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COMPUTATIONAL INTELLIGENCE Imitating Life

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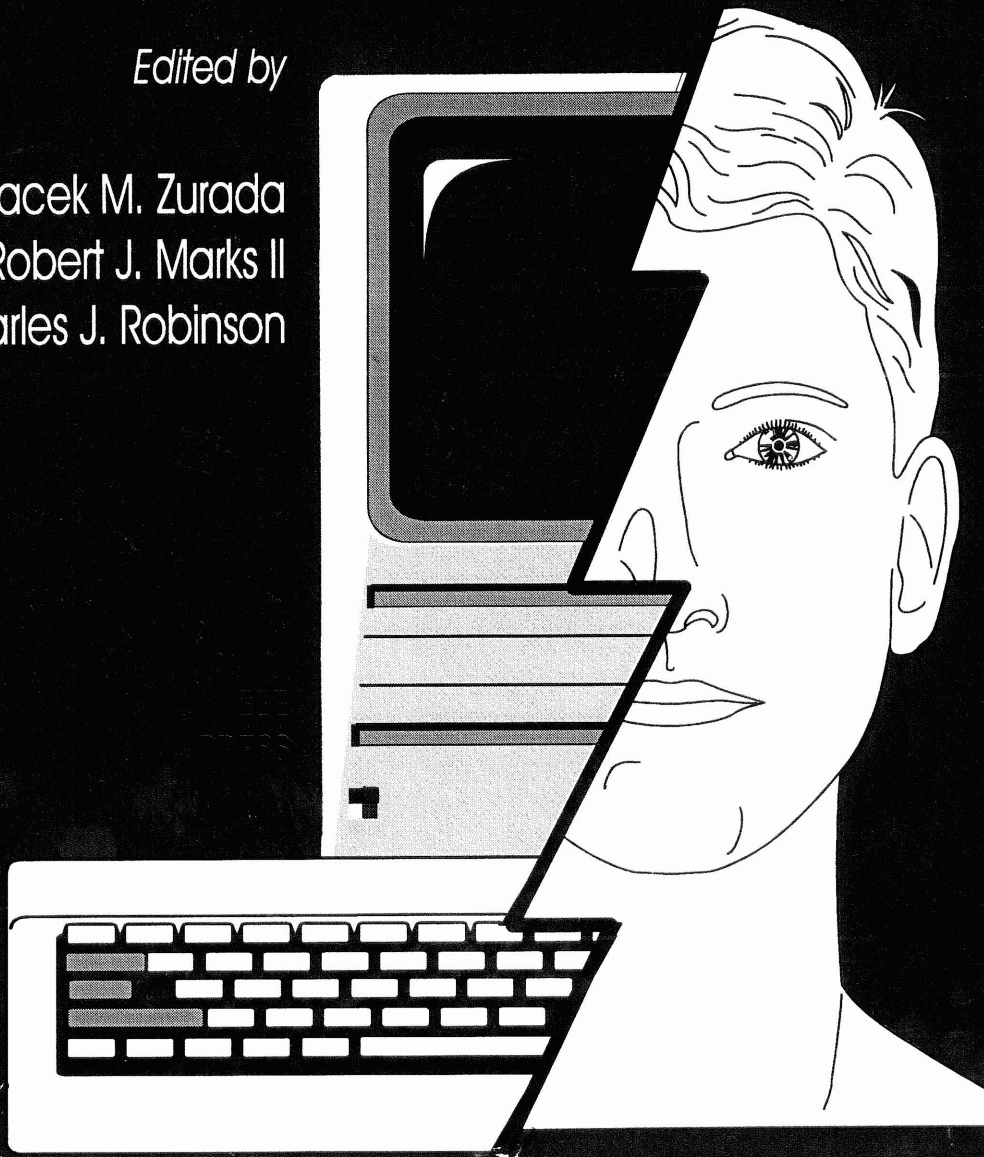

