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Knowledge Engineering for Real Time Intelligent Control

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Abstract. The key to real-time intelligent control lies in the knowledge models that the system contains. Three main classes of knowledge are identified: parametric, geometric/iconic, and symbolic. Each of these classes provides unique perspectives and advantages for the planning of behaviors by the intelligent system.

1. Introduction

The concept of intelligence in control applies to a variety of approaches to extending classical control theory that include learning, non-linear control, model-based control, and, in general, control of complex systems that will "do the right thing" when confronted with unexpected or unplanned situations [1]. "Intelligent" systems have some knowledge of the system to be controlled or that they use some model of the system in calculating control outputs. The American Heritage Dictionary [10] defines intelligence as "the capacity to acquire and apply knowledge."

Creating, capturing, and using the knowledge of the system to be controlled is one branch of what is known as knowledge engineering. The real-time aspects of control make

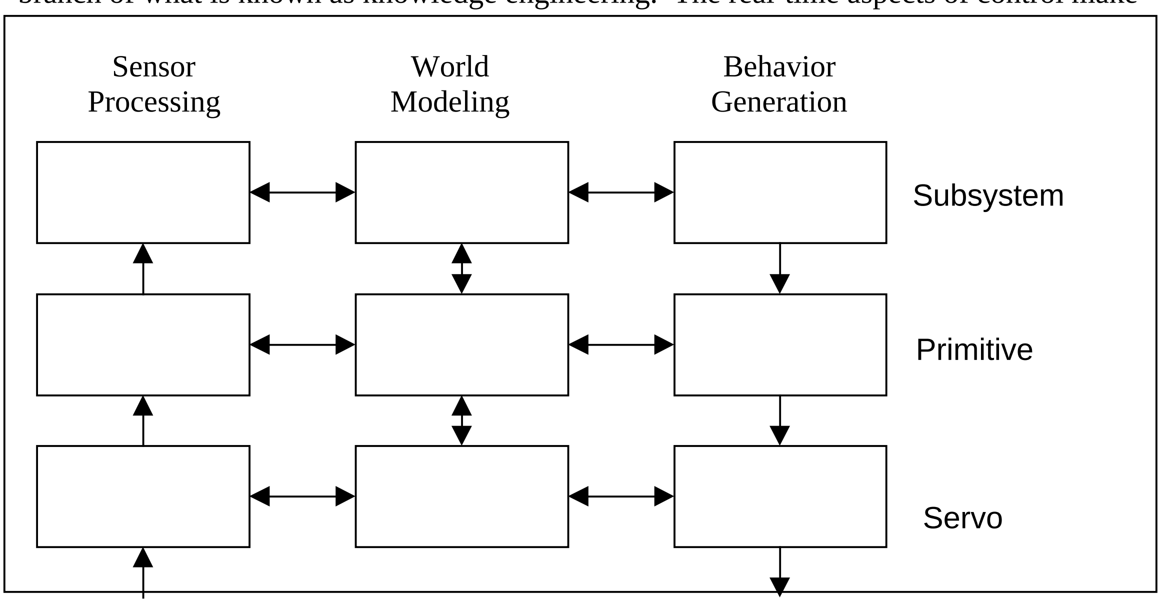

Figure 1: General Framework for an Intelligent Control System

this problem domain uniquely different than other knowledge engineering problems. Intelligent control requires several different types of "knowledge," and the highest levels of control require the same symbolic knowledge as ontologies, expert systems, or logic systems.

2. Classes of Knowledge

A general framework for a model-based control system is shown schematically in Fig. 1. This framework shows a hierarchical control structure with a world model hierarchy explicitly interposed between the sensor processing hierarchy and the behavior generation or task decomposition hierarchy, allowing for model-based perception and model-based control [2], [3]. Example labels for three of the levels (subsystem, primitive, and servo), per [2] are shown. This paper presents an overview of the types of data needed for the world model hierarchy.

We argue that there are three distinctly different classes of knowledge in such a control hierarchy: system parameters at the servo level; maps and images at the middle levels, and symbolic data at the highest levels. We will consider each of these below.

We can further distinguish knowledge that is learned or acquired, which we will call *in situ* knowledge, from knowledge that is pre-programmed or referenced from an outside database, which we will call *a priori* knowledge. This provides a framework for considering learning and adaptive control.

2.1. Parametric Level Knowledge

The lowest levels of any control system, whether for an autonomous robot, a machine tool, or a refinery, are at the servo level, where knowledge of the value of system parameters is needed to provide position and/or velocity and/or torque control of each degree of freedom by appropriate voltages sent to a motor or a hydraulic servo valve. The control loops at this level can generally be analyzed with classical techniques and the "knowledge" embedded in the world model is the specification of the system functional blocks, the set of gains and filters that define the servo controls for a specific actuator, and the current value of relevant state variables. These are generally called the system parameters, so we refer to knowledge at this level as parametric knowledge. Fig. 2 shows a traditional PD servo control for a motor of a robot arm.

