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# Desire-Driven Reasoning for Personal Care Robots

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**ABSTRACT** In this paper, in order to reduce the burden of caring for individuals who are bedridden, we present a method of reasoning about the objects and actions that could satisfy their physiological needs. First, we introduce a method of representing knowledge about everyday objects in terms of their properties and functions. Based on this representation, we then propose a desire-driven reasoning approach that bridges the gap between physiological desires and robot actions. This can also deal with issues caused by uncontrolled domains, including incomplete knowledge and dynamic environments. Finally, we evaluate the proposed method by applying our newly developed KUT-PCR personal care robot to real household scenarios.

**INDEX TERMS** Personal care robot, knowledge representation, physiological need, reasoning.

## I. INTRODUCTION

Caregivers who look after people that are bedridden, due to aging, illness, or an accident, need not only physical strength but also a proper understanding of their patients' physiological needs. Professional caregivers are required to carry out such tasks in nursing homes and hospitals, while visiting caregivers are needed in individuals' homes [1]. However, in order to deal with the nursing shortage [2]–[4] and improve care efficiency, a small number of caregivers are unable to focus on specific care recipients but instead must check in on them periodically.

This means that, currently, patients who are bedridden sometimes have no-one to take care of their needs while caregivers are unavailable. If we could develop personal care robots capable of carrying out simple care tasks (such as delivering goods), the burden on caregivers would reduce dramatically. Such robots would hopefully make patients' lives more comfortable by, for example, delivering drinks or adjusting the temperature and lighting while human caregivers are unavailable.

Several types of robots have been developed to provide this kind of care. For instance, there are robots that can provide mechanical assistance to caregivers or care recipients: a nursing-care assistance robot called RIBA [5] is able to transport a patient between their bed and a wheelchair; exoskeletons can amplify the strength of caregivers [6]; and transfer robots from TOYOTA can carry out tasks when operated locally by a caregiver. In recent years, non-contact robots have also been developed that can carry objects or open and close curtains, such as TOYOTA's HSR [7].

Since the first type of robot operates directly on patients who are bedridden, caregivers who understand their operations must also be present. By contrast, since robots of the latter type do not make direct contact with patients, caregivers are not required to be present. However, these robots must still be given clear commands, such as "fetch a bottle of tea" or "set the room temperature to 25 degrees," and patients may struggle to remember whether there is any tea in the refrigerator or decide what exact temperature they want to set for the room. Patients generally find it much easier to express their physiological needs, such as hunger, thirst, being too hot or cold, needing brighter or dimmer light, or wanting fresh air. If personal care robots could understand such physiological needs and take appropriate actions to satisfy them, a higher intelligence level would have been reached, and these robots could eventually contribute in real caring scenarios.

For personal care robots to perform actions that satisfy given physiological needs when caregivers or home helpers are unavailable, they must at least have the following

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functions: (i) estimate their own location and those of the target objects; (ii) reach the desired destination while avoiding obstacles; (iii) recognize the presence and state of objects; (iv) manipulate objects; (v) identify patients' physiological needs; and (vi) reason about the objects and operations required to satisfy these physiological needs.

Functions (i) and (ii) have long been fundamental to research into autonomous mobile robots. In recent years, simultaneous localization and mapping (SLAM) [8] proved to be highly successful and has been applied in various fields [9], [10]. Function (iv) is critical for industrial robots, for which several different mechanical designs have been proposed, along with methods of controlling the end effectors [11]. Great progress has also been made toward function (iii), including the development of image sensors (high-speed industrial cameras [12] and depth cameras [13]) and advanced algorithms (deep learning [14]). In particular, dramatic advances have been made by combining work on functions (iii) and (iv), as demonstrated by multiple global competitions, such as the DARPA Robotics Challenge (DRC) [15] and the Amazon Picking Challenge (APC) [16].

These techniques can also be applied to personal care robots. For instance, given the command to serve a bottle of water, HSR can pick up the bottle and serve it to the care recipient [7], while Dora [17] can navigate between rooms to search for a book given its name. Such achievements have gained much attention in robotics research and shown convincing results. However, to the best of our knowledge, there has been little discussion on how to recognize physiological needs (such as thirst) and infer how they can be satisfied by particular objects or actions.

Our previous studies on personal care robots presented results related to functions (iii) and (v) [18], [19]. In this work, we instead concentrate on function (vi) and propose a method of reasoning about the objects and operations needed to satisfy a given physiological need. In addition, we also evaluate the proposed approach in real household scenarios. Implementing function (vi), however, presents two main difficulties.

First, there is a range of possible options: since more than one object or action may be able to satisfy a given need, we need a reasoning method that can determine which one to choose. For example, there may be several instances of a particular object class in multiple locations (e.g., a house can have two or more windows and doors) or a single action may involve different states (e.g., an electrical switch can be on or off). Second, operations can be uncertain; for example, a robot may reach the target location only to find that an object does not exist or an action is impossible to perform.

