On Further Development of Soft Computing, Some Trends in Computational Intelligence

Dragan Z. Šaletic

School of Computing, Knez-Mihailova str. 6
University "Union", Belgrade, Serbia
dragan_saletic@ieee.org

Abstract: This paper gives an overview and considers impacts of some theories developed around uncertainty representation paradigms, theory of neural networks and of evolutive computing on development of computing systems. Possible further development of soft computing and impacts of that development on the development of computing systems in general, is considered.

Keywords: soft computing, computing, expert systems, fuzzy systems, neural systems, informatics, computational intelligence

1 Introduction

The objective of this paper is to consider the impacts of different uncertainty representation paradigms models, such as fuzziness and roughness, and of the neural networks theory and evolutionary computing on computing systems development. The short overview of the acchieved results is given, and, based on that, predictions of future development are given. The traditional approach to computing sometimes is referred as hard computing. Fuzzy logic with expert systems, neural networks, probabilistic reasoning, belief networks, genetic algorithms, chaos theory and parts of learning theory makes complementary partnership of disciplines and technologies known as soft computing, which gives methods for solving complex problems in designing intelligent systems with the ability to exploit the tolerance for imprecision, uncertainty and partial truth, to achieve tractability, robustness and low solution cost, (cf. [1]). A combination of hard and soft computing should give synergistical improvements of computing system's performances.

In the paper, after this Introduction, in Section 2, the advantages of using fuzzy systems as a part of computing systems are considered. Section 3 deals with rough sets, and Section 4 deals with neuro-computing systems. In Section 5 soft computing is considered, and granular computing is considered in Section 6. The Conclusions are given, as well as directions for possible further research work.

2 Fuzzy Systems

A computer architecture, based on the program counter used to address and fetch machine instructions from a memory, and to run instructions in a processor with accumulator and other registers, is referred to as von Neumann's computer architecture, and all traditional computer systems belong to that kind of computer architecture, [2], [3], [4].

Turing not only was thinking about the digital computing, i.e. he gave the theoretical base of informatics or computer science, [3], [4], but he also, prophetically, was considering thinking machines, maybe even in year 1947, [4], but surely in [5]. Although the beginnings in artificial intelligence commonly, for example in [6, pp. 4] are connected with other authors.

Artificially (computational) intelligent systems are perceived as machine systems built layer by layer, Fig. 1. A layer that has features of intelligent performances is implemented in a form of an intelligent program, using as the support existing layers of hardware and software. Each new layer is built on the existing layers below, and is extending the flexibilities of the layers below it.

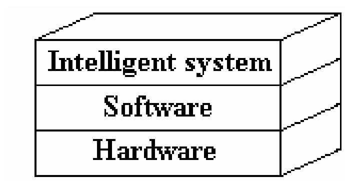

Figure 1
Computational intelligence, represented by layers

One of the most successful area of the traditional artificial intelligence is the area of expert systems. One of aspects by which the flexibility of expert systems was extended was developed in the context of the fuzzy sets theory: namely, Aristotel's binary view of the reality, represented by the set theory and two-valued logic, has been extended in non-Aristotelean way, by introduction of three-valued logic, and, then by multi-valued logics. Soon after that, Zadeh has generalized the characteristic function from sets theory, expanding the region of characteristic function values from $\{0,1\}$ on $[0,1]$, [7], [8], [9], that is, founding fuzzy systems theory, see for example, [10].

The first step in improving of Zadeh's approach was made by Dujmovic, in [11], [12], in the same time when the paper [13] was published. In [13] the modelling of union ('OR') and intersection ('AND') in fuzzy sets theory by *min* and *max*, has been discussed, taking it as adequate and only possible in that way. Dujmovic has generalized the concepts of 'AND' and 'OR' connectives in dual connective 'AND/OR'. That generalization is an addition to the Zadeh's approach. It also has opened research space in which many significant results have been achieved, like that in papers of Yager [14] and Torra [15], among the others.

Fig. 2 gives a detailed scheme of a fuzzy system, [10], [16]. The flow of information is from left to right, and in the case when rules are first activated, and after that aggregation happens, the first option in brackets is valid and the aggregation of fuzzy sets B_i', i = 1,2, ... , r, takes place. In the other case, when the aggregation of rules into one equivalent rule is followed by activation, the second option in brackets is valid, and the aggregation of relations R_i occurs, and then activation takes place.

