Künstl Intell (2016) 30:257–265
DOI 10.1007/s13218-016-0436-x

REVIEW

# Integrating Qualitative Reasoning and Human-Robot Interaction in Domestic Service Robotics

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Received: 30 April 2016 / Accepted: 9 July 2016 / Published online: 22 July 2016


**Abstract** In this paper we discuss a system layout for cognitive service robots and our implementation of such a system. Our focus is on integrating qualitative reasoning and human-robot interaction. After introducing the domestic service robotics domain with its challenges and the RoboCup@Home initiative we present our robot platform, its basic capabilities and its high-level reasoning system. Then, we discuss a system layout for a cognitive service robot in domestic domains, and we show how components of our service robot implement elements of such a system layout. We discuss strengths and limitations of these components and of the overall system.

**Keywords** Qualitative reasoning · Human-robot interaction · Domestic service robotics · RoboCup@Home · Situation calculus

## 1 Introduction

Research areas in robotics are as diverse as the possible applications of robots. We are concerned with what is often called *cognitive robotics*. Cognitive robotics as introduced by the late Ray Reiter is to be understood as "the study of the knowledge representation and reasoning problems faced by an autonomous robot (or agent) in a dynamic and incompletely known world" [18]. Our application domain is domestic service robotics. It deals with socially assistive robots that perform helpful tasks for humans in and around the house. These robots must be able to engage in communication with the humans around them. What is more, when a robot needs to assist humans with complex and cognitively challenging tasks, it must be endowed with some form of reasoning that allows to take decisions on the course of action in complex scenarios. In addition, autonomous operation for extended periods of time is only possible if the robot can handle certain variations and unavoidable errors by itself. Also, it should be flexible in dealing with human fallibility. We refer to such a robot as a cognitive service robot system.

In this paper, we discuss the overall system layout of such a cognitive service robot for domestic domains that integrates qualitative reasoning and human-robot interaction. The remainder is structured as follows. We start with introducing the domestic service robotics domain with its challenges and the RoboCup@Home initiative. After that, we present our domestic service robot Caesar, its basic capabilities and its high-level reasoning. Then we discuss a system layout for a cognitive service robot in domestic domains and we show how components of our domestic service robot realize elements of such a system layout. The paper is based on the contributions of my doctoral dissertation thesis [24]. Parts of this work have earlier been presented in [28] already. A discussion of lessons learnt from developing the platform can be found in [13].

## 2 The Domestic Service Robot Caesar

We start with introducing the domestic service robotics (DSR) domain. Then, we present the RoboCup@Home initiative as a testbed and as a benchmark for service robotics in domestic environments. After briefly reviewing related approaches on developing personal service robots

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we present our domestic service robot Caesar, its basic capabilities and its high-level reasoning system.

### 2.1 Challenges for Domestic Service Robots

A service robot in a human environment needs to have a set of basic capabilities. That is, it needs to be able to localize itself and it needs to navigate around humans in a safe way. Further, it should be able to detect and recognize objects and it should be able to manipulate things in its environment. When working around and together with humans such a robot should also be able to detect, recognize and track people. It must be able to communicate with the humans around it and it needs to interpret the commands these humans use to instruct the robot. What is more, the robot also needs a powerful and flexible high-level control that can come up with a course of action for complex tasks that require an intelligent combination of its basic capabilities. This is even more important when the robot should assist an elderly or disabled person with a cognitively challenging task.

### 2.2 The RoboCup@Home Initiative

In order to bring forward the development of domestic robots that can meet the challenges described above, there exist a number of efforts. One among them is the RoboCup@Home initiative [35, 36], which particularly focuses on domestic service robot applications. RoboCup@Home was established as a distinguished league inside the RoboCup initiative [17] in 2006. The motivation was to provide a testbed and a benchmark for domestic service robotic systems that brings such robots out of their confined lab conditions into the real world. RoboCup@Home is designed to be both, a scientific competition and a benchmark for domestic service robots [37]. It is an effort to test individual components of DSR systems as well as the integration of the system as a whole.

The general idea in the RoboCup@Home competition is to set up a home-like scenario that is as realistic as possible and to let robots perform a set of tests in that environment. Tasks are, for example, acting as a party host, welcoming and seating people or helping with fetching items in the house. An example of the arena is shown in Fig. 1b.

### 2.3 Developing Personal Service Robotics

There is a huge body of related work on developing personal service robots, not only in the context of RoboCup@Home. Our focus is on qualitative reasoning and human-robot interaction which is why we only briefly discuss a few related approaches. For a more detailed review we refer the interested reader, for example, to [24].

