) Audio: ensure that frequency is within common hearing range of older adults and volume is adjustable so that if hearing impaired the volume can be altered to ensure clear communication (b) Visual: make sure that guidelines are followed for older adults by providing high contrast, large print, and simple steps for navigation

For example, if the older adult fell and now has increased sensitivity due to bruising on their legs or hips, the robot must be able to adjust the way it performs the task of bathing or transferring to prevent incurring pain or discomfort to the older adult. If the robot care provider performs the task the same way as before and the older adult experiences discomfort, it may prevent the older adult from trusting the robot in the future.

When designing robot care providers, it is must be remembered that the robot will now be a part of the older adult's home. This requires not only designing for the older adult, but also taking in consideration the social environment such as family or pets. In addition, as robot care providers might be replacing a part of social interaction that the older adult was previously receiving, it is essential to the older adults that they still feel cared for. Designers should consider building in social components to these robot care providers so that older adults can still feel as though the care they are receiving is purely for their benefit. This study also demonstrated that designers should consider having some options for personalization of the robot in both social and capability aspects. For example, if prior to needing care an older adult would always clean the kitchen before cleaning the rest of the house, they might trust a robot care provider more if they could adjust its behavior to mirror what they previously did.

This study also highlights that clear communication between the older adult and the robot care provider is a key aspect of creating a trusting relationship. Designers should ensure that the robot care provider supports the older adult's knowledge of how the robot will perform the task and simple steps for navigation should be provided to access this information [33]. In addition, designer should pay specific attention to visual and auditory declines associated with aging, whether robots are designed to have a physical interface such as a screen or communicate via auditory displays. Recommendations for designing displays for older adults has been provided by prior literature such as ensuring that text is large and has high contrast of text [33]. For auditory communication, designers should consider having the frequency of communication in the typical audible range for older adults as well as the ability to adjust to volume.

This study provides initial insight into the variables that support trust between older adults and robot care providers, but it was not without limitations. Qualitative interviews allowed for obtaining in-depth information about the factors that support trust within this context, but as the older adults did not interact with a real robot or care technology these findings only provide insights about their attitudes, not their actual interaction behavior. We chose to not expose the older adults to specific robots as many of these technologies are either not in existence or still being developed (not commercially accessible) and we did not want to limit our study to a few specific robots. These initial factors should be further validated as these robots are developed. Another issue is that some individuals in this cohort of older adults have

limited experience with technology. It is unclear how further experience with technology might impact these factors as well, but we do know that older adults with technology experience are more likely to adopt newer technologies [23]. Therefore, future studies should explore how various technology experiences influences individuals' perceptions of new technologies such as robot care providers. This study provided insights about what factors need further exploration in the future and what aspects older adults perceived as contributing to successful care between them and a robot care provider.

This study expanded the theoretical understanding of what factors support trust in the older adult and care provider context by solidifying that themes from other pieces of trust literature are pertinent to this context, but also by identifying factors that emerged specifically within this context such as gentleness. In addition, these findings give insight into how to design a care provider robot in a way that can support the older adult trusting it. By understanding what factors support trust in this context, we can improve not only the older adults' acceptance of the robot but improve the lives of older adults as well by creating successful interactions between the human and robot care providers.

Disclosure

NIDILRR is a center within the Administration for Community Living (ACL), Department of Health and Human Services (HHS). The contents of this publication do not necessarily represent the policy of NIDILRR, ACL, or HHS, and the reader should not assume endorsement by the Federal Government. Some details of the method—but none of the results—were presented at a workshop [34].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The contents of this publication were developed under a grant from the National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR Grant no. 90RE5016-01-00) under the auspices of the Rehabilitation and Engineering Research Center on Technologies to Support Successful Aging with Disability (TechSAge; http://www.techsage.gatech.edu). The authors appreciate the insights of Charlie Kemp and Jamie Gorman on this project. They would also like to thank Emily McDonald and Lyndsie Koon for their help with the qualitative analysis.

References

[1] World Health Organization., "Research for the reorientation of national health systems," *World Health Organization. Technical Report Series*, 2015.

[2] R. C. Mayer, J. H. Davis, and F. D. Schoorman, "An integrative model of organizational trust," *Academy of Management Review*, vol. 20, no. 3, pp. 709–734, 1995.

[3] L. L. Couch and W. H. Jones, "Measuring levels of trust," *Journal of Research in Personality*, vol. 31, no. 3, pp. 319–336, 1997.

[4] L. Trojan and O. Yonge, "Developing trusting, caring relationships: home care nurses and elderly clients," *Journal of Advanced Nursing*, vol. 18, no. 12, pp. 1903–1910, 1993.

[5] L. Berg and E. Danielson, "Patients' and nurses' experiences of the caring relationship in hospital: An aware striving for trust," *Scandinavian Journal of Caring Sciences*, vol. 21, no. 4, pp. 500–506, 2007.

[6] R. Parasuraman and V. Riley, "Humans and automation: use, misuse, disuse, abuse," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 39, no. 2, pp. 230–253, 1997.

[7] Y. Seong and A. M. Bisantz, "The impact of cognitive feedback on judgment performance and trust with decision aids," *International Journal of Industrial Ergonomics*, vol. 38, no. 7-8, pp. 608–625, 2008.

[8] P. Madhavan and D. A. Wiegmann, "Similarities and differences between human–human and human–automation trust: An integrative review," *Theoretical Issues in Ergonomics Science*, vol. 8, no. 4, pp. 277–301, 2007.

[9] J. D. Lee and N. Moray, "Trust, self-confidence, and operators' adaptation to automation," *International Journal of Human - Computer Studies*, vol. 40, no. 1, pp. 153–184, 1994.

[10] S. M. Merritt and D. R. Ilgen, "Not all trust is created equal: Dispositional and history-based trust in human-automation interactions," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 50, no. 2, pp. 194–210, 2008.

[11] T. Sanders, K. E. Oleson, D. R. Billings, J. Y. C. Chen, and P. A. Hancock, "A model of human-robot trust: Theoretical model development," in *Proceedings of the 55th Human Factors and Ergonomics Society Annual Meeting, (HFES '11)*, vol. 55, pp. 1432–1436, USA, September 2011.