The fuzzy system's diagram from Fig. 2 is more general than similar diagrams in [6] and [17].

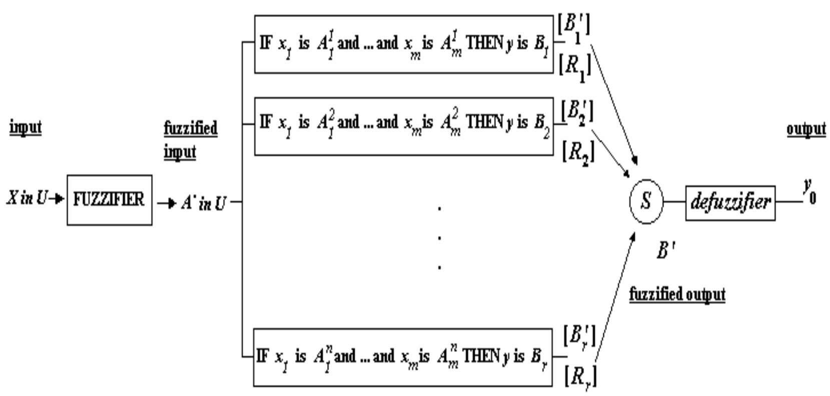

Figure 2

A fuzzy system based on IF-THEN rules

A fuzzy system, Fig. 2, is an information system, computational model implemented on the base of concepts from fuzzy sets theory, fuzzy IF-THEN rules and fuzzy reasoning. It is applied in many areas, such as expert systems, control, pattern recognition, data analysis, prediction based on time series, robotics, [18], [19], decision-making, and data classification, as, for example and not only, in chemical and power process technologies.

Due to its multidisciplinary nature, a *fuzzy system* is also known as: *fuzzy expert system, fuzzy system based on rules, fuzzy model, fuzzy associative memory*, *fuzzy-logic controller*, and *fuzzy inference system*.

Different from probability, but complementary description of uncertainty has been introduced by fuzzy sets theory. A fuzzy system is able to process an uncertainty due to linguistic ambiguity. Uncertainty is a basic and unavoidable feature of reality. In order to be able to process uncertainty in an intelligent way, it should be representable and the possibility to reason with it should exist. Fuzzy systems theory offers tools for those tasks. A fuzzy system characterized by (*a*) specific fuzzy reasoning, (*b*) certain kind of fuzzy implication, (*c*) aggregation method, (*d*) defuzzification method, is able to approximate any real continuous function on a compact set, with any accuracy. Fuzzy systems enable interfacing of heuristics expressed in linguistic in some context, with the abilities of numerical processing of traditional computing systems.

The theory of fuzzy systems brings to the computing a mathematical frame of modelling of graduality in reasoning systems. Graduality can be numerical, but also non-numerical, based on ordering, [7].

3 Rough Sets

The theory of rough sets was introduced by Z. Pawlak, as result of fundamental research of logic properties of computing systems, [20]. Rough sets theory deals with classification analisys of imprecise, uncertain and uncomplete information or knowledge, represented by data collected through experience. The basic concepts of rough sets theory are, [20], an approximation space, lower and upper set approximations. *An approximation space* is a classification of domain of interest in mutually disjoint categories. A classification formally represents the knowledge about the domain, that is, in that context, the knowledge is understood as an ability to describe all classes of the classification considered, for example in terms of features of objects belonging to the domain. Objects belonging to the same class are not distinguishable, which means that their membership status with respect to an arbitrary subset of the domain may not always be clearly definable. This fact leads to the definition of the set considered by lower and upper approximations. *The lower approximation* of the considered subset is a description of domain objects, which are known with certainty to belong to the subset of interest. *The upper approximation* of the subset gives a description of the domain objects that may belong to the subset. *The negativity region* is made of those domain objects, which are known with certainty not to belong to the subset considered. Any (sub)set defined by its lower and upper approximations is called a *rough set*.

Fig. 3 is an illustration of rough set approximations.

A rough set is essentially different from a fuzzy set; a fuzzy set and a rough set represent concepts that, in some way, are complementary. Indiscernibility (roughness) and fuzziness (vagueness) are different aspects of imperfect knowledge. They are two different forms of uncertainty. In an image processing language, the theory of rough sets deals with a pixel size, while fuzzy set theory deals with existence of more then two grey levels [10, Chapter 2], [21].