The remainder of this paper is structured as follows. First, we discuss related work in the field. Next, we give a brief overview of the mechanical design and functions of the robot we have developed to care for patients who are bedridden (KUT-PCR). Then, we propose a reasoning algorithm that can, based on descriptions of everyday objects in terms of their properties and functions, identify objects and actions that will satisfy the given physiological needs. After that, we evaluate the proposed methods in real household scenarios. Finally, we conclude the paper and discuss future work.

## II. RELATED WORK

In recent years, developments in mechanical design [20], actuator performance [21], and sensor properties [22] have resulted in increasing numbers of robots being deployed in various fields. Robots can now navigate complex environments [23], [24], interact with people [25], and manipulate different types of objects [26]. However, in order for them to perform such tasks more intelligently, further research into knowledge representation and reasoning will be required.

Various approaches to this problem have been proposed, all focusing on generating a series of robot actions given a clear command such as "fetch a bottle of cola." For such human–robot interaction (HRI) tasks, the BC action language can be used to formalize both sensing and physical actions, enabling service robots to behave intelligently while dealing with incomplete information, underspecified goals, and dynamic changes [27].

Answer set programming (ASP), a declarative programming paradigm, is suitable for representing and reasoning with commonsense knowledge [28]. Partially observable Markov decision processes (POMDPs) provide a principled mathematical framework that enables autonomous robots to solve motion-planning problems in uncertain and dynamic environments [29]. ASP and POMDPs can also be combined to automatically tailor sensor input processing and navigation methods for robots deployed in partial domains [30]. In addition, PDDL [31] is a domain definition language for specifying deterministic planning domains and problems. When combined with heuristic search methods, such as the fast downward planning system [32], it can address many planning or even control problems.

Researchers also attempted to build higher-level knowledge systems that are not limited to one or two representations but can instead handle different tasks by taking advantage of different techniques. Integrating various methods (such as probabilistic graphs, PDDL, or POMDP solvers) into one framework can enable robots to plan in the face of uncertain and incomplete information [17], and this idea has been implemented in a mobile robot platform.

The ontology-based unified robot knowledge (OUR-K) framework [33] has also been introduced for service robots, and it includes both knowledge descriptions and associations. Other researchers also discussed how to structure knowledge-bases by combining different knowledge areas [34], going on to propose the KNOWROB framework, which introduces representational structures and a common vocabulary for representing knowledge.

Although these frameworks have successfully addressed problems in various fields, most researchers have concentrated on solving the problems caused by vague or incomplete information when given task-oriented instructions; as far as we are aware, few have considered situations where there

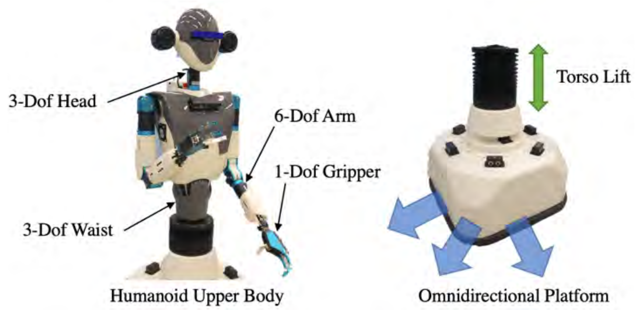



**FIGURE 1.** Upper body (left) and mobile platform (right) of our KUT-PCR personal care robot.

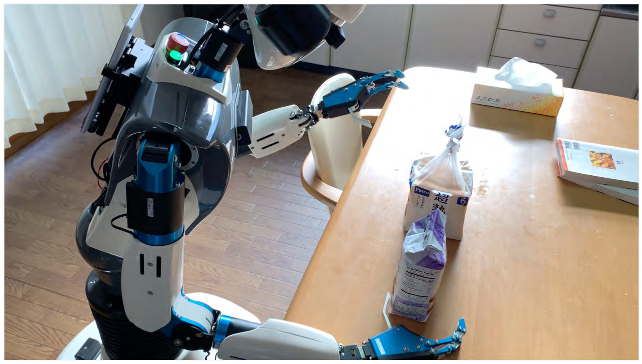


**FIGURE 2.** KUT-PCR picking up a pack of biscuits from a desk.

are no instructions in the first place. In scenarios involving caring for patients who are bedridden, there is a gap between their abstract physiological needs (e.g., "hunger") and the corresponding instructions (e.g., "fetch a pack of biscuits").

## III. PLATFORM

Our newly developed KUT-PCR personal care robot (Fig. 1) is a mobile humanoid robot. Its humanoid upper body and omnidirectional mobile platform enable it to be highly capable of both object manipulation and planar motion.

### A. OMNIDIRECTIONAL MOBILE PLATFORM

Instead of having a lower body with legs, similar to ASIMO, KUT-PCR relies on an omnidirectional platform for mobility (Fig. 1). The combined motion of four omnidirectional wheels allows it to drive in any direction in a planar space and rotate with a zero turning radius, thus enabling it to freely navigate through narrow and uncontrolled environments (such as household environments). A torso lift is also mounted on the platform so that it can reach both objects on the floor and those on a shelf by simply adjusting the lift height.