**(a)** Caesar **(b)** RoboCup@Home arena from 2008

**Fig. 1** The domestic service robot Caesar and an example of a RoboCup@Home competition arena

There are various ways to implement the high-level behavior of an autonomous mobile service robots. While for a lot of specific sub-tasks, statistical methods are used, for the high-level control sometimes plan-based approaches come into play. For example, well-founded formal basics allow for an open-ended application of personal robots in human environments such as for every-day manipulation tasks [2]. The authors in [1] report on how they include the presence of humans in their robot control and the robot's decisional abilities. The approach reported on in [6] uses classical AI planning techniques to determine a course of action to execute commands of a human user with taking into account the current situation. The domestic service robot presented in [7] features reasoning capabilities using an ontology and HTN planning. In [8], the authors report on developing a service robot that uses a broad spectrum of AI techniques. For instance, to integrate natural language processing with action planning, they use answer set programming and to improve on their robot's abilities they use commonsense reasoning and non-monotonic reasoning.

The approaches above present only a selection of feasible solutions to particular challenges and some have favorable properties in their integration efforts. In this paper, we focus on the layout and the components of a cognitive service robot system that uses a logic-based approach in its high-level control. Building on existing work [12] we discuss an approach to integrate qualitative reasoning and human-robot interaction by allowing for using human-oriented representations and control. Along with semantic information that can be attached to lower level data this makes for a valuable step towards a capable service robotic system. Also, we consider increasing robustness by some form of self-maintenance and maintaining flexibility in interpreting possibly faulty commands given to the robot by human users.

### 2.4 The Domestic Service Robot Caesar

Starting in 2006, we continuously developed CAESAR, a mobile service robot that we use in domestic settings and in the ROBOCUP@HOME competitions. It is based on a platform initially designed and used for the ALLEMANIACs ROBOCUP MSL team. It received several improvements dedicated to the specific requirements of domestic service robotics since then. The robot platform from 2012 can be seen in Fig. 1a.

Two wheelchair motors forming a differential drive allow the robot to drive up to 3 m/s. A 360° laser range finder is used for localization and collision avoidance. Two additional laser range finder increase the perception for range operations. An RGB-D camera on a pan-tilt unit provides visual input, two microphones on the same unit complement the perception with an aural cue. The robot is further equipped with an anthropomorphic arm with five degrees of freedom for manipulation.

We started off with a software framework called RCSOFT that was already used in the ROBOCUP MIDDLE soccer competitions. It features a blackboard architecture where any component can post data to a blackboard that then other components can read from. Since 2009 we started slowly migrating our software components to the Fawkes[1] robot framework [20]. Also, we started to port the mid-level behaviors that were previously implemented as state machines to a Lua-based behavior engine [21]. A discussion of lessons learnt from developing CAESAR can be found in [13].

### 2.5 Basic Capabilities

The robot CAESAR is equipped with a set of basic capabilities that are fundamental for every mobile robot. A method for local navigation and collision avoidance [16] enables the robot to safely move around in human populated environments. Localization is provided by a method initially developed for the soccer domain [34]. It works very well in domestic settings as well since its application in office like scenarios was already planned for in the first place. The maps used for localization are created with a mapping scheme that allows for including semantical annotations [27]. It provides the robot with metric maps for localization just as well as with additional semantic information that can be used on higher levels in the robot software architecture. As an example, the path planning works with an A* search on a topological graph that is generated by the semantic mapping tool. CAESAR also has different modules for perception and manipulation in place. A component among these modules that bridges between the low-level sensory information and the qualitative reasoning on higher levels is the object detection and recognition system [22]. Objects known to the robot are stored and labeled with descriptive attributes. This allows for creating and recognizing object classes on the fly by combining several of these attributes at run-time. A more detailed account can be found in [24].

### 2.6 High-Level Control

The high-level control of our robot is based on READYLOG, a dialect of the Golog family. It is based on Reiter's version of the situation calculus [19, 23], which is a sorted first-order logical language[2] with equality that allows for reasoning about actions and their effects. Properties of the world are described by so-called functional and relational fluents whose value depends on the situation. The world then evolves along actions. Starting in a situation $s$, performing the actions *grab* and *pickup* results in a situation $s' = do(pickup, do(grab, s))$. There is a dedicated initial situation $S_0$ where no action has occurred yet. Golog is an agent language based on the situation calculus. It combines Algol-like programming constructs with non-deterministic constructs. To be able to reason about a actions and change in a particular world, one has to provide a so-called Basic Action Theory (BAT) [23]. It specifies what is true in the initial situation as well as action preconditions and action effects.

