

# Knowledge Base Learning Control System - Part 2: Intelligent Controller

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**Abstract:** - In Part 1 of this article, a generic architecture was reported in conjunction with knowledge base learning control system (KBLCS). When implemented, the architecture is mapped onto a specialized software that uses artificial intelligence (AI) methods such as expert system in control problem solving. The intelligent controller represents the driving force that allows intelligent machines to achieve prescribed goals autonomously and embodies a symbolic capability for generating knowledge *via* inferences as well as a crude data management system using a numeric functionality for conventional control. The controller is composed of a rule base, a fact base and an inference engine. When environments treat more than one state of the process to be controlled, then it is careful to separate between control and inference, both functionally and architecturally. As the core of the generic architecture described earlier, we now report the main components of an intelligent controller. Robot control and grammatical control are taken as special applications of the proposed intelligent controller.

**Key-Words:** - Intelligent control, Intelligent systems design, Knowledge base control system (KBCS), Hybrid systems, Control engineering processes, Robot control, Grammatical control

## 1. Introduction

Among the procedures involved in the generic architecture, previously-proposed in Part 1 of the present paper, in conjunction with knowledge base learning control system (KBLCS), we find two main design paths. One feed-forward path in design involves numeric/symbolic manipulations for knowledge base control system (KBCS). One inner feedback loop of design involves learning. As part of KBCS application, our aim here is to emphasize the importance of these two paths as applied to the special context of robot arm (RA) control. In the feed-forward path, we report the RA knowledge base approach [9]. In the inner loop, learning *via* grammatical inference is exemplified [7] with a tentative application to RA control [8]. We need an integrated environment [12] capable of handling elastic concepts [17]. RA is defined as the process whereby a physical system, namely a set of robotic linked arms, is made compliant with some prescribed task such as following an imposed trajectory or keeping in pace with a given angular velocity [15]. Welding and assembly-line robots are

popular examples of RA industrial applications. RA Control is a much diversified field. As a result, it makes concentrated research a difficult task. While RA control has been extensively studied from the pure control side [4], for the last four decades, or so, very little attention has been made with regard to knowledge base control (KBC) and even less attention to KBLCS. Indeed, the symbolic approach efforts as applied to control at large remain quite isolated [10]. Our fundamental aim is to contribute to the integration of RA control within KBC, considered as a mapping from the proposed KBLCS architecture; this latter being defined as a computational methodology that provides automatic means of improving control tasks from heuristics and experience. As a subfield of intelligent control, KBC attempts to elaborate a control law on the basis of heuristics and is therefore consistent with the overall goal of intelligent control. As such, KBC automatically generates a control law from heuristic rules and actual facts describing the actual RA status characterized by errors evaluation and various trajectories behavior. The end-product is knowledge

used for control.

In the next section we give an overview of the basic control problem and issues raised in intelligent control settings [2], [5]. Section 3 describes the intelligent controller and its core components for enhancing actual control systems and stresses the transition from data to information and ultimately to knowledge. This section also points to KBC for RA control and grammatical control as special applications of the proposed architecture with the possible impacts that the proposed technologies are thought to induce on future control systems. The paper ends with a conclusion summing up the main results and pointing towards some potential future developments.

## 2. Problem formulation

### 2.1 From standard RA control to KBC

The specific KBC problem that we want to tackle can broadly be expressed as follows:

<b>// Overall Methodology //</b>	
<b>Given:</b>	
- A plant configuration library describing actual system to be controlled (e.g. RA)	
- A library of control algorithms with various degrees of complexity	
<b>Find:</b>	
One (class of) algorithm(s) that control one plant configuration	
<b>Application:</b>	
Address simulation of RAs dynamics under various control schemes	

### 2.2 Intelligent control diverse issues

In order to apply the above methodology, we rely on the so-called numeric/symbolic interaction or the exploitation-exploration cooperation. We consider the knowledge-based control (KBC) approach within the broader context of intelligent control.

