Ontology Representation and Instantiation for Semantic Map Building by a Mobile Robot

Gi Hyun Lim[1], Chuho Yi[1], Il Hong Suh[2], Dong Wook Ko[3], and Seung Woo Hong[3]

[1] Department of Electronics and Computer Engineering, Hanyang University, Seoul, Korea 133–791
{hmetal,d1uck}@hanyang.ac.kr

[2] Department of Computer Science and Engineering, Hanyang University, Seoul, Korea 133–791
ihsuh@hanyang.ac.kr

[3] Department of Intelligent Robot Engineering, Hanyang University, Seoul, Korea 133–791
{pumpblack, swcoke01}@gmail.com

Abstract. To offer sustainable robotic services, service robots must accumulate knowledge by using recognition results and choose a action for services intelligently. Robust knowledge instantiation and update by using imperfect sensing data such as misidentification of perception is a main issue to implement semantic robot intelligence. In this paper, robust knowledge acquisition method is proposed to enable robots to detect falsity of object recognition for robust knowledge instantiation, where spatial reasoning, temporal reasoning, movable properties and data confidences are considered.

1 Introduction

The robotic service is up-and-coming application to receive attention in various research fields of robotics [1]. Various robots is expected to be one of the most important issues to occur in the residential space to offer services. However, service environments are said to be partially observable and uncertain with respect to service robots. Even though a robot may often fail to perform service tasks, given service tasks should be sustained to satisfy the user's requests.

Performing service tasks successfully, such as taking orders semantically from a person, moving to various type of residential space, and finding an object which meets person's needs, autonomous robots are required to have substantial knowledge [2]. Service robots are designed to complete service tasks semi or fully automatically in a service environment [3]. Service robots will need to understand semantic relationships of objects, spaces and contexts in order to assist humans in their everyday lives, and then the robot must carry out its service tasks with its primitive behaviors. For this, a robot needs many kinds of data from low level sensor data to high level symbolic data. High level perceptual tasks such as context awareness, object recognition and navigation are essential for intelligent robots. Also a robot must combine its atomic behaviors.

S. Lee et al. (Eds.): Intelligent Autonomous Systems 12, AISC 193, pp. 387–395.
springerlink.com

Robots must interact semantically with humans as well as understand user intentions to enable socially collaboration [4], [5]. When interacting with humans, it will be needed for robots to be able to understand semantic and contextual information regarding objects. For example, if a robot needs to find a cup from a table that contains other objects such as kettle and the cup are occluded by the kettle, some additional information can give more chances to find the cup. This might take the form of a spatial relationship, such as “kettle is left of the cup.” If a service robot recognized the kettle, the cup might be right of the kettle. Semantic knowledge also evaluates candidate objects based on spatial semantic properties such as the door handle should be found in one of a few areas once the door is detected [6]. Semantic navigation is another example to show the validity of semantic robot knowledge. Humans do not necessarily use accurate quantitative information to perceive space where one is located or to move to another place. Instead, they remember a few landmarks that constitute the space such as a specific structure or distinct objects, they restructure the knowledge based on a spatial contexts and then utilize the knowledge again [7]. Moreover, humans interact others with symbolic information, which are not just simple data but semantic knowledge which is represented by network or graph which represents semantic relations between concepts. Through the relationships, humans can acquire additional information beyond given information in interaction.

Service tasks always creates some social situation which is framed to pay attention to restricted and related domains [8]. Moreover, service tasks have successive interrelation of number of subtasks as service flow. From the service provider’s vies, there are obstacles to look for recurrent sequence of subtasks from many various kinds of service tasks. Service tasks tend to be repeating pattern of task sequence. Each service captures specific tasks to be carried out (forming a very flexible sort of subtasks) and their respective precondition and post conditions. These service tasks can be modeled with each subtasks being further linked to a rich description as a scenario. However, a situation cannot be understood using sensory information such as object recognition, robot localization and human recognition, it requires contextual interpretation of the scene using not only robot-embodied sensors but also exogenous sensors [9]. Understanding situation provides clues for the appropriate and efficient action selection for sustainable service tasks.

In knowledge management literature it has often been pointed out that the relation between knowledge, information and data is important, and often misunderstood. It has also been argued that this misunderstanding leads to problems in information system design [10]. Data has commonly been seen as simple facts that can be structured to become information. Information, in turn, becomes knowledge when it is interpreted, put into context, or when meaning is added to it. There are several variations of this widely adopted theme. The common idea is that data is something less than information, and information is less than knowledge. Moreover, it is assumed that we first need to have data before information can be created, and only when we have information, knowledge can emerge.

