Intelligent wireless sensor networks (iWSNs) in cyber-physical systems

Chapter · April 2016

DOI: 10.1049/PBCE096E_ch10

3 authors, including:

Farhad Mehdipour
Otago Polytechnic - Auckland International Campus

Int. J. of Computers, Communications & Control, ISSN 1841-9836, E-ISSN 1841-9844
Vol. III (2008), Suppl. issue: Proceedings of ICCCC 2008, pp. 132-138

Intelligent Systems

Plenary invited paper & workshop invited key lecture

Imre J. Rudas, János Fodor

Abstract: In this paper we give an overview of intelligent systems. We discuss the notion itself, together with diverse features and constituents of it. We concentrate especially on computational intelligence and soft computing.
Keywords: intelligent systems, computational intelligence, soft computing.

1 Introduction

Intelligent systems (IS) provide a standardized methodological approach to solve important and fairly complex problems and obtain consistent and reliable results over time [2]. Extracting from diverse dictionaries, *intelligence* means the ability to comprehend; to understand and profit from experience. There are, of course, other meanings such as ability to acquire and retain knowledge; mental ability; the ability to respond quickly and successfully to a new situation; etc.

The definition of intelligent systems is a difficult problem and is subject to a great deal of debate. From the perspective of computation, the intelligence of a system can be characterized by its flexibility, adaptability, memory, learning, temporal dynamics, reasoning, and the ability to manage uncertain and imprecise information [9].

Independently from the definition, there is not much doubt that artificial intelligence (AI) is an essential basis for building intelligent systems. According to [13], AI consists of two main directions. One is *humanistic AI* (HAI) that studies machines that think and act like humans. The other one is *rationalistic AI* (RAI) that examines machines that can be built on the understanding of intelligent human behaviour. Here are some illustrative explanations from [9] where references to their original sources can also be found.

HAI is the art of creating machines that perform functions that require intelligence when performed by people. It is the study of how to make computers do things at which, at the moment, people are better. *RAI* is a field of study that seeks to explain and emulate intelligent behavior in terms of computational processes. It is the branch of computer science that is concerned with the automation of intelligent behavior.

Intelligent systems as seen nowadays have more to do with rationalistic than with humanistic AI. In addition to HAI features, IS admits intelligent behaviour as seen in nature as a whole; think, for example, on evolution, chaos, natural adaptation as intelligent behaviour. Moreover, IS are motivated by the need to solve complex problems with improving efficiencies.

Based on these and other similar considerations, an acceptable definition of intelligent systems was formulated in [9]. We adopt it here as follows.

Definition 1. [9] An *intelligent system* is a system that emulates some aspects of intelligence exhibited by nature. These include learning, adaptability, robustness across problem domains, improving efficiency (over time and/or space), information compression (data to knowledge), extrapolated reasoning.

The main aim of the present paper is to give an overview of diverse features and constituents of intelligent systems. After highlighting the notion of computational intelligence and its relationship to artificial intelligence, we go on with soft computing and hybrid systems.

2 Computational Intelligence

The development of digital computers made possible the invention of human engineered systems that show intelligent behaviour or features. The branch of knowledge and science that emerged together and from such systems is called *artificial intelligence*. Instead of using this general name to cover practically any approach to intelligent systems, the AI research community restricts its meaning to *symbolic representations and manipulations in a top-down way* [3]. In other words, AI builds up an intelligent system by studying first the structure of the problem (typically in formal logical terms), then formal reasoning procedures are applied within that structure.

Alternatively, non-symbolic and bottom-up approaches (in which the structure is discovered and resulted from an unordered source) to intelligent systems are also known. The conventional approaches for understanding and predicting the behavior of such systems based on analytical techniques can prove to be inadequate, even at the initial stages of establishing an appropriate mathematical model. The computational environment used in such an analytical approach may be too categoric and inflexible in order to cope with the intricacy and the complexity of the real world industrial systems. It turns out that in dealing with such systems, one has to face a high degree of uncertainty and tolerate imprecision, and trying to increase precision can be very costly [11].