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Introduction

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Many pioneering scientists, including Newton and Maxwell, were motivated by a quest to discover the art and order in creation - to know the mind of God through study of His creations. Nearly all inventions have a counterpart in or are an extension of nature. Thermonuclear explosions occur in the stars, pulse modulation occurs in the human nervous system, bats have sonar and dolphin pings serve as a subterranean telephone. Nature likewise inspires invention. Engineering uses science and mathematics to emulate and extend nature. As the bird motivated heavier than air flight, so does human intelligence motivate study of advanced computational paradigms. We know, with no doubt, that intelligence is achievable. The evidence lies between our ears.

Attempts to artificially mimic intelligence have a rich history. Langton [1] traces the history of artificial life from the pneumatic animal gadgets of Hero of Alexandria in the first century, through John von Neumann's first computational approach to machine reproduction behavioı, to Norbert Wiener's "study of control and communication in the animal and the machine", *i.e.*, cybernetics. More recently, the field of *Artificial Intelligence* has attempted to capture the essence of intelligence.

In the 1980's, the field of artificial neural networks (NN's) [2] was reborn - largely through the promotion of Hopfield and the popularization of backpropagation to train multilayer perceptrons. NN's can be categorized as artificial intelligence. We argue, however, that NN's are not properly categorized as *Artificial Intelligence* (note the capital letters). The term *Computational Intelligence* is more descriptive [3, 4]. Evolutionary Computation, artificial life and certain topics of fuzzy systems are also subsumed in *Computational Intelligence* (CI).

Definition

What is CI and how does it differ from AI? The first definition of *Computational Intelligence* was offered by James C. Bezdek [3]. At our invitation, Bezdek also eloquently elaborates on the contrast between CI and AI in this volume [5]. According to Bezdek [3], in the strictest sense, *Computational Intelligence* "depends on numerical data supplied by manufacturers and (does) not rely on 'knowledge'." Artificial intelligence, on the other hand, uses what Bezdek calls "knowledge tidbits". Many NN's called 'artificial' should, Bezdek argues, be called computational NN's.

CI versus AI

Even though the boundary between CI and AI is not distinct, we can, making certain assumptions, monitor the volume of research activity in each [6]. Indeed, the separate identities of CI and AI are confirmed by inspection of the recent volume of publishing and patent activity.