Our variant of Golog is called READYLOG [12] and it integrates various (existing) extensions to cope with the real world. It features a transition semantics where a logical predicate $trans(\sigma, s, \sigma', s')$ is used to indicate that executing one step of program $\sigma$ in situation $s$ yields the remaining program $\sigma'$ and results in situation $s'$. A feature of particular importance is decision-theoretic planning using Markov Decision Processes in the spirit of [4].

As an example, consider a coffee delivery domain where the robot's task is to serve people with coffee.

```
proc DeliverCoffee
    while ∃x.WantsCoffee(x) do
        pickBest x.WantsCoffee(x);
            if ¬HasCoffee(x) then
                goto(CoffeeM); loadCoffee
            endif
            goto(x); giveCoffee(x)
    endwhile
endproc
```

The above (simplified) READYLOG program uses its decision-theoretic planning to select an element $x$ from the set of persons that want coffee, using the underlying optimization theory. That person is then served with coffee.

[1] http://www.fawkesrobotics.org.

[2] With a second-order axiom.

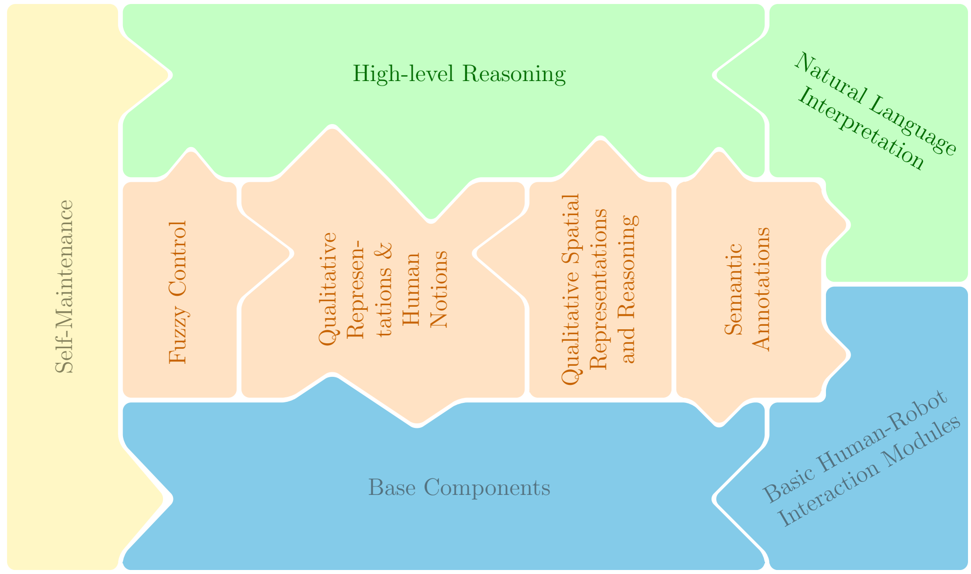


**Fig. 2** A cognitive service robot system layout

This cycle is repeated for as long as there is someone that wants coffee.

### 2.7 Caesar in Action

To illustrate the potential of integrating modules for human-robot interaction with the qualitative reasoning we showcase an application in a domestic setting [25]. Consider the robot's task is to help set the table. In particular, the robot should rearrange a set of three differently colored cups. Just to exemplify how the high-level reasoning capabilities of the robot can pay off, the robot should compute a reordering with a minimum number of moves. To arrive at a natural interaction we use some basic human-robot interaction (HRI) components (cf. Sect. 3.1) to inquire with the human user on how the rearrangement should look like. More precisely, the human user can use speech input and pointing gestures (which again involve face detection) to point to positions on a table and to specify where certain items should be put. To arrive at a sequence of actions with a minimum number of moves for the robot to execute, it uses decision-theoretic planning like it is available in Readylog. Although the application seems rather simplistic at first, it indicates that the capability of high-level reasoning can be seamlessly integrated in a natural interaction and that the robot can assist the human user with cognitively challenging tasks.

## 3 A Cognitive Service Robot System Layout

We now discuss a cognitive system layout for applications in domestic service robotics. After giving an overview of the layout we go through the components and present their particular features and their contribution to the overall system.

### 3.1 System Layout Overview

Figure 2 shows an overview of the elements that we think are necessary and useful for a cognitive robotic system. The particular focus is on integrating qualitative reasoning and human-robot interaction for applications in domestic domains.

The blue elements are components that provide basic capabilities like collision avoidance and localization. The green boxes represent high-level components, that is, components featuring a sophisticated reasoning mechanism. The orange components bridge between the high-level and the human or extend the high-level with mechanisms to facilitate intuitive interaction. The yellow box finally, is an optional but desirable component to enable enduring autonomy. It is an extension of the high-level control that has tight connections to the basic components We detail the particular components in the following.