In the face of difficulties stated above fuzzy logic (FL), neural networks (NN) and evolutionary computation (EC) were integrated under the name *computational intelligence* (CI) as a hybrid system. Despite the relatively widespread use of the term CI, there is no commonly accepted definition of the term.

The birth of CI is attributed to the IEEE World Congress on Computational Intelligence in 1994 (Orlando, Florida). Since that time not only a great number of papers and scientific events have been dedicated to it, but numerous explanations of the term have been published. In order to have a brief outline of history of the term the founding and most interesting definitions will be summarized now.

The first one was proposed by Bezdek [1] as follows.

Definition 2. [1] A system is called *computationally intelligent* if it deals only with numerical (low-level) data, has a pattern recognition component, and does not use knowledge in the AI sense; and additionally, when it (begins to) exhibit (i) computational adaptivity; (ii) computational fault tolerance; (iii) speed approaching human-like turnaround, and (iv) error rates that approximate human performance.

Notice how the role of pattern recognition is emphasized here. In addition, remark that Bezdek concerns an artificially intelligent system as a CI system whose "added value comes from incorporating knowledge in a nonnumerical way."

In [10], one of the pioneering publications on computational intelligence, Marks defined CI by listing the building blocks being neural nets, genetic algorithms, fuzzy systems, evolutionary programming, and artificial life. Note that in more recent terminology genetic algorithms and evolutionary programming are called by the common name evolutionary computing.

In the book [5] Eberhart *et al.* formulated their own definition and its relationship to the one of Bezdek.

Definition 3. [5] Computational intelligence is defined as a methodology involving computing (whether with a computer, wetware, etc.) that exhibits an ability to learn and/or deal with new situations such that the system is perceived to possess one or more attributes of reason, such as generalisation, discovery, association, and abstraction.

Eberhart *et al.* stress adaptation rather than pattern recognition (Bezdek). They say it explicitly: *computational intelligence and adaptation are synonymous.* That is, in this sense CI do not rely on explicit human knowledge [7]. Notice that adaptability is one of the key features of intelligent systems also in Definition 1.

Closing this section, we briefly recall three typical opinions on the relationship between AI and CI, leaving to the reader to judge them.

In [10] Marks wrote: "Although seeking similar goals, CI has emerged as a sovereign field whose research community is virtually distinct from AI." This opinion declares that CI means an alternative to AI.

Bezdek in [1], after an analysis based on three levels of system complexity, came up with the conclusion that CI is a subset of AI. This viewpoint was criticized in [5].

Fogel formulated a third opinion in [7]. Starting from *adaptation* as the key feature of intelligence, and observing that traditional symbolic AI systems do not adapt to new problems in new ways, he declares that AI systems emphasize *artificial* and not the *intelligence*. Thus, it may be inferred that AI systems are not intelligent, while CI systems are.

3 Soft Computing

Prof. Lotfi A. Zadeh [14] proposed a new approach for Machine Intelligence, separating Hard Computing techniques based Artificial Intelligence from Soft Computing techniques based Computational Intelligence (Figure 1).

Hard computing is oriented towards the analysis and design of physical processes and systems, and has the characteristics precision, formality, categoricity. It is based on binary logic, crisp systems, numerical analysis, probability theory, differential equations, functional analysis, mathematical programming, approximation theory and crisp software.