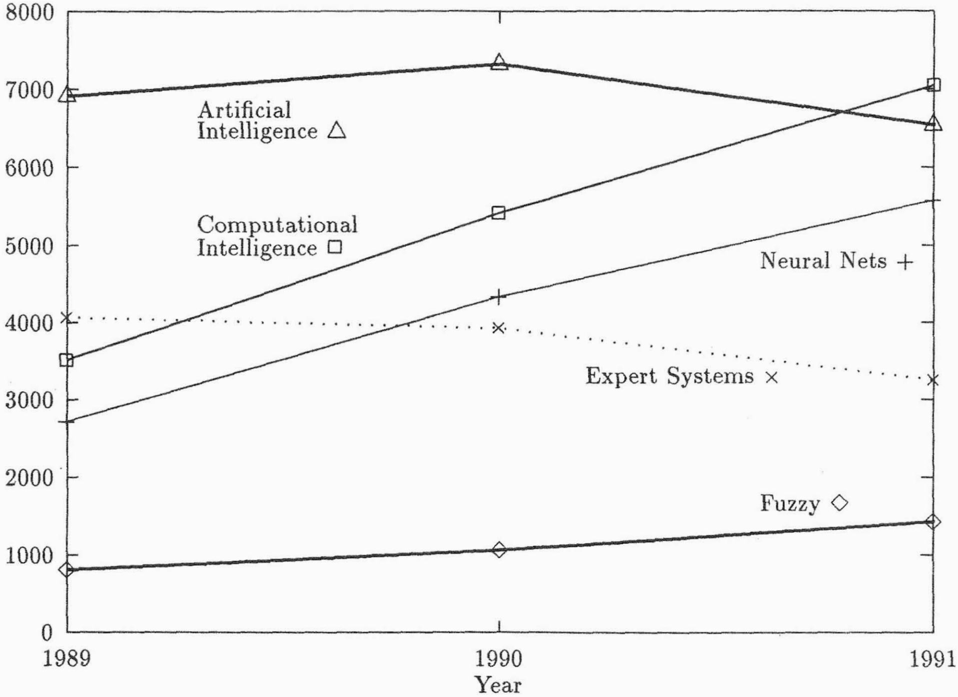

Figure 1: Numbers of papers and other works generated in areas of computational and artificial intelligence according to the INSPEC data base (From Marks [4]).

Publishing activities can be assessed through perusal of the INSPEC (*Information Service for Physics and Engineering Communities*) data base compiled by the IEE and the IEEE. The INSPEC data base contains titles, authors and abstracts from over 4000 journals and is augmented with entries of books, reports and conference records. It is focused on the fields of physics, electrical engineering, computer science and electronics. Over one million entries have been logged into INSPEC since 1989. Contents are updated monthly. Searches for key words are performed over titles, authors, journal titles, and abstracts. Results of AI and CI publication activity, as revealed by INSPEC query, are shown in Figure 1.

Statistics from INSPEC and CASSIS are neither the perfect nor the only measure by which to monitor the vitality of a field. They are, however, quite useful in monitoring the trends and the relative activity. CASSIS, in particular, is vital for monitoring applications and implementation. Patent data, though, has a greater time delay in the measure of activity than does INSPEC data. The following are searches performed after the July 1993 INSPEC update and July 20, 1993 CASSIS update.

Since 1989, there have been an astounding 16,574 INSPEC entries logged for neural networks [4]. Over half (7429), are associated with IEEE activities. As we write, the data for 1992 is not yet complete.

US Patent data can be obtained from CASSIS (*Classification for Search Support Information System*). Searches are also performed over titles and abstracts.

For patents, CASSIS lists 262 neural network patents since 1969. Figure 2 shows nearly all of them have been issued in the past few years.

Only 10% of the INSPEC artificial intelligence [8] entries were also flagged as works in neural networks. As the graph in Figure 1 shows, research activity in AI, as gauged from the number of INSPEC entries, remains quite high. (We identified but a single entry for artificial stupidity'.) Cumulatively, there are 28,166 AI entries in INSPEC; 5832 associated with IEEE activities. A total of 266 patents have been issued for AI.

Expert Systems are the most successful application of AI. A total of 131 Expert Systems patents have been issued and, as seen in Figure 2, the volume trends upwards. The number of INSPEC entries for Expert Systems, on the other hand, clearly trends down in Figure 1. There are 15,575 Expert Systems entries in INSPEC.

Also shown in Figure 1 is a steadily increasing publication volume in fuzzy systems. A total of 4811 fuzzy INSPEC entries have been logged since 1989 - 22% of them cross categorized in the Expert System category and 12% with neural networks. Fuzzy patents total 109.

Computational Intelligence has experienced remarkable growth and has 21,307 INSPEC entries and 384 patents. Yearly breakdowns are shown in Figures 1 and 2. In 1991, there were 7050 INSPEC listed works in CI and 6540 in AI. The CI patents (168) in 1992 exceed in number the sum of all patents issued from 1986 though 1991 (167).

How much overlap is there between the fields of CI and AI? Judging from the numbers, not a lot. Only 14% of the INSPEC entries identified as AI were also categorized as CI. Only one third of the patents fell in both categories. Bezdek [5] places CI $\in$ ai. This is not inconsistent with our contention, supported by the statistics, that CI $\notin$ AI.

