A Knowledge Representation and Reasoning Module for a Dialogue System in a Mobile Robot

Luís Seabra Lopes, António J. S. Teixeira and Marcelo Quinderé

IEETA, Departamento de Electrónica e Telecomunicações
University of Aveiro,
3810-193 Aveiro, Portugal

Abstract. The recent evolution of Carl, an intelligent mobile robot, is presented. The paper focuses on the new knowledge representation and reasoning module, developed to support high-level dialogue. This module supports the integration of information coming from different interlocutors and is capable of handling contradictory facts. The knowledge representation language is based on classical semantic networks, but incorporates some notions from UML. Question answering is based on deductive as well as inductive inference.

1 Introduction

Due to the successive advances in robotics-related technologies, robots are closer to humans. Intelligent service robots capable of performing useful work in close cooperation/interaction with humans are the next generation of robots.

However, in order to reach that phase, it is necessary to include in their design such basic capabilities as linguistic communication, reasoning, reactivity and learning. "Integrated" Intelligence identifies an approach to building intelligent artificial agents in which the integration of all those aspects is considered [1].

This is the scope of CARL (*Communication, Action, Reasoning and Learning in Robotics*), a research project started in our institute in 1999, in the framework of which a robot prototype was developed, Carl [2]. The software architecture of Carl is based on a set of Linux processes. One of them handles general perception and action, including navigation. Other processes are dedicated to speech processing and touch screen interaction. An animated face displays appropriate emotions. High-level reasoning and natural language generation are mostly based on the Prolog engine. The central manager is an event-driven system.

The human-robot communication process is modeled as the exchange of messages, much like is done in multi-agent systems. The set of performatives or message types in our Human-Robot Communication Language (HRCL) is inspired in KQML [3]. The currently supported set of performatives includes *tell, ask, ask_if, and achieve*. The Spoken Language Understanding (SLU) module combines a robust parser with memory based learning and is capable of performing deep analysis - in grammatically correct sentences (or mostly correct), and shallow analysis - in sentences with severe errors [4].

The current knowledge management system of Carl supports the acquisition of knowledge obtained from interaction with human interlocutors [2]. The interaction with

Seabra Lopes L., J. S. Teixeira A. and Quinderé M. (2005).
A Knowledge Representation and Reasoning Module for a Dialogue System in a Mobile Robot.
In *Proceedings of the 2nd International Workshop on Natural Language Understanding and Cognitive Science*, pages 172-177
DOI: 10.5220/0002573901720177

Carl is viewed as a sequence of interaction sessions. All that is done is to associate the collected information to the respective interaction session. The current system does not perform any kind of information integration and, in particular, does not attempt to resolve contradictions between pieces of information obtained from the different interlocutors.

The latest developments of Carl are focused on the knowledge representation and reasoning (KRR) module, designed to increase the actual dialogue capabilities of the robot. This new module implements a semantic network and is capable of integrating information obtained from different interlocutors, even if they are contradictory. When a question is directed to Carl, inference mechanisms process all the acquired data to give the best response.

Although there are various works on knowledge representation (KR) for robotics, few of them are focused on supporting the dialogue system. Skubic et al developed a framework to use spatial language in human-robot dialogues [5]. However, they are not focused on acquiring information from different interlocutors and do not consider the acquisition of non-spatial knowledge.

Kamp and Reyle proposed the Discourse Representation Theory (DRT), which - like the other theories of dynamic semantics - accounts for the context dependence of meaning. DRT uses Discourse Representation Structures (DRS) for semantic representation and a model-theoretic interpretation of those DRSs. The new version of DRT uses a bottom-up approach in the construction of the representations instead of the top-down approach of the original version [6].

Benferhat et al presented strategies for conflict resolution developed to deal with exception handling and iterated belief revision, but which could also be applied in merging information from different sources [7]. Their work consists on weakening the contradictory data, rather than eliminating them completely.

Brazdil and Torgo have developed a method to construct an integrated knowledge base from several separated ones [8]. In their method, the knowledge bases used as input can either be obtained by querying an expert or on the basis of data, using inductive learning tools.

In this work, all the acquired data is kept on the knowledge base, and the responsibility of resolving contradictions is left to the inference mechanisms. Besides that, it supports a natural language dialogue system and it was designed to be applied in an intelligent mobile robot.

The paper is structured as follows. Section 2 describes the KR language. The inference mechanisms are explained on section 3. The KRR module is presented on section 4 and section 5 concludes the paper with reference to future work.

2 Knowledge Representation Language

Complex domains, like the one of a dialogue system in an intelligent mobile robot, require a general and flexible KR [9].

The scenario in which the robot must act involves conversation with various interlocutors and exchange of information with them. The module should provide functionalities for knowledge acquisition and question answering. It's important to note that the agent should be able to start with no prior knowledge.

