Soft Computing for Advanced Control Applications: Teacher Experience

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Abstract — *Fuzzy-neuro modeling, together with a new driving force from stochastic, gradient-free optimization techniques such as genetic algorithms and simulated annealing, form the constituents of so-called soft computing, which is aimed at solving real-world decision-making, modeling, and control problems. These problems are usually imprecisely defined and require human intervention. Thus, soft computing, with their ability to incorporate human knowledge and to adapt their knowledge base via new optimization techniques, are likely to play increasingly important roles in the conception and design of hybrid intelligent systems. Moreover, soft computing is a relatively new field and continues to evolve rapidly within the scope of computational and artificial intelligence. This article presents notes from the introduction of the interdisciplinary course on soft computing taught at the University of Minnesota Duluth at the graduate level. The course is new in the sense that it covers three main parts of soft computing as well as their integration to develop hybrid intelligent systems. While individual parts have been applied successfully to solve technical problems, the current trend is to create combination of these parts. The objective of this course is to lead students to specialization in the particular parts of soft computing. The curriculum, assessments, implementation are described.*

Index Terms — Artificial neural network, Fuzzy sets, Genetic algorithms, Computational intelligence, Soft computing

INTRODUCTION

Most real-world problems are large scale and inevitably incorporate built-in uncertainties, this precludes using conventional approaches that require detailed description of the problem being solved. Soft computing is an integrated approach that can usually utilize specific techniques within subtasks to construct generally satisfactory solutions to real world problems [2,10].
These application domains are mostly computation intensive and include adaptive signal processing, adaptive control, nonlinear system identification, nonlinear regression, and pattern recognition [9,11,12].
Soft computing, an innovative approach to constructing computationally intelligent systems has just come into the limelight. It is now realized that complex real-world problems require intelligent systems that combine knowledge, techniques, and methodologies from various sources. These intelligent systems are supposed to posses humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how they make decisions or take actions.
The quintessence of designing intelligent systems of this kind is fuzzy-neuro computing: fuzzy inference systems that incorporate human knowledge and perform inference and decision making; neural network that recognize patterns and adapt themselves to cope with changing environments.
The integration of these two complementary approaches, together with certain derivative-free optimization techniques, results in a novel discipline called soft computing.
In hard computing, the prime desiderata are precision, certainty, and rigor. By contrast, the point of departure in soft computing is the thesis that precision and certainty carry a cost and that computation, reasoning, and decision making should exploit the tolerance for imprecision and uncertainty [3]. The exploitation of the tolerance for imprecision and uncertainty underlies the remarkable human ability to understand distorted speech, summarize text, recognize and classify images, drive a vehicle in dense traffic and, more generally, make rational decisions in an environment of uncertainty and imprecision. In effect, soft computing uses the human mind as a role model and, at the same time, aims at a formalization of the cognitive processes humans employ so effectively in the performance of daily task. The year of 1990 may be viewed as a turning point in the evolution of the Machine Intelligence Quotient (MIQ) of consumer products.

FUZZY SETS THEORY

The human brain interprets imprecise and incomplete sensory information provided by perceptive organs. Fuzzy set theory provides a systematic calculus to deal with such information linguistically, and it performs numerical computation by using linguistic labels stipulated by membership functions.

