Automatic Generation of a Simulated Robot from an Ontology-Based Semantic Description

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Abstract: Humans are capable of generating simulated mental worlds based on their past experiences and use such an environment for prospecting, planning, and learning. Such capabilities could enhance current robotic systems, allowing them to plan ahead based on predicted outputs, and even compare their performance with a different agent. In this work, we propose a semantic robot modeling framework, which is able to express intrinsic semantic knowledge in order to better represent the robot and its surrounding environment. We also show that such data can be used to automatically generate a simulated model, allowing robots to simulate themselves and other modeled agents.

Keywords: semantic descriptors, mental simulation, knowledge sharing

1. INTRODUCTION

Learning by experience might be our first thought when reckoning about the nature of learning. Indeed, our first learning experiences as a toddler come from our interaction with the environment and the observed outcome of it. It was shown, however, that such learning techniques are not limited to real-world interactions.

Early studies on cognitive science[1] showed that humans are able to simulate situations by revisiting past experiences and learn by imagining possible outcomes of novel actions. This complex principle consists of building a simulated world inside one's mind, capable of working on its own, and then inferring about new ways of acting, which can be later applied in real situations. Such skill is paramount when planning about optimal ways to act given certain circumstances. Humans tend to reason about potential outcomes before performing critical actions.

The concept of mental simulation, although capable of enhancing current robot learning and planning capabilities, has yet to be thoroughly explored in the robotics field. This work contributions are as follows:

- An expansion of the TOSM(Triplet Ontologic Semantic Model)[2] in order to model and store robot description data.
- A parser capable of automatically generating a simulated model of a robot by querying relevant information described using the aforementioned framework. By using such approach, a robot can simulate itself without the need for human intervention.

2. RELATED WORK

Methods of incorporating knowledge into robots have been extensively studied in the past decades. Prominent works like CYC[3] and SUMO[4], despite gathering a substantial amount of manually encoded encyclopedic knowledge, lack the needed information to be applied on the robotics field. The OMICS[5] project created a common-sense database which contains required knowledge in order for an indoor robot to successfully complete a variety of tasks. In a similar fashion, RoboEarth[6] was created to be the World Wide Web for robotics, a complete database that would gather information about objects, tasks, places, and behaviors. This work, however, was primarily focused on manipulation tasks. Such tasks were also explored by KnowRob[7] and its recently presented successor[8], a knowledge processing system able to perform reasoning using both a semantic knowledge database and a mental simulation capable of replaying past experiences in order to explore new outcomes.

The mental simulation concept was also applied to several virtual and real agents. Leonardo, from [9], was developed to infer human intentions by simulating its own body model and acting on the human's behalf. Several other works used a "*putting yourself on other's shoes*" approach [10], [11], [12]. [10] created a bot capable of anticipating it's opponents actions, while [11] utilized it's own behavior model to predict an agent movement. In [12], an animated mouse uses it's own motor and action representations to interpret and imitate the behaviors of similar counterparts. Nonetheless, such approaches are limited by the agent's own model. Our work aims to offer a tool to facilitate the simulation of oneself and different agents, by proposing a semantic model and a way to generate a simulated robot directly from the modeled data.

3. FRAMEWORK OVERVIEW

Humans demonstrate an outstanding ability to generate, update and maintain spatial maps of known environments. Researches on the cognitive science and neuroscience fields[13], [14] showed that the human brain has a "GPS" mapping system, with spatial scalability yet to be seen in robotic systems. Aiming to match the brain GPS capabilities, the TOSM was proposed[2]. This novel

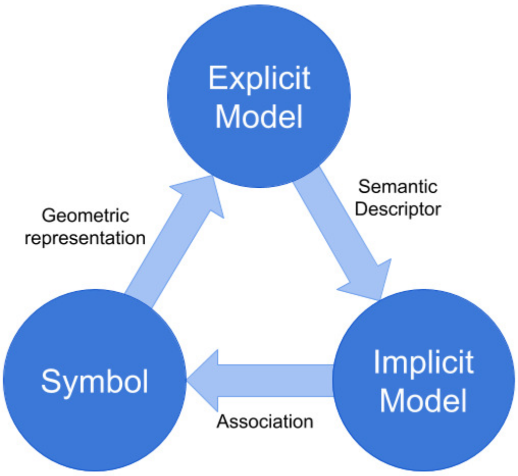

Fig. 1 Triplet Ontologic Semantic Model (TOSM) representation.

representation can be divided into three interconnected models, as showed in Fig. 1.