[12] P. A. Hancock, D. R. Billings, K. E. Schaefer, J. Y. C. Chen, E. J. De Visser, and R. Parasuraman, "A meta-analysis of factors affecting trust in human-robot interaction," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 53, no. 5, pp. 517–527, 2011.

[13] N. Ezer, "Is a robot an appliance, teammate, or friend? Age-related differences in expectations of and attitudes towards personal home-based robots".

[14] D. R. Billings, K. E. Schaefer, J. Y. C. Chen, and P. A. Hancock, "Human-robot interaction: Developing trust in robots," in *Proceedings of the 7th Annual ACM/IEEE International Conference on Human-Robot Interaction, (HRI '12)*, pp. 109-110, USA, March 2012.

[15] W. A. Rogers and T. L. Mitzner, "Human-robot interaction for older adults," *Encyclopedia of Computer Science and Technology*, pp. 1–11, 2017.

[16] C.-A. Smarr, T. L. Mitzner, J. M. Beer et al., "Domestic robots for older adults: attitudes, preferences, and potential," *International Journal of Social Robotics*, vol. 6, no. 2, pp. 229–247, 2014.

[17] J. Beer, A. Prakash, C. Smarr et al., "Older users' acceptance of an assistive robot: Attitudinal changes following brief exposure," *Gerontechnology*, vol. 16, no. 1, pp. 21–36, 2017.

[18] K. E. Olson, *Understanding the construct of human trust in domestic service robots*, Georgia Institute of Technology, 2013.

[19] A.-S. Melenhorst, W. A. Rogers, and D. G. Bouwhuis, ""Older adults" motivated choice for technological innovation: evidence for benefit-driven selectivity," *Psychology and Aging*, vol. 21, no. 1, pp. 190–195, 2006.

[20] A. C. Costa, "Work team trust and effectiveness," *Personnel Review*, vol. 32, no. 5, pp. 605–672, 2003.

[21] D. Bernstein, K. Crowley, and I. Nourbakhsh, "Working with a robot: Exploring relationship potential in human-robot systems," *Interaction Studies*, vol. 8, no. 3, pp. 465–482, 2007.

[22] R. E. Stuck, *Understanding Dimensions of Trust between Older Adults and Human or Robot Care Providers*, Georgia Institute of Technology, 2017.

[23] S. J. Czaja, N. Charness, A. D. Fisk et al., "Factors predicting the use of technology: findings from the center for research and education on aging and technology enhancement (CREATE)," *Psychology and Aging*, vol. 21, no. 2, pp. 333–352, 2006.

[24] L. H. Barg-Walkow, T. L. Mitzner, and W. A. Rogers, "Technology Experience Profile".

[25] J. A. Sanford, P. C. Griffiths, P. Richardson, K. Hargraves, T. Butterfield, and H. Hoenig, "The effects of in-home rehabilitation on task self-efficacy in mobility-impaired adults: A randomized clinical trial," *Journal of the American Geriatrics Society*, vol. 54, no. 11, pp. 1641–1648, 2006.

[26] Z. S. Nasreddine, N. A. Phillips, V. Bédirian et al., "The montreal cognitive assessment, MoCA: a brief screening tool for mild cognitive impairment," *Journal of the American Geriatrics Society*, vol. 53, no. 4, pp. 695–699, 2005.

[27] D. Wechsler, *WAIS-III: Wechsler adult intelligence scale*, Psychological Corporation, 1997.

[28] C. T. K. C, R. W. Mitzner T, and C. T. K. C. R. W. Mitzner, "Identifying the potential for robotics to assist older adults in different living environments," *International Journal of Social Robotics*, vol. 6, no. 2, pp. 213–227, 2014.

[29] H. F. Hsieh and S. E. Shannon, "Three approaches to qualitative content analysis," *Qualitative Health Research*, vol. 15, no. 9, pp. 1277–1288, 2005.

[30] C. Pope, S. Ziebland, and N. Mays, "Qualitative research in health care Analysing qualitative data," *British Medical Journal*, vol. 320, no. 7227, pp. 114–116, 2000.

[31] J. Saldana, *The Coding Manual for Qualitative Researchers*, vol. 36, Sage Publications, England, UK, 2nd edition, 2014.

[32] T. L. Mitzner, R. Stuck, J. Q. Hartley, J. M. Beer, and W. A. Rogers, "Acceptance of televideo technology by adults aging with a mobility impairment for health and wellness interventions," *Journal of Rehabilitation and Assistive Technologies Engineering*, vol. 4, 2017.

[33] A. D. Fisk, W. A. Rogers, N. Charness, S. J. Czaja, and J. Sharit, *Designing for older adults: Principles and creative human factors approaches*, 2009.

[34] R. E. Stuck and W. A. Rogers, "Understanding older adult's perceptions of factors that support trust in human and robot care providers," in *Proceedings of the 10th International Conference on PErvasive Technologies Related to Assistive Environments (PETRA '17)*, pp. 372–377, Greece, June 2017.

Hindawi
Journal of Robotics
Volume 2018, Article ID 1018086, 9 pages
https://doi.org/10.1155/2018/1018086

Research Article

Stabilization of Teleoperation Systems with Communication Delays: An IMC Approach

Yuling Li

School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing 100083, China

Correspondence should be addressed to Yuling Li; lyl8ustb@gmail.com

Received 9 November 2017; Accepted 17 January 2018; Published 20 February 2018

Academic Editor: Brady King

The presence of time delays in communication introduces a limitation to the stability of bilateral teleoperation systems. This paper considers internal model control (IMC) design of linear teleoperation system with time delays, and the stability of the closed-loop system is analyzed. It is shown that the stability is guaranteed delay-independently. The passivity assumption for external forces is removed for the proposed design of teleoperation systems. The behavior of the resulting teleoperation system is illustrated by simulations.

1. Introduction

Teleoperation systems enable humans to extend their capacity to manipulate interfaces with better safety, at less cost, and even with better accuracy. A typical teleoperation system is composed of five parts: a human operator, a master robot which is operated by the human operator, a slave robot, the environment interacting with the slave, and the communication channel between the master and the slave. The main objectives of control design for a bilateral system are the stability of the closed-loop system, position coordination between the master and the slave, and the haptic force display of environment to the human operator.

