Using Ontology-based Experiences for Supporting Robot Tasks - Position Paper

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Abstract. In this paper, we consider knowledge needed for interaction tasks of an artificial cognitive system, embodied by a service robot. First, we describe ideas about the use of experiences of a robot for improving its interactivity. Our approach is based on an multi-level ontological representation of knowledge. Thus, ontology-based reasoning techniques can be used for exploiting experiences. A robot interacting as a waiter in a restaurant scenario guides our considerations.

1 Introduction

For effective interactions of an artificial cognitive system in a non-industrial environment, not every piece of knowledge can be manually acquired and modeled in advance. Learning from experiences is one way to tackle these issues. Experiences can be defined as "an episodic description of occurrences and own active behavior in a coherent space-time segment". Experiences can be used for future situations by generalization. Generalizations (or *conceptualizations*) build the basis for further interactions and possible implications. Such interactions then constitute the current source for experiences which again can be integrated and combined with existing conceptualizations.

For approaching this task of experience-based learning, we consider a service robot acting in a restaurant environment, see the simulated environment in Figure 1.

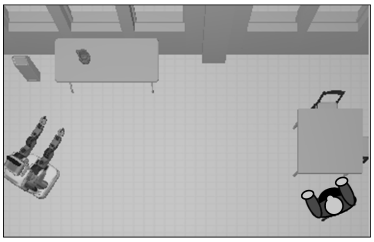

Figure 1: Simulation example: A robot serves a cup to a guest.

In such an environment, domain-specific objects, concepts, and rooms have to be represented. Objects can e.g. be used for a certain purpose and can have impacts on the environment. Different types of relationships between objects have to be considered: taxonomical on the one hand and spatial or temporal relationships on the other hand. Terminological knowledge about dishes, drinks, meals as well as actions and possible occurrences is needed. Areas which may contain served orders (at a table) may be distinguished from seating areas. To perform complex tasks, we consider the interaction that is needed to serve a guest. Moreover, to learn a model for such a process, we examine experiences that result from performing such operations, and investigate how to generalize them.

Our approach is based on ontological knowledge, which comprises models, presented in Section 2 and experiences, introduced in Section 3. Section 4 presents possible generalizations that lead to new conceptualizations in form of new ontological models. A short overview of the architecture of our approach will be given in Section 5 and a discussion of our approach finalizes the paper in Section 6.

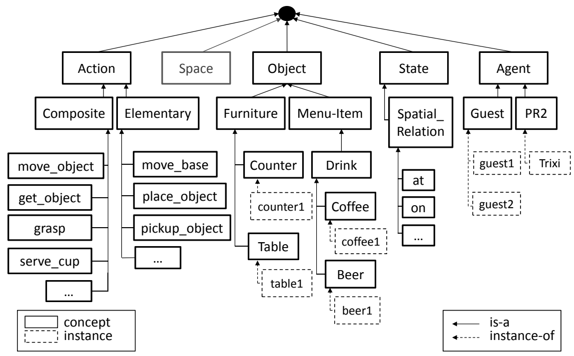

Figure 2: Taxonomical relations of actions and physical objects

2 Ontology-Based Approach

Due to the service domain as well as the inherent interaction with the environment and thereby with agents within, a continuous need of knowledge adjustment to such a dynamic application area is essential. In our approach, an ontology represents the knowledge an agent needs for interacting. This knowledge covers concepts about objects, actions, and occurrences in a TBox (like cup, $plate$, $grasp$, $serve\_cup$ etc.) as well as concrete instances of such concepts in an ABox [1]. Taxonomical relations (depicted in Figure 2) and compositional relations, presented in 3 are essential means for modeling.

A complex activity like serve_cup is decomposed into finer activities until we get a sequence of elementary actions, that the robot can execute directly. Not only these taxonomical and compositional relations, but temporal constraints represent the possible order of actions, like e.g. for the action serve_cup: "Take coffee mug from counter and place it on tray. Go to table, look for guest and place coffee mug in front of guest." Technically, we model binary relations with OWL2[2]

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[2] www.w3.org/TR/owl2-overview

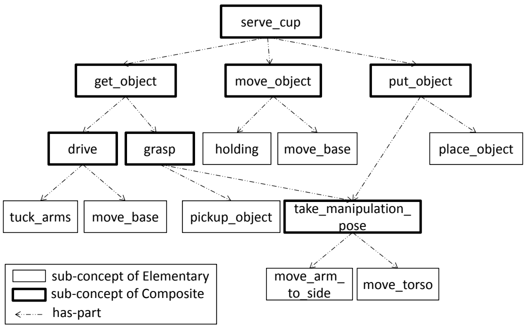

Figure 3: Compositional relations of actions

and n-ary relations, like temporal constraints for complex actions, with SWRL[3], see [2].

