International Journal of Innovative
Computing, Information and Control
Volume 17, Number 1, February 2021

ICIC International ©2021 ISSN 1349-4198
pp. 335–343

HYBRID KNOWLEDGE BASE FOR CARE ROBOTS

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Received July 2020; revised November 2020

Abstract. *Care robots could be of great assistance confronting the shortage of caring force for the elderly. Still, only limited services can be provided now, as care robots do not have a thorough understanding of the environments and care recipients. We introduce a hybrid knowledge base capable of integrating both commonsense knowledge and instance knowledge. The graph-based knowledge base can be initialized and updated considering human preferences and environmental changes. By combining the knowledge base with a desire-driven reasoning system, care robots will be able to understand the environments and human desires, resulting in satisfied care services. The proposed knowledge base has been evaluated in a real household domain, in which its effectiveness in enabling desire-driven care services has been proved.*

Keywords: Care robot, Knowledge base, Commonsense knowledge, Instance knowledge

1. **Introduction.** As people live longer lives, the world is facing an increasing demand for the daily care of older adults [1,2]. However, due to the shortage of caregivers, in a lot of cases, there is no one available when the bedridden elderly has requests; as a result, the quality of life (QOL) of them cannot be guaranteed. As one of the possible solutions, care robots have been continuously investigated [3] as they do not need rest time and can be massively produced if required. In other words, if simple tasks such as serving food/drinks can be conducted while human caregivers are not around, the QOL of the care recipients can be increased effectively.

In the existing research, knowledge bases in the field of robotics are typically limited to describing the existence of objects in the environments. As Figure 1 shows, a knowledge base (KB) which can be updated by the perception of the environment is required so that approaches such as task planning [4-6] can be used. As the results of task planning approaches, a series of actions can be obtained concerning a specific task, such as "give me a cup of water from the refrigerator".

From a general perspective, all the task planning approaches require knowledge bases. A graph-structured, sum-product networks (GraphSPNs) was introduced in [7], which was designed for probabilistic semantic maps with topological spatial relations. [8] presented a fully implemented robotic system using conditional planning for generating and executing short-term interactions, in which case, the knowledge required is stored in a knowledge base consisting of an ROS MongoDB [9] and a PDDL model. Facing the key knowledge

DOI: 10.24507/ijicic.17.01.335

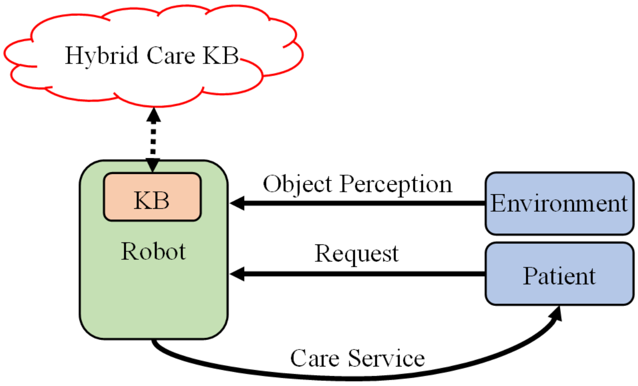

FIGURE 1. Basic idea of knowledge bases

representation and reasoning challenges, [10] presents an architecture that exploits both partially observable Markov decision processes (POMDPs) probabilistically and Answer Set Prolog (ASP) as a step toward addressing the challenges.

Additionally, extensive research has been conducted, so that the task planning system can work as the knowledge bases are incomplete or disagree with real environments [11,12]. However, as far as we are concerned, while the requests are highly abstracted (e.g., hunger, thirst, and cold) rather than specific commands, there are no knowledge descriptions that can provide effective information that allows a robot to act accordingly.

In this work, we argue that a knowledge base for care robots should not only be aware of the existence of objects in the environment but also provide information concerning: (i) how these objects fulfill abstracted human desires; and (ii) what are the properties of the objects (e.g., weight, size, and location).

The contributions of this work are as follows:

1) we extend the traditional definition of a robotic knowledge base into a hybrid type consisting of both commonsense knowledge and instance knowledge;
2) we present a graph-type structure that realizes the introduced hybrid type knowledge base;
3) finally, we integrate the proposed knowledge base into a desire-driven reasoning system and conduct experiments in a real household environment.

