Modelling Spatial Understanding: Using Knowledge Representation to Enable Spatial Awareness in a Robotics Platform

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***Abstract*—Robotics in the 21st century will progress from scripted interactions with the physical world, where human programming input is the bottleneck in the robot's ability to sense, think and act, to a point where the robotic system is able to autonomously generate adaptive representations of its surroundings, and further, to implement decisions regarding this environment. A key factor in this development will be the ability of the robotic platform to understand its physical space. In this paper, we describe a rationale and framework for developing spatial understanding in a robotics platform, using knowledge representation in the form of a hybrid spatial-ontological model of the physical world. While such a system may be implemented with classical ontologies, we discuss the advantages of non-hierarchical modes of knowledge representation, including a conceptual link between information processing ontologies and contemporary cognitive models.**

Keywords-Human Robot Interaction; Autonomous Navigation; Knowledge Representation; Spatial Ontology

I. INTRODUCTION

The process of transitioning away from hard-coded robotics applications, which carry out highly pre-determined actions such as the traditional manufacturing robot, is already well underway. With notions such as cloud robotics [1] entering the *zeitgeist*, and highly publicized events such as the DARPA Robotics Challenge (Dec 19-21 2013, Miami FL) bringing public attention to these advances, it is foreseeable that robots will be entering the mainstream realm of human activity – more than in fringe applications (robotic vacuum cleaner; children's toys), but in key areas such as caring for the aged [2], operating vehicles [3], disaster management [4], and undertaking autonomous scientific investigation [5].

The hurdles that must be overcome in reaching these goals, however, are neither few nor small. This can be plainly seen, for example in the aforementioned 2013 Robotics Challenge, in which simple spatial tasks that are routine for a human being (open a door, climb a ladder) are still critically difficult for even the most advanced and highly funded robotics projects. While the state-of-the-art is impressive, it is evident that physical robotics hardware is far in advance of the control systems that are in place to guide the robot. The challenge is, thus, to develop systems whereby a robot can perceive a physical space and understand its position in that space, the components that exist within the space, and how it can or *should* interact with these components in order to achieve implicit or explicit goals. This is furthermore impacted by the requirement that robotic systems be able operate in outdoor environments where distributed connections may not be available; however, describing the development of long-range data networks for robotic communication is beyond the scope of this paper.

While there are a number of ways that the problem of providing a robot with a spatial understanding can be approached (e.g., neuro-fuzzy reasoning [6], dynamic spatial relations via natural language [7]) it is our proposition that leveraging the current advancements in knowledge representation via ontologies [8][9], in combination with an understanding of human spatial-cognitive processing [10][11], and enabled by real-time scene modeling [12] will provide a powerful and accessible methodology for enabling spatial understanding and interaction in a mobile robotics platform. As argued by Sennersten et al. [13], the advantage of using cloud-based repositories of perceptual data annotated with ontology and metadata information is to take advantage of humanly-tagged examples of sense data (e.g., images) to overcome the symbol grounding problem. Symbol grounding refers to the need for symbolic structures to have valid associations with the things in the world that they refer to. Achieving symbol grounding is an ongoing challenge for robotics and other intelligent systems (see, for example, Brooks, 1999 [14]). Using cloud-based annotations attached to sensory exemplars takes advantage of the human ability to ground symbols, obviating the need for robots to achieve this independently of human symbolic expressions.

This paper provides a conceptual overview of how spatial understanding can be developed in a robotics platform. We discuss traditional knowledge representation (classical information processing ontologies), describe the development and use of "cognitive" ontologies, and how this may be transitioned into the development of a physical-spatial ontology, including a possible system of comprehension for spatial position. Finally, we discuss the notion that truly non-hierarchical systems such as complex chemical structure, and such as the human cortex, may require the development of systems of knowledge representation that transcend the structural limits of today's systems.

II. KNOWLEDGE REPRESENTATION

The development of specific nomological hierarchies for concept representation is currently taking place across many fields of academic endeavor (e.g., genetics, medicine, neuroscience, biology, chemistry, physics). Under the guise of the philosophical concept of an *Ontology*, such applications seek to outline the knowledge which exists within a domain at three levels of representation: Classes, Properties, and Relationships. These nomological hierarchies provide a way of describing the precise relationship that terms in a given domain have to one another. As an information processing construct, the definition of an ontology is refined as an "explicit formal specification of the terms in the domain and relations among them", or more concisely, "a specification of a conceptualization" [15].

A system that operates with such knowledge representation within its core functionality may be considered to be 'knowledge-based'. A knowledge-based system is a computer program that stores knowledge about a given domain (also known as an "expert system", when the knowledge is considered to be from a highly specialized domain). However, an ontology does not intrinsically represent the kinds of truth-functional mappings or procedures captured by rules in more complete knowledge bases. Hence, an ontology provides classifications and the ability to infer associations via subclass/superclass relationships. More complex forms of reasoning required for most forms of useful cognitive task performance require task-oriented rules. As such, the domain knowledge in a knowledge base includes ontology representations, while most task-oriented reasoning is achieved by the use of rules that refer to ontological constructs in the form of domains within rule tuples.

