Knowledge Base Learning Control System - Part 1: Generic Architecture

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Abstract: - Different levels of intelligence hierarchically require data, information and knowledge. Knowledge base control systems (KBCSs) represent an artificial intelligence-based paradigm that accounts for the use, generation and management of knowledge in control systems. As in any intelligent machine, the codification of knowledge in KBCSs is responsible for the performance of anthropomorphic tasks, autonomously or interactively with a human operator in structured or unstructured, familiar or unfamiliar environments. On the basis of the main technologies available to us, including cloud computing, Web and data mining technologies, we describe a generic architecture for numeric/symbolic data processing capable of addressing issues related to the imprecision and incompleteness characteristics of the controlled plant. Some tasks trade-offs as part of the control process are also considered.

Key-Words: - Intelligent control, Intelligent systems design, Knowledge base control system (KBCS), Learning control system, Generic control systems architecture, Hybrid systems, Control engineering processes

1. Introduction

We consider a knowledge base control system (KBCS) methodology as a generic architecture within the broader context of intelligent control. Unlike conventional control, intelligent control does not level itself to precise formalization. The shift from the first aproach to the second has been done along several lines of sophistication. A swift transition has been done from prescription to description, from model of the system to the model of operation, from relational aspects to rule-based ones, from crisp logic to fuzzy logic, and from rigidity to elasticity of concepts, [16] Additionally, machine learning procedures and concepts have been adopted within intelligent control and incorporated neural networks, genetic algorithms, data mining and other hybrid methods among others [17]. Intelligence-based or AI-based programs and procedures are the basic characteristics of KBCS. Indeed, for reasons of prohibitive complexity, 'brute force' use of procedural heuristics-free algorithms is simply useless. Clearly, because of the nature of most control problems, a more 'intelligent', *i.e.* heuristics-based problem solving approach is required since human expertise codification is necessary. KBCS principles and tools enhance existing solutions because they incorporate advanced human expertise in the form of easily-modifiable code. Furthermore, the intelligent control community has adopted general guidelines by which operational constraints continuously adjust the focus of world modeling, the specification of control criteria, and the allocation of resources to address current goals and metagoals. This flexibility is clearly required from systems which are confronted with unfamiliar and uncertain environments, which are subject to critical spatial and temporal constraints and which are expected to perform satisfactorily in a diverse task domain.

As a result to commitment to integrated systems, researchers were challenged to reconsider the assumptions underlying research in modular technologies, [10]. To operate autonomously in a dynamic and non-deterministic environments, such systems must meet the following requirements :

1. Observe the salient features of the world and incrementally refine and extend world models using past and actual results. The world refers to either the physical world where designed system is to evolve or to the abstract world of design.

2. Construct control procedures which can make use of incomplete and uncertain information and which recover smoothly from the errors that might occur.
3. Determine how to partition available resources dynamically as constraints on timing and solution quality vary.

To contribute to this challenging issues, we propose a generic architecture using the knowledge base learning control system (KBLCS) approach.

In the next section we give an overview of the basic ideas and issues raised in intelligent control settings. Section 3 describes the knowledge-based control learning system (KBLCS) and its core technologies for enhancing actual control systems and stresses the transition from knowledge to its discovery, including Web technologies and cloud computing. The paper ends with a conclusion summing up the main results and pointing towards some potential future developments.

2. Basic ideas

In order to describe the main building blocks of our architecture, we make an emphasis on technologies spanning (crude) data, information, refined information including decision support, ultimately leading to the most refined and expensive piece of information, *i.e.,* knowledge and its discovery in large and diversified databases over the Web, based on cloud computing solutions. A human-machine interactive knowledge-based learning control system (KBLCS) is our far-reaching goal.

