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Intelligent Control: A Review

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Abstract: Intelligent Control, which includes Fuzzy, Neural, Neuro-Fuzy and Evolutionary Control, is result of applying computational intelligence to the control of complex systems. This class of unconventional control systems differs radically from conventional (or hard control) systems that are based on classical and modern control theory. The techniques of intelligent control are being applied increasingly to industrial control problems and are leading to solutions where conventional control methods have proved unsuccessful. This paper reviews computational intelligence (branch of soft computing) which includes Expert Systems, Fuzzy Logic, Artificial Neural Networks, and Evolutionary Computing with emphasis on its application to control engineering.

Key Words: Intelligent Control, Evolutionary Computing, Neural Networks Fuzzy Control

Introduction

Intelligence in human beings possesses robust attributes such as distributed sensors and control mechanism. The brain acquires information about the environment through various natural sensory mechanisms such as vision, hearing, touch, taste, and smell and integrates this information and provides appropriate interpretation. Furthermore, the faculty of learning, recollection, and high level decision-making techniques for reasoning under uncertainty, resulting in appropriate muscular control by means of a complex neural network distributed in central nervous system has made human beings superior animals in many aspects.

Today, the complexity of man-made systems has placed severe strains on existing feedback design techniques. Conventional control approaches require known mathematical models of the system, or make assumptions that are violated by actual systems. Many feedback controllers designed using today's technology proved to be unsuccessful to cater complex, non-linear, uncertain and ill-structured systems (i.e., the goal can be defined only vaguely, and decision path from initial to the desired state may not follow a specific pattern) such as space robots, roving robots, flexible manufacturing systems and like these.

To deal with the above problems, the researchers working in the filed of intelligent control typically consider using an approach to control that is motivated by the form of representation and decision making in human/animal/biological systems. Intelligent control and intelligent systems have been defined in various ways:

Intelligent control is the discipline in which control algorithms are developed by emulating certain characteristics of intelligent biological systems (Passino, 1995).

An intelligent system has the ability to act appropriately in an uncertain environment, where an appropriate action is that which increases the probability of success, and success is the achievement of behavioral subgoal that support the system's ultimate goal (Antsakalis, 1994).

An intelligent control system has the ability to comprehend, reason and learn about processes, disturbances and operating conditions in order to optimize the performance of the process (Astrom,1992).

In fact the discipline of intelligent control is now emerging as a technology that may open avenues for significant advances in many areas. Fueled by advancements in computing technology, it has already achieved some very exciting and promising results.

A Brief History: The history of control engineering can be traced back to ancient and medieval times. One of the earliest open-loop control system was Hero's device for opening the doors of a temple. James Watt's flyball governor for controlling speed, developed in 1788, can be considered the first widely used automatic feedback control system. The Second World War provided a new impetus to theory and practice of control engineering. Mathematical and analytical methods increased vastly during this period and control engineering then emerged as an independent discipline. Linear and nonlinear control theory, optimal control theory, and stochastic, adaptive, and learning control theories are now standard components of control curricula.

Since 1980 the field of control engineering has grown exponentially. Smaller, faster, more accurate, and less expensive computing technology has given spur to many innovative theoretical and practical developments fusing old control strategies with newer techniques such as the use of knowledge bases, fuzzy logic, and neural networks collectively known as soft computing. The discipline of Intelligent Control is the result of this fusion. Although the term Intelligent Systems was coined with the advent of Artificial Intelligence in 1950's but considerable progress in this direction has been in the recent years.

During the last two decades of 20th century, many conferences, symposia, and workshops have been specifically devoted to this subject. A lot of books (Spyros,1997; Ram,1997 and Gupta *et al.*, 1996) with the term intelligent or intelligence in their title have appeared during this time. A proliferation of research in the field of intelligent control has been scattered in the reprints and proceedings of various regional and international conferences, scientific journals, and special issues.

Intelligent Control Methods: Several well-established AI methods such as Expert Systems, Fuzzy Logic, Neural Networks and Evolutionary Computing have been used to design control systems. In the subsections that follow some of these techniques are discussed.

Knowledge-based Control: Knowledge-based controllers have been successfully employed in a variety of industrial control applications. An expert system (a computer program that is designed to emulate a human's skill in a specific problem domain) if designed to emulate the expertise of a human in performing control activities, it is called an expert controller (passino,1996).

Basically an expert system has three major components- a knowledge base, an inference engine, and a user interface. Knowledge base contains knowledge necessary for understanding, formulating, and solving problems. The inference engine provides methods for reasoning about information within the knowledge base and for drawing the conclusions therefrom. The characteristics of knowledge base and inference engine include heuristics, symbol manipulation, dynamic decision making, remembering previous information, prediction and inference. The user interface must be as friendly as possible to enable ease of use of system.