### 3.2 Basic Human-Robot Interaction Modules

Our domestic service robot is supposed to interact with laymen. Hence, it needs to be operable by such laymen and the interaction between the human and the robot needs to be as *natural* and intuitive as possible. This is why we argue for extending the basic capabilities with modules for three important human-robot interaction components, namely speech, face, and gesture recognition. We consider these components since they represent (perhaps the most) important modalities in human-robot interaction.

#### 3.2.1 Speech Recognition

Face to face communication between humans is mostly done using speech. Hence, *speech recognition* is a crucial ability for a mobile service robot that should communicate with humans. However, spoken language is a natural and convenient way to instruct a robot only if it is processed reliably. Modern speech recognition systems can achieve high recognition rates, but their accuracy often decreases dramatically in noisy and crowded environments. This is usually dealt with by either requiring an almost noise-free environment or by placing the microphone very close to the speaker's mouth. Although we usually already assume the latter, all requirements for a sufficiently high accuracy cannot always be met in realistic scenarios. Therefore, we developed and implemented a system that tackles the problem of robust speech recognition in noisy environments [10].

#### 3.2.2 Face Detection, Recognition, and Learning

Service robots aim at offering assistance to humans in general and to people with disabilities in particular. Such robots socially interact with human beings, i.e., they respond dynamically to requests and communicate. The interaction can be more natural if the robot can identify persons it encounters. We expect that on encountering unknown identities, the robot may introduce itself and add the new identity to its knowledge base. Therefore, a fast and reliable face recognition system is required, which, in a first step, detects faces and, in a second step, recognizes the persons. This task is complicated by the computational limitations of common mobile robots. We presented a one-step real-time method for face detection, recognition, and learning delivering on the above requirement in [3].

#### 3.2.3 Gesture Recognition

We already considered speech as a means for intuitive control and interaction with a domestic service robot. However, a huge part of meaning in communication is also transferred via non-verbal signals [11]. A very important mode of this non-verbal communication is using gestures. This is especially true in interaction with a domestic service robot, since controlling the robot often relates to entities in the world such as objects and places or directions. References to objects can conveniently be made by pointing gestures while other dynamic gestures can be used to indicate directions or commands. We designed and implemented a modular multi-step architecture [26] that avoids undesirable properties of existing approaches such as calibration requirements or high computational demands.

#### 3.2.4 Other HRI Components

Human-robot interaction can be made even more natural and affective. To be able to communicate with its human users we have some additional components in place. A convenient mode for the robot to deliver information to the user, especially when speech input has been used, is to generate spoken output. We do this using the freely available *Festival*[3] speech synthesis system. For displaying additional information and to support instructions or hints given to the user we have a display installed on the robot that can show pictures and other information. Since it is a touch display it can also be used to command the robot, e.g. if other inputs have failed. The monitor further shows a virtual face to increase the affectiveness of the robot. To be able to properly react to the presence of humans the robot uses its visual and aural sensors to detect and track persons over time.

### 3.3 High-Level Reasoning

A domestic service robot that needs to assist humans with complex and cognitively challenging tasks, must be endowed with some form of reasoning that allows it to take decisions in such complex scenarios. This high-level reasoning abstracts from the details of lower levels and provides mechanisms to come up with a dedicated course of action for a robot to reach a particular goal. Our robot features a logic-based high-level reasoning component as already described in Sect. 2.6. It allows for flexibly combining programming and planning in the behavior specification of the robot. Both ends of the spectrum, pure programmed behavior or using full planning to determine the course of action, are fully included.

### 3.4 Qualitative Representations

Humans use different means to represent their surroundings when talking to each other than a robot would do. In a technical system, in general, and in a robot, in particular, numbers are used to represent things like speed, distance, and orientation. In contrast, humans use imprecise linguistic notions. A robotic system that assists humans in their daily life, must be equipped with means to understand and to communicate with humans in terms and with notions that are natural to humans. To this end, we extended our high-level control to use qualitative representations using a semantics based on Fuzzy sets [14]. These so-called fuzzy fluents have a membership function attached to them. The membership function indicates to what degree a numerical value of a fluent belongs to a qualitative category. The

[3] http://www.cstr.ed.ac.uk/projects/festival/.

categories are given by *linguistic terms* such as near or fast. Whether or not a fuzzy fluent is member of one or more such categories (or a category's complement) can be queried by special predicates. Such qualitative representations using human notions can be formulated for many different entities that for a robot normally have numerical values.