2 Robot-Centered Ontology

OWL ontology [11] is used for representation of robot knowledge. Here, ontology that expresses semantics with concept hierarchy and their relationships is mainly formulated in the knowledge representation formalism and is necessary to enable the assimilation of information from diverse sources [12]. Semantics for robot knowledge refers to five knowledge classes including feature, object, space, context, and action, and how these classes are related to each other. Also, there is production system with two types of rules, uni-directional rules and bi-directional rules. Robot knowledge can be integrated from the different sources of knowledge including encyclopedic knowledge designed manually from expert knowledge or from Internet, action knowledge derived from observations of human motion, and robot knowledge about self-model and its surrounding world model [13], [14]. These robot knowledge should reflect actual environments as practice knowledge [15]. A robot perceives objects with its own sensors, models a world where it exists, plans some sequences of tasks, performs tasks with its own behaviors, and then perceives again [2], [16]. To comply with such cognitive capabilities, robot-centered ontology is designed to be composed of knowledge boards (KBoards) and rules, where KBoards is composed of five classes of knowledge (KClass): feature, object, space, action, and context as shown in Fig. 1. Here, context is a characteristic environmental situation around robots which

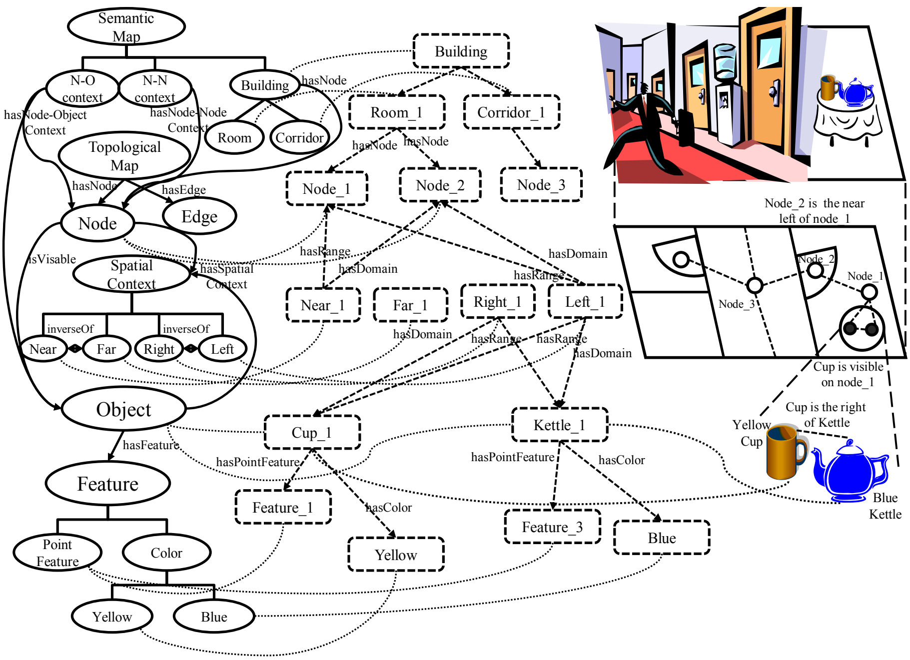


Fig. 1. An example of robot-centered ontology including schematic knowledge, an experimental environment and their knowledge instances

can provide clues of the proper action selection mechanism for a robot. A world model represents a robot's internal states reflecting perceived environments and consists of context, object, and space (COS) classes.

Each knowledge class has three knowledge levels (KLevel) such as high level, middle level and low level knowledge. Low level knowledge of feature class and action class (numerical descriptor, and behavior) are robot-specific knowledge for its own sensory motor capabilities, and COS classes of low-level knowledge consists of spatial context, part object, and metric map. Middle level knowledge visual feature, object, topological map, temporal context, and task are common robot knowledge at the abstract level and hide details of a particular set of low-level sensor data and motor commands. High-level knowledge of compound object, semantic map, situation, and service classes are common knowledge for robots as well as humans. Each knowledge level has three ontology layers (OLayer), such as the meta ontology layer for generic knowledge, ontology schema layer for domain knowledge, and ontology instance layer for knowledge instance. Meta ontology can be a template of the ontology schema layer, and the ontology schema layer is instantiated to instance layer.