The organization of this paper is as follows. In Section 2, we introduce two types of knowledge including commonsense knowledge and instance knowledge. Then, we explain how the different types of knowledge can be integrated into a hybrid knowledge base capable of desire-driven reasoning in Section 3. In Section 4, we give the experimental results and the conclusion can be found in Section 5.

2. **Two Types of Knowledge.**

Human caregivers are smart as they: (i) understand how objects can be helpful considering patient desires; (ii) be aware of not only the existence of objects, but also the concerned characteristics required for necessary reasoning.

To this end, we argue that a knowledge base for care robots should be hybrid including commonsense knowledge and instance knowledge.

2.1. **Commonsense knowledge.**

Commonsense knowledge describes how objects fulfill desires. For instance, while a human caregiver provides daily care services, suitable actions (e.g., service food/drink, close/open windows, and turn off/on TV) can be conducted only based on abstracted desires (e.g., hunger, thirst, fresh air, and silence).

For care robots to conduct similar services, the knowledge is described as how objects fulfill desires as Table 1 shows. The scores range from 0.0 to 1.0, where 0.0 indicates

TABLE 1. Commonsense knowledge

	Hunger	Thirst	Fresh Air	Silence
Milk	0.3	0.6	0.0	0.0
Juice	0.0	0.8	0.0	0.0
Banana	0.9	0.0	0.0	0.0
Tea	0.0	0.7	0.0	0.0
Cola	0.0	0.7	0.0	0.0
Water	0.0	0.9	0.0	0.0
Soup	0.3	0.6	0.0	0.0
Biscuit	0.7	0.0	0.0	0.0
Bread	0.9	0.0	0.0	0.0
Noodle	0.8	0.0	0.0	0.0
Hotdog	0.8	0.0	0.0	0.0
Yogurt	0.3	0.1	0.0	0.0
Window	0.0	0.0	0.8	0.0
Door	0.0	0.0	0.0	0.9
TV	0.0	0.0	0.0	0.9

the object has no relations with the desire and 1.0 suggests that the desire can be fully fulfilled by the object.

There are some characteristics of the knowledge base: (i) the scores could be zeros as the objects cannot contribute to fulfilling the desires; (ii) the relationship is multiple to multiple; (iii) the knowledge base can be initialized and updated considering various factors including the preference of the patients.

Accordingly, a few considerations should be noticed while using a commonsense knowledge base including: (i) zeros should be set carefully as zeros refer to absolutely no relations, weak relations should be set to small values rather than zeros; (ii) relative relations are more important than absolute relations; (iii) a good initialization is essential for providing qualified services.

Additionally, as Figure 2 shows, the commonsense knowledge base can be initialized considering multiple resources, including the general understanding of how objects fulfilling desires, questionnaires to the patient or interviews of the families/friends. In short, a

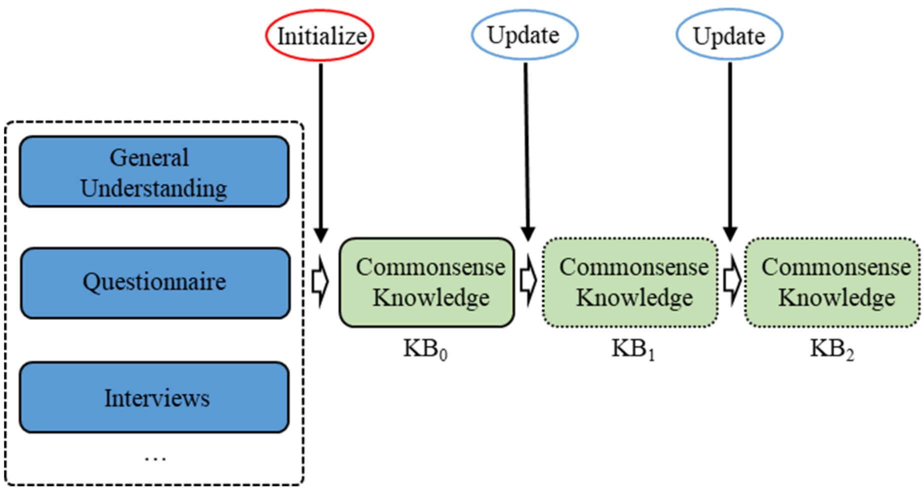

FIGURE 2. Initialization and update of a commonsense knowledge base

suitable initialization (close to the real preference of the care recipients) of the commonsense knowledge base will result in more reasonable services.