Since the robot can acquire data from different sources (interlocutors), the KRR module must handle contradictory pieces of information.

Semantic networks [10] address the main representation requirements to support a high level dialogue. It is very easy to represent the entities with them. Inference is simple, all one has to do is to follow the relations between entities. Semantic networks, not only provide ways for efficient computing, they also provide a very intelligible layout.

Using semantic networks we can easily apply the rule of inheritance, in which all properties of the supertype are copied to the subtypes, except if there is a redefinition of the property in the subtype.

We have based the definition of our KR language on typical definitions of semantic network and on class and object diagrams of UML [11].

We have used prolog predicates for this, including the declaration of types, objects (instances of types) and various relationships between them. This language assumes that objects are identified by system-generated identifiers. In the implementation, when a new object comes up, a new integer identifier is generated. The predicates that provide information on specific objects include *instance(ObjID, Type), name(ObjID, Name) and attribute(ObjID, Attribute, Value)*. Generalization is declared with *subtype/2*. Standard UML relations (aggregation, composition, association) are also supported.

3 Basic Inference Mechanisms

There are three main types of inference: deduction, induction and analogy [12]. Take the logical entailment (1), in which P represents the premise, BK the background knowledge and C the consequence.

$$P \cup BK \models C\,. \tag{1}$$

Deduction is truth preserving. It derives consequence *C* from a given premise *P* and background knowledge *BK*. Here, this kind of inference is used when the type has an attribute with a default value and a question is made about the object's attribute. Consider the Fig. 1 and suppose somebody asks *"how many legs does John have?"*. Since there is no information about legs in the object *John*, the module uses deduction to get answer *"2"* from the type *Human*.

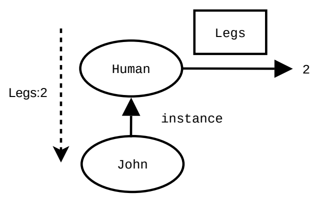

Fig. 1. Deduction

If there is *BK* and *C*, induction can be used to hypothesize a premise *P*. In this work, inductive inference is used when the objects of a type have some attribute information that the type itself does not have. Take the representation in Fig. 2. If the question *“what does a cat like?”* is made, induction is used to obtain the answer *“milk”* from the objects of the type *Cat*, since this information is not directly asserted in the type itself.

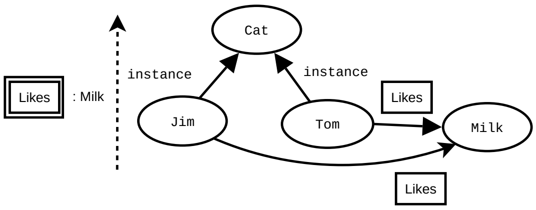

Fig. 2. Induction

Finally, analogy is a combination of deduction and induction. Considering the knowledge given in Fig. 3, suppose someone asks *“what does Bob like?”*. Since this information is given neither on the object *Bob* itself nor on the type *Cat*, the module has to: first use induction from the objects *Tom* and *Jim* to the type *Cat*; then use deduction from the type *Cat* to the object *Bob*.

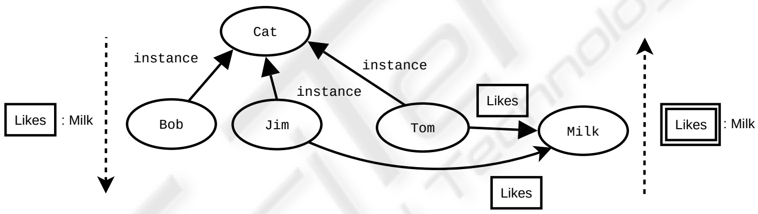

Fig. 3. Analogy

4 The Reasoning System

The functionalities of the KRR module are provided mainly by the procedure *tell(Int, Fact)* – the interlocutor *Int* tells *Fact* to the system; and *ask(Fact, Conf)* – the system is asked about *Fact*, the confidence in the answer, *Conf*, is returned.

The procedure *tell* simply stores the information given by the interlocutors. Inference is used in *ask* in order to provide the most suitable answer.

Confidences are calculated as follows. Consider a property of an object or type for which a certain value is supported by N interlocutors and that a total of T interlocutors provided values for this property. In this case, the confidence that the mentioned value is the correct one is given by:

$$Conf(N, T) = \frac{N}{T} * \left(1 - \frac{1}{T+1}\right) . \qquad (2)$$

Note that the confidence of answers based on few statements is reduced.