#### 2.2.1 Central issue

The central issue raised in Part 1 of this paper is related to the control of a system irrespective of its complexity, of our capability of separating it from the environment and localizing it; irrespective of the context in which this system operates, of the forms of knowledge available and the categories it

manipulates and of the methods of representation. In addition, there are other issues that can be divided into two categories according to whether they arise in pure calculating control settings or in the manipulation of non numeric knowledge.

#### 2.2.2 Other issues

##### 2.2.2.1 Automatic control conventional issues

From the standpoint of automatic control, some of the problems encountered in intelligent control are :

- the system under control can be very complex incorporating nonlinearities in RA, for instance;
- our knowledge of the system is imprecise such as unknown RA parameters, unknown conditions of operation, although gradually increasing during operation, in the optimistic case of successful identification process;
- the influence of the environment is strong dictated by outside perturbations and modelling errors, which will influence the current task;
- the goal of the system is described symbolically and may have internal hierarchy to be further investigated and structured.

If the answer to some of these challenges can be obtained from human experts or from experience, then this knowledge is codified within the knowledge base (KB) by knowledge engineers and built on it. If the answer is unknown, then offline experimentation is done by control engineers to gradually build an answer and codify it in the KB. In any case, the KBC designer has to constantly upgrade the KB with human expertise and/or manual experimentations [3].

##### 2.2.2.2 AI issues

Knowledge in KBC is handled by artificial intelligence (AI). From the standpoint of AI, the available methods cannot easily manipulate dynamic systems and have very little consideration for numerical manipulation. Indeed, computations of margins of stability, controllability, observability are alien to this field [16].

##### 2.2.2.3 Operation research issues

Moreover, both control theory and AI cannot properly operate out of the operations research (OR) paradigm. Its queues, graphs and game-theoretic situations are typical of the variety of applications. That is why an early proposal for the definition of intelligent control is to consider this field as the intersection of the three previously-cited disciplines namely control theory, AI and OR, [14]. Other fields such as cognitive science and machine learning

have been progressively integrated within the intelligent control discipline including the so-called soft computing methodologies such as genetic algorithms, neural networks, fuzzy systems and various other hybrid methods [18]. On the more general level, and in order to determine proper structures of most systems, significant attention is to be given to economic and social effects as well [6].

### 3. Intelligent controller architecture

#### 3.1 Proposed solution

##### 3.1.1 Symbolic/Numeric processing

In order to handle the so-called numeric/symbolic issue arising in control settings, we consider a knowledge-based control system (KBCS) methodology within the broader context of intelligent control. On the one hand, we focus on the use of symbolic processing (declarative, rule-based) for the purpose of controlling and exploiting numerical (procedural) systems. These latter describe the RA control algorithms. Rules represent the way the codified human expertise is explored and used in firing the adequate algorithm according to the actual situation. On the other hand, we pay special attention to the learning processes involved in control and rely on grammatical control to enhance the KBLCS process.

##### 3.1.2 Modes of operation

From the practical point of view, we consider two complementary environments, *i.e.* a numeric environment responsible for making calculations (trajectory, control law,...) and a symbolic environment responsible for making logical inferences incorporating human experience. These two environments are the main components of most KBC architectures. Two modes of operation are therefore possible. In the numerical or exploitation mode, the program generates the outputs using imposed algorithms. In the inferential or exploration mode, the algorithm is not known beforehand. Using the codified expertise in the KB, the program has to choose it from a library before firing the numeric mode. Usually, we first start by considering standard RA conventional control and then KBC [9].

#### 3.2 Controller components

The knowledge base learning control system (KBLCS) depicted in Fig. 1 below shows the main components that are useful in the formulation of our control problem [9], [11]. KBLCS incrementally builds on tools like data, information and knowledge, in addition to decision, discovery and

control as direct procedures with learning as supporting or feedback procedures.