When there exist significant delays in the communication channel of the teleoperation system, one major issue is the stability of the system [1]. The passivity-based control approaches which are based on scattering theory [1] or wave variable [2] concept are widely used to design stable teleoperation system with time delays. These controllers render the communication link passive and, thus, guarantee stable bilateral teleoperation of any passive environment by any passive user; see [3] and the references therein. For passivity-based controlled teleoperation system, passivity assumption for external forces is required. However, in reality, it is not so easy to satisfy this assumption, and thus this control strategy has its own limitation in real applications.

Realizing the disadvantages in applying passivity-based control schemes in controlling teleoperation systems, we propose an alternative method in which internal model control (IMC) structure is introduced to linear teleoperation system design in this work. IMC was a well-established control strategy around the 1980s and its original configuration and several modified structures have been successfully applied to various applications from chemical processes to automotive systems (see [4–7] and many references therein). The extension to nonlinear systems has also been reported as it shows attractive properties beyond linear system design [8]. Some intelligent methods were introduced to the modification of IMC structures and nonlinear extensions [9–12]. Moreover, there have been some efforts on extending the IMC design method to nonlinear systems in the linear parameter varying (LPV) framework [13, 14] in recent years. The application of IMC in teleoperation systems is also not prior art. Hayn and Schwarzmann have employed IMC structure to design positions controllers for a teleoperation system with a hydraulic manipulator as the slave and a haptic device as the master [15]. However, the authors in [15] assume that no delay exists in the communication. The authors in [16] proposed an IMC design for teleoperation systems with time-varying delays, while, actually, it is a smith-predictor-based design of teleoperation systems. In this work, an IMC-based control structure for delayed teleoperation systems is

proposed and no restrictive assumptions are made on this structure. The passivity assumption is not required for the proposed control scheme.

The arrangement of the remainder of this paper is as follows. In Section 2 the system modeling and some preliminaries are given. In Section 3, a control architecture is given and its stability is analyzed in Section 4. A simple DOF teleoperation system is given as an example to show the effectiveness of the proposed method in Section 5. Finally, the summary and conclusion of this paper are given in Section 6.

2. Preliminaries

A single-DOF linear master/slave manipulator can be written as [17]

$$\begin{aligned} m_m\ddot{x}_m(t) + b_m\dot{x}_m(t) + k_m x_m(t) &= f_h(t) + f_m(t), \\ m_s\ddot{x}_s(t) + b_s\dot{x}_s(t) + k_s x_s(t) &= -f_e(t) + f_s(t), \end{aligned} \tag{1}$$

where $x_i, \dot{x}_i, \ddot{x}_i$ are the joint positions, velocities, and acceleration values of the master and slave devices with $i = m$ or s representing master or slave robot manipulators, respectively. Similarly, m_i, b_i, k_i are the effective mass, damping, and spring coefficients of the master and slave devices. External forces applied to the devices by the human operator and the environment are represented by f_h, f_e, respectively, while f_m, f_s stand for control signals.

For simplicity, the transfer functions of the master and the slave are given as follows:

$$G_m : G_m(s) = \frac{y_m(s)}{f_h(s) + f_m(s)} = \frac{1}{m_m s^2 + b_m s + k_m}, \tag{2}$$

$$G_s : G_s(s) = \frac{y_s(s)}{-f_e(s) + f_s(s)} = \frac{1}{m_s s^2 + b_s s + k_s}. \tag{3}$$

In this work, the following assumptions are required.

Assumption 1. The forward and backward delays through the communication channel denoted by T_1, T_2, respectively, are assumed to be constant, but of arbitrary value.

Remark 2. Assumption 1 is made for simplicity. The main results in this paper are also valid for teleoperation systems with time-varying delays. In Section 5, we also provide some simulation study for the case with time-varying delays.

3. IMC Structure for Teleoperation Systems

This section proposes an IMC-based control structure which guarantees the delay-independent stability of the closed-loop system.

Let us start with the controller design process from one side of the teleoperation system, that is, from the master side, if no confusion arises. Inspired by the traditional IMC structure, we postulate the IMC structure for the master in Figure 1 where G_m represents the master dynamics as in (2) and $\widetilde{G}_m$ represents the model of the master manipulator. Note that the two-degree-of-freedom IMC structure [4] is utilized since the dynamic characteristics of the two inputs f_h, r_{sd} are substantially different. To describe the transparency, the reference signal r_{sd} should be the signals from the slave. Considering the communication delay between the master and the slave, the reference r_{sd} is delayed; that is,

$$r_{sd}(t) = r_s(t - T_2). \tag{4}$$

Obviously, the controllers C_{11}, C_{12} are an operator of r_m, r_{sd}, respectively; that is, $C_{11}(\cdot) = C_{11}(r_m(t))$ and $C_{12} = C_{12}(r_{sd}(t))$. The human operator $f_h(t)$ seems to be a kind of "disturbance" from the original IMC design interpretation; however, we may find that it should not be canceled in our design. The detailed discussion will be given later.

Analogically, the IMC structure for the slave side is depicted in Figure 2, where C_{21}, C_{22} are linear operators of r_s and r_{md}; that is, $C_{21}(\cdot) := C_{21}(r_{md}(t))$ and $C_{22}(\cdot) := C_{22}(r_s(t))$, and

$$r_{md}(t) = r_m(t - T_1). \tag{5}$$

The coordinating torques are given as

$$\begin{aligned} f_m(t) &= C_{12}(r_s(t - T_2)) - C_{11}(r_m(t)), \\ f_s(t) &= C_{21}(r_m(t - T_1)) - C_{22}(r_s(t)). \end{aligned} \tag{6}$$

Equations (6) can also be represented by their S-functions:

$$\begin{aligned} F_m(s) &= \begin{bmatrix} -C_{11}(s) & C_{12}(s)e^{-sT_2} \end{bmatrix} \begin{bmatrix} R_m(s) \\ R_s(s) \end{bmatrix}, \\ F_s(s) &= \begin{bmatrix} C_{21}(s)e^{-sT_1} & -C_{22}(s) \end{bmatrix} \begin{bmatrix} R_m(s) \\ R_s(s) \end{bmatrix}. \end{aligned} \tag{7}$$

The control architecture is shown in Figure 3.

Remark 3. From Figure 3 and compared with the classical IMC structure [4], we may find that the external forces f_h, f_e are the "disturbances" according to the classical IMC interpretation. The difference is that these "disturbances" act on the master and the slave directly. In reality, these forces are kind of "excitation signals" and should not be canceled.