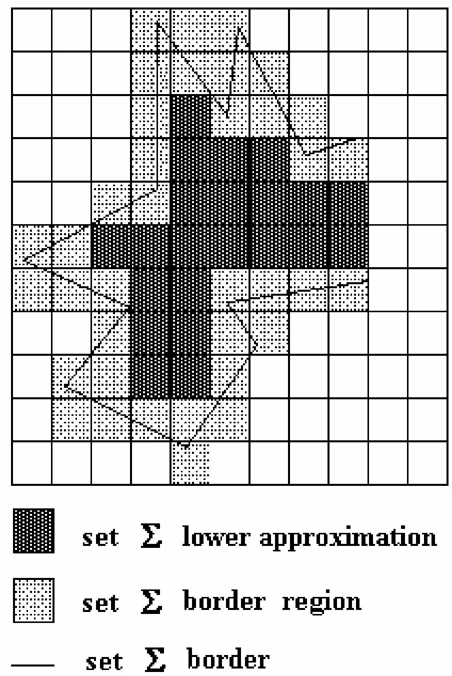

Figure 3
Approximations of a rough set Σ

Existence of uncertainty is determining feature of intelligent behaviour in an uncertain, that is a complex and dynamic environment, what makes the topic of uncertainty one of more important research areas in computing. Often, uncertainty occurs in reality in some hybrid form, that is described, for instance, by probabilistic-fuzzy approach (fuzzy quantified probability, probability of fuzzy events), by fuzzy-rough sets or by rough-fuzzy sets. Beside that, so called Type-2 fuzzy sets uncertain paradigm may be of interest, also.

4 Neuro-computing Systems

The area of neural networks, or neuro-computing systems, deals with study of ways of information processing in networks consisting of elementary numerical processors. It is a question of highly parallel distributed information processing systems. Some of the earliest published results in connection with neural networks, for instance [22], considers mutually connected systems of binary switches. The other early results stress adaptive systems [23]. Neurocomputing systems are developed in areas of engineering pattern recognition, supervised learning, control systems, especially optimal control. During 1970's and 1980's, learning based on numerical processing, present at neurocomputing systems, became attractive, as opposite to, until then, dominant, symbol processing in artificial intelligence systems, in knowledge modelling. Intelligence is comprehended as conditions fulfilling and pattern recognition, contrary to untill those days, dominant explicit symbol manipulation. The most popular form of neurocomputing system is a network with ability to learn based on backpropagation.

5 Soft Computing

A neural network can approximate a function, but it is impossible to interpret the result in terms of a natural language. A fusion of neural networks and fuzzy systems, a neuro-fuzzy system, a form of soft computing systems, provides learning as well as readability, Fig. 4. That is useful, because a process operators get possibility to interpret and complement a model.

A learning algorithm for systems with backward propagation of system error through a fuzzy system from Fig. 3, interpreted as a neural netowork, is shown at the bottom of Fig. 4.

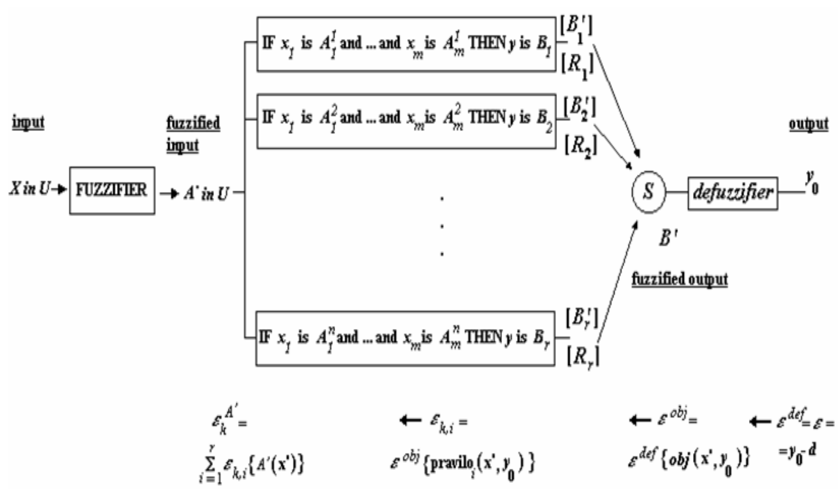

Figure 4

A general case of a kind of soft-computing system

As it was mentioned in the introduction, a combination of traditional and soft computing should generate synergistic improvements. One of those improvements is based on numerical processing, above which is a layer, enabling interfacing that numerical processing with an implementation of a model in which can exist linguistic variables (the theory of fuzzy sets). An intelligent system in the layer above the traditional computing system consists of a layer of expert system, able to process uncertainty on the base of fuzzy approach, to represent uncertain knowledge and to reason with uncertain knowledge. Although fuzzy-logic systems are numerical systems, an expert can describe his knowledge using natural language, or that knowledge can be adaptively infered from samples of data. That possibility can be essential in many applications. Therefore, soft-computing approach offers more possibilities to express knowledge than the traditional expert-system rules coding two-valued associations.

