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Review on the Knowledge Graph in Robotics Domain

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Abstract. With the development of Artificial Intelligence technology, the application of robots in production and life is more and more extensive. How to improve the autonomy of robots and make robots complete tasks more accurately and quickly become a new research topic. One of the most important key tools which enable the robots to work more autonomously is knowledge. Robots need the relevant knowledge of environment, tasks, action and robot's own abilities when perform a task. How to represent and organize the vast amount of knowledge and the complex relationships between these knowledges in a more effective way, so that the robot can retrieve relevant knowledge faster and conveniently, and reasoning based on the original knowledge to help the robot complete the task automatically, has been a new research problem. Subsequently, the concept of knowledge graph was proposed, and with its strong knowledge representation and organization ability, it has been widely studied in many domains. This paper mainly reviews the research status of knowledge graph of robotics domain, introduces several existing knowledge graphs, and compares and analyzes them in the aspect of knowledge representation, knowledge update, knowledge query and reasoning. Finally, we propose the shortage of the exiting knowledge graph and look forward to the future works.

Keywords: Knowledge Graph; Knowledge Sharing; Knowledge representation; Knowledge Update.

1. Introduction

With the development of Artifcial Intelligence technology, robots are more and more widely used in people's production and life, and they play an increasingly important role in industrial[1] service, education[2], military and so on. However, we must note that robots can't always complete the task successfully, and often require manual intervention when robot performs a task, so the autonomy of the robot needs to be further improved. One of the most important key tools which enable the robots to work more autonomously is knowledge[3].Robots need the relevant knowledge of environment, tasks, action and robot's own abilities when robots work. How to represent and organize the vast amount of knowledge and the complex relationships between these knowledge in a more effective way, so that the robot can retrieve relevant knowledge faster and conveniently, and reasoning based on the original knowledge to help the robot complete the task automatically, has been a new research problem.

The concept of knowledge graph was formally proposed by Google in 2012[4]. The original purpose was to enhance the search ability of its own search engine through knowledge graph to better satisfy the user's search experience. Compared with the traditional knowledge base, the knowledge graph mainly has the following advantages: 1) Larger scale. Compared with traditional knowledge bases, knowledge graph can organize richer knowledge, and to some extent, the scale of knowledge determines the utility of knowledge graph; 2)richer semantic relationship. The knowledge graph directly uses the edge to represent the relationship between the entities, and the rich semantic relationship is the key to help the robot understand the physical world; 3) higher knowledge quality. The knowledge sources of knowledge graph are diverse, and different data sources can be cross-tested. In addition, the construction method based on crowdsourcing technology also guarantees the quality of knowledge graph, and the quality of knowledge is the key to correctly understand and complete task planning; 4) Visualization. The knowledge graph supports visual display, which provides great convenience for human-computer interaction.

2. Knowledge Graph

Knowledge graph is a structured semantic knowledge base used to describe concepts and their interrelationships in the physical world in symbolic form. A common way to represent knowledge in knowledge graph is a tuple [5] $\mathrm{G} = \langle E, R, S\rangle$:

Where E={$e_1; e_2; e_{|E|}$} is a set of entities, including different $|E|$ entities; R={$r_1; r_2; r_{|R|}$} is a set of relationships in the knowledge base, including different $|R|$ relationships. $S \subseteq E \times R \times E$ represents the set of triples in the knowledge base.

According to the range of application, knowledge graph is roughly divided into two categories: general knowledge graph and domain knowledge graph. The general knowledge graph is similar to the structured encyclopedia for all domains in TABLE 1, including Cyc, WordNet, ConceptNet, Freebase, Wikidata, YAGO, Babelnet and so on.

Because the general knowledge graph focuses on the breadth of knowledge, emphasizing the representation of more entities and relationships, but for a specific application domain, the accuracy and granularity of knowledge in the general knowledge map are not enough. Therefore, the conception of domain knowledge graph is proposed. Domain knowledge graph are primarily targeted to domain-specifc data, including richer entity attributes and data models. Now, the application of domain knowledge graph becomes more and more extensive. Knowledge graph, like, Open PHACTS [13] in the pharmaceutical domain, Datafox and Spiderbook in the financial domain [14], are widely used in agricultural production, customer service [15], performance evaluation [16] and other domains.