The system attempts to mimic the reasoning of a human specialist by conducting reasoning across rules and in reference to a database of atomic facts. Matching sense data against metadata/ontology-annotated sense data on the web can provide a method of automatically mapping a current sensed situation to the annotations of past situations stored in the cloud. This allows the system to retrieve representations of the situation in an atomic form, as statements formulated using the symbolic forms of annotations which are retrieved by matching against associated sense data. Ontologies hold the potential, therefore, to provide the constructs for symbolic atomic fact expressions that rule-sets can then process for automated cognitive task performance.

A. Cognitive Ontologies

An increasing number of ontologies are available on-line that can potentially support this symbolic structure generation process. Knowledge representation via ontological structure has been applied to the field of cognitive science, both in relation to terminology used within the domain (e.g., DOLCE - Descriptive Ontology for Linguistic and Cognitive Engineering [16][17]) and for concepts relevant to empirical testing paradigms (e.g., CogPo [18]). Indeed, several cognitive ontologies have been developed in the recent years, including DOLCE, WordNet [19], CYC [20], and CogPo.

WordNet is an online lexical knowledgebase system, whose design is inspired by current psycholinguistic theories of human lexical memory, where each cognitive artifact can be semantically classified into English nouns, verbs, and adjectives, with different meanings and relationships in real-world scenarios. DOLCE is developed by Nicola Guarino and his associates at the Laboratory for Applied Ontology (LOA) [21]. It captures the ontological categories underlying natural language and human common sense. DOLCE, however, does not commit to a particularly abstract level of concepts that relate to the world (like imaginary thoughts); rather, the categories it introduces are thought of as cognitive artifacts, which are ultimately dependent on human perception, cultural imprints and social conventions.

The Cyc project goal is to build a larger common-sense background knowledgebase which is intended to support unforseen future knowledge representation and reasoning tasks. The Cyc knowledgebase contains 2.2 million assertions (fact and rules) describing more than 250,000 terms, including nearly 15,000 predicates.

Finally, the Cognitive Paradigm Ontology (CogPo) is developed based on two well-known databases, namely, the Functional Imaging Biomedical Informatics Research Network (FBIRN) Human Imaging Data base [22] and the BrainMap database [23]. The CogPo Ontology has categorized each paradigm in terms of (1) the stimulus presented to the subjects, (2) the requested instructions, and (3) the returned response. All paradigms are essentially comprised of these three orthogonal components, and formalizing an ontology around them is a clear and direct approach to describing paradigms. This well-formed standard ontology guides cognitive experiments in formalizing the cognitive knowledge.

While these ontologies are of great value to the community of researchers, and while the knowledge-based mapping of concepts within particular domains may enable robotic systems to rapidly access the linguistic identity of physical objects and their relations within the domain, they do not provide a means whereby the robot may become spatially aware. To achieve this goal, we will need to provide the robot with the ability to identify the spatial characteristics particular to an identified object, and the

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physical relations between these objects and the surrounding environment. A robot requires an internal representation of three-dimensional space. It could access two dimensional images on the web, by content-matching those images with contents of its own visual system. The matching process, and especially the ongoing three dimensional interpretation of the images, could be greatly aided if the ontology/metadata associated with images includes representation of the three dimensional context of image capture. The "ontological" schema of knowledge representation for images may provide this means if it is extended to include three dimensional spatial annotations.

III. REPRESENTING RELATIONSHIPS IN THREE DIMENSIONS: SPATIAL ONTOLOGIES

We propose here that this same methodology for specifying semantic relationships between concepts (the ontological structure of knowledge representation, i.e., Classes, Properties, and Relationships) may also be useful in specifying spatial relationships between physical objects. While a traditional ontology will hierarchically represent a concept and its relation to other concepts in a domain, a spatial ontology (e.g., Figure 1) will represent an object, (class), its spatial properties including a detailed 3d representation in a language such as the X3D XML-based file format, and its positional relation (x,y,z) to other objects existing within the scene by using the datatype properties.