However, in most cases, the initialization is inaccurate facing the fact of inaccurate answers or limited pre-knowledge. Therefore, although the commonsense knowledge is typically considered unchanged during the reasoning process, in a more general viewpoint, it is changeable. Either manual input or automatic update system can be integrated into the original commonsense knowledge base. As a result, the commonsense knowledge will get closer to the ground truth.

2.2. **Instance knowledge.** Instance knowledge describes instances of objects concerning various types of characteristics including the name, spatial properties, physical properties, and electrical properties. In practice, multiple objects of the same type are common (for example, multiple bottles of cola can be kept in the refrigerator). The instance knowledge of a type of objects is demonstrated as follows:

1) Name

Name defines the type of a kind of objects, such as “milk”, “window”, and “air conditioner”. With the name being defined, a class of objects along with the associated properties and features can be identified.

2) Physical properties

Physical properties including position, size, and weight provide information about how the objects will interact with the physical world. Such information provides useful references for robotic applications (e.g., object manipulation).

3) Electrical properties

Electrical properties are necessary for objects such as refrigerators, TVs, and air conditioners. Nowadays, various types of approaches are available for robots to control electric devices in household domains [13,14]. Being aware of the statues of the controllable devices allows further operations.

In practice, the instance knowledge base will be valuable only if it can be updated considering the environments through robotic perception technologies. Figure 3 shows how an instance knowledge base can be updated by conducting areplacing operation between the original base K to the newly perceived objects K_p.

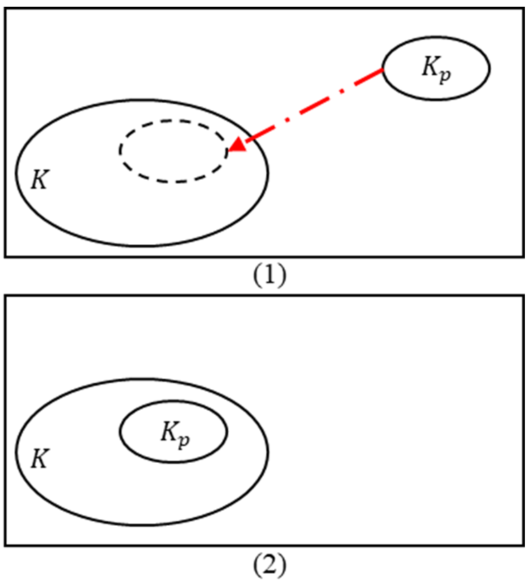

FIGURE 3. Method of integrating perceived objects

The operation is location based. Firstly, with a solid perception considering a series of objects K_p, a subbase from the original instance knowledge base will be extracted, which contains all the objects within the perceived locations (dotted circle). Then the perceived knowledge base will be integrated into K by replacing original objects within the dotted circle. By repeating this process once new objects are spotted, the instance knowledge base can be updated with respect to real domain environments.

3. **Hybrid Knowledge Base.** We have explained how the commonsense and instance knowledge can be used together for providing intelligent and satisfying robotic care services. In this section, we introduce a graph-type hybrid knowledge base that can manage both two types of knowledge effectively in a unified framework.

Figure 4 demonstrates the basic structure of a graph used as basic elements for the hybrid knowledge base. In our applications, the nodes are used to describe objects and desires, while the relations can be used to indicate knowledge such as "objects fulfill desires", or "locations have objects". Both nodes and relations are attributed so that various types of properties can be encoded as expected in a graph G:

$$G = (V, E) \tag{1}$$

where V represents all the nodes and E integrates the relations among the nodes, respectively.