The explicit model represents everything that can be "seen." Put differently, it can describe every information the robot is able to obtain using its sensors, including but not limited to shape, size, color, texture and three-dimensional pose. This type of data can be easily obtained and has been vastly employed in robotic applications. On the other hand, the implicit model subsumes knowledge that cannot be directly extracted from sensory data, hence needing to be inferred by reasoning about the environment semantic information. This data ranges from physical properties like mass and friction coefficients to object-relational information and high-level inferences such as "A laser range finder cannot detect a glass door." Lastly, the symbolic model defines every element using "human language" such as name, description and symbols that can represent it according to human standards.

The TOSM is not limited to objects and can also be used to represent places and occupants (i.e. people). They can be modeled in the same fashion as the objects, and be combined generating high-level semantic maps of an environment. In other words, the stored data can be queried on-demand and used to build different maps, as shown on Fig. 2. This eliminates the need of storing several different maps, unifying the robot spatial knowledge and reducing the storage requirement, which can grow indefinitely the more the robot explores. In this work, we expanded this usability, by defining guidelines on how to represent a robot using the TOSM framework.

We aim to achieve human-like data modeling with high modularity and expressiveness, further improving the robot understanding of the world and its own structure as well. This would reduce the need for domain expert tailored models and ease the integration between the real-world and the mental simulated environment. Also, by making this data available on a cloud database, it can be easily shared by different robots and applications.

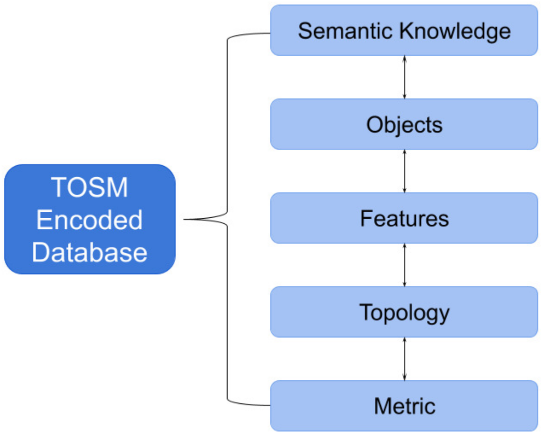

Fig. 2 On-demand map generation.

Fig. 3 Differential robot to be modeled.

4. ROBOT SEMANTIC DESCRIPTION

In this work, TOSM was used to represent the robot shown in Fig. 3. We chose to encode this data using OWL(Ontology Web Language) triplets, in order to store the data in a computer-readable format. OWL is a widely used format, with several tools and applications openly available. To manipulate and visualize the OWL triplets, the Protégé framework[15] was used.

A robot can be divided into structural parts, sensors, wheels and joints, each of them represented by explicit, implicit and symbolic data. The explicit data, being sensory data, is the same across all categories: pose, shape, size, color and material. The symbolic information is composed of a name and an identification number. The implicit data, however, varies greatly. For structural parts, it contains the main material and its mass. A wheel also encodes whether or not it is an active or a passive wheel, while joints store which two parts are connected. Finally, each sensor type can have a different range of implicit information. For example, a camera can be described by data like image resolution, field of view, frames per second and range(for RGB-D cameras). On the other hand, a laser range finder has properties such as range, angle and number of samples. The OWL data graph is shown on Fig. 4.

One of the main advantages of encoding this information using OWL is the ease of doing semantic reasoning and querying. Such data can be used for prospecting whether or not an object can be perceived by a certain sensor, and then plan the subsequent action accordingly. This is especially beneficial when reasoning about the feasibility of a task. By knowing its own structure, properties and limitations, a robot can prospect if it is capable of concluding such task successfully and, if not, request assistance or reassign the task to another agent with more significant chances of success, which can be inferred by simulating the same task using the other agent's model.

5. RESULTS AND DISCUSSION

Our work proposes to expand this usefulness by automatically generating a simulated robot model using only the available TOSM data. By combining semantic and implicit data, we can fully generate a URDF(Universal Robot Description Format) file and feed it automatically to a ROS(Robot Operating System) based architecture. Additionally, simulators typically require specific data, such as inertia matrices and friction coefficients, which might be difficult to obtain. By dividing the robot into simplified shapes and combining it with their mass, the inertia of the robot can be obtained. Moreover, as the materials of the wheels and various surfaces can also be stored, the relative friction coefficient can be queried, which can be useful for both, generating the simulated world and task planning on a large-scale outdoor environment. This can be seen as one of the key advantages of TOSM when compared to existing representation models, such as SRDF(Semantic Robot Description Format). The same data that is used for map building, navigation and planning, can be used to generate the simulated models. Having an unified database reduces the need of updating the same data in several locations, which is notably error-prone, and also saves storage space.