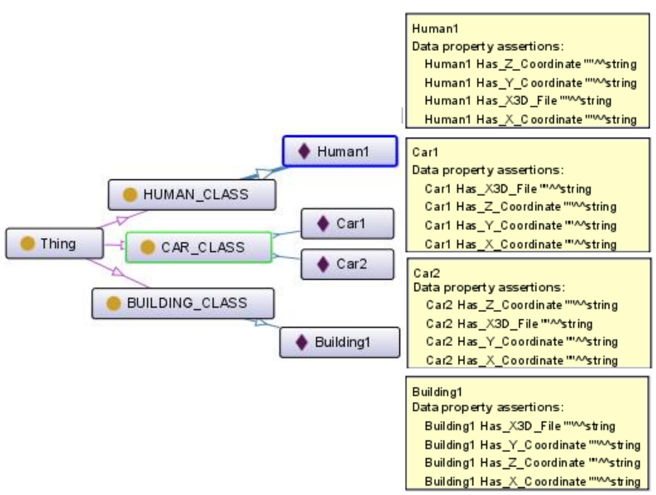

Figure 1. Example of a simple spatial ontology
(Note that the relations between objects are represented via "Data Properties" here.)

An entity (the "*individual*") in a prototypical ontology is comparable to an entity in a spatial ontology, being an object in the physical world. *Class* indicates the category into which the individual falls, for example "person", or "boat". *Attributes* traditionally describe the *individual* – features, properties, or characteristics of the object: a person has arms; a boat has a hull. In a spatial ontology this information will be appended with configural information regarding the object, for example the parent-child node relationship of a human body, including torso, appendages, etc. The *relation* between individuals is where the power of the traditional ontology arises, by specifying the precise ways in which different individuals relate to one another (e.g., "a catamaran is a subclass of boat"). Once again, in a spatial ontology the *relation* will be a precise indicator (a reference, or an 'object index') of the relative positionality of items in the physical space, as described in the following section. By thus, leveraging the existing functionality of ontological representation, augmented with relevant and necessary spatial referencing information, we may develop a knowledge-based system that enables a level of spatial awareness in a robotic platform.

A. A system of comprehension for spatial position

Following the above discussion about relationships in 3D space, we look into how coordinate systems can be synchronized. The physical scale requirement that a robot needs to have can be measured by the accuracy the robot needs to operate in via its navigation system. An autonomous robot must be able to determine its position in order to be able to navigate and interact with its environment correctly (e.g., Dixon and Henlich, 1997 [25]). When the *Class* of "robot" navigates from A to B it is a basic motion, which is similar to the movement of an in-game character via a default keyboard set-up where the key "W" moves the character forward, turning left using key "A", turning right using key "D" and go backwards using key "Z". The 3D digital world uses the X, Y, Z coordinate system called the Cartesian Coordinate Method (CCM) and is expressed in meters (m). To measure distance between two spherical points; X^1, Y^1, Z^1 and X^2, Y^2, Z^2 we take the Euclidean distance using a Cartesian version of Pythagoras' Theorem (1). The distance is the sum of their individual point differences in square.

$$\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \tag{1}$$

To determine a position in the physical world and navigate the robot in map-referenced terms to a desired destination point from A to B, Dixon and Henlich use what they call 1) *Global Navigation*. The positioning accuracy with a standard consumer Geographical Positioning System (GPS) is accurate within a range of 8 feet which is approximately 284 centimeters. This does not give high fidelity position accuracy. As such, when the robot has to operate in a typical indoor manufacturing environment, it needs detailed position support in order to create 3D reference points within the space. What Dixon and Henlich call 2) *Local Navigation*, is to determine one's own position relative to the objects (stationary or moving) in the environment, and to interact with them correctly. If we think of Human Robot Interaction (HRI) and the robot arm and its gripper(s) (hand/s), the gripper(s) must via eye(s) be able to recognize the object it will manipulate and how it shall be manipulated. The spatial centre points for individual objects are of importance, as well as group of objects and the robot's own centre point in relation to actual manipulation centre point for gripper. From a spatial ontology point of view, the centre points have to be able to change dynamically depending on interaction purpose.

For example, the Puma robot arm series has three different arms with slightly different sophistication and these are Puma 200, Puma 500, and the Puma 700 Series. These robot arms execute 3) *Personal Navigation* [D&H] which make the arm aware of the positioning of the various parts, its own positioning, and also in relation to each other and in handling objects. The Puma 200 Series has been used for absolute positioning accuracy for CT guided stereotactic brain surgery [26]. The Puma 200 robot has a relative accuracy of 0.05 mm. There are already 3D Spatial Vision Systems for robots out on the market which are driven via several cameras. This creates a local world solution for 3D vision robot guidance where the software first make the user calibrate the cameras and the robot and then loading standard CAD files of parts the system shall track.

IV. BEYOND ONTOLOGIES – COMPLEX RELATIONSHIPS, AND ALTERNATIVES TO HEIRARCHICAL DATA REPRESENTATION

As we move from relatively canonical data sets for which the information processing ontology was designed (i.e., semantic relations within a particular knowledge base) to more complex relationships (such as ad-hoc physical relations) in which the hierarchical order is not nearly so explicit, or potentially non-existent, will the classical ontology suffice? Or alternately, will something more adaptive need to take its place? Because relationships in the physical world are multifaceted and multidirectional, it is useful to have a schema which can represent this interconnectedness. The key strength of an ontology is that it provides a concrete nomological environment from which to operate within the chosen domain. Table 1 summarizes the traditional information processing ontology.