The platform is equipped with a range of sensors that allow KUT-PCR to perceive its environment and operate autonomously in unknown and dynamic environments. Two laser rangefinders and six ultrasonic sensors enable it to carry out tasks such as SLAM, obstacle avoidance, and path planning. Four haptic sensors and four bumper switches also provide additional safety measures to prevent collisions with obstacles such as furniture or people.

### B. HUMANOID UPPER BODY

KUT-PCR's humanoid upper body (Fig. 1) is designed to provide rich perception and manipulation capabilities. The head has three degrees of freedom, namely roll, pitch, and tilt. Each arm has seven degrees of freedom as well as an end effector with one degree of freedom. Finally, the waist has three degrees of freedom. This design allows the robot to perform various kinds of tasks, including object manipulation and HRI.

The robot's upper body also includes a range of sensors. It uses two RGB-depth (RGB-D) cameras, mounted on the head and chest, to perceive its environment using RGB images and point clouds. Force sensors attached to the wrists provide information about the objects it holds, while microphones and speakers allow natural language communication and multimedia applications.

As Fig. 2 illustrates, to pick up an object, the robot uses its RGB-D camera to estimate the object's position and then grasps it by coordinating the actuation of its mobile platform, arms, waist, and torso.

## IV. HOUSEHOLD ENVIRONMENT DESCRIPTION

Human caregivers can provide appropriate service because they have two types of knowledge: commonsense knowledge that describes how various objects could contribute to satisfying a need and instance knowledge that describes properties of objects in the household environment, such as their locations and weights.

### A. COMMONSENSE KNOWLEDGE

It is generally assumed that cognitive activities, such as reasoning and decision making, presuppose the existence of a conceptual system in the person's memory. For example, a caregiver may give someone a bottle of tea if that person feels thirsty because their understanding of "tea" includes the idea that "tea can satisfy thirst." For a robot to do likewise, it would also need a thorough understanding of concepts related to household environments, which we call commonsense knowledge.

Table 1 gives ten desires and ten objects commonly seen in personal care scenarios, listing the contribution of each object to satisfying each desire on a scale from 0.0 to 1.0, where 0.0 indicates that the object makes no contribution. For instance, milk makes contributions of 0.6 and 0.3 to satisfying thirst and hunger, respectively, while bread helps more with hunger (0.9) and juice helps more with thirst (0.8). Here, we only list some of the commonsense knowledge $K_c$ related to one individual who is bedridden; the detailed values will vary between patients depending on their personal preferences and may also change during the personal care process.

In this study, we do not focus on the acquisition and updating of commonsense knowledge so we consider $K_c$ to be fixed for a given patient.

**TABLE 1. Commonsense knowledge.**

| | HUNGER | THIRST | FRESH AIR | SILENCE | HIGHER TEMPERATURE | LOWER TEMPERA-TURE | HIGHER HUMIDITY | LOWER HUMIDITY | HIGHER ILUMILAT-ION | LOWER ILLUMI-NATION |
|---|---|---|---|---|---|---|---|---|---|---|
| MILK | 0.3 | 0.6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| JUICE | 0 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| BISCUIT | 0.9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| BREAD | 0.9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| WINDOW | 0 | 0 | 0.8 | 0.9 | 0.8 | 0.8 | 0.6 | 0.6 | 0.3 | 0.3 |
| DOOR | 0 | 0 | 0.6 | 0.9 | 0 | 0 | 0 | 0 | 0.8 | 0.8 |
| TV | 0 | 0 | 0 | 0.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| AIR CONDITI-ONER | 0 | 0 | 0 | 0 | 0.9 | 0.9 | 0.8 | 0.8 | 0 | 0 |
| HEATER | 0 | 0 | 0 | 0 | 0.9 | 0 | 0 | 0 | 0 | 0 |

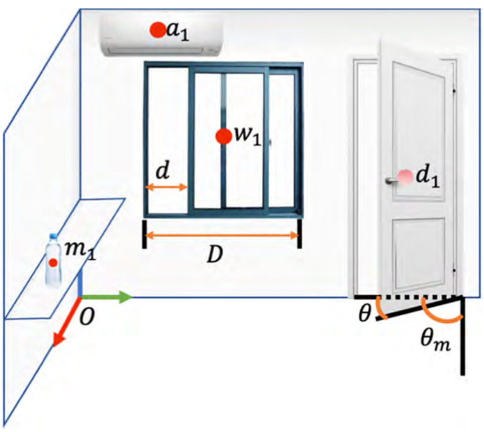



**FIGURE 3. Instance knowledge for the objects in one room.**

## B. INSTANCE KNOWLEDGE

Unlike commonsense knowledge, instance knowledge is dynamic, as it describes the objects' properties; here, this means their names, spatial properties, characteristics, and electrical states.

### 1) NAME

An object's name identifies its type.

### 2) SPATIAL PROPERTIES

The position of an object in the world can be defined using three-dimensional coordinates $(x, y, z)$. For example, the positions of door $d_1$ and window $w_1$ could be represented as $(x\_d_1, y\_d_1, z\_d_1)$ and $(x\_w_1, y\_w_1, z\_w_1)$, respectively (Fig. 3). In addition, for objects such as doors, windows, and refrigerators, the positions of their movable parts can substantially affect their functional attributes.