3 Experiences

Experiences must be gained by the robot, while the robot is accomplishing a task and will be processed afterwards. In our ontological approach, experiences are also represented as ABox instances (see Figure 4). Thereby, experiences can be represented at all abstraction levels: the complete compositional structure of robot activities, including motions, observations, problem solving and planning, and inter-agent communication. Furthermore, relevant context information, like description of static restaurant parts and initial states of dynamic parts, as well as an indicator of the TBox version are used during experience gaining.

Parallel to robot's interactions, raw data is gathered in subsequent time slices (*frames*) for a certain time point. From these slices, time segments (ranges) of object occurrences and activities are computed (e.g. *grasp* in Figure 5). Such an experience is passed on to a generalization module which integrates the new experience with existing ones.

The initial experience is based on an action of the handcrafted ontology. The outcome of the generalization module will be integrated in the ontology. In general, experiences are gained continuously, thus during every operation, but are dedicated to a goal. We reckon with a manageable number of experiences, because of the successive execution of goals.

Since the experiences are relevant to specific goals, we do not distinguish between experiences that are more important than others at present. But according to "background noise" in the scenery (like a dog walking past during a serve action) some parts of experience might be more significant than others. The accomplishment of this circumstance is presented in the following Section 4.

4 Generalization

We consider an incremental generalization approach, where an initial ontology is extended based on experiences using suitably chosen generalization steps. New experiences are integrated into existing conceptualizations in a cyclic manner. Table 1 shows typical generalization steps based on Description Logic (DL) syntax. Those can be standard DL services (like subsumption of concepts or realization of instances) and non-standard services (like least common subsumers (LCS) [1]). As an example, consider two experiences gained serving coffee to guests, depicted in Figure 4. In principle, all instance tokens are candidates for generalization, e.g. *table1* to *table*. Depending on the commonalities and differences between distinct experiences, however, promising generalizations can be selected, e.g. *coffee1, coffee2* → *coffee* → *drink*. In order to deal with new situations the robot extends its competence.

Over-generalization, e.g. generalizing *coffee* not to *drink* but to *thing* can be avoided by applying the LCS, by the use of the LCS *drink* is selected. However, when the integration of new concepts is impossible over-generalization can not be prevented.

Generalization Path: from → to	Reasoning Service
instance → set of instances	realization
instance → closest named concept	realization
instance → concept expression	realization
set of instances → concept expression	realization
concept → superconcept	subsumption
set of concepts → concept expression	LCS
role cardinality range → larger role cardinality range	range union
role filler concept restriction → generalized role filler concept restriction	LCS
numerical ranges → larger numerical ranges	range union

Table 1: Ontology-based generalizations and their computation through reasoning services

In Section 3 we raised the issue of experience parts that might be more significant than others, on the example of a dog walking past during a serve activity. We cover this circumstance by integrating cardinalities to mark that a dog may appear but it is not mandatory.

In addition to ontological generalization, temporal and spatial constraints can be generalized. Figure 5 presents an example for a temporal generalization. Quantitative temporal orderings by concrete time points are generalized to qualitative temporal relations.

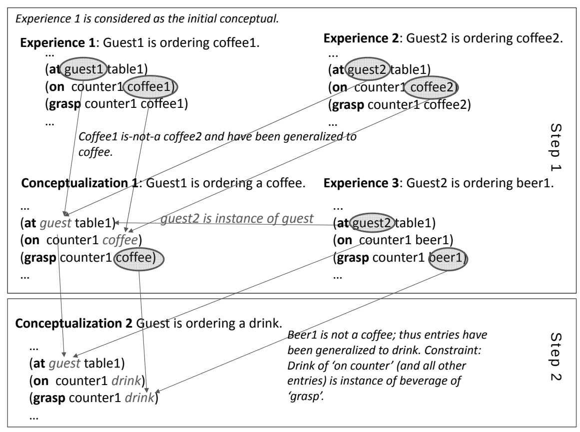

Figure 4: Example for creating conceptualizations from two experiences, or one experience and a conceptualization