TABLE 1: TRADITIONAL ONTOLOGY CHARACTERISTICS

- allows a common understanding of the structure of information
- enables reuse of domain knowledge
- makes domain assumptions explicit
- separates domain knowledge from operational knowledge
- defines a common vocabulary for researchers
- provides machine readable definitions of basic concepts and the relationships among them

However, there are instances (albeit few as of this writing) in which it is being recognized that the intrinsic limitations of the "ontology" such it is commonly understood in 2014, (e.g., OWL-based [Web Ontology Language]) are sufficient as to demand a modification whereby the innate complexities of a real-world phenomenon may be modeled. That is: complex, potentially non-hierarchical relationships.

For example, it has been noted in the field of chemical molecular informatics that while ontologies are able to represent tree-like structures, they are unable to represent cyclical or polycyclical structures [27]. Similarly, the difficulty in building classifications of nano-particles has led some researchers to begin to look into taxonomies based on "physical / chemical / clinical / toxic / spatial" characteristics of an object, supplemented by structural information, in order to account for shapes, forms and volumes [28]. Other examples of representing complex structural relations which stretch the boundaries of ontological representation include using Description Graph Logic Programs (DGLP) to represent objects with arbitrarily connected parts [29], and a hybrid formalism whereby the authors propose a "combination of monadic second order logic and ordinary OWL", where the two representations are bridged using a "heterogeneous logical connection framework" [30].

It is evident that the potential applications of a formalism such as the ontological method of information representation far outreach the initial conceptualizations of the language. While it may be possible to model 3 dimensional spatial information within the constraints of a hierarchical ontology, it is also to be considered that this notion, as well as applications such as those described above, may require the development of progressive, flexible alternatives, which capture the strengths of the ontology (i.e., the points from Table 1), while managing to represent arbitrary or non-hierarchical relationships.

A. Cognitive Models and Ontologies

One information system where a non-hierarchical organization may be necessary, when attempting to map the internal structural relations, is the human brain. For more than half a century, researchers across many fields (e.g., Cognitive Psychology, Neuroscience, Cognitive Science) have been using models to posit and test hypothetical interpretations of how the human brain is structured. These range from the very simple (e.g., Baddely's working memory model, [31]) to complex neurological models (e.g., [32]), though no current model has even begun to approach the actual complexity of the human brain. On a neuronal level, and certainly even on a functional level such as between brain regions, this is a non-hierarchical system.

It is remarkable that at a superficial level, the development of ontologies draws a strong parallel with some theoretical interpretations of how the human cognitive system might be structured (see Table 2). This relation is further discussed in Sennersten et al. [13].

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TABLE 2: COMPARISON OF CLASSIC ONTOLOGY, OAR, AND ACT-R MODELS

OAR Model	Ontology Components	ACT-R ACT-R/E
Object(s) Attribute(s) Relation(s)	Class Properties Relationship(s)	ChunkType Chunk Slot(s) Function(s)

In OAR (Object, Attribute, Relation) Wong [10] develops a model which most certainly shares conceptual roots with ontological knowledge representation. Likewise, parallels may be drawn with Anderson's ACT-R model [11] and Trafton's "embodied" version [32] ACT-R/E. In each model, *Objects* in the real world possess characteristics (i.e., *attributes*, or *properties*) and also *relations* with one another. If we can augment these heretofore largely semantic components with a functional representation of three dimensional space (e.g., at the 3 levels *Global*, *Local*, and *Personal*), we may have the fundaments of a system of Spatial Understanding for a robotic platform.

V. SUMMARY

One of the few certainties regarding the immediate future is that robotic control technology will advance from systems which are coded for specific applications, to systems which are designed with an innate adaptability to unexpected environmental situations. This will require new methods of providing on-the-fly relational information to the robot, in order for it to gain an understanding of both its spatial position, and the position of other objects in the vicinity, their characteristics, and the ways in which it can relate to them. A reworking of the traditional OWL-based ontology, with an eye for 3-dimensional spatial relations on 1) Global, 2) Local, and 3) Personal levels of specificity may be sufficient to this end.

It is also noted that as data sets become more complex, and especially as we begin to consider that most complex of biological control systems, the human cognitive system, it may very well become necessary to develop hybrid ontological-type systems of knowledge representation which 1) encompass the full realm of advantages provided by the use of specific nomologial hierarchies, and 2) enable the encoding of arbitrary or non-hierarchical relationships. The development knowledge-based systems that can account for abstract, non-hierarchical relations could potentially facilitate the next generation of spatially aware robotics applications.

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