Although the expert system paradigm has on many occasions successfully emulated the human learning process and is therefore an efficient tool to model systems for industrial control purposes, it lacks a very important capability of human intelligence-the ability to learn from experience (Chaudhury *et al.*, 1996). Some works dealing with the architecture and design of knowledge-based intelligent control systems can be found in (Tzafestas, 1997; Madan, *et al.*, 1996; Sriran, 1997; Shin and Cui, 1991; Astrom *et al.*, 1986 and Arzen, 1989).

Fuzzy Control: Fuzzy logic is a way of representing vagueness and uncertainties associated with human cognitive processes, such as thinking and reasoning through membership functions. There are two main characteristics of fuzzy systems that give them better performance for specific applications:

- Fuzzy systems are suitable for uncertain or approximate reasoning, especially for the system with a mathematical model that is difficult to drive.
- Fuzzy logic allows decision making with estimated values under incomplete or uncertain information.

Up to now the fuzzy controllers also known as linguistic controllers have achieved their greatest success among fuzzy systems in industrial and commercial applications. Fuzzy control is an unconventional approach for dealing with the problem class. Although fuzzy control is quite new approach, its effectiveness is now well proven. Over the past two decades engineers have applied fuzzy control methods very successfully, both to large-scale systems, such as cement kilns, a subway train system, and waste treatment stations; and on smaller scale, including over hundred different models of home appliances. In many cases fuzzy control mechanisms automated control of the subject plant much more completely than with conventional methods (Harold, 1997). To explore this subject further refer (Jain and Martin, 1999; Harold, 1997; Tzafestas, 1997; Gupta and Sinha, 1996 and Tzafestas and Venetsanopoulos, 1994).

Neural Networks for Control: Artificial neural networks are structures that emulate the biological process of human learning on a greatly simplified scale. They can learn from training data and are a form of mathematical function approximators. In the absence of training data, artificial neural networks can be used as pattern associators or associative memories, learning internal connections so that novel patterns that are similar to previously presented patterns that will cause the network to transit to a state that is associated with the similar stored pattern.

Artificial neural networks have been used to design control systems, and astonishingly, accurate performance has resulted in many cases, owing to the fact that they are designed to emulate, on a much simpler scale, the brain, which is still the only true intelligent controller available to us. The term neurocontrol, the use of neural nets as controllers, is now in use in control system literature, and refers to control methods that employ neural networks (Chaudhury *et al.*, 1996).

Neural network controllers which are adaptive in the sense that they can learn to adjust the control law such that the system, after degradation or due to unforeseen changes of parameters, structure, environment, and so fourth will continue to carry out its control task. Artificial neural networks have performed four kinds of useful functions in control (Paual, 1996):

- subsystem functions, such as pattern recognition or neuroidentification, for sensor fusion or diagnostics and so fourth;
- cloning functions, such as copying the behavior of a human being able to control the target plant;
- tracking function, such as making a robot arm follow a desired trajectory or reference model or making a chemical plant stay at a desired set point;
- optimization functions, such as maximizing throughput or minimizing energy use or maximizing goal satisfaction over the entire future.

Readers who wish to explore this subject further are referred to (Jain and Martin, 1999; Tzafestas, 1997; Madan, *et al.*, 1996; Sriran, 1997; Lewis and Jagannathan, 1999; Gupta and Rao, 1994).

Evolutionary Computing: Collection of algorithms based upon the functioning of biological evolutionary systems towards a solution of a problem. Indeed, the

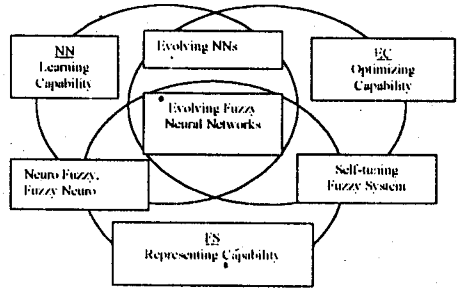

Figure 1. Emerging synthesis of NN's, FF, and EC.