2.2. Iconic or Geometric Level Knowledge

Above the servo level are a series of control loops that coordinate the individual servos and that require what can be generally called "geometric knowledge," "iconic knowledge," or "patterns." Iconic knowledge includes maps, images, models of the kinematics of the machines being controlled, and knowledge of the spatial geometry of parts or other objects

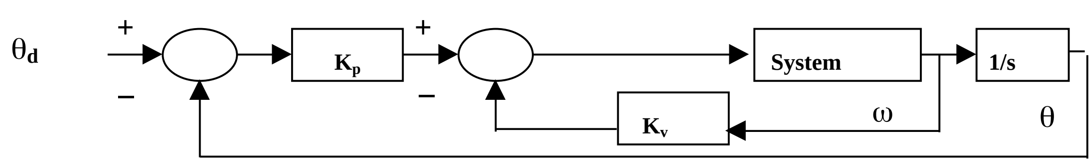

Figure 2: PD Servo Control

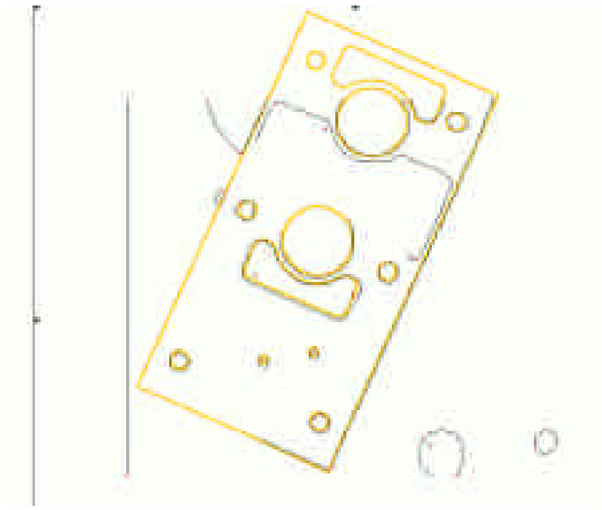

Figure 3: Part Pose Computation

that are sensed and with which the machine interacts in some way. This is where objects and their relationship in space and time are modeled so as to represent and preserve those spatial and temporal relationships, as in a map, image, or trajectory.

For industrial robots, machine tools, and coordinate measuring machines, the first level above the servo level deals with the kinematics of the machine, relating the geometry of the different axes to allow coordinated control. Linear, circular and other interpolation and motion in world or tool coordinates are enabled by such coordination. The "knowledge" here may be the kinematic equations or Jacobian coefficients that define the geometric relationships of the axes, or the mathematical routines for interpolation or coordinate transformations. It is at this level that systematic multi-dimensional geometric errors such as non-orthogonality of axes of a machine tool and Abbe offset errors are considered [4]. Fixtureless inspection is an example of the applying such equations. Fig. 3 shows a fixtureless part which is placed on the table of an inspection machine and the pose of the part is determined by matching an image of the part (dark edges) with a predicted image derived by rotating and translating a CAD model of the part (light edges) [5].

2.3. Symbolic Knowledge

At the highest levels of control, knowledge will be symbolic, whether dealing with actions or objects. It is at this level that a large body of relevant work exists in knowledge engineering for domains other than real-time control, such as formal logic systems or rule based expert systems. Whether the knowledge is represented in terms of mathematical logic, rules, frames, or semantic nets, there is a formal linguistic structure for defining and manipulating and using the knowledge. A good presentation of different concepts of knowledge representation is found in Davis [6].

An example of a formal description of a solid model of a part is shown in Fig. 4. A block is being described using International Standards Organization Standard for the Exchange of Product Model Data (STEP) Part 21 [7]. Note the fundamentally different nature of this linguistic representation from a geometric representation where, for example, a block might be represented by equations of six planes with bounding curves and a coordinate transformation matrix to position the block within a given coordinate system.

Linguistic representations provide ways of expressing knowledge and relationships, and of manipulating knowledge, including the ability to address objects by property. Tying symbolic knowledge back into the geometric levels provides the valuable ability to identify

```
DATA;
#10 =
BLOCK_BASE_SHAPE(#20,#30,#70,#80);
#20 = NUMERIC_PARAMETER('block Z
dimension',50.,'mm');
#30 = ORIENTATION(#40,#50,#60);
#40 = DIRECTION_ELEMENT((0.,0.,1.));
#50 = DIRECTION_ELEMENT((1.,0.,0.));
#60 = LOCATION_ELEMENT((62.5,37.5,0.));
#70 = NUMERIC_PARAMETER('block Y
dimension',75.,'mm');
#80 = NUMERIC_PARAMETER('block X
dimension',125.,'mm');
#90 = SHAPE((),#10,());
#100 = PART('out','rev1','','simple
part','insecure',(),#90,(),(),(),$,(),
(#110),(),());
#110 = MATERIAL('aluminum','soft
aluminum',$,(),());
```