The automatically generated robot simulation is shown on Fig. 5. By comparing to the real robot on Fig. 3, it can be observed that even though the overall shape of the simulated robot resembles the real one, it is limited by the use of primitive shapes. However, studies claimed that, when performing mental simulations, humans do not need to use a highly accurate physical model of the environment in order to reason about their actions[16]. Therefore, when performing mental simulations, it is sufficient to produce a model that, if not physically accurate, is consistent with the real world. Nonetheless, there are still areas where our framework alone is not sufficient and need domain experts to tailor its values, such as projecting effort controllers for the simulated robot. The control response was shown to be sensitive to changes on the robot shape and dynamics, often requiring some fine tuning to work properly.

6. CONCLUSION AND FUTURE WORK

In this paper, we presented the application of a semantic modeling framework to represent a mobile robot. The expressiveness of the TOSM framework enabled us to create a URDF model generator capable of building a fully functional simulated robot without the need for fine-tuning or human intervention. Such models can be directly integrated into ROS and physics simulators like Gazebo, which may allow future applications to simulate themselves and even other agents in order to enhance its planning and learning capabilities. We plan to extend such framework to also generate a full simulated map of the environment and create a cloud knowledge database where robots, objects and environment models can be shared between different robotic applications.

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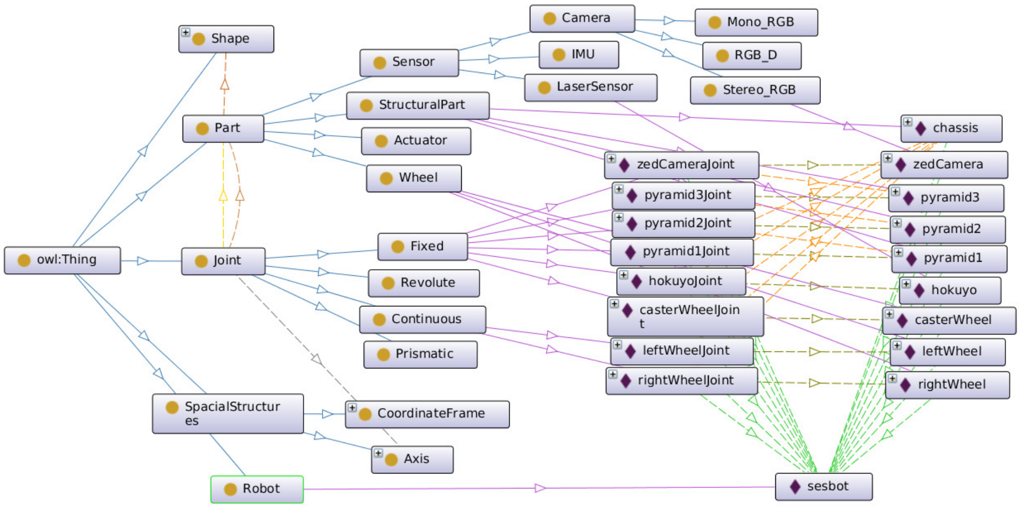

Fig. 4 OWLGraph of the created robot description ontology. Yellow circles represent a class, while the purple diamonds are instances of such classes. Blue lines show a subclass relationship, green lines state which parts and joints are contained in a given robot and purple lines express from which class an instance is derived. Finally, yellow and orange lines specify the connection between two body parts and a joint.

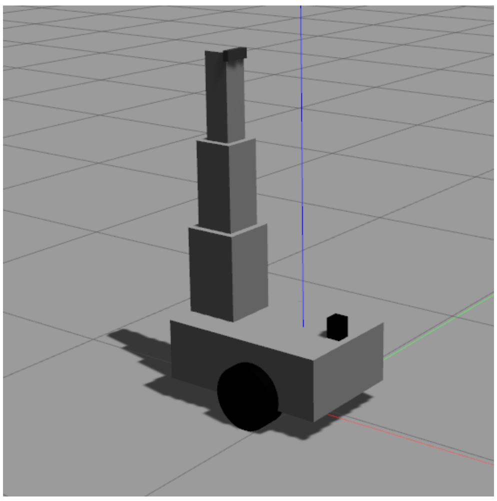

Fig. 5 Generated simulated robot.

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