

Chapter 22

Knowledge Processing Using EKRL for Robotic Applications

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ABSTRACT

This article describes a semantic framework that demonstrates an approach for modeling and reasoning based on environment knowledge representation language (EKRL) to enhance interaction between robots and their environment. Unlike EKRL, standard Binary approaches like OWL language fails to represent knowledge in an expressive way. The authors show in this work how to: model environment and interaction in an expressive way with first-order and second-order EKRL data-structures, and reason for decision-making thanks to inference capabilities based on a complex unification algorithm. This is with the understanding that robot environments are inherently subject to noise and partial observability, the authors extended EKRL framework with probabilistic reasoning based on Markov logic networks to manage uncertainty.

1. INTRODUCTION

A major research challenge regarding intelligent robotic applications is to provide robots tools to understand the human environment, and help them in the decision-making process (Kollar, 2012). Indeed, environment becomes capable of understanding real-world events (Kamei, 2010) and robots becoming skilled enough to perform rather complex tasks, a detailed symbolic description of the knowledge involved is required to ensure a proper execution of these latter. Thus, knowledge representation and processing is crucial to manage real world robot-environment interactions.

For example, in pervasive multimodal systems, humans, robots and smart components cooperate with one another to perform a specific task. In such systems, a rich symbolic representation is needed to store facts or knowledge concerning the interaction of the robots with different entities and objects in the

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environment. Given that, it is desirable to use an expressive knowledge representation language (KRL) that closely resembles human natural language (NL) (Fong, 2003). Such KRL can be used to communicate events between agents and services, and to represent knowledge about the state of the world. Such knowledge should represent entities, actions (i.e., events produced by entities) and general knowledge of what is happening in the environment in order to make appropriate decisions (Schmidt-Rohr, 2008).

Unfortunately, most of the existing approaches used in knowledge-based robotic platforms (Tenorth, 2010) (Lemaignan, 2016) (Saffiotti, 2008) (Schlenoff, 2012) rely on binary knowledge representation languages to model the robot environment. Binary predicates are used to represent object properties and relations between objects. Such a representation is not sufficient to represent the richness of information that may be involved in a robotic interaction application. According to Zarri (Zarri, 2009), usual KRL - both in their 'traditional' and 'semantic web' versions like RDF and OWL - are not very suitable for dealing with elementary or complex events. For example, a situation (event) described in NL as "at 15h40pm, robot nao brings the medicine to the living room for eric" couldn't be represented using only one binary predicate, since it links only two concepts (objects), whereas the situation implies to link different concepts together (eric, medicine, nao) and also with the spatial and temporal information to fully describe the situation. Reification is an alternative to represent n-ary predicates with OWL which consists in encoding n-ary relations as classes (Severi, 2010).

Figure 1 shows how the relation (binary predicate) is reified into an object `moveEntity01` that itself has binary relationships, typically called roles, identifying all the elements of the situation.

However, resorting to such a mechanism entails to significant problems described in (Welty, 2006). We can cite the problem of object proliferation, in which for each reified relation an object is created along with a binary relationship for every role. Redundant objects can also reify the same relation if the knowledge modeler is not careful in its modeling.

Hence, reification requires additional work, which can make knowledge bases more difficult to read and understand.

In contrast, Figure 2 shows that EKRL n-ary data structures natively manage to represent the example situation (event) without any additional mechanism thanks to the frame based data structure of EKRL. It represents each piece of information present in the situation with an argument that corresponds semantically to the appropriate role. EKRL distinguishes between standard objects and events including them in two distinct ontologies. A detailed explanation is presented below.

Besides, when it comes to represent even more complex situations, a more expressive KRL is needed. Second-order syntax (expressions) is appropriate to express such situations, and binary approaches are unable to represent this kind of knowledge.

EKRL makes use of second-order data structures which is the composition of two first-order data structures, in other words, an n-ary predicate can take as role argument another n-ary predicate (see Section 5). In this paper, we present the kernel ideas of EKRL (environment knowledge representation language), highlighting its ability to build complex n-ary data structures providing a great expressiveness power, and second, we detail high-level reasoning operations that rely on a complex unification algorithms.

We discuss also the necessity of using such a framework in the context of robotic applications, and the importance of reasoning over expressive knowledge like second-order data structures to solve decision-making problems. We give some examples of the use of EKRL and its reasoning abilities.

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