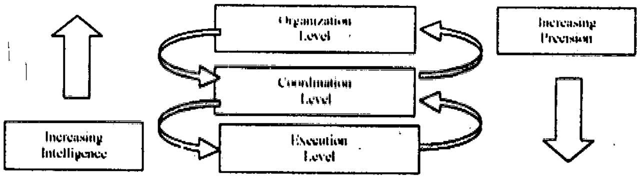

Figure 2. Structure of Intelligent Machines

field of evolutionary computing is one of the fastest growing areas of computer science and engineering for just this reason; it is addressing many problems that were previously beyond reach, such as rapid design of medicines, flexible solutions to supply-chain problems, and rapid analysis of battlefield tactics for defense. Potentially the field may fulfill the dream of artificial intelligence: a computer that can learn on its own and become an expert in any chosen area (Fogel and David, 2000).

Three types of evolutionary computing techniques have been reported recently. These are (Jain and Martin, 1999):

1 Genetic Algorithms (GAs)
2 Genetic programming (GP)
3 Evolutionary Algorithms (Eas)

These algorithms differ in the way a new population is generated from present one, and in the way the members are presented with in the algorithm.

The evolutionary computing techniques perform a parallel, stochastic, but directed search to evolve the most fit population. The population of possible solutions evolves from one generation to the next, ultimately arriving at a satisfactory solution. An evolutionary algorithm begins by initializing a population of candidate solutions to a problem. New solutions are then created by randomly varying those of the initial population. All solutions are measured with respect to how well they address the task. Finally, a selection criterion is applied to weed out those that are below par. The process is iterated using the selected set of solutions until a specific criterion is met (Fogel and David, 2000). . Genetic programming methods have been successfully applied in a variety of settings including box pushing, ant trail following, truck trailer backing, and inverted pendulum balancing. These and other demonstrations of the versatility of the techniques are described in (Koza, 1992).

Genetic programming and genetic algorithms research papers appear in Proceedings of the Conferences on Genetic Programming, the IEEE Transactions on Evolutionary Computing, and the Proceedings of the International Conferences on Genetic Algorithms. Readers are referred to (Jain and Martin, 1999; Grefenstette, 1986; Randly and Haupt, 1998; Goldberg, 1989) to explore this subject more.

Hybrid Systems: The trend to fuse these novel paradigms for offsetting the demerits of one technique by merits of another technique while dealing with complex systems. Some of these techniques are fused as (Jain and Martin, 1999):

1 Neural networks for designing fuzzy systems
2 Fuzzy systems for designing neural networks
3 Evolutionary Computing for designing fuzzy systems
4 Evolutionary computing in automatically training and generating neural network architectures.

Fig. 1 shows the synthesis of NN's, FS, and EC to build highly intelligent systems (Koza, 1992). .

Architectures for Intelligent Autonomous Controllers: A generalized autonomous controller can be looked as a three-level system with each level having considerable autonomy. The three levels are (Saridis and Valavanis, 1988):

1 Organization Level
2 Coordination Level
3 Execution Level

This hierarchical architecture obeys the so-called " Principle of increasing precision with decreasing intelligent (IPDI Principle)". The three levels are shown in Fig. 2 (Zafestas, 1997).

The execution layer connects to the process under control via sensors and actuators. It contains all the hardware such as VME buses, short memory units, processors, actuators, and special purpose devices required by intelligent machine to execute tasks. It executes

- low-level numeric signal processing
- control algorithms such as PID, optimal, adaptive, and intelligent controls
- parameter estimators
- failure detection and identification routines

After the successful completion of the job, feedback information is generated at this level for evaluation and parameter updating of the whole machine.

Coordination level receives instructions from the organization level and feedback information from the process for each subtask to be executed and coordinates execution at the lowest level. This level is responsible for

- tuning, scheduling, supervising, and redesigning the execution level algorithms
- handling crisis management, planning and learning capabilities for the coordination of execution level tasks
- higher-level symbolic decision-making for FDI and control algorithm management.

The organization level, the mastermind of an intelligent system, accepts and interprets the input commands and related feedback from the system. This level

- supervises the lower level functions

manages the interface with human and other systems
interacts with the users in generating goals for the controller and in assessing the capabilities of the system
monitors the performance of low-level systems
in cooperation with a human personnel learns at a high level about the user and low-level algorithms.

Intelligent systems and controllers may be employed as appropriate in the implementation of various functions at any of the three levels. For example, the adaptive fuzzy control may be used at the execution level for adaptation. Genetic algorithms may be used at the coordination level to pick an optimal coordination strategy. And planning systems may be used at management level for sequencing operations (Kevin, 1995).

Conclusion

This paper provides a review of principle concepts, ideas, and techniques of intelligent control, which is one of the most active areas of the research in control theory and applications. The ultimate aim of bio-inspired intelligent systems is to design machines with the ability to learn from experience, reason under uncertain and incomplete knowledge, adjust their courses of actions to meet goals and compensate certain system failures without external intervention. Despite some successes in this direction current research in autonomous system design is still in its infancy. With the great advances in the microelectronics and microcomputers augmented with the huge funding, it is hoped that in the coming years we will be able ripe the great potentialities of this promising field.