As Zadeh pointed out in 1965 in his seminal paper entitled "Fuzzy Sets" [1] such imprecisely defined sets or classes "play an important role in human thinking, particularly in the domains of pattern recognition, communication of information, and abstraction". Note that the fuzziness does not come from the randomness of
the constituent members of the sets, but from the uncertain and imprecise nature of abstract thoughts and concepts. The main contribution of fuzzy logic is a methodology for computing with words [3]. The premises are assumed to be express as propositions in a natural language. For purposes of computations, the propositions are expressed as canonical forms, which serve to place in evidence the fuzzy constraints that are implicit in the premises. Then the rules of inference in fuzzy logic are employed to propagate the constraints from premises to conclusion. At this juncture, the techniques of computing with words underlie almost all applications of fuzzy logic [14,18,19,20]. A key aspect of computing with words is that it involves a fusion of natural languages and computation with fuzzy variables. A selection of fuzzy if-then rules forms the key component of fuzzy inference system that can effectively model human expertise in specific applications. The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and gives facts to derive a conclusion. Because of its multidisciplinary nature, the fuzzy inference system is known also by other names, such as fuzzy expert system, fuzzy-rule-based system, fuzzy associative memory, fuzzy logic controller, and fuzzy system.
The actual research on fuzzy controllers was initiated by Mamdani and his students Assilian at Queen Mary College in London in 1975.
Mamdani's work influenced other researches to explore the applicability of fuzzy controllers to various control problems. Some of these efforts resulted in laboratory prototypes, and only one of them led eventually to the development of a commercially available fuzzy controller for cement kilns by Holmblad and Ostergaard in 1982. According to the literature, this was the first commercially availably fuzzy controller. In the late 1980s, the interest in fuzzy controllers increased very rapidly in Japan and rest of the world. Although the fuzzy inference system has a structured knowledge representation in the form of fuzzy if-then rules, it lacks the adaptability to deal with changing external environments. Thus, we incorporate neural network learning concepts in fuzzy inference systems, resulting in fuzzy-neuro modeling, a pivotal technique in soft computing.

NEURAL NETWORKS

Inspired by biological nervous systems, many researches, especially brain modelers, have been exploring artificial neural networks, a novel nonalgorithmic approach to information processing. They model the brain as a continuous-time nonlinear dynamic system in connectionist architectures that are expected to mimic brain mechanisms to simulate intelligent behavior. Such connectionism replaces symbolically structured representations with distributed representations in the form of weights between a massive set of interconnected processing units. It does not need critical decision flows in its algorithms.
Artificial neural networks, or simple neural networks (Nns), have been studied for more six decades since neuron model introduced by McCulloch and Pitts in 1943. In the late 1950s, Rosemblatt designed the perceptron with a view toward explaining and modeling pattern-recognition abilities of biological visual systems. In 1986, Rumelhart at al. used the procedure to find the gradient vector in multilayer neural network. Their procedure was called the backpropagation learning rule, inspired enormous interest in research on neural network [4,5,6,10].

EVOLUTIONARY COMPUTATION

Simulating complex biological evolutionary processes may lead us to discover how evolution propels living systems toward higher-level intelligence. Greater attention is thus being paid to evolutionary computing techniques such as genetic algorithms, which are based on the evolutionary principle of natural selection.
Heuristically informed search techniques are employed in many AI applications. When a search space is too large for blind search and it is difficult to identify knowledge that can be applied to reduce the search space, we have no choice but to use more efficient search techniques to find less-than-optimum solutions. The GA offers the capacity for population-based systematic random searches.
Genetic algorithms are derivative-free stochastic optimization method. They were first proposed and investigated by John Holland at the University of Michigan in 1975. Their popularity can be attributed to their incorporation of these characteristic [7,8,10]:

- GAs are parallel-search procedures that can be implemented on parallel-processing machines for massively speeding up their operations.

- GAs are applicable to both continuous and discrete (combinatorial) optimizations.
- GAs are stochastic and less likely to get trapped in local minima, which inevitably are present in any practical optimization applications.
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- GAs' flexibility facilitates both structure and parameter identification in complex models such as neural networks and fuzzy inference systems.

SOFT COMPUTING CHARACTERISTIC

The characteristics of soft computing can be summarized as follows [10]:

Human expertise

Soft computing utilizes human expertise in the form of fuzzy if-then rules, as well as in conventional knowledge representations, to solve practical problems.

Biologically inspired computing models

Inspired by biological neural networks, artificial neural networks are employed extensively in soft computing to deal with perception, pattern recognition, and nonlinear regression and classification problems.

New optimization techniques

Soft computing applies innovative optimization methods arising from various sources: they are genetic algorithms inspired by the evolution and selection process, simulated annealing motivated by thermodynamics, the random search method, and downhill Simplex method. These optimizations methods do not require the gradient vector of an objective functions, so they are more flexible in dealing with complex optimizations problems.