Since there are various different types of mechanical structures, we define a parameter $\zeta$, called the "opening degree," to describe an object's spatial state. For example, the opening degree of a sliding window is described by $\zeta = 2d/D$, while $\zeta = \theta/\theta_m$ describes a push-pull door.

**TABLE 2. Instance knowledge.**

| | Name | Spatial Properties | Characteristics | Electrical State |
|---|---|---|---|---|
| $w_1$ | "Window" | {(0.0, 3.0, 4.0),0.7} | – | – |
| $d_1$ | "Door" | {(0.0, 7.0, 3.0),0.2} | – | – |
| $m_1$ | "Water" | {(2.0, 0.3, 2.0), ""} | {2.5, 0.3,"*Liquid*"} | – |
| $a_1$ | "Air-conditioner" | {(0.2, 1.5, 6.0), ""} | "" | "*Heating*" |

The specific algorithms used for perception and to calculate $\zeta$ are delegated to the robot controller, and only $\zeta$ is stored in the spatial description. Thus, the spatial properties of the window in Fig. 3 are completely described by $P_s = \{(x, y, z), \zeta\} = \{(0.0, 3.0, 4.0), 0.7\}$.

### 3) CHARACTERISTICS

An object's characteristics describe its physical properties, namely its weight, volume, and state. For example, a bottle of milk may be defined as $P_c = \{w, v, s\} = \{2.5, 0.3, \text{“}Liquid''\}$.

### 4) ELECTRICAL STATE

An appliance may have multiple different functional states, which can dramatically affect its operation; we capture this in the electrical state $\vartheta$. For example, an air-conditioner is described by $\vartheta \in \{\text{OFF}, Heating, Cooling, Ventilation\}$ and $size(\vartheta) = 1$, meaning that it has four operational states but can only be in one of them at any given time.

Table 2 lists all the instance knowledge about the objects in the room shown in Fig. 3.

Now that we have defined both commonsense and instance knowledge, we can introduce the complete description for an object $O$. Since commonsense knowledge is used to describe the functions of an object class, each instance inherits the commonsense knowledge of its class. Specifically, an object

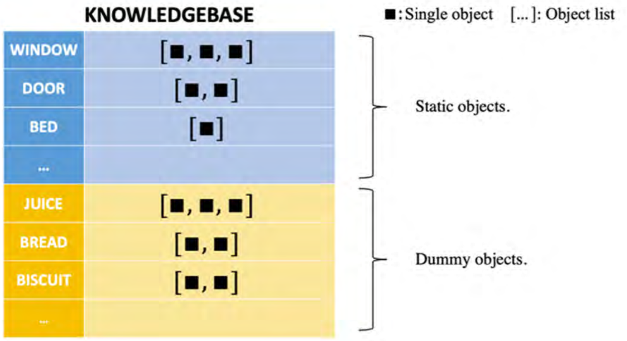



**FIGURE 4.** Example of initializing a knowledgebase.

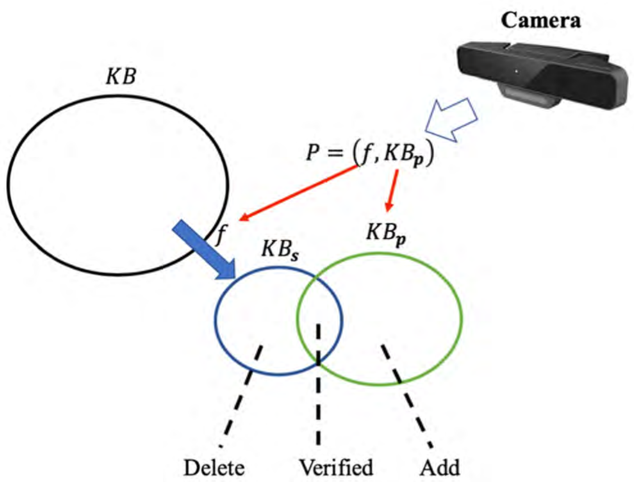



**FIGURE 5.** Updating the knowledgebase.

$O$ can be described as

$$O = (n, K, P_s, P_c, P_e), \tag{1}$$

where $n$ is the object's name. Here $K$ is the commonsense knowledge retrieved from $K_c$ based on $n$, namely

$$K = K_c(n) = \{C_0, \ldots, C_k\}, \tag{2}$$

where $C_0, \ldots, C_k$ are the contributions to the $k$ desire types.

In addition, $P_s$, $P_c$, and $P_e$ represent the object's spatial properties, characteristics, and electrical state, respectively:

$$P_s = \{(x, y, z), \zeta\}, \tag{3}$$

$$P_c = \{w, v, s\}, \tag{4}$$

$$P_e = \{\vartheta\}. \tag{5}$$

### C. KNOWLEDGE INTEGRATION

Now we have a way to describe objects in household environments, the other fundamental challenge is how to build and maintain a personal care knowledgebase involving the objects in personal care scenarios. The robot should have a certain degree of prior knowledge when initially activated and then integrate new knowledge while interacting with the environment. Knowledge integration is the task of identifying how new and prior knowledge interact with each other and incorporating additional information into an existing knowledgebase.