The feature KClass has three KLevels. The low level knowledge of feature is the numerical descriptor level that includes a set of numerical descriptors of image processing algorithms, which are produced by robots' own sensors and data processing algorithms. The middle level knowledge of feature is the visual feature level that includes visual features, which are extracted by numerical descriptors in the low level. The high level knowledge of feature is the visual concept level that is grounded with visual features in feature knowledge class and object feature in the object knowledge class or metric map in the space knowledge class. The following is a DL representation of *blue*.

$$Blue := ColorFeature \wedge \exists hasColor.HueValue$$
$$\wedge \exists hasAlgorithm.extractColor$$

Each COS class consists of three knowledge levels for the representation of the robot world model. Low levels such as an object part, metric map, and spatial context are used for matching with perceptual feature. Middle levels include object, topological map, and temporal context that contain its name and functionality. High levels such as situation, compound object, and semantic map are abstract level, which easily describe relationships between other knowledge classes. In the Description Logic (DL) example below, a cup has a *colorFeature*.

$$Cup := Object \wedge \exists isObject.Container$$
$$\wedge \exists hasColor.ColorFeature$$

Context is not a list of objects and their locations, but implies abstract and characteristic situations that can be represented by relationships between objects and object properties. The low level knowledge of context denotes the spatial context level that has a spatial concept such as *on*, *in*, *left* and *right*, which are inferred by using the object level and space level instances in the model class.

The middle level knowledge of context represents the temporal context level that has temporal concepts defined by Allen [17]. Finally, the high level knowledge of context is the high-level context. The following is a DL representation of *left*.

$$Left := SpatialContext \wedge \forall hasSubjective.Object$$
$$\wedge \forall hasObjective.Object$$

3 Robust Knowledge Acqusition

Successfully accomplishing everyday service tasks requires autonomous robots to have substantial knowledge with their own sensors. These robot knowledge should be instantiated and updated by using imperfect perception data, such as misidentification of object recognition [15]. The feature knowledge of visual observation can be instantiated as ontology, which ensures that only sound and complete data are asserted and propagated with ontology inference. Noisy sensor data, such as false positives and false negatives, should be filtered for robust robot knowledge acquisition. For instance, a misidentified object may make erroneous spatial relationships. Moreover, inferred erroneous facts will result in false consequences for reasoning; this generates a vicious cycle, and errors are difficult to correct, even with additional true negative results.

To address the failure of knowledge instantiation, a reasoning mechanism with knowledge acquisition rules are proposed to instantiate and update knowledge by estimating confidence of the perception results. There are four properties to build robust knowledge acquisition rules: temporal reasoning to check the validity of relationships between time intervals, statistical reasoning to determine the confidence level of the perception results, ontological reasoning to check if a perceived feature satisfies object properties or space properties.

3.1 Likelihood Confidence Interval (LCI)

Our way to estimate the confidence of likelihood for perception is to extend some form to formalize the *common sense law of inertia*, whereby an event is assumed to persist unless there is reason to believe otherwise, and to be perceived perfected without recognition failure or misidentification [18]. The extend form considers the uncertainty of perception on the basis of the *confidence law of inertia*, whereby knowledge instance is assumed to persist unless there is confidence to believe otherwise as shown in Fig. 2.

Confidence of recognition is determined by an likelihood interval-counter (γ) from the measurement likelihood for each object recognition result. If the measurement likelihood of object `A` is x_A, then (1-x_A) is the probability that the recognition data for `A` can be false. From that, $(1\text{-}x_A)^{\gamma_A}$ can be calculated to define probability when the values of γ_A consecutive data are all false. If the result of $(1\text{-}x_A)^{\gamma_A}$ is less than 5% (0.05), then it can be said that the data have been obtained within a confidence interval (1.96σ, $P = 0.05$) of the 95% confidence level. For example, if the measurement likelihood of object `A` is 80%successively,

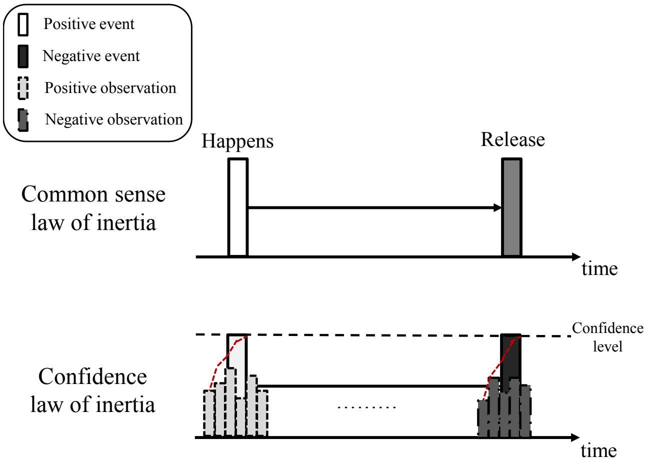


Fig. 2. The *confidence law of inertia* as an extended form of the *common sense law of inertia*