Surveying the Book

As the numbers indicate, research, application and implementation of CI, is accelerating. The purpose of this book is to place between two covers a broad CI background relevant to engineers, applied mathematicians and computer & other scientists. Although the papers in this volume are highly focused on the relevant research in CI, they are, for the most part, highly tutorial in nature. The book is organized into seven sections.

In this Introduction, we provide a small glimpse into the meaning of CI and its contrast with AI. In the lead paper in this volume, Bezdek provides a panoramic view. The question asked by his title, *What is Computational Intelligence?*, is answered thoroughly.

Section 1 of this volume is titled *Computational Learning Theory*. The first paper, by Oja and Lampinen, provides a comprehensive discussion of unsupervised learning of features. For high-dimensional patterns this nonlinear space transformation learning is of singular significance in machine vision and pattern recognition. Berenji nicely covers learning using reinforcement learning techniques. His paper focuses on temporal-difference and Q-learning in fuzzy systems. Learning in neural-fuzzy systems as a process of adaptive interpolation based on data is discussed by Khedkar. Such learning combines the best properties of the complementary fields of fuzzy systems and neural nets by providing an interpretable and adaptive model of knowledge. Robert Hecht-Nielsen presents an application of a new self organization methodology to databases. The procedure has an impressive ability to generate context vectors useful in providing an index for the database. Touretzky, Wan,