We divide the knowledge integration task into two basic operations: initialization and updating.

**TABLE 3.** Knowledgebase updating algorithm.

**Algorithm**: UPDATE (*KB, P*)

**Input**: Knowledgebase *KB*, Perception $P = (f, KB_p)$

**Output:** Updated knowledgebase *KB*

*// Fetch all objects from KB that are located in the field P.f.*

$$KB_s \leftarrow KB.find(P.f)$$

*// Calculate objects to add to the knowledgebase.*

$$KB_{add} \leftarrow \{o|o \notin KB_s \text{ and } o \in P.KB_p\}$$

*// Calculate objects to delete from the knowledgebase.*

$$KB_{del} \leftarrow \{o|o \in KB_s \text{ and } o \notin P.KB_p\}$$

*// Perform the addition and deletion operations.*

$$KB \leftarrow KB.add(KB_{add})$$

$$KB \leftarrow KB.delete(KB_{del})$$

**RETURN** *KB*

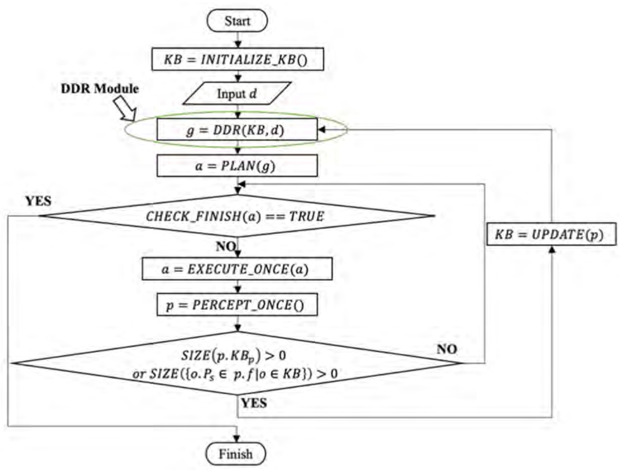



**FIGURE 6.** Flowchart for the desire-driven reasoning system.

#### 1) INITIALIZING THE KNOWLEDGEBASE

The initialization step provides basic prior knowledge about two types of objects: static and dynamic objects.

We define the knowledgebase as *KB*. Static objects, such as doors and windows, are added directly to *KB*, while dynamic objects, such as food and drinks whose quantities and locations are unknown, are initialized as dummy objects based on commonsense understanding.

For example, in Fig. 4, each type of object maintains a list of objects of that type in the current environment. Here, the house is assumed to have two doors, three windows, and one bed. The figure shows *KB*'s initial state; the locations of the static objects are fixed and will not be further verified by the robot system, while the initial dummy objects for juice,

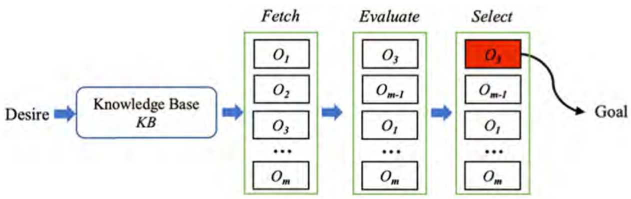



**FIGURE 7. DDR module workflow.**

**TABLE 4. DDR algorithm.**

**Algorithm**: DDR($KB$,$d$)

**Input**: Knowledgebase $KB$, Desire $d$
**Output**: Goal $G$
*// Fetch objects that can contribute to fulfilling the given desire.*

$$\boldsymbol{O} \leftarrow KB.FIND(d)$$

*// Evaluate the objects and create a list of object–rank pairs.*

$$\boldsymbol{O}_{rank} \leftarrow EVALUATE(\boldsymbol{O}, d)$$

*// Select the highest-scoring object as the goal.*

$$G \leftarrow SELECT(\boldsymbol{O}_{rank})$$

**RETURN** $G$

**TABLE 5. Object ranking algorithm.**

**Algorithm**: $RANK(o, d)$

**Input**: Object $o$, Desire $d$
**Output**: Rank $R$
*// Fetch the object's contribution to meeting the given need.*

$$R_{contribution} \leftarrow o.K.FIND(d)$$

*// Calculate the cost of transportation and manipulation.*

$$R_{cost} \leftarrow COST(o.P_c, o.P_s, o.P_e, d)$$

*// Calculate the overall rank.*

$$R = \alpha R_{contribution} + \frac{\beta}{R_{cost}}$$

**RETURN** $R$

bread, and biscuits (based on commonsense understanding) will be verified and updated as the robot searches the environment.

### 2) UPDATING THE KNOWLEDGEBASE

The update step proceeds based on the robot's perceptions. The result of a valid perception is denoted as $P = (f, KB_{\mathbf{p}})$, where $f$ describes the spatial field that the robot has perceived and $KB_{\mathbf{p}}$ is a small knowledgebase containing the objects identified.