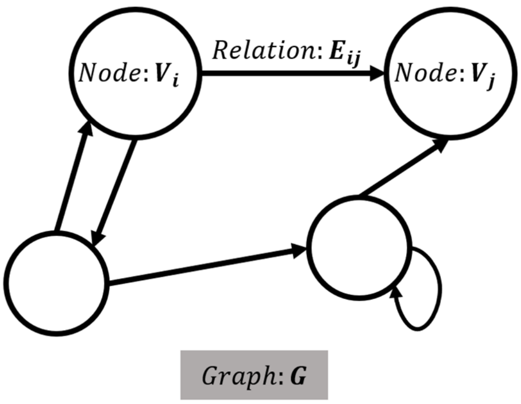

FIGURE 4. Structure of the knowledge base

More specifically, in this research, we adopt a template graph to define the basic types of knowledge required in caring scenarios, and an instantiated graph that consists of the actual desires and objects. In practice, the workflow of integrating knowledge into the knowledge base is demonstrated in Figure 5.

Two update resources are considered: (i) camera perception for the instance knowledge; and (ii) manually input for the commonsense knowledge. All the perceived instances or commonsense knowledge are integrated into real knowledge graphs with a template graph defining all the types of knowledge that can be stored and manipulated in the knowledge base. For instance, a template graph would consist of information such as "Drinks fulfill Desires", while an instantiated graph manages the actual drinks and desires, such as "Milk fulfills Thirst by 0.6" and "Juice fulfills Hunger by 0.0".

More detailly, Figure 6 is a sample template graph for explanation. In the graph, the nodes of types "Desire", "Food & Drink", "Appliance", and "Location" define the required objects and desires in a household domain. Relations such as "Has" and "Fulfill" define the commonsense knowledge (objects fulfilling desires) and instance knowledge (properties of objects).