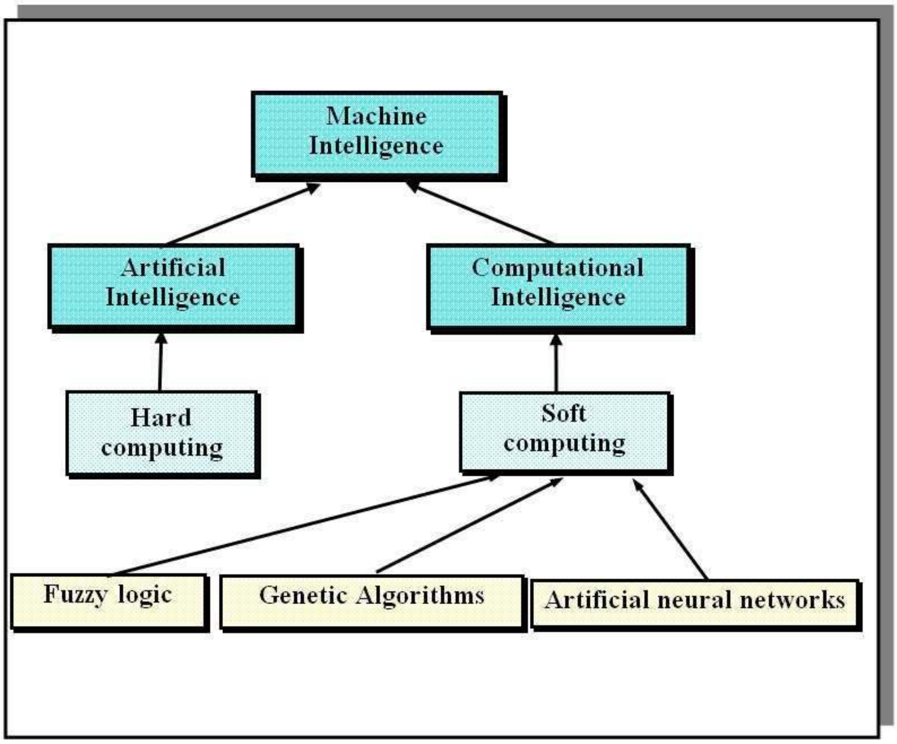

Figure 1: Artificial Intelligence vs. Computational Intelligence

Soft computing is oriented towards the analysis and design of intelligent systems. It is based on fuzzy logic, artificial neural networks and probabilistic reasoning including genetic algorithms, chaos theory and parts of machine learning and has the attributes of approximation and dispositionality.

Although in hard computing imprecision and uncertainty are undesirable properties, in soft computing the tolerance for imprecision and uncertainty is exploited to achieve an acceptable solution at a low cost, tractability, high Machine Intelligence Quotient (MIQ). Prof. Zadeh argues that soft computing, rather than hard computing, should be viewed as the foundation of real machine intelligence.

Soft computing, as he explains, is

- a consortium of methodologies providing a foundation for the conception and design of intelligent systems,
- aimed at a formalization of the remarkable human ability to make rational decision in an uncertain and imprecise environment.

The guiding principle of soft computing is: *Exploit the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness, low solution cost and better rapport with reality.*

Fuzzy logic (FL) is mainly concerned with imprecision and approximate reasoning, neural networks (NN) mainly with learning and curve fitting, evolutionary computation (EC) with searching and optimization. The constituents of soft computing are complementary rather than competitive.

The experiences gained over the past decade have indicated that it can be more effective to use them in a combined manner, rather than exclusively. For example an integration of fuzzy logic and neural nets has already become quite popular (neuro-fuzzy control) with many diverse applications, ranging from chemical process control to consumer goods.

The constituents and the characteristics of hard and soft computing are summarized in Table I.

3.1 Fuzzy Logic

Fuzziness refers to nonstatistical imprecision and vagueness in information and data. Most concepts dealt with or described in our world are fuzzy. In classical logic, known as crisp logic, an element either is or is not a member of a set. That is, each element has a membership degree of either 1 or 0 in the set. In a fuzzy set, fuzzy membership values reflect the membership grades of the elements in the set. Membership function is the basic idea in fuzzy set theory based on fuzzy logic, which is the logic of "approximate reasoning." It is a generalization of conventional (two-valued, or crisp) logic. Fuzzy sets model the properties of imprecision, approximation, or vagueness. Fuzzy logic solves problems where crisp logic would fail.

Fuzzy logic is being applied in a wide range of applications in engineering areas ranging from robotics and control to architecture and environmental engineering. Other areas of application include medicine, management, decision analysis, and computer science. New applications appear almost daily. Two of the major application areas are *fuzzy control* and *fuzzy expert systems.*

3.2 Neural Networks

An artificial neural network (briefly: neural network) is an analysis paradigm that is roughly modeled after the massively parallel structure of the brain. It simulates a highly interconnected, parallel computational structure with many relatively simple individual processing elements. It is known for its ability to deal with noisy and variable information.