Compared to the knowledge graph above-mentioned, the robot domain needs more detailed description of the physical world, such as load manipulation task or mobile in the environment and other related knowledge, and the quantities and types of relevant knowledge and relations between these knowledges is also more complex, so the robotics domain knowledge graph construction is more difficult. At present, the related knowledge graph in robotics domain mainly include RoboEarth, RoboBrain and openEASE.

3. Research of Knowledge Graph in Robotics Domain

The current knowledge graph in robotics domain mainly include RoboEarth, RoboBrain and openEASE.

3.1 RoboEarth

The RoboEarth project [17] was launched by European scientists in early 2011. RoboEarth aims at providing a distributed cloud-based web platform from robots for robots that is publicly accessible and enables robots to autonomously share knowledge among each other and to generate new knowledge from previously stored data. As a result, robots don’t have to gain the same knowledge over and over again, but can build upon it right from the start.

RoboEarth system consists of various software components, with the core cloud infrastructure provided by the RoboEarth databases (RoboEarth DB) and the RoboEarth Cloud Engine (Rapyuta) [18]. Fig.1 shows the simplifed architectural diagram of the integrated RoboEarth system.The cloud database is used for storing and sharing knowledge about task planning for robot uploading (eg, object model, action plan, environment map, etc.). And Rapyuta is a cloud search engine for Query relevant knowledge from the cloud knowledge base.Moreover, KnowRob[19]is a robot local knowledge base mainly including the environmental knowledge (the attributes of objects in the environment and the semantic relationship between objects), task knowledge (eg, action methods, operational strategies), pattern recognition models (eg, image recognition, object recognition), and others. The underlying components consists the components about perception, navigation and manipulation.

Table 1. Introduction of Several Typical General Knowledge Graph

Knowledge Graph Name	**Introduction**	**Application**
Cyc	Cyc [5] is a common-sense knowledge base. It was founded in 1984 by Douglas Lenat. The goal is to cover ontology and common-sense knowledge in various domains and build the largest common-sense knowledge base of human beings.	Basis for developing domain ontology, eg. KnowRob[6].
WordNet	WordNet [7] is a knowledge base of English vocabulary. It was researched and developed by Princeton University in 1985. It divides vocabulary according to part of speech and then build semantic relationship between related words.	Semantic disambiguation (English).
ConceptNet	ConceptNet [8] riginated from the crowdsourcing project Open Mind Common Sense, which was launched in 1999 at the MIT Media Lab and was designed to help computers understand the meanings of words that people use.	Natural language understanding
FreeBase	FreeBase [9] is a knowledge base developed on the basis of MetaWeb acquired by Google, but has been closed by Google and its content has been imported into the Wikidata project.	Google Search Engine
Wikidata	Wikidata[10] is supported by the Wikimedia Foundation to build the world's largest knowledge base, but currently faces the problem of missing data.	Wikidata
YAGO	YAGO [11] is a linked-database developed by the by the German Max Planck Institute. It mainly integrates three databases of Wikidata, WordNet, and GeoNames, making YAGO a richer classification system. In addition, YAGO3 integrates time and space knowledge into the knowledge base, enriching the dimensional representation of the knowledge base.	YAGO
Babelnet	Babelnet [12] is a multi-language dictionary knowledge base similar to WordNet. The goal is to solve the problem of lack of data in WordNet in non-English languages. He integrates WordNet with Wikipedia.	Natural language understanding

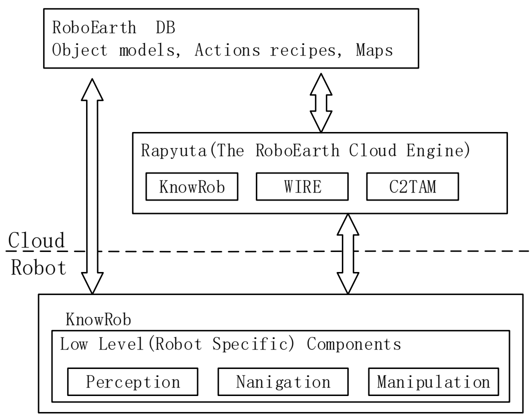

Fig 1. A simplifed architectural diagram of the integrated RoboEarth system.