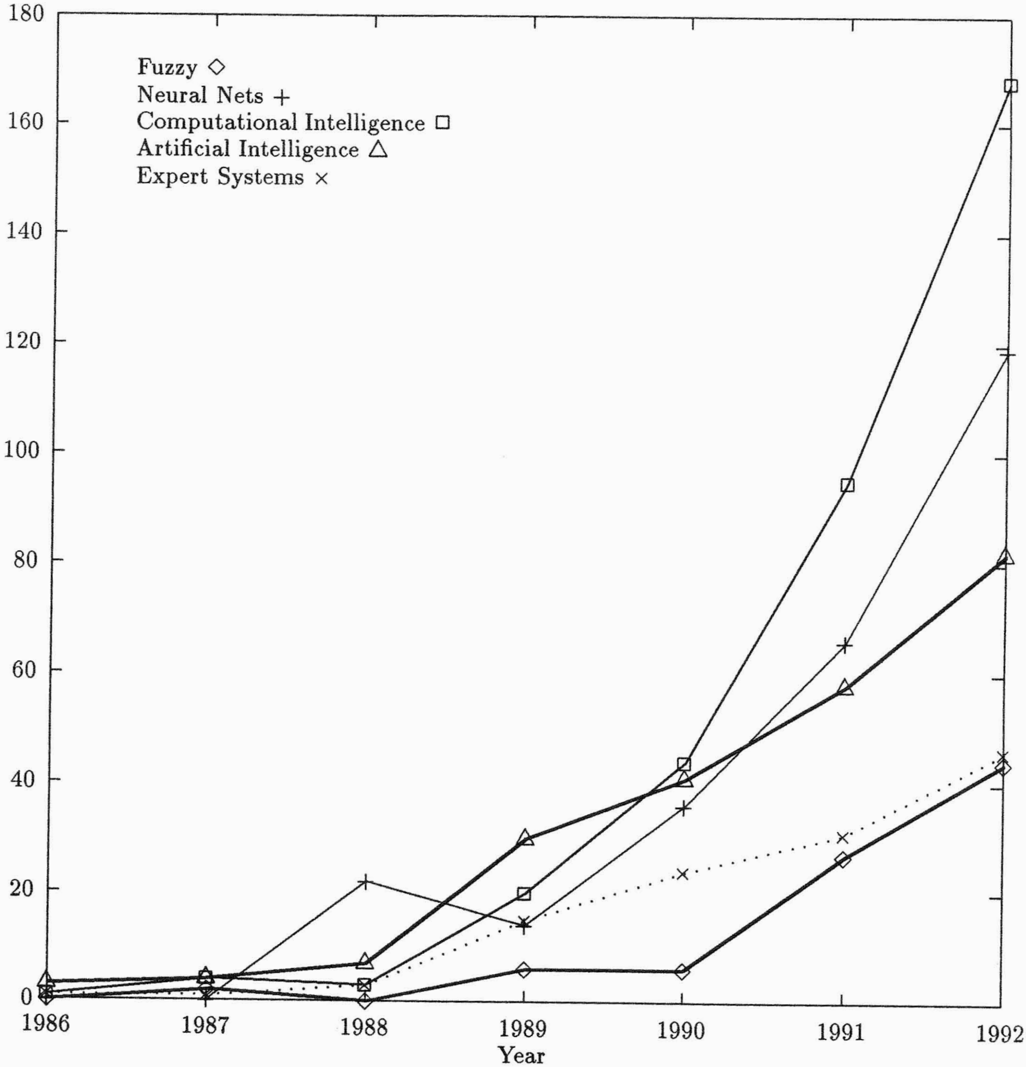

Figure 2: Patents activity according to the CASSIS data base (From Marks [4]).

and Raddish directly examine nature to learn about learning. They describe a computer model of navigation learning based on rat behavior. Place recognition, path integration and maintenance of direction are involved. The model reproduces results from a variety of behavioral experiments and is consistent with recording data from hippocampal place cells as well as postsubicular and parietal head direction cells.

Section 2 of the book contains contributions on *Approximate Reasoning*. The papers deal with concepts and techniques in modeling - and fuzzy & approximate reasoning & modeling. Dubois and Prade provide an outstanding overview of fuzzy similarity relations and suggest fuzzy sets as a suitable framework for representing proximity and similarity. They also show that qualitative and interpolative, case-based, and analogical reasoning benefit from proper handling of fuzzy relations. Spatial relation determination among vaguely defined regions in a digital image using fuzzy set theory is discussed by Keller. An important unified conceptual structure of fuzzy modeling is given by Pedrycz. The paper by de Mantaras deals with two fundamental aspects of problem solving. He shows that reasoning under uncertainty and learning-controlled knowledge can provide effective learning by experience in expert systems.

Section 3 is entitled *Evolutionary Computation*. The first paper, by Schwefel, provides a lucid overview of motivations in the imitation of life by evolutionary computation. A 25 year perspective of the design and implementation of genetic algorithms is presented by De Jong. He identifies important open issues which are in need of further research. Fogel describes the perspective of evolutionary programming he originally devised over three decades ago. Evolution is expressed as a top-down process of adaptive behavior, rather than a bottom-up process of adaptive genetics. The paper by Rechenberg reviews evolution strategy which imitates the effect of genetic information processing. The strategy is used to develop a magic square, an optical lens and a stone throw trajectory. Kitano skillfully illustrates that evolutionary computing is applicable to a wide class of problems. The issue of selecting genetic operators for combinatorial optimization problems is presented by Manderick and Spiessens. They illustrate the use of correlation coefficients of genetic operators for tasks such as the traveling salesman problem and flow shop scheduling. Müehlenbein and Schlierkamp-Voosen focus on predicting the behavior of breeder genetic algorithms. They show how the response to selection equations and the concept of heritability can be applied to analyze and control the algorithm.