As Fig. 5 shows, for a given perception $P = (f, KB_{\mathbf{p}})$, the objects in $KB$ located within the perceived field $f$ are first fetched and then used to build a sub-knowledgebase $KB_s$. The intersection between $KB_s$ and $KB_{\mathbf{p}}$ consists of the objects verified by the perception $P$. Objects that are in $KB_s$ but not $KB_p$ should be deleted from $KB$, since they cannot be identified in their recorded locations, while objects in $KB_p$ but not $KB_{\mathbf{s}}$ should be added to $KB$. Table 3 shows the algorithm used to update the knowledgebase.

An object $o$ can be considered to belong to the knowledgebase $KB$ if there is an object $o_k$ in $KB$ that is equal to $o$.

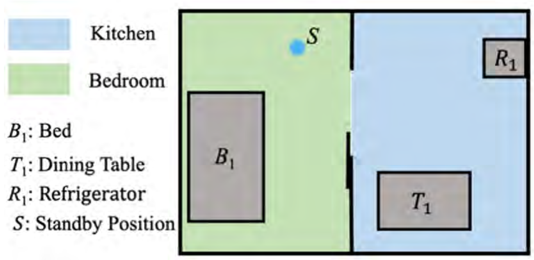



**FIGURE 8. Experimental domain, showing the rooms and static objects.**

**FIGURE 9. Photographs of the personal care domain, showing the bedroom (left) and kitchen (right). The maps in the bottom-left corners indicate the camera's viewpoint.**

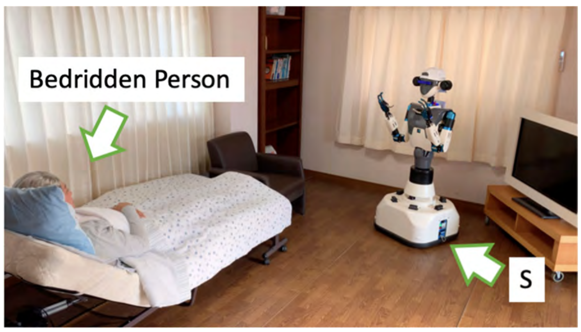



**FIGURE 10. Personal care scenario, showing the bedridden person and personal care robot.**

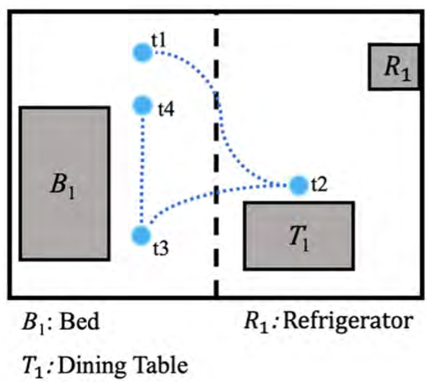
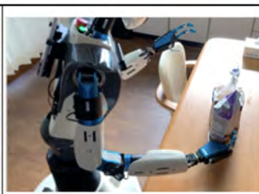
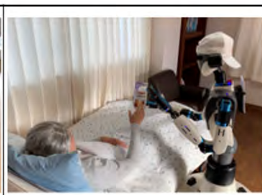



**FIGURE 11. KUT-PCR's route during Trial 1.**

| Photograph |  |  |  |  |
|---|---|---|---|---|
| **Action** | Startup with a request. | Fetch the biscuits. | Serve the biscuits. | Return to the standby position. |
| **KB** | $Bed_1$, $Table_1$, $Refrigerator_1$, $Bread_1$, $Biscuit_1$, $Milk_1$, $Cola_1$, $Juice_1$ | $Biscuit_1$ | $Biscuit_1$ | |
| **Target Object** | $Biscuit_1$ | $Biscuit_1$ | $Biscuit_1$ | |

Green: added objects. Red: deleted objects. Blue: refreshed objects.

**FIGURE 12.** Photographs taken at times $t_1 - t_4$ during Trial 1.

The definition of object equality is as follows:

$$\boldsymbol{IF}\, o_k.name = o.name \ \boldsymbol{AND}\ DIS\left(o_k.P_s, o.P_s\right) < \gamma, \quad \boldsymbol{THEN}\ o = o_k,$$

where the *DIS* function calculates the spatial distance between the two objects and the threshold $\gamma$ accounts for factors such as localization and perception error.

## V. DESIRE-DRIVEN REASONING

Desire-driven reasoning is defined as reasoning via a sequence of steps with the aim of meeting given desires (in this case of people who are bedridden).

### A. DESIRE-DRIVEN REASONING SYSTEM

Fig. 6 shows a flowchart of the proposed desire-driven reasoning (DDR) system. First, the knowledgebase *KB* is initialized, as described in Section IV. When the robot is activated by a particular patient desire $d$, this is passed to the DDR module. This then reasons about suitable goals, considering $d$ and *KB*. The resulting goal is then sent to the planner, which generates an action list for the robot to execute.

Two main loops define the robot's behavior, including execution, perception, and knowledge updating. The robot controller executes a loop consisting of a motion execution command followed by a perception query command. If nothing is identified during a given iteration, the loop continues until the action list is confirmed exhausted, indicating the task is complete. If, during this process, the robot acquires a valid perception (either recognizing objects or the locations of objects in *KB*), *KB* is updated using the knowledge integration method described in Section III, and a new action list is calculated with the same $d$ but the newly updated *KB*. Then, the controller begins executing the newly generated action list.