RoboEarth has many applications in robot knowledge sharing and task planning. Di Marco et al. [20] proposed to create a 3D object model for robots and vision applications by using the RoboEarth system to store the created object model, and to reuse the model immediately after creating and loading the model. Waibel, M.[21] used RoboEarth for hospital service robots that serves a drink to a patient in a mock-up hospital room. And if the action recipes query fails, the action recipe is planned based on the knowledge in the local KnowRob. In addition, Li-Chee-Ming et al. [22] used the

RoboEarth Cloud Engine (RCE) to ofoad heavy computation and store data to secure computing environments in the cloud to complete the task of rapid mapping and tracking with small unmanned aerial systems.

3.2 RoboBrain

RoboBrain [23] project was founded by scholars from Cornell university and Stanford university in 2015. It aims to create a large-scale knowledge base that can be accessed by any device to perform tasks through multi-mode big data mining.Fig.2 shows the RoboBrain system architecture.It consists of four interconnected knowledge layers and supports various mechanisms for users and robots to interact with RoboBrain. Firstly, through the knowledge acquisition layer, RoboBrain gets access to new information from various sources that contain Internet Knowledge Base, RoboBrain Project Partners, and other sources. Knowledge parser layer convert the knowledge acquired from knowledge acquisition layer to a consistent format for the storage layer. Then, Knowledge storage layer is responsible for storing different representations of the data. Last, the machine learning plugins in the Knowledge inference layer along with other learning algorithms, that constitute the learning and inference framework, operate on the knowledge graph.

RoboBrain allows robots to learn and share knowledge representations from many different data sources and its knowledge representation method takes into account many forms, including symbols, natural language, haptic senses, robot trajectories, visual features and many others. It establishes connections with these knowledges from multiple external data sources, allowing the robot to perform different tasks by integrating reasoning based on multiple data forms.

On the one hand, RoboBrain can be used as-a-service that robots can complete some tasks like anticipating human activities [24], grounding of natural language sentences [25], path planning [26] and other aspects by accessing it. On the other hand, RoboBrain can also share knowledge within the projects and throughout the Internet to help robots complete many tasks more quickly. Ashutosh Saxena et al. [23] analyze and contrast the experimental results of robots planning trajectory tasks using no knowledge, a single knowledge base (OpenCyc), and RoboBrain and the experiment using RoboBrain have the best results.it shows that strong knowledge sharing ability can effectively support robots to complete tasks.

3.3 OpenEASE

OpenEASE project [27] are launched in 2015. Like RoboEarth, openEASE is also a web-based knowledge service providing robot and human activity data. openEASE contains three parts: a big-data database, an ontology and software tools for querying, visualizing, and analyzing the manipulation task episodes. The database stores

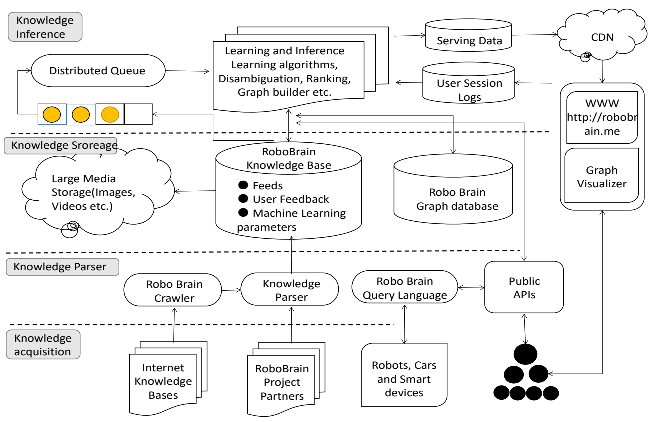

Fig 2. RoboBrain system architecture.

comprehensive data about episodes in which humans and robots perform complex manipulation tasks while the ontology is an encyclopedic knowledge base that provides a conceptual model of manipulation activities.

OpenEASE also receives a lot of attention in robotics domain. Asil Kaan Bozcuoglu et al. [28] used OpenEASE to share the information of describing the world model, the state of the agent and the problem that was being dealt with between researchers and robots to help robot avoid repeating planning on the same problem. Bozcuoglu et al.[29],using openEASE that equipped with ontologies about the kitchen domain as the cloud application, execution logs of three robots operating in two different kitchens, and semantic descriptions of both environments, supported two PR2 robots and a Fetch robot to successfully adapt each other's plan parameters and subsymbolic data to the experiments that they are conducting.