Numerical computation

Unlike symbolic AI, soft computing relies mainly on numerical computation. Incorporation of symbolic techniques in soft computing is an active research area within this field.

Model-free learning

Neural networks and adaptive fuzzy inference systems have the ability to construct models using only target system sample data. Detailed insight into the target system helps set up the initial model structure, but it is not mandatory.

Fault tolerance

Both neural networks and fuzzy inference systems exhibit fault tolerance. The deletion of a neuron in a neural network, or a rule in a fuzzy inference system, does not necessary destroys the system. Instead, the system continues performing because of its parallel and redundant architecture, although performance quality gradually deteriorates

Goal driven characteristics

The path leading from the current state to the solution does not really matter as long as we are moving toward the goal in the long run. This is particularly true when used with derivative-free optimization schemes, such as genetic algorithms. Domain-specific knowledge helps reduces the amount of computation and search time, but it is not a requirement.

New application domain

Soft computing has found a number of new application domains besides that of AI approaches. These application domains are mostly computation intensive and include adaptive signal processing, adaptive control, nonlinear system identification, nonlinear regression, and pattern recognition.

COURSE Curriculum:

TEXTBOOKS:

J. S. R. Jang, C._T. Sun, E. Mizutani, Neuro-Fuzzy and Soft Computing, Prentice Fall, 1997.
Karray O. F. and De Silva C. Soft Computing and Intelligent Systems, Pearson Education, New York, 2004.
M. S. Stachowicz, Lance Beall, Fuzzy Logic Package,Wolfram Research,Inc. 2003.
Christian Jacob, Illustrating Evolutionary Computation with Mathematica, Morgan Kaufmann Publishers, 2001.
M.A. Bhatti, Practical Optimization Methods with Mathematica Applications, TELOS/Springer Verlag, 2000.

OBJECTIVES:

This course provides the comprehensive treatment of the constituent methodologies underlying neuro-fuzzy and soft computing, an evolving branch within the scope of computational intelligence that is drawing increasingly more attention as it develops. Its main features includes fuzzy set theory, neural networks, genetic algorithms, data clustering techniques, and several stochastic optimization methods that do not require gradient information which is aimed at solving real world decision-making, modeling, and control problems. In particular, course put equal emphases on theoretical aspects of covered methodologies, as well as empirical observations and verifications of various applications in practice.

CREDIT AND PREREQUISITES: 3 credits.

Student is expected to have knowledge of linear algebra and computer programming
Lecture topic:
Introduction to computational intelligence,
Fuzzy Sets,
Fuzzy Rules and Fuzzy Reasoning
Fuzzy Inference Systems,
Derivative-Free Optimization,
Adaptive Neural networks,
Supervised Learning Neural Networks,
Learning from Reinforcement,
Unsupervised Learning and other Neural Networks,
Neuro-Fuzzy Modeling,
Data Clustering Algorithms,
Rule-base Structure Identification,
Fuzzy sets and Genetic Algorithms in Game Playing.

CONCLUSION

This interdisciplinary course is unique in the sense that it introduces students to major parts of soft computing in a one semester.

The field of soft computing is evolving rapidly; new techniques and applications are constantly being proposed. In the main, soft computing is not a single methodology. Rather, it is a partnership [13]-[23] For this reason, it is frequently advantageous to use fuzzy sets, neural networks, and genetic algorithms in combination rather than exclusively, leading to hybrid intelligent systems. The most visible systems of this type are fuzzy-neuro systems. We also see fuzzy-genetic, and fuzzy-neuro-genetic systems. The principal aim of soft computing is to achieve tractability, robustness, low solution cost, and high Machine Intelligence Quotient (MIQ) through the exploitation of the tolerance for imprecision and uncertainty.

We can see that a firm foundation for soft computing is being built through the collective efforts of researchers in various disciplines all over the world.

Research oriented projects are educate students that the field of soft computing is promising for solving many interdisciplinary problems. Several course students ended up with a thesis topic involving at least one part of soft computing.

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