Section 4 contains contributions in the area of *Biological Computation and Pattern Recognition*. Each paper provides an overview of recent advances in neurocomputing and biological computing recognition of patterns, visual processing and auditory modeling. Jain and Mao provide a comprehensive state-of-the-art review of links between neural networks and statistical pattern recognition. They insightfully contrast capacities, assumptions and applicability of various approaches developed in the two disciplines. Anderson and Van Essen discuss the probabilistic measures of analog quantities as a suitable representation on which to build reasoning systems. The incorporation of modern information and signal processing approaches described in the paper provide a fundamental foundation for understanding neurobiological computational systems. Algorithms for perception of motion and texture are outlined by Sperling, Chub, Holoman and Liu. They report a series of examples and demonstrations which support their proposed visual preprocessing model. Waxman, Seibert and Gove summarize neurocomputing architectures that learn 3D objects using contrast conditions, color fusion, image motion learning and spatial maps recognition. Psychological observations on the topic of color vision and visual pathway are given by Usui and Nakauchi. They demonstrate that neural networks provide valuable insight into color representing individual pathways. Payton provides an important summary of the current state of auditory computational modeling. These models are improving the understanding of hearing mechanisms and are proving important in recent efforts to improve automatic speech recognition. Novel adaptive neural nets for information processing are reported by Eckmiller. These networks, operating with asynchronous impulse processing and adaptive delays, offer a chance to "copy" certain biological neural functions for important applications in industry and medicine.

The papers is Section 5, *Intelligent Control*, are devoted to learning control systems. Omatu applies neural concepts to linear and nonlinear temperature control. Langari focuses on integration of hierarchically structure control systems which incorporate conventional control strategies and involve nonlinear singular perturbation. A method of qualitative modeling of systems using both knowledge and numerical data is proposed by Sugeno and Yasukawa. This composite model is designed for fuzzy feedback control and is useful for dynamic and mechanical systems. Bonissone reports on fuzzy logic controllers for nonlinear dynamic systems using an interactive computing environment. He provides an insightful overview of other industrial applications of fuzzy controllers. Learning in neural controllers both symbol and signal level is discussed by Yabuta, Yamada and Manabi. They outline a basic framework for signal level learning methods such as adaptive control, neural control, learning control, and genetic algorithms. Fujii and Ura provide a description of an autonomous underwater vehicle controlled by a self-adaptive neural controller. The control is achieved in a self-organizing neural net controller showing a remarkable capability of adjustment to natural environments.

Section 6, *Hybrid Computational Intelligence*, contains contributions wherein a combination of fuzzy, neural and genetic operandi are used for problem solving. Fukuda and Shibata present an ingenious fuzzy-neural-GA based hierarchically control for intelligent robots. Zimmermann discusses hybrid approaches for fuzzy data analysis and configuration using genetic algorithms and evolutionary methods. An comprehensive introduction to approaches to combine genetic algorithms with neural networks or fuzzy systems is given by Schaffer Yamakawa reports on a new neural model developed through fusion of fuzzy logic and neural signs. This model facilitates fast guaranteed learning within conventional feedforward layered neural networks.

Section 7 is dedicated to *Applications* of CI to technology and business. Fogelman-Soulié presents successful industrial applications of reduced-complexity neural networks. In a delightfully readable essay, Rogers, Kabrisky, Ruck and Oxley relate how neural networks can be used to fight crime. Davis discusses three examples of successful applications of genetic algorithm optimization - game scheduling, fiber optic network design and facial image formation of perpetrators using eyewitness input. Background on a United Kingdom government funded program which promotes business applications of neural computing is provided by Wiggins. Brown outlines new paradigms for technology transfer in the R & D environment. Some of the inherent problems and views of technology transfer are compared and contrasted with the new paradigms.

Finis

From the world's leading experts, we have, for the first time, solicited tasty ingredients of most all aspects of contemporary CI to prepare this definitive chef's salad. *Bon appétit.*

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[4] R.J. Marks II, "Intelligence: Computational Versus Artificial", *IEEE Transactions on Neural Networks*, vol.4, no.5, (September 1993).

[5] James C. Bezdek, "What ... Is Computational Intelligence?", a chapter in this book.

[6] Search words for 'neural networks' used are neural net(s), neural network(s) and neurocomputer(s).

[7] Search words for 'artificial intelligence' used are artificial intelligence, expert system(s), machine intelligence and intelligent system(s).

[8] Search for 'computational intelligence' included the search words used for neural networks as well as fuzzy, genetic algorithm(s), evolutionary programming and artificial life.