### 3.5 Qualitative Control

Sometimes, in the behavior specification of a mobile service robot rather reactive control is just enough. For such cases, we implemented and integrated the concept of a fuzzy controller into READYLOG as well [15]. T his allows to specify a set of simple if-then-else rules using the qualitative notions introduced before to assign values to certain control variables.

### 3.6 Qualitative Spatial Representations and Reasoning

Many of the qualitative notions used in domestic service robotics settings are spatial. Whenever either the robot or the human refer to real objects or places they need to express positional information. To account for this and to further bridge the gap between the robot and its human user we developed a particular extension of our qualitative reasoning for positional information [29]. As a special form of fuzzy fluents we introduce *positional fluents*. Building on the similarity to polar coordinates, a position can be referred to by a distance and an orientation component. These two components can be individually abstracted to qualitative categories following [9]. By additionally associating a frame of reference to each such positional fluent, we are able to account for contextual information like different scales, an intrinsic front direction and reference objects.

### 3.7 Semantic Annotations

Another building block to mediate between the raw sensor data and the numerical information that the base components of a cognitive robot work with are semantic annotations. In our cognitive robot system, for instance, we allow for generating semantically annotated maps [27]. This attaches semantic information to places like functions of a room or where it is likely to find people in an apartment. Another example is part of our object recognition [22], where objects are described by a set of (semantic) attributes. This way, we can dynamically build classes of objects, for example, all objects with a specific color.

### 3.8 Natural Language Interpretation

Humans tend to be imprecise and imperfect in their natural spoken language. Therefore, when natural language is used to give instructions to a robot, the robot is potentially confronted with incomplete, ambiguous, or even incorrect commands. Aiming for a robust and flexible system we developed a method for natural language interpretation that can account for handling such fallibility to a certain degree [30, 31].

### 3.9 Self-Maintenance

A robotic system that is capable of planning and executing complex tasks is a complex system itself. That is why such a system is itself vulnerable to errors. These errors are not restricted to action execution but span to internal system errors as well. As an additional component in the system layout we proposed a constraint-based system for self-maintenance [32, 33] that is able to detect and circumvent certain errors. Thus we increase the system's robustness and enable longer-term autonomous operation.

## 4 Discussion

A system implemented along the layout sketched above makes for an accessible assistive robot. In this section we review details and discuss the strengths and limitations of individual components of our cognitive service robot as well as of the overall system layout.

### 4.1 Basic Human-Robot Interaction

The necessity for providing a cognitive service robot with means to support common modes of human communication is rather clear. Consequently, most domestic service robots feature modules for human-robot interaction. What sets apart our approaches to such basic HRI components will be discussed in the following.

#### *4.1.1 Speech Recognition*

Our basic speech recognition component comprises two steps. First, we use a threshold based close speech detection module to segment utterances targeted at the robot from the continuous audio stream recorded by the microphone. Then, we decode these utterances with two different decoders in parallel, namely one very restrictive decoder based on finite state grammars and a second more lenient decoder using *N*-grams. We do this to filter out false positive recognitions by comparing the output of the two decoders and rejecting the input if it was not recognized by both decoders. This allows us to combine the reliability of a grammar based approach with the flexibility of *N*-gram approaches. We can avoid to have the robot react on single keywords that would be falsely mapped to a full command by grammar-only approaches. For details on our dual-decoder based speech recognition we refer to [10].

#### 4.1.2 Face Detection, Recognition, and Learning

We approach a one-step system that addresses both face detection and recognition in an integrated framework using *random forests* (RF) with haar-like features. The advantages of RFs have been thoroughly investigated [5] and it has been shown that RFs are fast and have good generalization capabilities. Additionally, we introduce *identity learning*, as an extension to this framework. A collection of face images for a new identity captured by the robot can be added to the knowledge base in real-time, i.e., the robot learns to recognize new persons from that instant. This is made feasible as a result of a very short training time. The unified framework allows for training complete trees for realistic application scenarios with about ten identities in below a millisecond. For a more detailed account of our one-step real-time method for face detection, recognition, and learning we refer to [3].

#### 4.1.3 Gesture Recognition

We subdivide the process of gesture recognition into four main steps: *hand detection*, *posture recognition*, *hand tracking*, and finally *gesture recognition*. Hand detection is the task of finding the position of one or more hands in an image, where we follow a color-based approach. Instead of using a pre-trained skin-color, we extract its value from face detection, which also yields robust operation for different lighting conditions. To increase robustness against false detections, we additionally apply a *hand verification* step. Posture recognition then is to determine the shape of the hand, that is to say the configuration of the fingers (e.g., a *fist* or an *open hand*) and the orientation of this *posture*. Both, hand verification and posture recognition are performed using random forests with haar-like features for classification. Hand tracking refers to recording the position of the hand (and its posture) over a sequence of images. Finally, gesture recognition is understood as identifying a specific dynamic movement of the hand from the trajectory formed over time. The modular architecture allows to replace single items with versions with a better performance at any time. Also, the intermediate steps yield useful information that can be used for interaction already. The details of our gesture recognition are presented in [26].