Remark 4. Actually, the output y_m, y_s can be positions or velocities, or even the states of the master and the slave. In this paper, we assume that only the position is available for measurement; that is, $y_m = x_m$ and $y_s = x_s$.

4. Stability Analysis

In this section, the stability of the closed-loop system is discussed.

Suppose $\mathbf{r}(t) := \begin{bmatrix} r_m(t) \\ r_s(t) \end{bmatrix}$, $\mathbf{u}(t) := \begin{bmatrix} f_m(t) \\ f_s(t) \end{bmatrix}$, $\mathbf{y}_o(t) := \begin{bmatrix} y_m(t) \\ y_s(t) \end{bmatrix}$, and $\mathbf{w}(t) := \begin{bmatrix} f_h(t) \\ -f_e(t) \end{bmatrix}$; then the closed-loop system in Figure 3 can be redrawn as in Figure 4 where $\mathbf{G}(s) = \begin{bmatrix} G_m(s) & 0 \\ 0 & G_s(s) \end{bmatrix}$ and $\widetilde{\mathbf{G}}(s) = \begin{bmatrix} \widetilde{G}_m(s) & 0 \\ 0 & \widetilde{G}_s(s) \end{bmatrix}$.

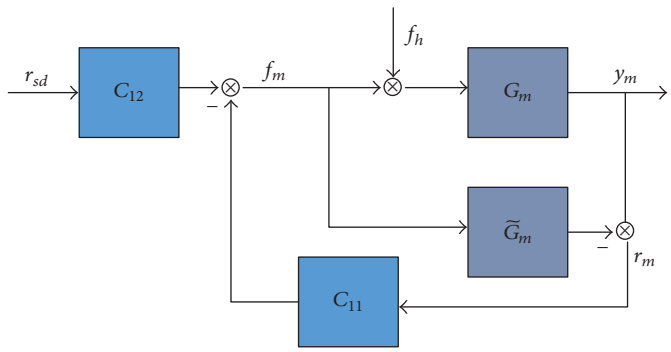


Figure 1: IMC structure of the master subsystem.

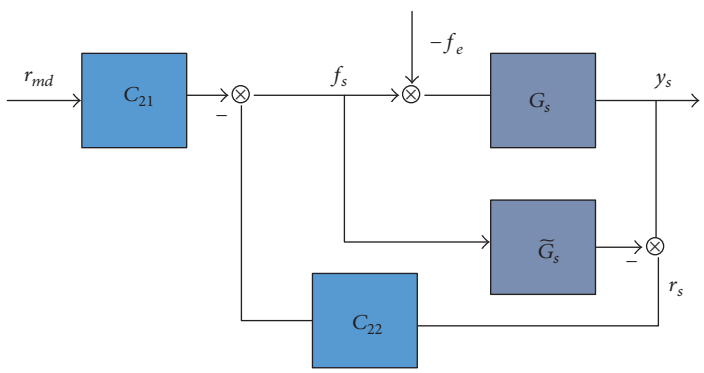


Figure 2: IMC structure of the slave subsystem.

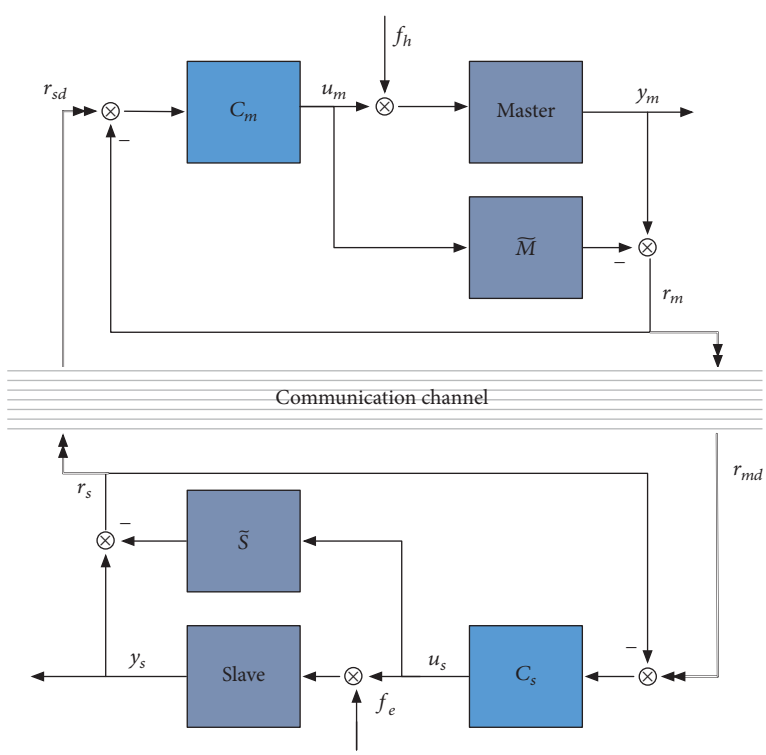


Figure 3: IMC structure of teleoperation systems.

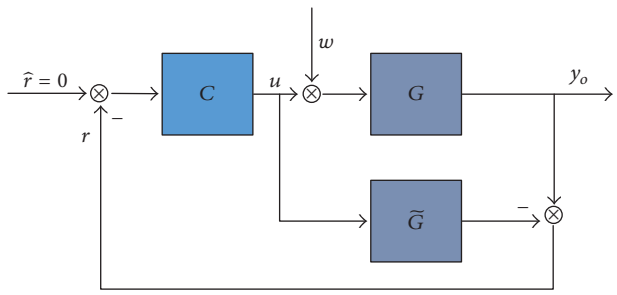


Figure 4: Equivalent IMC structure of teleoperation systems.