2.1 Related works

Intelligent control is a term coined in [6] and later developed in [15]. An early, but constantly refined definition of this field describes itself as that area beyond adaptive, learning and self-organizing systems which represents the meeting point between artificial intelligence (AI), automatic control (AC) and operations research (OR). International intelligent control symposia have been held every year since 1985 and numerous contributions appear regularly in the specialized and thoroughly documented literature where novel original definitions of the field are proposed *e.g.* [13]. Extensions of the field are reported in [3], [4], [5] and [7]. Other approaches have also been considered by researchers like the cognition-oriented approach with applications, [10]. Theoretical and applied results go back to [15] who proposed the so-called entropy-based "principle of decreasing precision with increasing intelligence".

2.2 Intelligent control central issue

One of the fundamental issues that concerns intelligent control is related to the degree to which it is possible to control the dynamic behaviour of a system, including the abstract design process, independently of:

- its complexity
- our capability of separating it from the environment and localizing it
- the context in which this system operates
- the forms of knowledge available and the categories it manipulates
- the methods of representation.

As stated, this question cannot be handled by either control theory or AI. On the one hand, control theory has a vey localized vision of the problem. This prevents it from looking beyond the localized constraints self-imposed by the designer and hidden within the mechanism of the mathematical representation. On the other hand, the available methods in AI, cannot easily handle dynamic systems and have very little consideration for numerical manipulation; computations of margins of stability, controllability, observability are indeed alien to this field.

2.3 Scope of intelligent control

Intelligent control as a discipline provides a generalization of the existing control theories and methods on the basis of the following elements [10], [4]:

- combined analysis of the plant and its control criteria,
- processes of multisensor operation with information (knowledge) integration and recognition in the loop,
- man-machine cooperative activities, including imitation and substitution of the human operator,
- computer structures representing these elements.

3. Technological components

The knowledge base learning control system (KBLCS) depicted in Fig. 1 below shows the interaction of the main technologies that are useful in the formulation of our control problem. KBCLS incrementally builds on tools like data, information and knowledge, in addition to decision, discovery and control as direct procedures with pervasiveness and learning as supporting or feedback procedures.

3.1 From data to control

We stress the stratification of KBCLS processes into

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levels. This stratification motivates for the introduction of incrementally-sophisticated technologies. The proposed solution to the issues addressed here is to be considered under six hierarchical and complementary levels, namely data base management system (DBMS), information system (IS), decision support system (DSS), knowledge-based system (KBS), data mining (DM) and knowledge base control system (KBCS). One of the main aims is to integrate learning methods, encompassed by the knowledge base learning control system (KBLCS) framework.

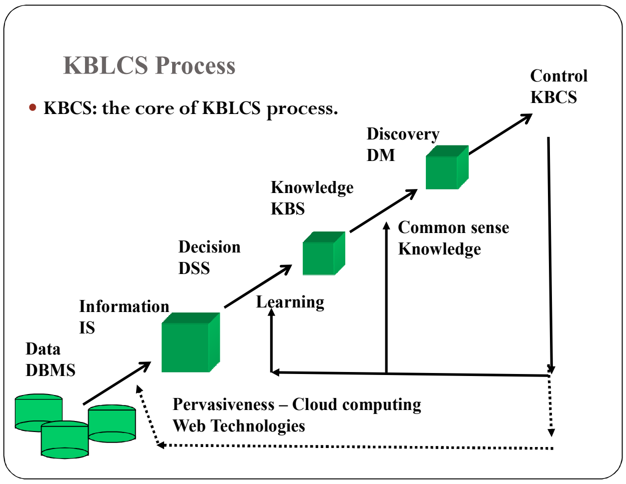

Figure 1. Basic layers of KBLCS

3.2 Inner loop: learning and control

3.2.1 Machine learning

In KBLCS, machine learning acts as an inner loop. Machine learning is an adaptive process that makes computers improve from experience, by example, by analogy, or otherwise. Learning capabilities are therefore essential for automatically improving the performance of a computational or control system over time on the basis of previous history. A basic learning model typically consists of the following four components:

- learning element, responsible for improving its performance,
- performance element, or decision support system (DSS) responsible for the choice of actions to be taken, whether these actions are decisions or controls,
- critical element, which tells the learning element whether the criteria are met within some critical boundaries,

and

- problem generator, responsible for suggesting actions that could lead to new or informative experiences [14].