If the question is about an attribute value in a type, Algorithm 1 is used to determine the value. The tree traversal step of the algorithm computes the frequency of occurrence of the possible values of the Attribute in the type and all its subtypes (and sub-subtypes, etc) and respective objects. If there is a supertype, the result of the tree traversal step is combined with a similar result inherited from the supertype.

Algorithm 1: GET_VALUE

```
input  : Type, Attribute
output: ((V_1, C_1), .., (V_k, C_k)) in which V stands for Value, C for confidence and k the
        number of different values of Attribute

begin
    V_1, .., V_K ⟵ possible values of Attribute
    In a tree traversal, compute the frequencies of occurrence, N_1, .., N_k, of each
    possible value of Attribute in Type and all its subtypes (and sub-subtypes, etc) and
    respective objects
    T ← Σ_{i=1}^{k} N_i (total number of statements about values of Attribute)
    for i ← 1 to k do
        C_i ⟵ conf(N_i, T) (According to Equation 2)
    if Type has no supertype then
        return ((V_1, C_1), .., (V_k, C_k))
    ST ⟵ supertype of Type
    ((V_1, C'_1), .., (V_k, C'_k)) ⟵ GET_VALUE(ST, Attribute)
    for i ← 1 to k do
        C''_i ⟵ (C_i + C'_i)/2
    return ((V_1, C''_1), .., (V_k, C''_k))
end
```

If the question is about an attribute value in an object, confidences for all possible values are computed in the object (equation 2) and in the type (Algorithm 1). The value with the highest combined confidence is returned.

Although deduction is truth preserving, type information provided by interlocutors is not necessarily more reliable than object information, so deductive inference does not have a stronger weight than inductive inference.

The implementation of this module, as described, was done in Prolog.

5 Conclusion and Future Work

In this paper, the recent evolution of the intelligent mobile robot Carl was presented. The paper focuses on the new KRR module. The KR language is based on semantic networks and incorporates some notions from UML. The reasoning system combines deductive and inductive inference.

Some important aspects have not yet been addressed. One of them is induction on attributes with continuous values. Another problem is that inheritance does not take into account the confidence on the generalization links (subtype). A third problem is that when evaluating the values of an attribute it is assumed that only one is correct. This is a limitation since, in general, an object or type can have several simultaneously correct values for an attribute or relation.

Besides these limitations, we also plan to allow differentiating the interlocutors. It would be reasonable to give more value to the information coming from someone trusted by the robot. We are considering the development of a heuristic to give weight to the interlocutors in order to have more truthful answers, especially when they involve contradictory facts.

Current work addresses the development of a module to extract the same semantics used by the KRR module from the sentences recognized.

References

1. Seabra Lopes, L. and Connell, J.H. (eds.): *Semisentient Robots*: special issue of *IEEE Intelligent Systems*. vol. 16, n. 5. Computer Society (2001) 10-14.
2. Seabra Lopes, L.: Carl: from Situated Activity to Language Level Interaction and Learning. *Proc. IEEE Int'l Conf. on IROS*, Lausanne, Switzerland (2002) 890-896
3. Labrou, Y. and Finin, T.: A Proposal for a New KQML Specification. *Technical Report CS-97-03,* University of Maryland at Baltimore County, (1997).
4. Rodrigues, M., L. Seabra Lopes, and A. Teixeira, An Hybrid Approach for Spoken Natural Language Understanding Applied to a Mobile Intelligent Robot. Proc. Natural Language Understanding and Cognitive Science (NLUCS), (2004) 145-150
5. Skubic, M., D. Perzanowski, et al.: Spatial Language for Human-Robot Dialogs. IEEE Transactions on Systems, Man, and Cybernetics, C 34(2): (2004) 154-167
6. Kamp, Hans, J. van Genabith, U. Reyle Discourse Representation Theory. Chapter in: Handbook of Philosophical Logic (2005), D. Gabbay and F. Guenthner (eds.)
7. Benferhat, Salem, et al.: Weakening conflicting information for iterated revision and knowledge integration. Artif. Intell, 153(1-2), (2004) 339–371
8. Brazdil, P. and L. Torgo: Knowledge Acquisition via Knowledge Integration. Current Trends in AI, B. Wielenga et al.(eds.), (1990) IOS Press, Amsterdam.
9. Russell, Stuart and Peter Norvig Artificial Intelligence: A Modern Approach. Prentice Hall, 1st edition (1995); 2nd edition (2003).
10. Sowa, John F.: Semantic Networks. *MIT Encyclopedia of Cognitive Science*, http://www.jfsowa.com/pubs/semnet.htm
11. Rational Software Corporation: UML Semantics, v1.0. Santa Clara, CA (1997).
12. Michalski, R. S.: Inferential Theory of Learning: Developing Foundations for Multistrategy Learning. Machine Learning: A Multistrategy Approach, 1994