Let $\mathbf{R}, \mathbf{U}$ be the Laplace transform of $\mathbf{r}, \mathbf{u}$; then the controllers (7) can be rewritten as

$$\mathbf{U}(s) = -\mathbf{C}(s)\mathbf{R}(s), \tag{8}$$

where

$$\mathbf{C}(s) = \begin{bmatrix} C_{11}(s) & -C_{12}(s)e^{-sT_2} \\ -C_{21}e^{-sT_1} & C_{22}(s) \end{bmatrix}. \tag{9}$$

From the block diagram of the IMC structure shown in Figure 4, the output $\mathbf{y}_o$ is related to the input $\mathbf{w}$ as

$$\mathbf{Y}_o(s) = \mathbf{G}\left(\mathbf{I} + \mathbf{C}\left(\mathbf{I} - \widetilde{\mathbf{G}}\mathbf{C}\right)^{-1}\mathbf{G}\right)^{-1}\mathbf{W}(s). \tag{10}$$

Since $\mathbf{C}(\mathbf{I} - \widetilde{\mathbf{G}}\mathbf{C})^{-1} = (\mathbf{I} - \mathbf{C}\widetilde{\mathbf{G}})^{-1}\mathbf{C}$, (10) can be rewritten as

$$\mathbf{Y}_o(s) = \mathbf{G}\left(\mathbf{I} - \mathbf{C}\widetilde{\mathbf{G}} + \mathbf{C}\mathbf{G}\right)^{-1}\left(\mathbf{I} - \mathbf{C}\widetilde{\mathbf{G}}\right)\mathbf{W}(s). \tag{11}$$

When the system model $\widetilde{\mathbf{G}}$ matches the plant $\mathbf{G}$ perfectly, that is, $\widetilde{\mathbf{G}} = \mathbf{G}$, one has

$$\mathbf{Y}_o(s) = \mathbf{G}(\mathbf{I} - \mathbf{C}\mathbf{G})\mathbf{W}(s). \tag{12}$$

It can be seen that the internal stability is always ensured as long as a stable parameter $\mathbf{C}_0(s) = \begin{bmatrix} C_{11}(s) & C_{12}(s) \\ C_{21}(s) & C_{22}(s) \end{bmatrix}$ is used to control the stable plant $\mathbf{G}$. Like the traditional IMC system, we have the following important property.

Theorem 5 (dual stability). *Assume that the master/slave model and the master/slave manipulator dynamics match perfectly; that is, $\mathbf{G}_i(s) = \widetilde{\mathbf{G}}_i$ $(i = m, s)$. Then the stability of $\mathbf{C}_0$ is sufficient for the stability of the overall closed-loop system.*

Remark 6. In the proposed control design, there are no passivity assumptions for human forces f_h and environmental forces f_e. These forces can be any bounded signals from the IMC interpretation.

Remark 7. Actually, when $\mathbf{G} = \widetilde{\mathbf{G}}$, the system is basically open loop. Hence this IMC-based design of teleoperation systems provides the open-loop advantages. When the perfect model is not available, that is, $\mathbf{G} \neq \widetilde{\mathbf{G}}$, the overall system is a closed-loop system. Thus, the IMC control strategy has the advantages of both the open-loop and the closed-loop structures [18]. However, the stability condition for the case that $\mathbf{G} \neq \widetilde{\mathbf{G}}$ becomes complex, since the subdiagonal delays exist in $\mathbf{C}$, and this will be a subject of ongoing research.

Remark 8. For the case $\mathbf{G} = \widetilde{\mathbf{G}}$, the benefit of this structure is that the communication time delays do not enter into the feedback channel. Hence the stability of the overall system can be simplified given the stable controllers $C_{11}(s)$, $C_{12}(s)$, $C_{21}(s)$, and $C_{22}(s)$. In another way, it means that this control structure can guarantee the stability of the overall system with the communication delays varying from 0 to arbitrary value. This implies a way to choose suitable $C_{11}(s)$, $C_{12}(s)$, $C_{21}(s)$, and $C_{22}(s)$ with sound performance.

Remark 9. Theorem 5 is also applicable to teleoperation systems with time-varying delays since the communication delays do not enter into the feedback loop.

5. Simulation and Results

We consider a simple single-DOF teleoperation system with the dynamics (1) with $m_m = 0.3$ kg, $m_s = 1$ kg, $b_m = 1$ Ns/m, $b_s = 3$ Ns/m, $k_m = 10$ N/m, and $k_s = 10$ N/m.

The operator is assumed to be with the following dynamics:

$$f_h(t) = f(t) - b_{\text{op}}\dot{x}_m(t) - k_{\text{op}}x_m(t), \tag{13}$$

where $f(t)$ is a rectangle signal depicted in Figure 5, $b_{\text{op}} = 3$, and $k_{\text{op}} = 200$. The environmental force is chosen as $f_e(t) = -k_{\text{env}}x_s(t)$ $(k_{\text{env}} = 400)$.

We first implement the control in Figure 3 assuming that there are no delays in communication channel and obtain the simulation results shown in Figures 7 and 8. The chosen control parameters C_{ij} are represented by their step responses, which are depicted in Figure 6. It can be seen that the master and the slave respond stably. As shown in Figure 7, the slave's motion follows the master's quickly with no delay; however, there is a bit of oscillation in the position of the master, which means the control parameters C_{ij} could be better chosen. Even though the positions between the masters and the slaves achieve perfect tracking, there is static error between the human force and the environmental force (Figure 8). This error may not be canceled since the position

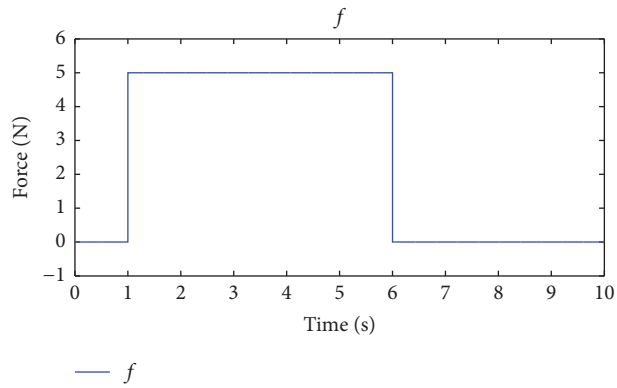


Figure 5: External force $f(t)$.