### 4.2 Qualitative Representations and Control

While other domestic personal service robots provide options for qualitative representations as well, we see two major benefits with our method. First, our formalism is flexible enough to allow for applying it to a very large range of entities. Whether it is about emotional states like happy and sad or spatial information like distance or orientation, the framework fits equally well. Second, the tight integration with our high-level reasoning allows not only for easily using human-like statements in the behavior specification. It also facilitates the seamless interaction between the robot and the human in a straightforward fashion. The qualitative representations can be used for a reactive form of control in the robot's high-level system also. Implementing the concept of a Fuzzy controller, the representations can be used to formulate a set of simple if-then-else rules to quickly and easily specify reactive behavior. This simplifies the design of agent controllers for straightforward tasks like to follow a person.

Since spatial references are frequently used in domestic applications, our extension for representing and reasoning with qualitative positional information pays off well. Again, naturalness can be increased and the available reasoning capabilities of the robot can be made available seamlessly. By keeping the connection between the numerical and the qualitative values of fluent we are able to integrate qualitative fluents in our formal framework in such a way, that we can transfer between the qualitative and the quantitative counterparts automatically whenever this is necessary.

### 4.3 Semantic Annotations

To bridge between the raw data provided by the low-level components on the one hand and the semantic concepts and terms used by humans and in the high-level control on the other hand we need to establish connections between the two. We presented two examples for how we do that, namely the generation of semantically enriched maps and the labeling of objects with descriptive attributes. In both cases, the link between the raw data and the semantic annotations is maintained. This allows to descriptively reference items throughout the system. What has not been addressed in our system yet though is a proper object identity management in the sense that objects with the same semantic properties can not necessarily be distinguished from one another.

### 4.4 Natural Language Interpretation

The general idea of our language interpretation is to try to map human instruction to an available robot capability.

The process uses a syntactical decomposition of the utterance first to distill what we refer to as the essence of the utterance. Then, we cast the interpretation as a decision-theoretic planning problem. In the planning, we try to find best fits for mapping the verb in a command to an action of the robot and for mapping the objects in the command to parameters of the action.

Consider the situation where the robot is trying to interpret the utterance "*Robot, go to the kitchen*". The system tries to assign a robot action to the verb extracted from the utterance first. This includes all actions on the robot that have *go* listed as a synonym. Then, for every possible action, it tries to assign the objects that are contained in the utterance to the parameters of the selected action. In our example, there's one object, namely the target location *the kitchen*. Again, all objects with corresponding synonyms are considered. A successful state is reached if all elements could be assigned appropriately. In case of missing assignments or ambiguities the system issues steps for clarification by asking the user. The fact that we can account for human fallibility or inaccuracies in the speech recognition increases the naturalness of our system and enables longer term autonomy. A more detailed account of the natural language interpretation is given in [31].

### 4.5 Self-Maintenance

Personal service robots can only be deployed if they can operate autonomously for extended periods of time. To this end, we integrated a simple form of self-maintenance in our system. The proposed method implements a transformation of the robot's high-level programs by plugging into the transition semantics. It uses two separate models, one for the *task domain*, that is the actions the robot can perform in the world, and another for the *maintenance domain*, which contains the actions the robot can perform on itself such as (re-)starting and stopping modules. The two models are connected by temporal constraints, for example, that *before* the robot is able to move around, the laser range finder used for collision avoidance needs to be calibrated and the camera subsystem needs to be scanning for obstacles as well. Even though, in its current form, the proposed method can only prevent or deal with a limited set of potential errors, it is a valuable addition to the autonomy of our service robot. A more concise description can be found in [32].

### 4.6 Overall System Layout

As already mentioned, we think that high-level reasoning is a necessary capability for any cognitive service robot. This is even more true in domestic domains, where the robot needs to assist humans with complex and cognitively challenging tasks. However, the high-level reasoning can only fully play its role when it is integrated with the components for human-robot interaction. That is because the task of the robot is commonly determined by the human user. To fulfill the user's request, the robot therefore has to be able to interpret human notions and it has to incorporate semantic information about the environment as well. Also, the representational gap has to be closed by allowing for human-like notions to be used throughout the system.