the recognition failure rate of object `A` might be 20% (0.2). The result rate of recognition failure of two consecutive observations is 4% (0.04) and 4% is beyond the 95% confidence interval($P = 0.05$), so γ of object `A` is 2. At that time, the instance of object `A` is created and vice versa. The likelihood interval-counter using β likelihood distribution can be represented as follows:

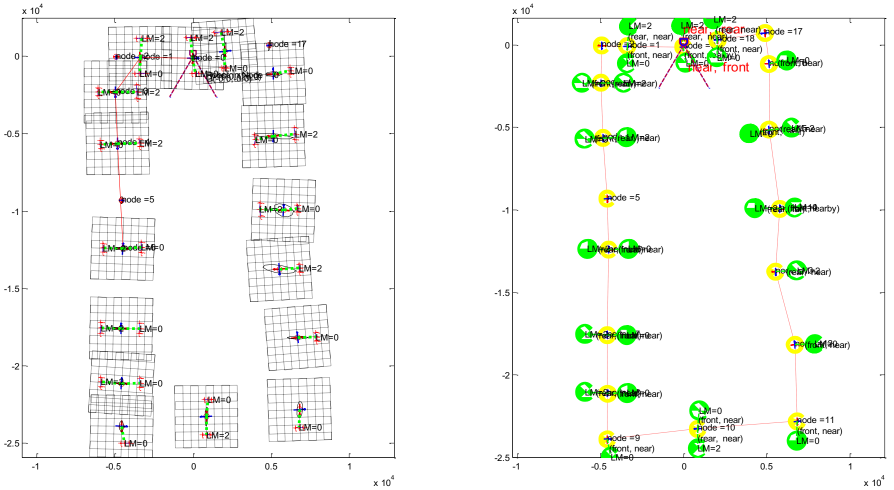
$$\gamma_\beta = \min\{\gamma \in I | \prod_{i=1}^{n} (1 - x_{\mathrm{obj}}) \le P\}, \tag{1}$$

where $P = 0.05 = 1 - 95\%$ confidence level.

3.2 Temporal and Statistical Reasoning

According to continuous observations from robot movement, object instances might be created or deleted whether certain number of consecutive observation likelihoods exceed the likelihood confidence interval. Time intervals of object instances which exist or not is determined by the durations between the changes of confidence. Temporal relations between intervals are inferred using temporal reasoning. The temporal relation was first proposed by Allen [17] and represents temporal relations using before, after, meets, met-by, overlaps, overlapped-by, and so on. If two intervals meet or overlap, then they are merged into one interval. The merged interval begins at the start point of the former and ends at the end point of the latter. Temporal confidence reasoning (TCR) is based on the assumption that recognized objects cannot go away and come back within a single time interval.

When an object instance of `A` is registered, if other objects are also considered to be true positive instances and to have a temporal relation of *overlapped* with



(a) Metric-Topology Map

(b) Semantic-Topology Map

Fig. 3. An example of space knowledge instance

object `A`, then spatial relations among the objects can be inferred. Then, the spatial relation between them can be reasoned and set using spatial reasoning. All object instances and their spatial relations can be registered in the instance database.

3.3 Space Knowledge Class

Figure 3 show an experimental result of space knowledge class instance including metric-topology map and semantic-topology map. For this experiment, a pioneer 3 AT robot carrying a single consumer-grade camera was driven around the fourth floor of IT&BT building in Hanyang university. The TCR rules are applied to check the validity of the relationships between intervals and statistical reasoning to determine the LCI of visual perception from commercial vision system. As a result, there are 19 nodes and 27 objects.

4 Concluding Remarks

In this paper, a robust knowledge acquisition method that makes imperfect information of epistemic results toward robust and consistent knowledge is proposed as one of knowledge management methods. The method uses temporal reasoning to check the validity of relationships between intervals and statistical reasoning to determine the confidence interval (CI) of object recognition. The experimental results indicate that false positives in recognition results were corrected. The proposed method had difficulty registering some objects with a recognition rate less than 52.9% ($\gamma = 4$). In spite of this, the method can determine misidentification well, and thus dependable semantic knowledge for service robots can be instantiated.