There are five areas where neural networks are best applicable [6]:

- Classification;
- Content Addressable Memory or Associative Memory;
- Clustering or Compression;
- Generation of Sequences or Patterns;
- Control Systems.

3.3 Evolutionary Computing

Evolutionary computing comprises machine learning optimization and classification paradigms roughly based on mechanisms of evolution such as biological genetics and natural selection. The evolutionary computation field includes genetic algorithms, evolutionary programming, genetic programming, evolution strategies, and particle swarm optimization. It is known for its generality and robustness. Genetic algorithms are search algorithms that incorporate natural evolution mechanisms, including crossover, mutation, and survival of the fittest. They are used for optimization and for classification. Evolutionary programming algorithms are similar to genetic algorithms, but do not incorporate crossover. Rather, they rely on survival of the fittest and mutation. Evolution strategies are similar to genetic algorithms but use recombination to exchange information between population members instead of crossover, and often use a different type of mutation as well. Genetic programming is a methodology used to evolve computer programs. The structures being manipulated are usually hierarchical tree structures. Particle swarm optimization flies potential solutions, called particles, through the problem space. The particles are accelerated toward selected points in the problem space where previous fitness values have been high.

Evolutionary algorithms have been applied in *optimization* to multiple-fault diagnosis, robot track determination, schedule optimization, conformal analysis of DNA, load distribution by an electric utility, neural network explanation facilities, and product ingredient mix optimization. *Classification* applications include rule-based machine learning systems and classifier systems for high-level semantic networks. An application area of both optimization and classification is the evolution of neural networks.

4 Hybrid Systems

Hybrid systems combine two or more individual technologies (fuzzy logic, neural networks and genetic algorithms) for building intelligent systems. The individual technologies represent the various aspects of human intelligence that are necessary for enhancing performance. However, all individual technologies have their constraints and limitations. Having the possibility to put two or more of them together in a hybrid system increases the system's capabilities and performance, and also leads to a better understanding of human cognition.

Table I. The constituents and the characteristics of hard and soft computing after [11].

HARD COMPUTING		SOFT COMPUTING	
Based on	***Has the characteristics***	***Based on***	***Has the characteristics***
• binary logic	• quantitative	• fuzzy logic	• qualitative
• crisp systems	• precision	• neurocomputing	• dispositionality
• numerical analysis	• formality	• genetic algorithms	• approximation
• differential equations	• categoricity	• probabilistic reasoning	
• functional analysis		▪ machine learning	
• mathematical programming		▪ chaos theory	
• approximation theory		▪ evidental reasoning	
• crisp software		▪ belief networks	

Several models are used for integrating intelligent systems. The one used in [8] classifies hybrid architectures into the following four categories:

Combination: typical hybrid architecture of this kind is a sequential combination of neural networks and rule- or fuzzy rule-based systems.

Integration: this architecture usually uses three or more individual technologies and introduces some hierarchy among the individual subsystems. For example, one subsystem may be dominant and may distribute tasks to other subsystems.

Fusion: a tight-coupling and merging architecture, usually based on the strong mathematical optimization capability of genetic algorithms and neural networks. When other techniques incorporate these features, the learning efficiency of the resulting system is increased.

Association: the architecture that includes different individual technologies, interchanging knowledge and facts on a pairwise basis.

Lotfi A. Zadeh expectation was explained as follows: *"in coming years, hybrid systems are likely to emerge as a dominant form of intelligent systems. The ubiquity of hybrid systems is likely to have a profound impact on the ways in which man-made systems are designed, manufactured, deployed and interacted with."*

Fuzzy logic is mainly concerned with imprecision and approximate reasoning, neural networks mainly with learning and curve fitting, evolutionary computation with searching and optimization. Table II gives a comparison of their capabilities in different application areas, together with those of control theory and artificial intelligence.