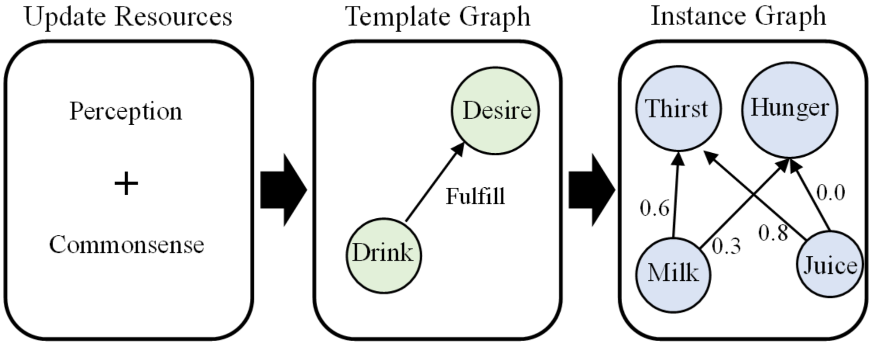

FIGURE 5. Workflow of integrating knowledge into the knowledge base

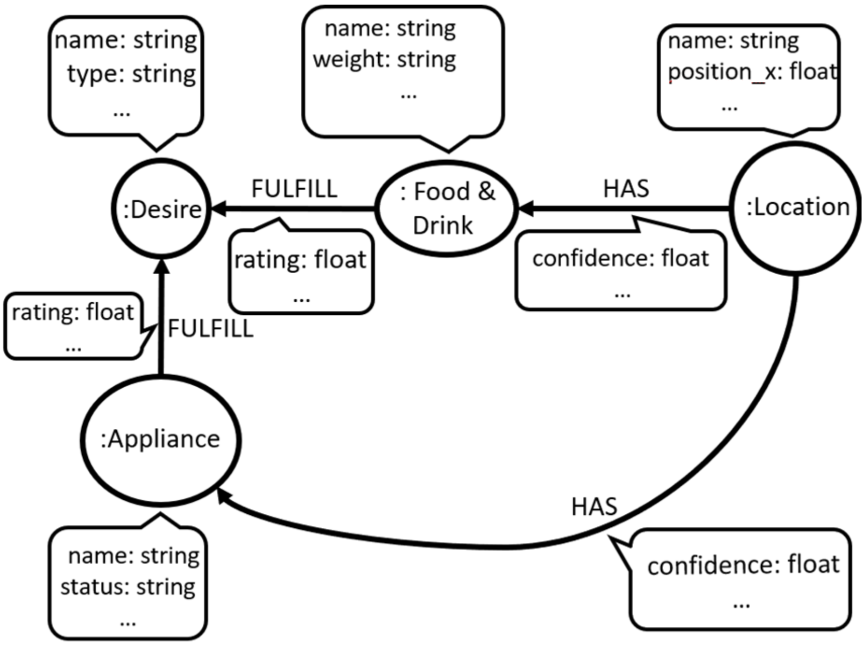

FIGURE 6. Template graph

All the nodes and relations are attributed so that the information we introduced in Section 2 can be formatted effectively into the knowledge base. For instance: "rating" indicates the commonsense knowledge of object fulfilling desires; "confidence" describes the probability of an object in space (which is set to be 1 by default).

4. **Experiments.** We have conducted experiments in a real household domain to evaluate the hybrid knowledge base presented. The effectiveness of the approach can be confirmed by integrating the presented knowledge base into a desire-driven reasoning system.

4.1. **Experimental scenario.** Figure 7 presents the personal care robot KUT-PCR and the experimental domain which is designed for the convenience of bedridden people.

KUT-PCR is a mobile humanoid robot comprising an omnidirectional mobile base and two manipulators. Various types of sensors including two RGB-D cameras, four ultrasonic sensors, two laser-range finders are integrated. Therefore, with its motion and perception capability, daily services concerning object manipulation and indoor navigation can be conducted as required [15].

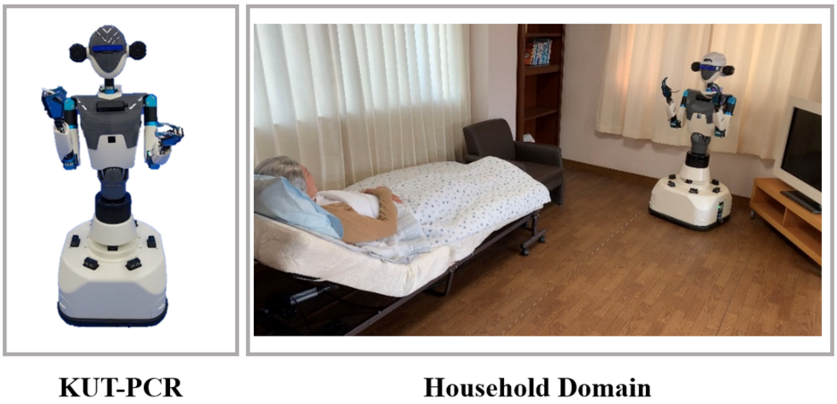

FIGURE 7. Experimental domain

During the experimental trials, a patient lay on the bed in the bedroom, where KUT-PCR stood by for possible requests. The kitchen was next to the bedroom where food and drinks were stored. The commonsense knowledge was initialized manually considering general understanding, and the instance knowledge was updated by the camera configured on the head of the robot through object recognition approaches.

4.2. **Experimental trials.** Extensive care trials were conducted for the desire-driven personal care considering the proposed hybrid knowledge base. One of the trials is shown in Figure 9.

As shown in Figure 8, the knowledge base was initially initialized with: "bread_1, bread_2, milk_1, juice_1" considering both commonsense and personal preferences. During the trial, the patient expressed his feeling of "hunger", then by the desire-driven reasoning system, "bread_1" in the kitchen table was selected as the target as it contributed to fulfilling hunger with 0.8, and was closer than "bread_2" which was in the refrigerator. The robot navigated to the kitchen table, finding that there was also a bag of biscuits on the table. Then the instance knowledge base was updated by adding "biscuit_1". As long