Figure 4: STEP Representation of a Block

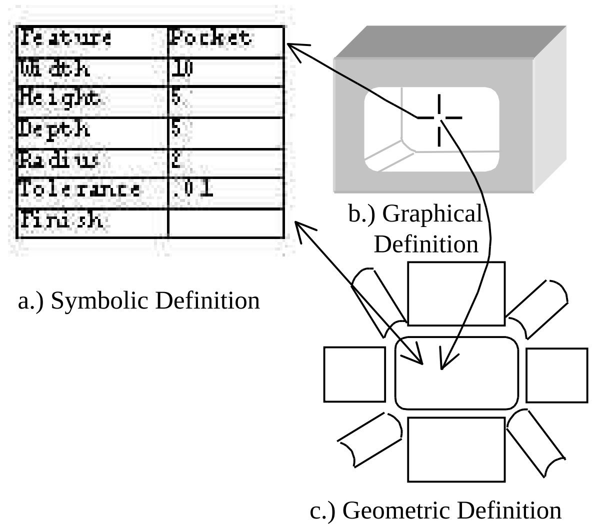

Figure 5: Pocket Feature

objects from partial observations and then extrapolate facts or future behaviors from the symbolic knowledge. In the manufacturing domain, using a feature-based representation (which is symbolic) is reasonable at the generative planning level (Fig. 5a). The geometric representation of each edge and surface that comprise a feature (Fig. 5c) can be tied to the feature definition in order to facilitate calculations for generating the tool paths. Graphical primitives (Fig. 5b) that relate to the geometry can also be tied to features to easily let users pick a feature by selecting on a portion of it on the screen.

STEP Part 21 files are one of many ways of representing symbolic information. Different representation techniques often offer different advantages. For example, as is the case in almost any planning and control system, it is often advantageous to be able to reason over information that is represented. This includes being able to infer information that may not be explicitly represented, as well as the ability to pose questions to the knowledge base and receive answers in return. One way of enabling this functionality is to represent the symbolic information in the world model in a logic-based, computer-interpretable format, such as in the Knowledge Interface Format (KIF) representation [8].

Through the use of an inference engine or theorem prover, information represented in this format could be queried, and logically-proven answers could be returned. As an example, a manufacturer may want to know whether a given set of fixture positions is suitable to fully inspect a part. Assuming that the necessary inspection points, access volumes, and machine capabilities are represented in KIF, the manufacturer could enter in the fixture positions and the system could logically-prove whether those positions are sufficient to fully inspect the part. Future work will be exploring this area in more detail via the implementation of logic-based ontologies to represent the symbolic information in the control hierarchy.

3. Control With Multiple Levels of Knowledge

The most significant and complex autonomous mobile robot built to date is the Army's Experimental Unmanned Vehicle (XUV) being developed for scout missions (reconnaissance, surveillance, and target acquisition (RSTA) missions). The architecture for this vehicle is called 4D/RCS, merging the work of Dickmanns in Germany on road following [9] and the work of Albus at NIST [3]. Both use data from multiple sensors to build a world model and then use that model for planning what the vehicle should do.

The Army XUV has successfully navigated many kilometers of off road terrain, including fields, woods, streams and hilly terrain, given only a few way points on a low resolution map by an Army scout. The XUV used its on-board sensors to create high definition multi-resolution maps of its environment and then navigated successfully through very difficult terrain. Over the next several years, symbolic knowledge will be added to enable tactical behaviors and human-machine interaction.

4. Conclusion

No single type of knowledge representation is adequate for all purposes. Davis [6] argues that representation and reasoning at the symbolic level are inextricably intertwined, and that different reasoning mechanisms, such as rules and frames, have different natural representations that must be integrated in a representation architecture to achieve the advantages of multiple approaches to reasoning.

We would go further and argue that there is a requirement for integrating iconic and parametric knowledge with multiple types of symbolic knowledge and that, as Davis argues, there is a basic need for a representational architecture to provide a basis for intelligent control, which we have presented above in Figure 1.

For example, with the ability for the Army XUV not only to sense when there is an obstacle in its path, but also to be able to compare that sensed data (possibly represented in an occupancy grid) with a priori knowledge of obstacles (possibly represented in KIF in a symbolic world model), the XUV can make more informed decisions about the best action to take, taking into consideration the type of obstacle it encounters. If the obstacle is deemed to be a boulder, the XUV must take evasive maneuvers. However, if it is simple tumbleweed, the XUV may be able to drive through it. This is the essence of intelligent control.

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