Acknowledgement. This work was supported for the Intelligent Robotics Development Program, one of the 21st Century Frontier R&D Programs funded by the Korea Ministry of Knowledge Economy.

References

[1] Stefanov, D., Bien, Z., Bang, W.: The smart house for older persons and persons with physical disabilities: structure, technology arrangements, and perspectives. IEEE Transactions on Neural Systems and Rehabilitation Engineering 12(2), 228–250 (2004)
[2] Lim, G.H., Suh, I.H., Suh, H.: Ontology-based unified robot knowledge for service robots in indoor environments. IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans 41(3), 492–509 (2011)
[3] Kawamura, K., Pack, R., Iskarous, M.: Design philosophy for service robots. In: IEEE International Conference on Systems, Man and Cybernetics, Intelligent Systems for the 21st Century, vol. 4 (1995)
[4] Severinson-Eklundh, K., Green, A., Hüttenrauch, H.: Social and collaborative aspects of interaction with a service robot. Robotics and Autonomous Systems 42(3-4), 223–234 (2003)
[5] Choi, C., Huckaby, J., Rogers III, J., Trevor, A., Case, J.P., Christensen, H.I.: Towards Semantic Perception Towards Semantic Perception for Mobile Manipulation. In: International Conference on Intelligent Robots and Systems (IROS) 2009 Workshop on Semantic Perception for Mobile Manipulation, Citeseer (2009)
[6] Klingbeil, E., Saxena, A., Ng, A.: Learning to open new doors. In: Robotics Science and Systems (RSS) Workshop on Robot Manipulation, Citeseer (2008)
[7] Yi, C., Suh, I.H., Lim, G.H., Jeong, S., Choi, B.-U.: Cognitive Representation and Bayeisan Model of Spatial Object Contexts for Robot Localization. In: Köppen, M., Kasabov, N., Coghill, G. (eds.) ICONIP 2008, Part I. LNCS, vol. 5506, pp. 747–754. Springer, Heidelberg (2009)
[8] Wetzel, I., Klischewski, R.: Serviceflow Beyond Workflow? Concepts and Architectures for Supporting Inter-organizational Service Processes. In: Pidduck, A.B., Mylopoulos, J., Woo, C.C., Ozsu, M.T. (eds.) CAiSE 2002. LNCS, vol. 2348, pp. 500–515. Springer, Heidelberg (2002)
[9] Lim, G.H., Chung, J.L., Ryu, G.G., Kim, J.B., Lee, S.H., Lee, S., Suh, I.H., Choi, J.H., Park, Y.T.: Ontological Representation of Vision-based 3D Spatio-Temporal Context for Mobile Robot Applications. Artificial Life and Robotics, AROB (2007)
[10] Tuomi, I.: Data is more than knowledge: implications of the reversed knowledge-hierarchy for knowledge management and organizational memory. In: Proceedings of the 32nd Annual Hawaii International Conference on System Sciences, HICSS-32 (1999)
[11] Smith, M., Welty, C., McGuinness, D.: Owl web ontology language guide. W3C recommendation, vol. 10 (2004)
[12] Doerr, M., Hunter, J., Lagoze, C.: Towards a core ontology for information integration. Journal of Digital information 4(1) (2011)

[13] Tenorth, M., Beetz, M.: Knowrob - knowledge processing for autonomous personal robots. In: IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2009, pp. 4261–4266. IEEE (2009)
[14] Waibel, M., Beetz, M., Civera, J., D'Andrea, R., Elfring, J., Galvez-Lopez, D., Haussermann, K., Janssen, R., Montiel, J., Perzylo, A., Schiessle, B., Tenorth, M., Zweigle, O., van de Molengraft, R.: Roboearth. IEEE Robotics Automation Magazine 18(2), 69–82 (2011)
[15] Lim, G.H., Suh, I.H.: Robust robot knowledge instantiation for intelligent service robots. Intelligent Service Robotics, 115–123 (2010)
[16] Suh, I.H., Lim, G.H., Hwang, W., Suh, H., Choi, J.H., Park, Y.T.: Ontology-based multi-layered robot knowledge framework (OMRKF) for robot intelligence. In: IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2007, pp. 429–436 (2007)
[17] Allen, J.: Planning as temporal reasoning. In: Proceedings of the Second International Conference on Principles of Knowledge Representation and Reasoning, vol. 13, pp. 25–45. Citeseer (1991)
[18] Shanahan, M.: The event calculus explained. Artificial Intelligence Today, 409–430 (1999)