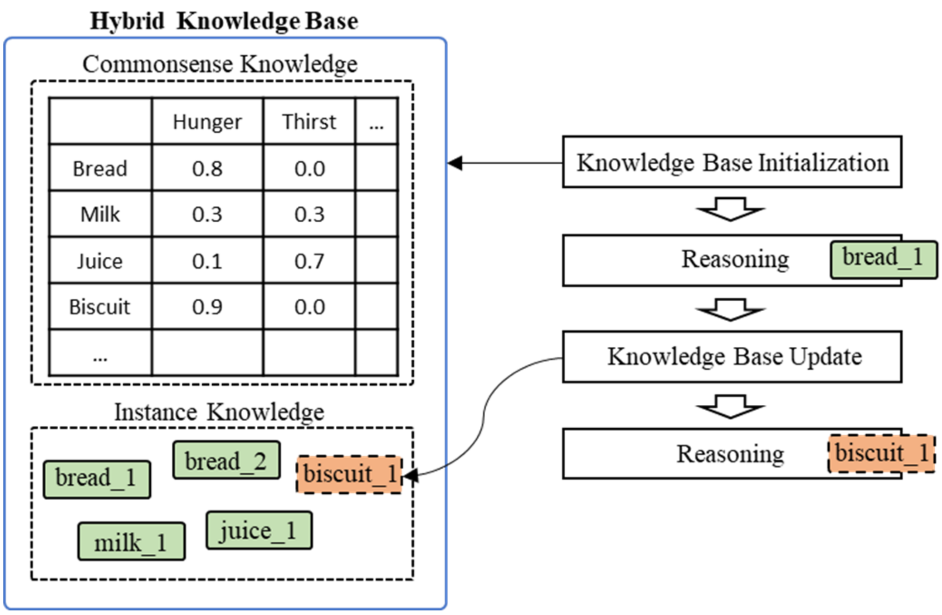

FIGURE 8. Reasoning considering the desire "hungry"

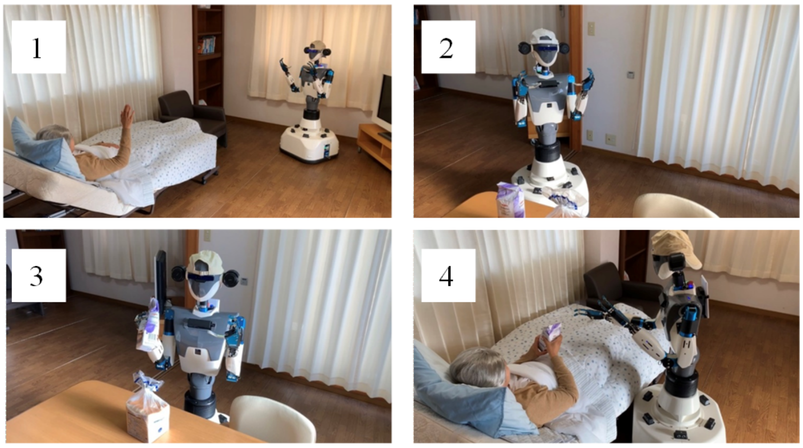

FIGURE 9. Experimental trial

as the knowledge base changes, reasoning should be conducted again for possible different results. As a result, "biscuit_1" was selected, as it was scored 0.9 for hunger considering the habit of the patient. Eventually, KUT-PCR served the biscuit to the patient. Figure 9 illustrates the photos during the trial.

4.3. **Discussion.** By real daily care trials in a real household environment, the hybrid knowledge base has been proved to be effective in providing useful information that allows the care robots to conduct care services similar to human caregivers (which are smart and do not necessarily require a detailed command).

By using such kind of hybrid-type knowledge bases, applications concerning high-level reasoning are possible.

5. **Conclusions.** This paper has presented a hybrid knowledge base that allows the management of both commonsense knowledge and instance knowledge. Desire-driven reasoning can be conducted considering the proposed knowledge base. To this extent, we presented a graph-type structure, so that different types of knowledge can be integrated into a unified framework. By utilizing the presented approach, satisfying daily care services can be provided by robots considering only the abstracted desires of the care recipients.

In future work: (i) we will conduct further experiments to evaluate how the hybrid knowledge base performs concerning domains that are more dynamic and complex; (ii) quantitative evaluation and analysis of the hybrid knowledge base will be conducted.

Acknowledgment. This work is supported by JSPS KAKENHI Grant No. 15H03951, the Canon Foundation, and the Casio Science Promotion Foundation.

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