Table II. after [12]

	Mathematical Model	Learning Data	Operator Knowledge	Real Time	Knowledge Representation	Nonlinearity	Optimization
Control Theory	*Good*	*X*	*Needs*	*Good*	*X*	*X*	*X*
Neural Network	*X*	*Good*	*X*	*Good*	*X*	*Good*	*Fair*
Fuzzy Logic	*Fair*	*X*	*Good*	*Good*	*Needs*	*Good*	*X*
Artificial Intelligence	*Needs*	*X*	*Good*	*X*	*Good*	*Needs*	*X*
Genetic Algorithms	*X*	*Good*	*X*	*Needs*	*X*	*Good*	*Good*

Explanation of Symbols: Good=Good or suitable, Fair=Fair, Needs=Needs some other knowledge or techniques, X=Unsuitable or does not require.

5 Summary and Conclusions

In this paper we gave an overview of intelligent systems, computational intelligence and soft computing. The notions have been discussed in considerable details. Essential features were highlighted together with typical applicational areas. In our plenary lecture at ICCCC 2008 we will analyse further the constituents and their simultaneous usage.

References

[1] J.C. Bezdek, "What is computational intelligence?", In: J.M. Zurada, R.J. Marks II, and C.J. Robinson, Eds., *Computational Intelligence, Imitating Life,* IEEE Computer Society Press, pp. 1-12, 1994.

[2] T.A. Byrd and R.D. Hauser, "Expert systems in production and operations management: research directions in assessing overall impact," *Int. J. Prod. Res.*, Vol. 29, pp. 2471-2482, 1991.

[3] B.G.W. Craenen, A.E. Eiben, "Computational Intelligence," *Encyclopedia of Life Support System,* EOLSS Co. Ltd., http://www.eolss.net, 2003.

[4] W. Duch, "What is Computational Intelligence and where is it going?", In: W. Duch and J. Mandziuk, Eds., *Challenges for Computational Intelligence,* Springer Studies in Computational Intelligence, Vol. 63, pp. 1-13, 2007.

[5] R. Eberhart, P. Simpson, and R. Dobbins, *Computational Intelligence PC Tools,* Academic Press, Boston, 1996.

[6] R.C. Eberhart and Y. Shui, *Computational Intelligence - Concepts to Implementations,* Elsevier, 2007.

[7] D. Fogel, "Review of computational intelligence imitating life,"*IEEE Transactions on Neural Networks,* Vol. 6, pp. 1562-1565, 1995.

[8] M. Funabashi, A. Maeda, Y. Morooka and K. Mori, "Fuzzy and neural hybrid expert systems: synergetic AI," *IEEE Expert*, August, pp. 32-40, 1995.

[9] K. Krishnakumar, "Intelligent systems for aerospace engineering – an overview," *NASA Technical Report*, Document ID: 20030105746, 2003.

[10] R. Marks, "Computational versus artificial," *IEEE Transactions on Neural Networks,* Vol. 4, pp. 737-739, 1993.

[11] I.J. Rudas, Hybrid Systems (Integration of Neural Networks, Fuzzy Logic, Expert Systems, and Genetic Algorithms), In: *Encyclopedia of Information Systems,* Academic Press, pp. 114-1 - 114-8, 2002.

[12] I.J. Rudas and M.O. Kaynak, "Techniques in Soft Computing and their Utilization in Mechatronic Products," In: C.T. Leondes, Ed., *Diagnostic, Reliability and Control System Techniques,* Gordon and Beach International Series in Engineering, Technology and Applied Science Volumes on Mechatronics Systems Techniques and Applications, Vol. 5, Singapore, pp. 101-138, 2000.

[13] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach,* Prentice Hall, New Jersey, 1995.

[14] L.A. Zadeh, "Fuzzy Logic and Soft Computing: Issues, Contentions and Perspectives," In: *Proc. of IIZUKA'94: Third Int.Conf. on Fuzzy Logic, Neural Nets and Soft Computing,* Iizuka, Japan, pp. 1-2, 1994.

[15] L.A. Zadeh, "Fuzzy Logic, Neural Networks, and Soft Computing," *Communications of the ACM,* Vol. 37, pp. 77-84, 1994.

Imre J. Rudas, János Fodor
Budapest Tech
Institute of Intelligent Engineering Systems
Bécsi út 96/b, H-1034 Budapest, Hungary
E-mail: {rudas,fodor}@bmf.hu