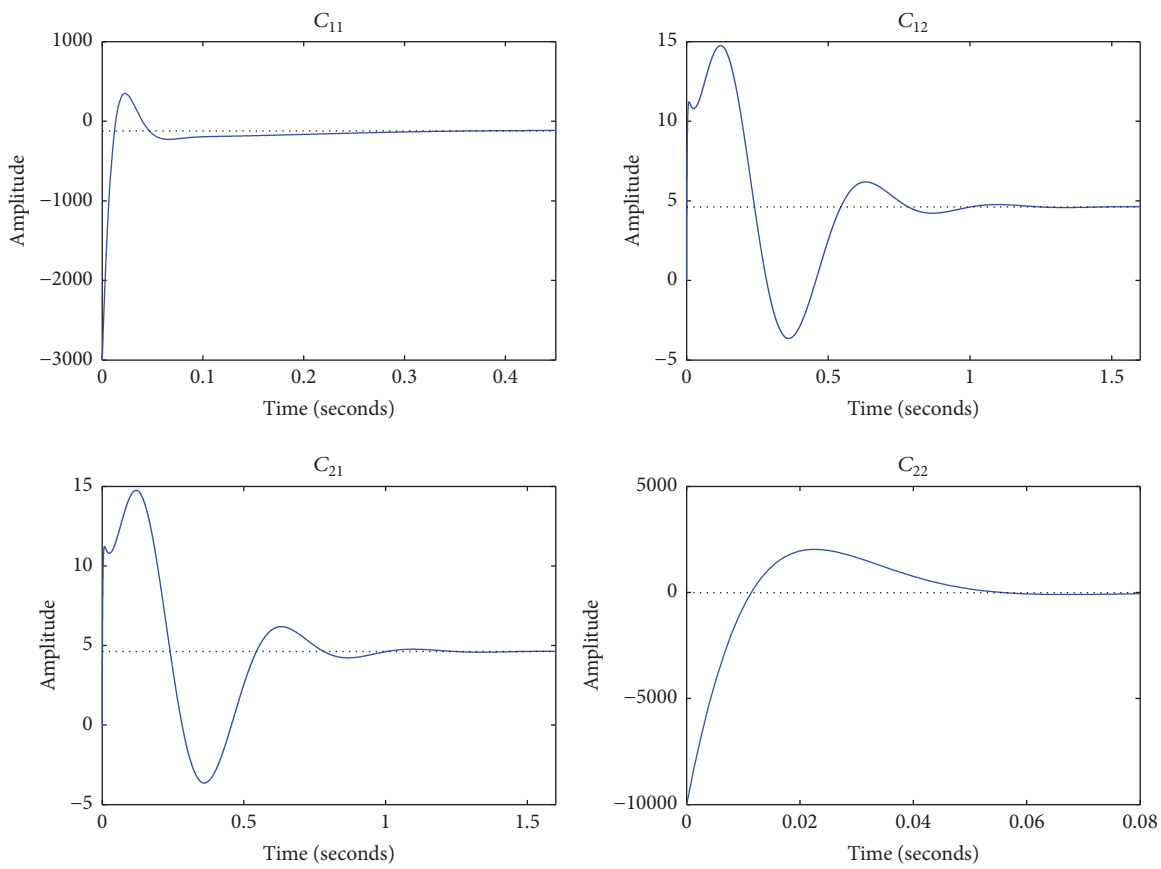


Figure 6: Step responses of $C_{11}(s)$, $C_{12}(s)$, $C_{21}(s)$, and $C_{22}(s)$.

tracking and the force tracking are two objectives which require trade-offs.

Now we make simulations for the case when there exist delays in the communication channel. Let us firstly assume that the time delays in the forward channel and backward channel are symmetric; that is, $T_1 = T_2 = 1$ s. The system performance with the designed controller under this case is depicted in Figures 9 and 10. It can be seen from Figure 10 that when the operator exerted the force to the master around $t = 1$ s, the slave contacted the environment after the delay of 1 second and then received an active force f_e. The (delayed) position tracking performance depicted in Figure 9 is similar to the one when there are no delays in the communication channel.

We furthermore make simulations for the system with sudden appearing communication delays and sudden disappearing communication delays (both around $t = 4$ s), but the delays are symmetric. For simplicity, we only provide

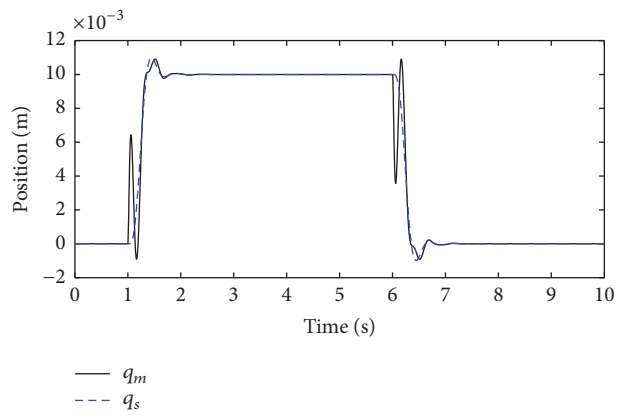


Figure 7: Position tracking performance when there are no delays in the communication channel.

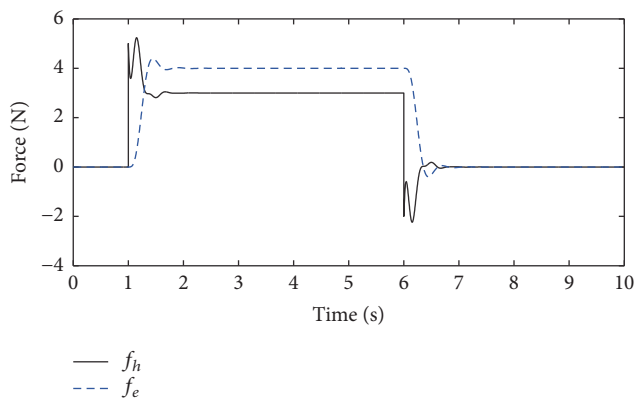


Figure 8: Force tracking performance when there are no delays in the communication channel.

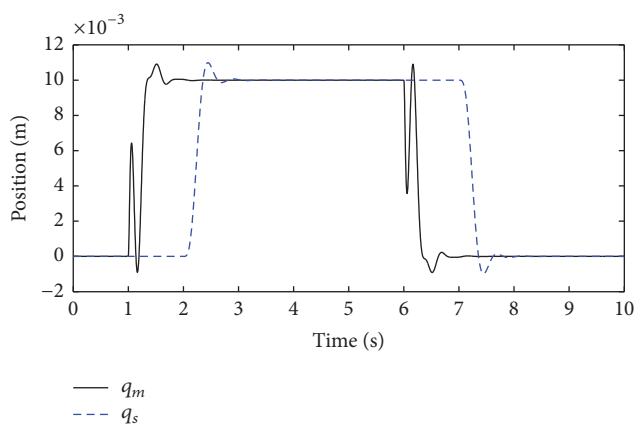


Figure 9: Position tracking performance ($T_1 = T_2 = 1$ s).

the position tracking performances which are depicted in Figures 11 and 12. It is easy to see that the closed-loop system stays stable in this case. For the time interval with communication delays, the slave follows the master's motion after corresponding delays.