The importance of learning automatically grows as the external environment continues to generate and integrate large quantities of diversified data, generated by the problem generator, or otherwise.

3.2.2 Supervised *vs.* unsupervised learning

As far as relevant machine learning is concerned, there are basically two categories of learning schemes, namely supervised learning and unsupervised learning. Supervised learning learns the data with a known answer at hand. From the control standpoint, this is a typical feedback control system. The parameters are modified according to the difference of the actual output and the desired known output, or expected answer. Grammatical control is one aspect of supervised learning [8], [9]. Classification falls into this category. On the other hand, unsupervised learning learns without any knowledge of the outcome. Clustering belongs to this category. It finds data with similar attributes and aggregates them in the same cluster [1].

3.3 Outer loop: control and cloud computing

3.3.1 Cloud computing

Another major technology that is susceptible to address stringent control issues is cloud computing. This novel technology provides a way to develop applications in a virtual environment where computing capacity, bandwidth, storage, security, and reliability aren't issues because users don't need to install costly software on their own system. In a virtual computing environment, users can develop, deploy, and manage applications, paying only for the time and capacity used while scaling up or down to accommodate changing needs or external requirements. Cloud computing has the main characteristics of distributed applications, pervasiveness, and service-oriented architecture (SOA).

3.3.2 Open Networking Foundation (ONF)

On 21st of March 2011, six companies that own and operate some of the largest networks in the world announced the formation of the Open Networking Foundation (ONF), a nonprofit organization dedicated to promoting a new cloud-focused initiative approach to networking called Software-Defined Networking (SDN). ONF, through SDN, allows owners and operators of networks to control and manage their networks to best serve their needs. ONF's first priority is to develop and use the so-called OpenFlow protocol [http://www.openflow.org/], [12]. The main functionalities of OpenFlow is to seek to increase network functionality while lowering the cost associated with operating networks through simplified hardware and network management [http://www.opennetworkingfoundation.org/].

3.3.3 From Web 1.0 to Web 2.0

There was a natural transition to Web 2.0 after the so-called dot-com crash of Web 1.0 in late 2001. The main Web 2.0 technologies include wikis, blogs, RSS filters, folksonomies, mashups, podcasts, crowdsourcing, social networks, and virtual worlds [2] [http://oreilly.com/web2/archive/what-is-web-20.html], [11].

4 Conclusion

We have shown how to proactively increase the collaboration between different technologies in order to address the issue of knowledge base control. On top of the multitude of methods and tools that are prone to be integrated, it remains highly expected that the technologies reported here will uncover even more useful hidden structures in KBLCS processes. In addition to various algorithmic and numerical and symbolic/numeric methods now available, however intelligent these might be, future KBLCS have to include simulation scenarios capable of producing highly anthropomorphic behavior of the resulting intelligent machines. Further integration of these technologies into specific application-oriented contexts is indeed a challenging task for years to come.

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Examples of KBS
CLIPS: http://clipsrules.sourceforge.net/
Example of DSS: http://www.goaefis.com/about-aefis/faqs/
DBMS/Data Mining Tools/ Machine Learning Software
http://www.microsoft.com/sqlserver/en/us/
http://www.oracle.com/technetwork/database/options/odm/index.html
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
Cloud computing
(http://www.cloudcomputingdefined.com/learn/)
Examples of Cloud Computing Solutions
http://www.ibm.com/developerworks/cloud/ec2.html
http://www.opennetworkingfoundation.org/
http://www.openflow.org/
http://www.microsoft.com/sqlserver/en/us/editions/azure.aspx