References

Astrom K. J., and T. J. MacAvoy, 1992. "Intelligent Control: an Overview and Evaluation," in D. White and D. Sofge, (eds.), Handbook on Intelligent Control, Van Nostrand Reinhold, New York, 3-34.

Astrom, K. E., Anton J. and Arzen K. E., 1986. "Expert Control," Automatica, 3: pp. 277-286.

Arzen K. E., 1989. "An Architecture for expert System Based Feedback Control," Automatica, .

Antsakalis P., 1994. " Defining Intelligent Control," IEEE control Systems, Report of the Task Force on Intelligent Control.

Fogel, David B., 2000. "What is Evolutionary Computing?," IEEE Spectrum, 26-32.

Goldberg, D. E., 1989. Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, N.

Grefenstette, J. J., 1986. "Optimization of Control Parameters for Genetic Algorithms," IEEE Trans. on Man Machine and Cyb., 1, 122-128.

Lewis, F. L., S. Jagannathan, A. Yesildirek,1999. Neural Netwok Control of Robot Manipulators and Nonlinear Systems, Talor & Francis Inc., London.

Lakhmi C. Jain, N. M. Martin, 1999. " Introduction to Neural Networks, Fuzzy Systems, Genetic Algorithms, and their Fusion," in Lakhmi C. Jain, N. M. Martin, (eds.), Fusion of Neural Networks, Fuzzy Systems, and Genetic Algorithms: Industrial Applications, CRC Press LLC.

Lewis Harold W., 1997. The Foundations of Fuzzy Control, Plenum Press, New York and London.

Madan M. Gupta, Naresh K. Sinha, 1996. (eds.), Intelligent Control Systems: Theory and Applications, IEEE, Inc., New York.

M. M. Gupta, D. H. Rao (eds.), Neuro-Control Systems: Theory and Applications, 1994, IEEE Press, Piscataway, N.J.

Passino Kevin M., Lunardhi Alfonsus D. 1996. "Qualitative Analysis of Expert Control Systems," in Madan M. Gupta, Naresh K. Sinha, (eds.), Intelligent Control Systems: Theory and Applications, IEEE, Inc., New York 404-442.

Passino Kevin M., 1995. " Intelligent Control for Autonomous Systems", IEEE Spectrum, 55-62.

Ram D. Sriran, 1997. Intelligent Systems for Engineering: A knowledge-based Approach, Springer-Velag London Limited, Great Britain.

Randly L. Haupt and Sue Ellen Haupt, 1998. Practical Genetic Algorithms, John Wiley & Sons, Inc., USA.

Saridis, G. N., and K. P. Valavanis, "Analytical Design of Intelligent Machines," Automatica, 123-133.

Spyros G. Tzafestas (ed.), 1997. Methods and Applications of Intelligent Control, Kluwer Academic Publishers, Netherlands.

S. Omatu, M. Khalid and R. Yousuf, 1996. Neuro-Control and its Application, Springer, Berlin/London.

Shin. K. G. and X. Cui, 1991. "Design of Knowledge-based Controller for Intelligent Control Systems," IEEE Trans. Syst. Man and Cybernetics, 21: 2, 368-375.

Tzafestas S. G. and A. N. Venetsanopoulos, 1994. Fuzzy reasoning in Information, Decision and Control Systems, 1994, Kluwer, Bostan/Dordrecht.

Tirthankar Ray Chaudhury, Leonard G. C. Hamey, and Rodney D. Bell, 1996. "From Conventional Control to Autonomous Intelligent Methods," IEEE Control Systems, 79-84.

Toshio Fukuda, Naoyuki Kubota, 1999. " An Intelligent Robotic System Based on Fuzzy Approach," Proceedings of the IEEE, 1448-1470.

Werbos, Paual J. " Neurocontrol and Elastic Fuzzy Logic," in Madan M. Gupta, Naresh K. Sinha, 1996. (eds.), Intelligent Control Systems: Theory and Applications, IEEE, Inc., New York, 327-343.

Y.Koza, J., 1992. Genetic Programming: On the Programming of Computers by Means of Natural Selection, Cambridge, MA: MIT Press.

Zafestas S. G., 1997. "Introduction: Overview of Intelligent Control," in Spyros G. Tzafestas (ed.), Methods and Applications of Intelligent Control, Kluwer Academic Publishers, Netherlands.