We further concern ourselves with the system's performance when the forward and backward communication delays are not the same. We decrease the forward communication delay to 0.5 s and increase the backward communication delay to 2 s and implement the control in Figure 3,

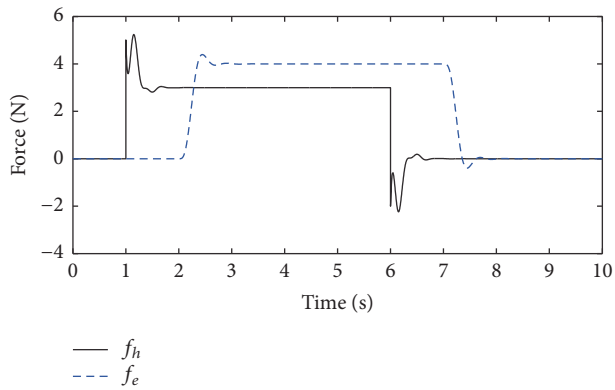


Figure 10: Force tracking performance ($T_1 = T_2 = 1$ s).

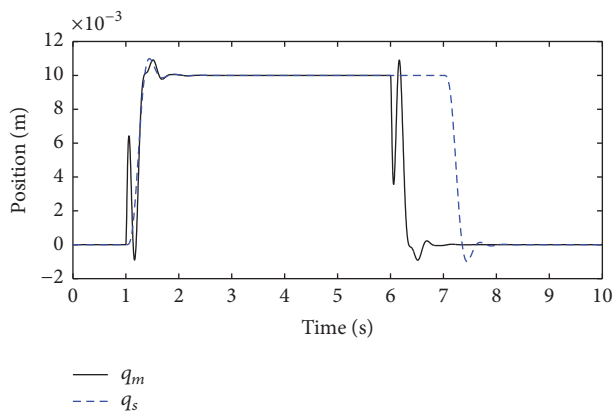


Figure 11: Position tracking performance with sudden appearing delays.

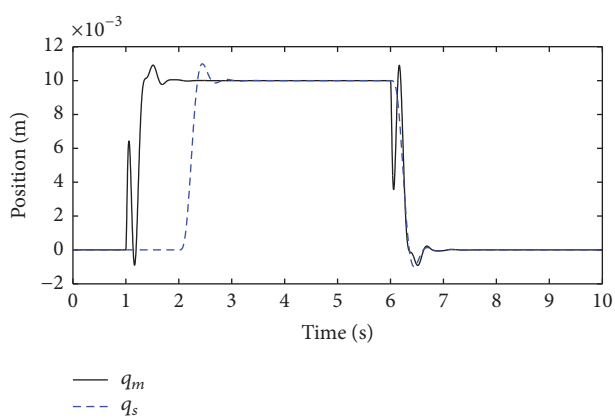


Figure 12: Position tracking performance with sudden disappearing delays.

and then we obtain the simulation results as in Figures 13 and 14. These figures implied that the closed-loop system's stability is guaranteed with unsymmetrical communication delays. Hence, it showed that the designed controller is a delay-dependent stable controller.

Finally, we make simulations for the teleoperation system with varying communication delays. The forward and backward time delays in the communication channel are modeled as $T_i(t) = |X_i(t)|$ $(i = 1, 2)$, where X_i are random variables with normal distribution characterized by its mean τ_v and standard deviation δ, denoted by standard notation $X_i(\cdot) \sim N(\tau_v, \delta^2)$. The forward and backward time delays in the communication channel are chosen with $X_i \sim N(0.4, 0.01)$. The position tracking performance and force tracking performance are depicted in Figures 15 and 16. It is shown that the system is stable with good tracking performance even

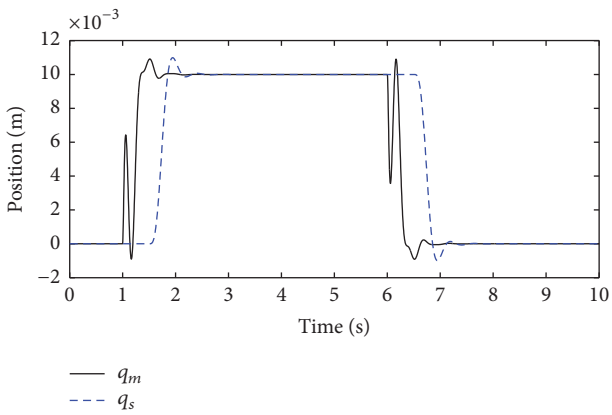


Figure 13: Position tracking performance ($T_1 = 0.5$ s, $T_2 = 2$ s).

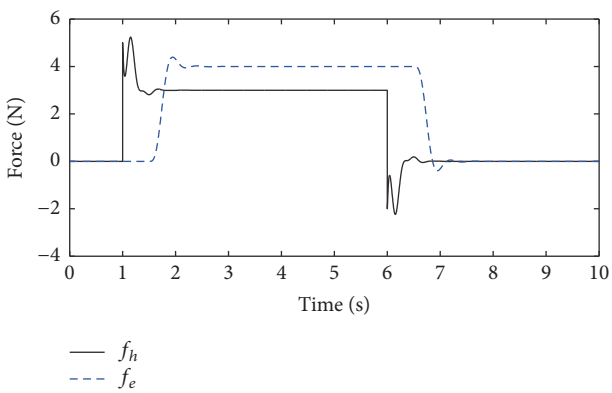


Figure 14: Force tracking performance ($T_1 = 0.5$ s, $T_2 = 2$ s).