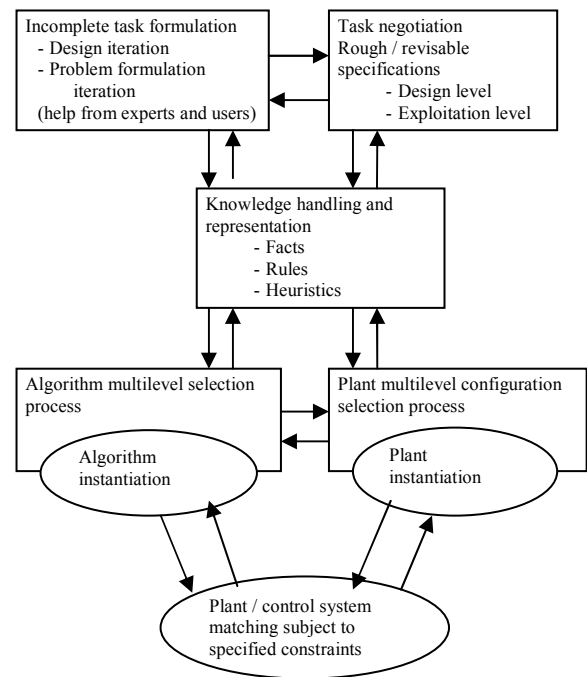


Figure 1 Intelligent controller architecture

#### 3.3 Learning in grammatical control

Machine learning processes and methods [1] are, at the heart of KBLCS. As a subfield of machine learning, grammatical inference attempts to learn structural models, such as grammars, from diverse data patterns, such as speech, artificial and natural languages, amongst others. GI broadest aim is therefore consistent with the overall goal of machine learning defined as a computational methodology that provides automatic means of improving tasks from experience. As a general computational method, grammatical inference is the process whereby a language is automatically generated from positive and eventually negative examples of sentences.

##### 3.3.1 Objective of grammatical control

The classical control objective is to generate the control  $U$  in order to maintain the output variable  $y$  within some prescribed values. In grammatical control, a terminal alphabet  $T$  is associated with the output variable  $y$  and the nonterminal alphabet  $N$  to the control variable  $U$ . The feedback control law generates the required value of control  $U$  so as to keep the controlled output  $y$  within a specified range.

##### 3.3.1.1 Quantification

For achieving the previous goal, a quantification of the variables is made, dividing the variables range into equal intervals and associating each interval to a terminal symbol in the alphabet.

### 3.3.1.2 Production rules

Some  $\pi$ -type productions are defined by the human expert as some substitution rules of a given form. These productions codify the evolution of the output variable, depending on its  $\pi$  past values and on the value of the control variable  $U$ . Therefore, there is a functional relationship between the dynamics of the system and the  $\pi$ -type productions.

### 3.3.1.3 Learning

A learning algorithm [13] is necessary to extract the productions from the experimental data. To obtain a sample of the language, a sequence of control signals is applied to the system in such a way that the output variable  $y$  takes values in a sufficiently wide region. The signal evolution is then quantified as described above, and a learning procedure is followed, [8].

## 4. Conclusion

We have shown how to project a generic knowledge base learning control system (KBLCS) architecture onto an intelligent controller. As a result, cooperation between numeric and symbolic aspects of control has been addressed. Learning aspects of control are introduced through grammatical inference. On top of the multitude of methods and tools that are prone to be integrated to solve the plant/control matching problem, it remains highly expected that the technologies reported here will uncover even more useful hidden structures in KBLCS processes. Much work is still required on both RA conventional control and KBKCS, for the development of fully-integrated systems that meet the challenges of efficient real-life applications.