## 5 Conclusion

In this paper, we reviewed the layout of a cognitive service robotic system that integrates qualitative reasoning and human-robot interaction for applications in domestic service robotics. The system layout features components that allow for implementing a capable service robotic system. The layout itself and our realization of the individual components address bridging the gap between the robot and the human with several measures. This is because we make available the qualitative notions that humans commonly use in the robot system, in general, and in the high-level reasoning, in particular. This allows for natural interaction and with its advanced reasoning the robot can assist its human users with complex and cognitively challenging tasks. This is especially useful with disabled or elderly people.

**Acknowledgments** Large parts of this paper are based on my doctoral dissertation. I would like to acknowledge the support that I have received from Gerhard Lakemeyer during my dissertation. Also, I appreciate the contributions made by Alexander Ferrein and Tim Niemueller. I further want to thank the anonymous reviewers for their valuable and helpful comments.

## References

1. Alami R, Clodic A, Montreuil V, Sisbot EA, Chatila R (2005) Task planning for human-robot interaction. In: Proc. Joint Conf. on Smart objects and ambient intelligence (sOc-EUSAI'05), pp 81–85. ACM
2. Beetz M, Jain D, Mösenlechner L, Tenorth M (2010) Towards performing everyday manipulation activities. Robot Auton Syst 58(9):1085–1095
3. Belle V, Deselaers T, Schiffer S (2008) Randomized trees for real-time one-step face detection and recognition. In: Proc. Int'l Conf. on Pattern Recognition (ICPR'08), pp 1–4. IEEE Computer Society
4. Boutilier C, Reiter R, Soutchanski M, Thrun S (2000) Decision-theoretic, high-level agent programming in the situation calculus. In: Proc. Nat'l Conf. on Artificial Intelligence (AAAI-00) and Conf. on Innovative Applications of Artificial Intelligence (IAAI-00). AAAI Press, Menlo Park, CA, pp 355–362