### B. DESIRE-DRIVEN REASONING MODULE

The system's core component is the DDR module, which reasons as follows (Fig. 7): (i) fetch candidates from the knowledgebase that can contribute to meeting the given need;

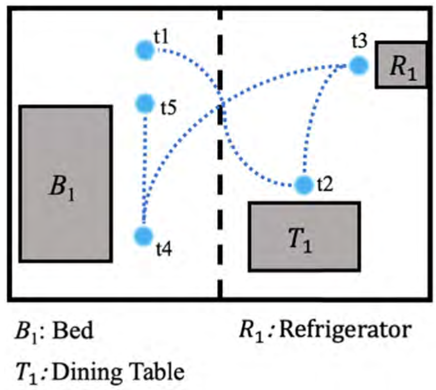



**FIGURE 13.** KUT-PCR's route during Trial 2.

(ii) evaluate the candidates; (iii) select the highest-rated candidate as the goal.

Table 4 describes the DDR algorithm. First, the *FIND* function fetches all objects that make contributions greater than 0 to the given desire $d$ from the knowledgebase *KB*. Then, the *EVALUATE* function ranks the objects. Finally, the *SELECT* function selects the highest-scoring object, which is returned to the task planner as the goal for further planning.

The key element of the *EVALUATE* function is the object ranking method, which considers two aspects: the object's contribution to fulfilling the need and the operation cost.

Table 5 describes how the object ranks are calculated. First, the *FIND* function retrieves the contribution $R_{contribution}$ made by the object $o$ to fulfilling the desire $d$ from the commonsense knowledgebase $K$. Next, the *COST* function calculates the operation cost $R_{cost}$, based on the given desire and the object's characteristics, spatial properties, and electrical state. Finally, the overall rank $R$ is calculated as a weighted sum of $R_{contribution}$ and $R_{cost}$. $\alpha$ and $\beta$ are selected so that the importance of desire fulfilling contribution and task conduction cost can be reflected.

The *COST* function depends on the object type, and the detailed implementation requires knowledge of navigation

| Photograph |  |  |  |  |  |
|---|---|---|---|---|---|
| Action | Startup with a request. | Check the table. | Fetch the milk. | Serve the milk. | Return to the standby position. |
| KB | $Bed_1$, $Table_1$, $Refrigerator_1$, $Bread_1$ ,$Biscuit_1$ , $Milk_1$ ,$Cola_1$ , $Juice_1$ | $Bread_1$ , $Biscuit_1$ | $Milk_1$ , $Cola_1$ , $Juice_1$ , | $Milk_1$ | |
| Target Object | $Biscuit_1$ | $Biscuit_1$ -> $Milk_1$ | $Milk_1$ | $Milk_1$ | |

Green: added objects. Red: deleted objects. Blue: refreshed objects.

**FIGURE 14. Photographs taken at $t_1$ – $t_5$ during Trial 2.**

and vision systems that is beyond the scope of this paper. In short, it evaluates the transportation distance and the manipulation complexity based on the robot and object states and the given desire. The higher $R_{cost}$ is, the more difficult it is for the robot to meet the given desire with the specified object.

## VI. EXPERIMENTS

To evaluate our KUT-PCR personal care robot, we conducted experiments in a real household domain. Here, the aim was to evaluate whether the proposed DDR method could enable the robot to carry out appropriate actions when given only a person's physiological needs.

### A. EXPERIMENTAL SETUP

The experimental domain (Fig. 8) consisted of two rooms, namely a bedroom and a kitchen. There were three static objects: a bed (bedroom), dining table (kitchen), and refrigerator (kitchen). The two rooms were connected by a sliding door. Fig. 9 shows photographs of the domain, taken from the bedroom (left) and kitchen (right).

In addition, a patient who was bedridden lay on the bed, and KUT-PCR was initially at position $S$ (Fig. 10). When the robot was activated by the patient's desire, it began to perform the operations generated by the proposed DDR system.

### B. RESULTS

In order to validate different aspects of our proposed reasoning system, we conducted three trials, each based on the patient feeling hungry but with different object configurations.

#### 1) TRIAL 1

In the first scenario, the food and drinks were placed in commonsense locations. Specifically, a loaf of bread and a packet of biscuits were placed on the kitchen table, while bottles of milk, juice, and cola were stored in the refrigerator.

The robot was activated by the "hunger" desire at time $t_1$. At that time, the robot initialized its knowledgebase with the static objects, namely the bed ($Bed_1$), dining table ($Table_1$), and refrigerator ($Refrigerator_1$), along with dummy objects

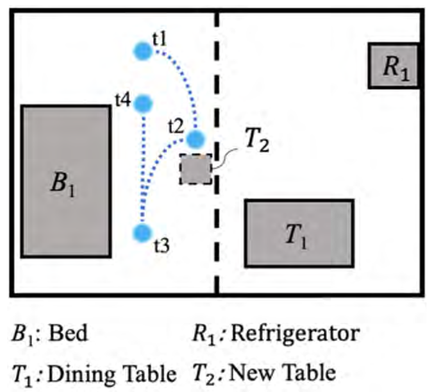



**FIGURE 15. KUT-PCR's route during Trial 3.**

for the biscuits ($Biscuit_1$), bread ($Bread_1$), milk ($Milk_1$), juice ($Juice_1$) and cola ($Cola_1$).