### References:

- [1] Alpaydin, E., *"Introduction to Machine Learning"*, MIT Press, 2004.
- [2] Åström, K.J. & T.J., McAvoy, "Intelligent control", *J. Process Control*, Vol. 2, no. 3, pp. 115-127, ISSN: 0959-1524, 1992
- [3] Cellier, F.E., L.C., Schooley, M.K., Sundareshan, & B.P., Ziegler, "Computer aided design of intelligent controllers: challenges of the nineties", In M. Jamshidi & C.J Herget (Eds.), *"Recent Advances in Computer-Aided Control Systems Engineering"*, Elsevier, Science Publishers, Amsterdam, Holland, 1992
- [4] Craig, J.J., *"Introduction to Robotics: Mechanics and Control"*, 3<sup>rd</sup> Ed., Pearson Prentice Hall, ISBN: 0201-54361-3, Upper Saddle River, NJ, USA, 2005
- [5] Fu, K.S., "Learning control systems and intelligent control systems: an intersection of artificial intelligence and automatic control", *IEEE Trans. Autom. Cont.*, Vol. AC-16, pp. 70-72, 1971
- [6] Hamano, F., "Intelligent control", *Expert Systems in Robotics, NATO ASI Series F*, Vol. 71; pp. 737-740, 1991
- [7] Hamdi-Cherif, A. & C., Kara-Mohammed (alias Hamdi-Cherif), "Grammatical inference methodology for control systems", *WSEAS Transactions on Computers*, Vol. 8, No. 4, page 610-619, ISSN: 1109-2750, 2009
- [8] Hamdi-Cherif, A., "Towards robotic manipulator grammatical control", Invited Book Chapter In: Suraiya Jabin (Ed.) *"Robot Learning"*, SCIYO Pub., pp. 117-136, ISBN: 978-953-307-104-6, October 2010
- [9] Hamdi-Cherif, A., "Knowledge-base control for robot arm", Invited Book Chapter In: Satoru Goto (Ed.) *"Robot Arms"*, Intech Pub., pp. 51-76, ISBN: 978-953-307-160-2, May 2011
- [10] Martins, J. F., Dente, J.A., A.J., Pires, & R., Vilela Mendes, "Language identification of controlled systems: modeling, control, and anomaly detection", *IEEE Transactions On Systems Man and Cybernetics- Part C: Applications And Reviews* Vol. 31, No. 2, pp. 234-242, ISSN: 1094-6977, 2001
- [11] Meystel, A., "Multiscale models and controllers", *Proceedings of the IEEE / IFAC Joint Symposium on Computer-Aided Control Systems Design (CACSD'94)*, Tucson, Arizona, 7-9 March, pp. 13-26, 1994
- [12] Rao, M., *"Integrated System for Intelligent Control"*, LNCIS, Vol. 167, Springer-Verlag, New York, USA, 1992
- [13] Russel, S., & P. Norvig, *"Artificial Intelligence – A Modern Approach"*, Prentice Hall in Artificial Intelligence, 2<sup>nd</sup> Edition, pp. 51-54, 2003.
- [14] Saridis, G.N., "Knowledge implementation: structures of intelligent control systems", *IEEE International Symposium on Intelligent Control*, Philadelphia, Pennsylvania, pp. 9-19, 19-20 January 1987
- [15] Siciliano, B., L., Sciavicco, L., Villani, & G., Oriolo, *"Robotics Modeling, Planning and Control"*, Springer, ISBN 978-1-84628-641-4, e-ISBN 978-1-84628-642-1, Series published under ISSN 1439-2232, London, UK, 2009
- [16] Simon, H.A., "Artificial intelligence: where has it been and where is it going?", *IEEE Transactions on Knowledge and Data Engineering*, Vol. 3, no. 2, pp. 128-136, 1991

- [17] Zadeh, L., "Knowledge evaluation: observation and computation for intelligent control", *IEEE International Symposium on Intelligent Control*, pp. 302-308, 19-20 January 1987
- [18] Zilouchian A., M. Jamshidi (Eds.). *"Intelligent Control Systems Using Soft Computing Methodologies"*, CRC Press LLC, 2001.
- Websites accessed as of November 2011*  
*Examples of KBS / Machine learning sites*  
*CLIPS*: <http://clipsrules.sourceforge.net/>)  
*CART*: <http://salford-systems.com/cart.php>  
*See5/C5.0*: <http://www.rulequest.com/see5-info.html>  
*Weka*: <http://www.cs.waikato.ac.nz/ml/weka/>  
*Tanagra*:  
<http://eric.univ-lyon2.fr/~ricco/tanagra/en/tanagra.html>