5. Breiman L (2001) Random forests. Mach Learn 45(1):5–32
6. Brenner, M.: Situation-aware interpretation, planning and execution of user commands by autonomous robots. In: The 16th IEEE International Symposium on Robot and Human interactive Communication (RO-MAN 2007), pp 540–545 (2007)
7. Breuer T, Giorgana Macedo GR, Hartanto R, Hochgeschwender N, Holz D, Hegger F, Jin Z, Müller C, Paulus J, Reckhaus M, Álvarez Ruiz JA, Plöger PG, Kraetzschmar GK Johnny (2012) An autonomous service robot for domestic environments. J Intell Robot Syst 66(1):245–272
8. Chen X, Jin G, Ji J, Wang F, Xie J (2011) Kejia project: towards integrated intelligence for service robots. Multi-Agent Systems Lab, University of Science and Technology of China, Tech. rep
9. Clementini E, Felice PD, Hernandez D (1997) Qualitative representation of positional information. Artif Intell 95(2):317–356
10. Doostdar, M., Schiffer, S., Lakemeyer, G.: Robust speech recognition for service robotics applications. In: Proc. Int'l RoboCup Symposium (RoboCup 2008), LNCS, vol 5399. Springer, Berlin, pp 1–12 (2008)
11. Engleberg IN, Wynn DR (2006) Working in Groups: Communication Principles and Strategies, 4 edn. Allyn & Bacon, Boston
12. Ferrein A, Lakemeyer G (2008) Logic-based robot control in highly dynamic domains. Robot Auton Syst 56(11):980–991
13. Ferrein A, Niemueller T, Schiffer S, Lakemeyer G (2013) Lessons learnt from developing the embodied AI platform CAESAR for domestic service robotics. In: Designing Intelligent Robots: Reintegrating AI II, Papers from the AAAI Spring Symposium. AAAI
14. Ferrein A, Schiffer S, Lakemeyer G (2008) A Fuzzy Set Semantics for Qualitative Fluents in the Situation Calculus. In: Proc. Int'l Conf. on Intelligent Robotics and Applications (ICIRA'08), pp 498–509. Springer, Berlin
15. Ferrein A, Schiffer S, Lakemeyer G (2009) Embedding fuzzy controllers into golog. In: Proc. IEEE Int'l Conf. on Fuzzy Systems (FUZZ-IEEE'09), pp 894–899. IEEE
16. Jacobs S, Ferrein A, Schiffer S, Beck D, Lakemeyer G (2009) Robust Collision Avoidance in Unknown Domestic Environments. In: Proc. of the Int'l RoboCup Symp. 2009 (RoboCup 2009), LNCS, vol 5949, pp 116–127. Springer, Berlin
17. Kitano H, Asada M, Kuniyoshi Y, Noda I, Osawa E (1997) RoboCup: The Robot World Cup Initiative. In: Proc. Int'l Conf. on Autonomous Agents, AGENTS '97, pp 340–347. ACM, New York, NY, USA
18. Levesque HJ, Lakemeyer G (2008) Cognitive Robotics. In: van Harmelen F, Lifschitz V, Porter B (eds) Handbook of Knowledge Representation, chapter 23. Elsevier, Amsterdam, pp 869–886
19. McCarthy J (1968) Situations, Actions, and Causal Laws. Technical Report Memo 2, Stanford University, California, USA (1963). Published in Semantic Information Processing, ed. Minsky M. The MIT Press, Cambridge
20. Niemueller T, Ferrein A, Beck D, Lakemeyer G (2010) Design principles of the component-based robot software framework fawkes. In: Simulation, Modeling, and Programming for Autonomous Robots (SIMPAR). Springer, Heidelberg, pp 300–311
21. Niemueller T, Ferrein A, Lakemeyer G (2010) A lua-based behavior engine for controlling the humanoid robot nao. In: RoboCup 2009: Robot Soccer World Cup XIII. Springer, Heidelberg, pp 240–251
22. Niemueller T, Schiffer S, Lakemeyer G, Rezapour-Lakani S (2013) Life-long learning perception using cloud database technology. In: Proc. IROS Workshop on Cloud Robotics
23. Reiter R (2001) Knowledge in Action. Logical Foundations for Specifying and Implementing Dynamical Systems. MIT Press, Cambridge, Massachusetts
24. Schiffer S (2015) Integrating qualitative reasoning and human-robot interaction for domestic service robots. Dissertation, RWTH Aachen University, Department of Computer Science
25. Schiffer S, Baumgartner T, Beck D, Maleki-Fard B, Niemueller T, Schwering C, Lakemeyer G (2012) robOCD: Robotic Order Cups Demo—An Interactive Domestic Service Robotics Demo. In: Poster and Demo Session at the 35th German Conference on Artificial Intelligence (KI 2012), pp 150–154
26. Schiffer S, Baumgartner T, Lakemeyer G (2011) A modular approach to gesture recognition for interaction with a domestic service robot. In: Intelligent Robotics and Applications. Springer, Berline, pp 348–357
27. Schiffer S, Ferrein A, Lakemeyer G (2006) Football is coming home. In: Proc. 2006 Int'l Symp. on Practical Cognitive Agents and Robots (PCAR'06). ACM, New York, NY, USA, pp 39–50
28. Schiffer S, Ferrein A, Lakemeyer G (2012) Caesar—an intelligent domestic service robot. J Intell Serv Robot 1–15
29. Schiffer S, Ferrein A, Lakemeyer G (2012) Reasoning with qualitative positional information for domestic domains in the situation calculus. J Intell Robot Syst 66(1–2):273–300
30. Schiffer S, Hoppe N, Lakemeyer G (2012) Flexible command interpretation on an interactive domestic service robot. In: Proc. Int'l Conf. on Agents and Artificial Intelligence (ICAART 2012). SciTePress, pp 26–35
31. Schiffer S, Hoppe N, Lakemeyer G (2013) Natural language interpretation for an interactive service robot in domestic domains. In: Agents and Artificial Intelligence, vol 358. Springer, Berlin, pp 39–53
32. Schiffer S, Wortmann A, Lakemeyer G (2010) Self-maintenance for autonomous robots controlled by readyLog. In: Proc. IARP Workshop on Technical Challenges for Dependable Robots in Human Environments. Toulouse, France, pp 101–107
33. Schiffer S, Wortmann A, Lakemeyer G (2010) Self-maintenance for autonomous robots in the situation calculus. In: Lakemeyer G, Levesque HJ, Pirri F (eds) Cognitive Robotics, no. 10081 in Dagstuhl Seminar Proceedings. Schloss Dagstuhl—Leibniz-Zentrum fuer Informatik, Germany, Dagstuhl, Germany
34. Strack A, Ferrein A, Lakemeyer G (2006) Laser-based localization with sparse landmarks. In: RoboCup 2005: Robot Soccer World Cup IX. Springer, Berlin, pp 569–576
35. van der Zant T, Wisspeintner T (2005) RoboCup X: a proposal for a new league where robocup goes real world. In: RoboCup. Springer, Berline, pp 166–172
36. van der Zant T, Wisspeintner T (2007) Robotic Soccer, chap. RoboCup@Home: creating and benchmarking tomorrows service robot applications. I-Tech Education and Publishing, pp 521–528
37. Wisspeintner T, van der Zant T, Iocchi L, Schiffer S (2009) RoboCup@Home: scientific competition and benchmarking for domestic service robots. Interact Stud 10(3):392–426