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Book review

Computational intelligence: The experts speak, David B. Fogel and Charles J. Robinson (Eds.), IEEE Press and Wiley, 2003, USD 83.95, ISBN 0-471-27454-2

This edited volume contains expanded versions of plenary and invited talks presented at the 2002 World Congress on Computational Intelligence (WCCI) that was held in Honolulu, Hawaii, on May 12–17, 2002. Together, these papers provide a unique multi-faceted overview of different aspects of computational intelligence.

Crudely speaking, computational intelligence encompasses techniques for solving complex problems that originated from observing how we human solve such problems. These methods come from three observation levels:

– We can emulate the directly observable phenomena: our (usually informal) reasoning. Methods that simulate such a reasoning fall under the rubric of fuzzy logic.
– We can emulate the biological processes behind this observed problem solving, namely, the activity of the brain cells during the problem solving. Methods that simulate such an activity are called neural network techniques.
– Finally, instead of simulating the current status of the brain, we can simulate the evolution that has led to this status. Methods that simulate evolution are called evolutionary or genetic algorithms.

All three types of techniques are actively represented in this volume.

By definition, methods of *fuzzy logic* enable us to describe our informal (natural language) reasoning in terms that are understandable to a computer. It is therefore reasonable to expect that fuzzy logic can help in designing dialogue systems that enable the computer to describe its results in natural language terms and thus, to make it possible for humans to communicate with computers in natural language. With respect to spatial relations, this ability is enhanced in a paper by J.M. Keller, P. Matsakis, and M. Skubic who describe how spatial relations like “to the right of” can be formalized.

Once the informal knowledge is translated into the computer-understandable language, we must solve the corresponding optimization problem. One technique that was efficiently used in fuzzy clustering is alternating optimization, where we first optimize over one set of variables, then over another, etc., until the process converges. J.C. Bezdek and R.J. Hathaway prove general results about the convergence of this technique.

For more computationally difficult discrete optimization problems like the ones that occur in manufacturing, management, etc., an overview of fuzzy techniques is provided by H.-J. Zimmermann.

For control applications, it is important not just to have an optimal control, but to make sure that the resulting control is stable relative to possible small perturbations. A new method for checking stability of fuzzy control is described in a paper by G. Feng, D. Sun, and L. Wang. Specifically, the author extend the traditional Lyapunov function techniques, techniques that are not always applicable, to more general piecewise-Lyapunov methods.

Several papers deal with neural networks, computational algorithms that simulate the biological neurons. Two papers compare artificial and biological neurons. A paper by L. Watts emphasizes the numerical difference between the sizes of actual and artificial neural networks, the difference that is shrinking fast. A paper by P.J. Werbos, the author of backpropagation algorithm, analyzes the difference between training in artificial and biological neural networks. While the neural networks themselves are modeled after biological neurons, the most widely used (and most effective) training algorithms like backpropagation are different from how actual neurons learn. Werbos’ paper not only explains this difference, it also shows that backpropagation is not simply a useful trick for training neural networks: its main ideas have wide applications far beyond neural.

Several papers overview applications of neural techniques. Mathematical foundations for using neural networks in non-linear dynamical situations are described by R.J.P. de Figueiredo; the use of neural techniques in unsupervised learning (clustering) is overviewed by S. Szu. P.J. Werbos himself writes about control applications, where the necessity to make control robust is an additional challenge, which is often efficiently handled by combining neural networks with off-line computations.

Several papers deal with the relation between fuzzy and neural approaches. R. Setiono shows how we can extract natural-language rules from the results of training a neural network; F. Fukuda and N. Kubota explain how to successfully combine neural and fuzzy approaches in making robots learn.

Evolutionary approach is also described in several papers. Evolutionary computations simulate evolution that has led to the appearance of the brain. It would therefore seem, at first glance, not to have much to do with the actual functioning of the brain. J. Wiles and J. Hallinan show that, contrary to this first opinion, many cognitive processes are done in a competitive environment similar to biological evolution: e.g., in pattern recognition, several patterns compete with each other. Evolutionary algorithms seem to be a perfect tool to describe such processes.

Several papers describe application of evolutionary algorithms: J. Pollack, H. Lipson, P. Funes, and G. Homby describe applications to robotics; T. Higuchi, E. Takahashi, Y. Kasai, T. Itatani, M. Iwata, H. Sakanashi, M. Murakawa, I. Kajitani, and H. Nosato describe applications to "evolvable hardware", hardware devices where evolutionary algorithms are implemented in controlling chips.

Traditionally, evolutionary algorithms are used to optimize (difficult-to-optimize but still) well-defined objective functions. In many application problems, we do not have a well-defined objective function; instead, we have an expert who can evaluate the relative quality of different alternatives. For example, when we design a seat with the maximal comfort, it is difficult to provide a formula that would gauge the comfort of different seats, but it is easy for a person to compare the comfort level of different designs. H. Takagi shows how we can modify evolutionary algorithms so that they can also be used to optimize such "fuzzy" objective functions as well. Crudely speaking, every time an evolutionary algorithm needs the value of the objective function, we ask an expert instead. Such algorithms are called interactive, and they have been very successful in solving the corresponding difficult-to-formalize optimization problems.

Several papers deal with the computational intelligence in general. D.H. Wolpert emphasizes the importance of having several intelligent agents work together; S. Rogers, M. Kabrisky, K. Bauer, and M.E. Oxley emphasize that it is much more efficient to design an intelligence system as an "intelligence amplifier" – that helps an intelligent person make a decision – rather than to try to design a system that makes intelligent decisions automatically.

Finally, J.F. McEachem and R.T. Miyamoto describe a class of challenging problems in which computational intelligent techniques are needed: problems related to processing information from underwater sensors. A large amount of sonar noise cannot be decreased by simply filtering, we need intelligence to separate noise from signal, and computational intelligence seems to be the right approach to make such separation.

Overall, this volume provides a valuable coherent snapshot of computational intelligence and its applications.

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