Based on this information, the DDR algorithm ordered the robot to serve $Biscuit_1$ to the patient so KUT-PCR turned and moved to the dining table, reaching it at $t_2$. When the robot perceived the food on the table, the knowledgebase was updated. Since the presence of these objects agreed with the initial commonsense knowledge, only the positions of $Biscuit_1$ and $Bread_1$ were updated. After that, the robot fetched $Biscuit_1$ and served it to the patient at $t_3$, during which time the planning module was paused. However, the moment that the robot handed over $Biscuit_1$, the knowledgebase was updated to change the position of $Biscuit_1$ to match that of $Bed_1$. Finally, at time $t_4$, KUT-PCR returned to the standby point. The route is shown in Fig. 11, while Fig. 12 shows photographs taken at times $t_1$-$t_4$.

Here, the reasoning system worked as anticipated throughout, without any unexpected situations.

#### 2) TRIAL 2

In the second trial, no food was placed in the environment, although the drinks were stored in the refrigerator as usual. KUT-PCR's initialization and reasoning processes were as in Trial 1, and it again attempted to serve $Biscuit_1$ to the patient. However, when the robot arrived at the dining table at $t_2$, it did not perceive any objects on the table and thus

| | | | | | |
|---|---|---|---|---|---|
| **Photograph** |  | | | | |
| **Action** | Startup with a request. | Find a new pack of biscuits. | Fetch the biscuits. | Serve the biscuits. | Return to the standby position. |
| **KB** | $Bed_1$, $Table_1$, $Refrigerator_1$, $Bread_1$, $Biscuit_1$, $Milk_1$, $Cola_1$, $Juice_1$ | $Biscuit_2$ | $Biscuit_2$ | $Biscuit_2$ | |
| **Target Object** | $Biscuit_1$ | $Biscuit_1$ -> $Biscuit_2$ | $Biscuit_2$ | $Biscuit_2$ | |

Green: added objects. Red: deleted objects. Blue: refreshed objects.

**FIGURE 16.** Photographs taken at times $t_1 - t_4$ during Trial 3.

deleted the dummy objects $Biscuit_1$ and $Bread_1$ that were initially located there. This triggered the reasoning process again, and this time, the robot was instructed to serve the bottle of milk ($Milk_1$) from the refrigerator. The robot then navigated to the refrigerator, picked up $Milk_1$ at $t_3$, and was able to successfully deliver the milk to the patient at $t_4$ before returning to its standby position at $t_5$. Fig. 13 and Fig. 14 show the route and photographs taken at times t1–t5, respectively.

### 3) TRIAL 3

In the third trial, both the food and drinks were placed as in Trial 1, but a new desk $T_2$ was also placed in the bedroom, with another packet of biscuits on it. As in Trials 1 and 2, the robot initially began navigating toward the dining table. However, on the way, it perceived the biscuits on the new table at $t_2$ and updated its knowledgebase with a new biscuit instance $Biscuit_2$ located at $T_2$. This triggered the reasoning process, leading the robot to select $Biscuit_2$ as the target object to serve due to it being spatially closer. The robot then picked up $Biscuit_2$ and served it to the patient at $t_3$ before returning to its standby position at $t_4$. Fig. 15 and Fig. 16 show the route and photographs taken at times $t_1$-$t_4$, respectively.

In summary, the first trial evaluated the DDR system when nothing unexpected occurred, while the second challenged it to deal with false instance knowledge, namely that an object was not at its expected location. Finally, the third trial tested whether the system could update itself to take advantage of dynamic knowledge. The proposed method enabled KUT-PCR to successfully complete all three trials.

## VII. CONCLUSION

This paper dealt with a previously missing element in enabling personal care robots to assist patients who are bedridden with their everyday activities: (i) first, we put forward a point of view that personal care robots can assist patients similar to human caregivers, only if the robots can reason based on human's physiological desires rather than requiring direct instructions; (ii) then, in order to provide the knowledgebase required by the reasoning process, we introduced a method of describing knowledge about the properties and functions of everyday objects; (iii) finally, we presented a DDR method that can identify beneficial objects considering the knowledgebase and plan appropriate actions to fulfill the given desire.

Experiments with our newly developed KUT-PCR personal care robot in a real household domain showed that the proposed method was able to successfully complete a range of trial scenarios.

In this paper, in order to focus on the main elements of our approach, we have not discussed all possible conditions (e.g., the condition that multiple requirements are presented at once) and have made multiple assumptions (e.g., the knowledgebase for a patient is assumed unchanged). In future work, we plan to address more complex domains and consider a wider range of potential issues. We hope that with our personal care robot, bedridden people can live a more comfortable life, and the load of caregivers could be effectively reduced.

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