5 Architecture

Experiences do not contain only observed data, like perceived actions, objects and relational information but also occurrences and robot's states. These experience contents are gathered by the components presented in Figure 6. Information on object detections (like the identification of *counter1*) and spatial relations (e.g. *(on counter1 coffee1)*) are released by the *object publisher*. The *action publisher*

[3] www.w3.org/Submission/SWRL/

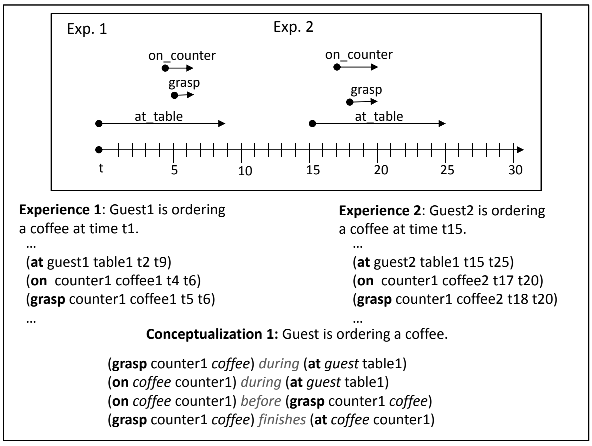

Figure 5: Temporal generalizations preserving temporal order

exports performed action informations, like *(grasp counter1 coffee1)*. Extremity informations of the robot, like the position of the torso or of an arm are published by the *actuator monitor*. These outputs are gathered by the *integration manager*. This manager provides the *experience manager* with this content. The *reasoner* offers reasoning services and the *learning* component generalizes current experiences (in the homonymous module) or complex scene examples to new models. All kinds of knowledge about objects, actions, occurrences and the environment are described in the *ontology*, which will be extended based on experiences made by the robot during it's processing. The *experience database* is a storage location, hold available already gained experiences in a specific format.

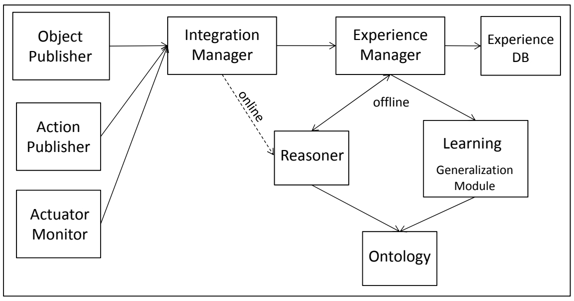

Figure 6: Architecture overview

6 Discussion

In this paper, we presented an ontology-based method for dealing with robot interaction tasks in a dynamic application area. The ontology model provides a central framework for all task relevant knowledge. By successively extending a hand-coded ontology through generalizing from experiences, a learning scheme is realized. [3] presents a similar approach for rudimentary actions like grasping or door opening, we consider aggregated actions like serving a cup to a guest. However, in both cases, experiences provide the basis for refinement of actions.

Representing a robot's knowledge in a coherent way by an ontology, we are able to use existing ontology-based reasoning techniques like DL services. Ontology alignment can also be applied to integrate experiences obtained with different TBoxes (e.g. differing because of new conceptualizations). Similar methods must be applied for generalizing temporal and spatial experiences. Although we propose continuous gathering of experiences, one might as well consider scenarios building the source for an experience that have explicit start and end points (similar to [3]).

Some parts of an experience may be more significant than others, it may be useful to focus on experiences which were made in respect to a specific goal. Furthermore, not every detail should be the subject of generalization, the temporal order or equality of instances in a complex action have to be preserved (more concrete: the cup that is served should be the same cup that was taken from the counter before).

With the aggregation of occurrences, states and elementary actions (covering also agent interactions) to composites and the expansion of knowledge via experience gaining an extension of the interaction ability with the environment and people within is achieved.

ACKNOWLEDGEMENTS

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REFERENCES

[1] F. Baader, D. Calvanese, D. McGuinness, D. Nardi, and P. Patel-Schneider, *The Description Logic Handbook*, Cambridge University Press, 2003.

[2] W. Bohlken, B. Neumann, L. Hotz, and P. Koopmann, 'Ontology-Based Realtime Activity Monitoring Using Beam Search', in *ICVS 2011*, ed., J.L. et al. Crowley, LNCS 6962, pp. 112–121, Heidelberg, (2011). Springer Verlag.

[3] Alexandra Kirsch, *Integration of Programming and Learning in a Control Language for Autonomous Robots Performing Everyday Activities*, Ph.D. dissertation, Technische Universität München, 2008.