4. Contrast and Analysis

In this section, we will contrast and analyze the RoboEarth, RoboBrain and openEASE in terms of knowledge representation, knowledge update and knowledge query and reasoning in TABLE 2.

4.1 Knowledge Representation

The formal representation of knowledge affects data types in the knowledge graph. The stronger the representation ability of knowledge representation methods in the graph, the more types of knowledge it could represent. The representation language of RoboEarth[30]is realized as an extension of the KNOWROB ontology, which is also used for grounding the downloaded descriptions from the cloud knowledge base on the robot. In KNOWROB, knowledge is represented in Description Logic using the Web Ontology Language (OWL) [31] which distinguishes between classes, instances of these classes, and properties. In openEASE, like RoboEarth, knowledge (like, logged plan interpretation data, the environment model and object detections) are also represented in the Web Ontology Language OWL. However, in RoboBrain, knowledge is represented as a graph structure [23], which nodes in the graph can be any concept of the robot domain (like, gripping features, trajectory parameters, and visual data and so on) and edges in the graph represent the relationship between the nodes. This graphical representation also allows other partners to easily integrate the concepts they have learned into RoboBrain.

Table 2. Comparison of Three Knowledge Graph

Knowledge Graph Name	Knowledge Representation	Knowledge Update	Knowledge Query and Reasoning
RoboEarth	Web Ontology Language (OWL)	Semi-automatic	Rapyuta
RoboBrain	Graph structure	Automatic	Querying software tools
openEASE	OWL	Semi-automatic	Robot Query Library (RQL)

4.2 Knowledge Update

The way of knowledge updating affects the extension and correction of knowledge in knowledge graph. In RoboEarth, the Knowledge update mechanism is that data generated from the Internet or the robot itself was processed primarily by humans to abstract knowledge from the data and establish the relationship with the KnowRob,for example, for “Cappuccino is a kind of coffee” ,Cappuccino must be related to the category of coffee by manual processing. The openEASE's knowledge update mechanism like the RoboEarth. However, in RoboBrain, as RoboBrain has a knowledge processing system, it can automatically acquire, parse, store and reason knowledge from the data generated by the Internet, cooperative projects and the robot itself, so as to enter the knowledge base. In addition, Robobrain can achieve knowledge update by using its own learning algorithm learn new knowledge from existing knowledge, while RoboEarth and openEASE can't update the knowledge in this way.

4.3 Knowledge Query and Reasoning

The way of knowledge query and reasoning affects the ability of knowledge graph application. The stronger ability of query and reasoning knowledge graph has, the stronger the application ability will be under the same knowledge reserve. RoboEarth query and reasoning knowledge through its own search engine Rapyuta [18], which queries relevant information from the cloud knowledge base. OpenEASE complete knowledge query and reasoning mainly through a series of supporting query software tools. RoboBrain mainly carries out knowledge query through the Robot Query Library [23] (RQL) query language, which provides a rich set of retrieval functions and programming constructs to perform complex traversals on the RoboBrain graph.

5. Conclusion and Prospect

This paper mainly reviews the research of knowledge graph in robotics domain, introduces the existing knowledge graph, and compares and analyzes them in terms of knowledge representation, knowledge update and knowledge query and reasoning. In summary, although there has been a lot of research on the knowledge graph in robotics domain, there are still some problems: 1) Most of the research at this stage is given to the indoor environment. Indoor knowledge is relatively closed, and it is easier to construct knowledge graph. In the outdoor environment, how to model a large number of different kinds of knowledge in the open feld is a problem worth studying; 2) Even in an indoor environment, the robot may occur a variety of mistakes during the task. The main reasons are lack of implicit knowledge and limited reasoning ability. Humans have a lot of implicit knowledge that they know but can't represent it, which limits a robot's comprehensive understanding of its environment and tasks. How to abstract implicit knowledge is also an important research problem in the feld of knowledge engineering. Studying the knowledge graph of the robot task planning feld is of great significance to help the robot to think and act like a human being. With the unremitting efforts of relevant scholars, robots will one day be able to complete tasks accurately and quickly in accordance with human requirements.

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