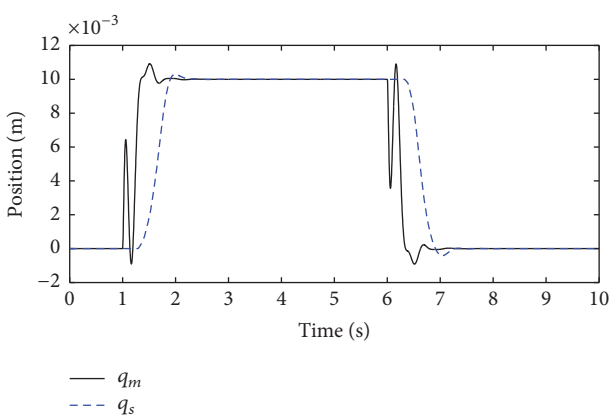


Figure 15: Position tracking performance ($T_i(t) = |X_i(t)|$ ($i = 1, 2$), $X_i \sim N(0.4, 0.01)$).

with bounded stochastic communication delays. This means that our method is also valid for teleoperation systems with varying delays.

6. Conclusion

In this paper, we investigate the IMC-based control design of linear teleoperation system with communication delays.

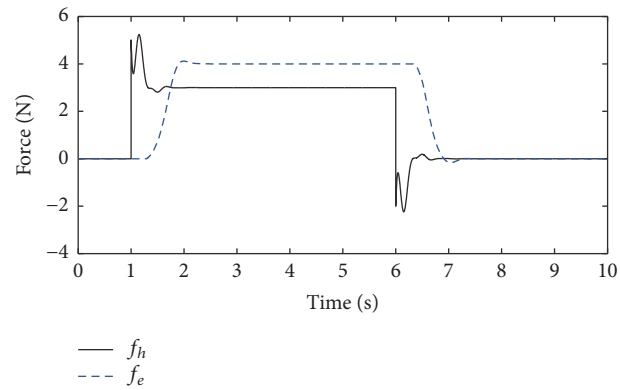


Figure 16: Force tracking performance ($T_i(t) = |X_i(t)|$ ($i = 1, 2$), $X_i \sim N(0.4, 0.01)$).

The stability of the overall system is guaranteed if the perfect model is available. This method removes the passivity assumption for external forces. Simulations of a single-DOF linear teleoperation system show that the stability is guaranteed when the designed controller is applied. Good tracking performance can be achieved if the parameters C_{ij} are chosen suitably. Extensions to the case when the models and the plants are not perfectly matched and to nonlinear teleoperation systems are under study and the research results will be reported in the near future.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was jointly supported by the National Natural Science Foundation of China (no. 61333002), the Fundamental Research Funds for the Central Universities (nos. FRF-TP-16-024A1 and FPR-BD-16-005A), and the Beijing Key Discipline Development Program (no. XK100080537).

References

[1] R. J. Anderson and M. W. Spong, "Bilateral control of teleoperators with time delay," *Institute of Electrical and Electronics Engineers Transactions on Automatic Control*, vol. 34, no. 5, pp. 494–501, 1989.

[2] G. Niemeyer and J.-E. Slotine, "Stable adaptive teleoperation," *IEEE Journal of Oceanic Engineering*, vol. 16, no. 1, pp. 152–162, 1991.

[3] E. Nuño, L. Basañez, and R. Ortega, "Passivity-based control for bilateral teleoperation: A tutorial," *Automatica*, vol. 47, no. 3, pp. 485–495, 2011.

[4] M. Morari and E. Zafiriou, *Robust process control*, Prentice hall, Englewood Cliffs, NJ, USA, 1989.

[5] D. Schwarzmann, *Nonlinear Internal Model Control with Automotive Applications*, Logos-Verlag, 2008.

[6] D. Kim, D. Lee, and K. C. Veluvolu, "Accommodation of actuator fault using local diagnosis and IMC-PID," *International*

Journal of Control, Automation, and Systems, vol. 12, no. 6, pp. 1139–1149, 2014.

[7] T. N. L. Vu, J. Lee, and M. Lee, "Design of multi-loop PID controllers based on the generalized IMC-PID method with Mp criterion," *International Journal of Control, Automation, and Systems*, vol. 5, no. 2, pp. 212–217, 2007.

[8] C. G. Economou, M. Morari, and B. O. Palsson, "Internal model control: extension to nonlinear system," *Industrial & Engineering Chemistry, Process Design and Development*, vol. 25, no. 2, pp. 403–411, 1986.

[9] D. W. C. Hot and Z. Ma, "Multivariable internal model adaptive decoupling controller with neural network for nonlinear plants," in *Proceedings of the 1998 American Control Conference, ACC 1998*, pp. 532–536, Philadelphia, Pa, USA, June 1998.

[10] K. Hunt and D. Sbarbaro, "Neural networks for nonlinear internal model control," *IEE Proceedings Part D: Control Theory and Applications*, vol. 138, no. 5, pp. 431–438, 1991.

[11] E. P. Nahas, M. A. Henson, and D. E. Seborg, "Nonlinear internal model control strategy for neural network models," *Computers & Chemical Engineering*, vol. 16, no. 12, pp. 1039–1057, 1992.

[12] I. Rivals and L. Personnaz, "Nonlinear internal model control using neural networks: application to processes with delay and design issues," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 11, no. 1, pp. 80–90, 2000.

[13] W. Xie and T. Eisaka, "Generalized internal model architecture for gain-scheduled control," *IMA Journal of Mathematical Control and Information*, vol. 25, no. 4, pp. 447–459, 2008.

[14] J. Mohammadpour, J. Sun, A. Karnik, and M. Jankovic, "Internal model control design for linear parameter varying systems," in *Proceedings of the 1st American Control Conference (ACC '13)*, pp. 2409–2414, Washington, DC, USA, June 2013.

[15] H. Hayn and D. Schwarzmann, "Control concept for a hydraulic mobile machine using a haptic operating device," in *Proceedings of the 2nd International Conferences on Advances in Computer-Human Interactions, ACHI 2009*, pp. 348–353, Mexico, February 2009.

[16] P. Jian and Q.-Q. Li, "Internal model control for force-reflecting teleoperation systems with varying time-delay," *Kongzhi Lilun Yu Yingyong/Control Theory and Applications*, vol. 24, no. 1, pp. 13–18, 2007.

[17] P. F. Hokayem and M. W. Spong, "Bilateral teleoperation: An historical survey," *Automatica*, vol. 42, no. 12, pp. 2035–2057, 2006.

[18] I. Kaya, "IMC based automatic tuning method for PID controllers in a Smith predictor configuration," *Computers & Chemical Engineering*, vol. 28, no. 3, pp. 281–290, 2004.