Rule elicitation from data is a modelling approach known from pattern recognition, or data mining. The goal of elicitation of rules from data is complexity reduction in the problem considered, reduction of amount of data joined to the problem, or generation a system description. The data-mining field consists of number of techniques, and one of them is clustering. Soft-computing systems allow models, which can have linguistic interpretation. So, that models can be integrated with expert rules and representing combinations of fuzzy systems and neural networks, as neuro-fuzzy models of systems. In order to make some phases of neuro-fuzzy system design automatic, genetic algorithm can be used. Neuro-fuzzy computing systems might be further generalised by automatic specification of parameters for changable adaptive topologies of fuzzy systems. In a system, and analogously to fuzzy neuron, a rough, or some other, neuron can be embedded. Research effort leads towards further development of linguistic and biologically motivated computing paradigms, [10], [24].

6 Granular Computing

Uncertainty processing paradigms can be considered as conceptual frames. information granule [25] is a conceptual frame of fundamental entities considered to be of importance in a problem formulation. That conceptual frame is a place where generic concepts, important for some abstraction level, processing or transfer of results in outer environment, are formulated. Information granule can be considered as knowledge representation and knowledge processing components. Granularity level (size) of information granules is important for a problem description and for a problem-solving strategy. Soft computing can be viewed in the context of computational frame based on information granules, and refered as granular computing, [25]. Essential common features of problems are identified in granular computing, and those features are represented by granularity.

Granular computing has ability to process information granules, then, ability to interact with other granular or numerical world, eliciting needed granular information and giving results of granular evaluations.

Granular computing enables abstract formal theories of sets, probability, fuzzy sets, rough sets, and may be others, to be considered in the same context, noticing basic common features of those formalisms, providing one more computing level, higher from soft computing, through synergy of considered approaches. Since several computing processes can be present in the same time, with possible mutual communication, a distributed processing model can be conceived In that model every process, or agent [26], Fig. 5, is treated as a single entity.

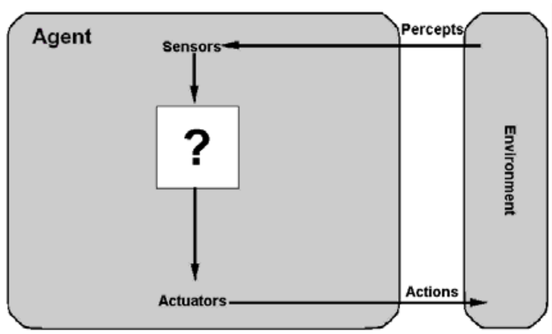

Figure 5
An agent

Every agent, Fig. 6, acts in his granular computing environment and communicates with other agents.

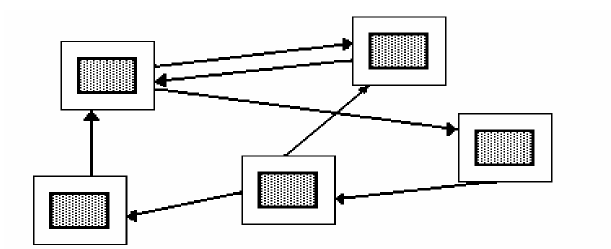

Figure 6
Granular computing implemented by agents

A formalni concept of granular computing can be expressed by four-tuple <X,F,A,C>, where: X – is universe of discourse, [10], F – is formal granulation frame, A – is a collection of generic information granules, and, C – is a relevant communication mechanism.

Conclusions

Granular computing becomes a layer of computational intelligence, a level of abstraction above soft computing. Granular computing synergically complements different aspects of representing, learning and optimization. A role of granular computing in development of intelligent systems, and so of computing systems can be significant, as in knowledge integration, and also in development of computing systems more adapted to user, linguistic and biologically motivated.

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