HYBRID COMPUTATIONAL INTELLIGENCE

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Summary

Throughout the years, different applications show a growing complexity in fields like optimization, learning or modeling. Under these circumstances, traditional approaches lack from the required properties to solve these problems appropriately. Fortunately, researchers and engineers have been able to overcome these difficulties by applying more sophisticated methodologies. Among all techniques, those related to *Computational Intelligence* can be stressed as one of the most well-suited solutions, since they are designed for adapting to the problem itself and therefore to provide a higher performance than standard algorithms.

The collaboration among the components of Computational Intelligence can even improve the results than applying them on isolation. In this work, we will carry out an overview of the main hybridizations that allow enhancing the quality of this kind of techniques. In particular, we will study the synergy of different approaches, including Genetic Fuzzy Systems, Neuro-Fuzzy Models and Evolutionary Artificial Neural Networks.

1. Introduction to Computational Intelligence

Current real applications in engineering are demanding for more resources in order to be able to successfully overcome the tasks to be performed, i.e. there are more complex problems which need to be addressed by high quality approaches. These approaches need to be also dynamical in order to adapt themselves to several types of scenarios in engineering and intelligent data analysis problems.

A family of strategies has shown to fit properly as a solution to this issue. They are known as Computation Intelligence (CI) or soft computing approaches. Although there is no exact definition on what we refer with CI, we will follow the guidelines from Bezdek (Bezdek 1994) which stated: "a *system is computational intelligent when it: deals with only numerical (low-level) data, has pattern recognition components, does not use knowledge in the artificial intelligence 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.*"

Although there is not yet full agreement on what CI exactly is, there is a widely accepted view on which areas belong to CI: Artificial Neural Networks (ANN), Fuzzy Sets (FSs) and Fuzzy Logic (FL) systems and Evolutionary Computation (EC). In addition, CI also embraces techniques that stem from the above three or gravitate around one or more of them, such as metaheuristics and optimization techniques (Verdegay et al. 2008) (swarm intelligence, artificial immune systems, and so on), as well as other knowledge representation approaches for managing imprecision or uncertainty, i.e., Dempster-Shafer theory, multi-valued logic, or rough sets, among others (Bello and Verdegay 2012).

The aim of this chapter is to go further on the topic of CI and to introduce several hybridizations that are derived with the objective of improving the performance and applicability of this kind of solutions. Specifically, we will introduce three different approaches which have been widely studied in the specialized literature. They are the joint of fuzzy systems with Evolutionary Algorithms (EAs), known as Genetic Fuzzy Systems (GFSs), the combination of fuzzy systems with ANNs, known as Neuro Fuzzy Models, and finally the integration of EC in the development of ANNs, which result in Evolutionary Artificial Neural Networks (EANNs).

In order to do so, this chapter is arranged as follows: in Section 2 we will introduce the core areas of Computational Intelligence, describing the main features of FSs and FL, EAs and NNs. Next, we will extend the information on the hybridization of these systems; GFSs will be developed in Section 3, whereas Section 4 will be devoted to Fuzzy Neural Networks and Section 5 will include the description for EANNs. Finally, Section 6 will conclude this work.

2. Core Areas of Computational Intelligence: Fuzzy Logic, Evolutionary Algorithms and Neural Networks

As we stated in the introduction of this work, CI (Craenen and Eiben 2005) is related to the areas of FS and FL, EAs and ANNs. In this section we will briefly introduce each one of these core areas in order to set the basis for the remainder of the chapter.

2.1. Fuzzy sets, Fuzzy Logic and Fuzzy Systems

An FS is distinct from a crisp set in that it allows its elements to have a degree of membership. The core of a FS is its membership function: a surface or line that defines the relationship between a value in the set's domain and its degree of membership. In particular, according to the original ideas of Zadeh 1965, membership of an element x to a fuzzy set A, denoted as $\mu_A(x)$ or simply $A(x)$, can vary from 0 (full non-membership) to 1 (full membership), i.e., it can assume all values in the interval [0, 1].

We must point out that this is clearly a generalization and extension of multi-valued logic, in which degrees of truth are introduced in terms of the aforementioned membership functions. These functions can be seen as mapping predicates into FSs (or more formally, into an ordered set of fuzzy pairs, called a fuzzy relation). FL can thus be defined as a logic of approximate reasoning that allows us to work with FSs (Klir and Yuan 1995, Zimmerman 2010). In this manner, it allows a simplicity and flexibility which makes them superior with respect to classical logic for some complex problems. This can be achieved as they are able to cope with vague, imprecise or uncertain concepts that human beings use in their usual reasoning (Pedrycz and Gomide 1998).

Fuzzy systems (Berthold 2004) are derived from the conjunction of the concepts of FSs and FL, and they compose one of the cornerstones of CI. Usually, it is considered a model structure in the form of fuzzy rule-based system (FRBS), which are composed of a Knowledge Base (KB) that includes the information in the form of IF-THEN fuzzy rules, whose antecedents and consequents are composed of FL statements, and an inference engine module. They have been successfully applied to control problems (Palm et al. 1997), modeling (Pedrycz 1996), classification or data mining (Kuncheva 2000; Ishibuchi et al. 2004), among other engineering applications (Mendel 1995).

Depending on the format of the rules, FRBSs can be roughly divided in several families, which differ in their ability to represent different types of information. The first includes linguistic models whose antecedents are linguistic labels and the system behavior can be described using a natural language. The consequent of the rule can be an output action or a class to be applied:

R_i : If X_1 is A_{i1} and ... and X_n is A_{in} then Y is B_i
or
R_i : If X_1 is A_{i1} and ... and X_n is A_{in} then C_k with w_{ik}

with $i=1$ to M, X_1 to X_n and Y being the input and output variables for regression respectively, and C_k the output class associated to the rule for classification, with A_{i1} to A_{in} and B_i being the involved antecedent and consequent labels, respectively, and w_{ik} being the certain factor associated to the class. These systems are usually called linguistic or Mamdani-type FRBSs (Mamdani 1974).

The second category is composed of logical rules that have a fuzzy antecedent and functional consequent parts. They can be represented as:

R_i : If X_1 is A_{i1} and ... and X_n is A_{in} then $Y = p(X_1, \ldots, X_n)$

with $p(\cdot)$ being a polynomial function, usually a linear expression, $Y = p_{i0} + p_{i1} \cdot X_1 + \ldots + p_{in} \cdot X_n$. The can be viewed as a combination of several linear systems and are called TS-type fuzzy systems (Takagi and Sugeno 1985).

Another category of fuzzy models are approximate or scatter partition-based FRBSs (Alcalá et al. 2001), which differ from linguistic ones because of their semantic-free rules. Each fuzzy rule presents its own semantic, i.e., the variables take different FSs as values (and not linguistic terms from a global term set). The fuzzy rule structure is then as follow:

R_i : If X_1 is $\hat{A}_{i1}$ and ... and X_n is $\hat{A}_{in}$ then Y is $\hat{G}_i$

with $\hat{A}_{ij}$ to $\hat{A}_{in}$ and $\hat{G}_i$ being FSs.

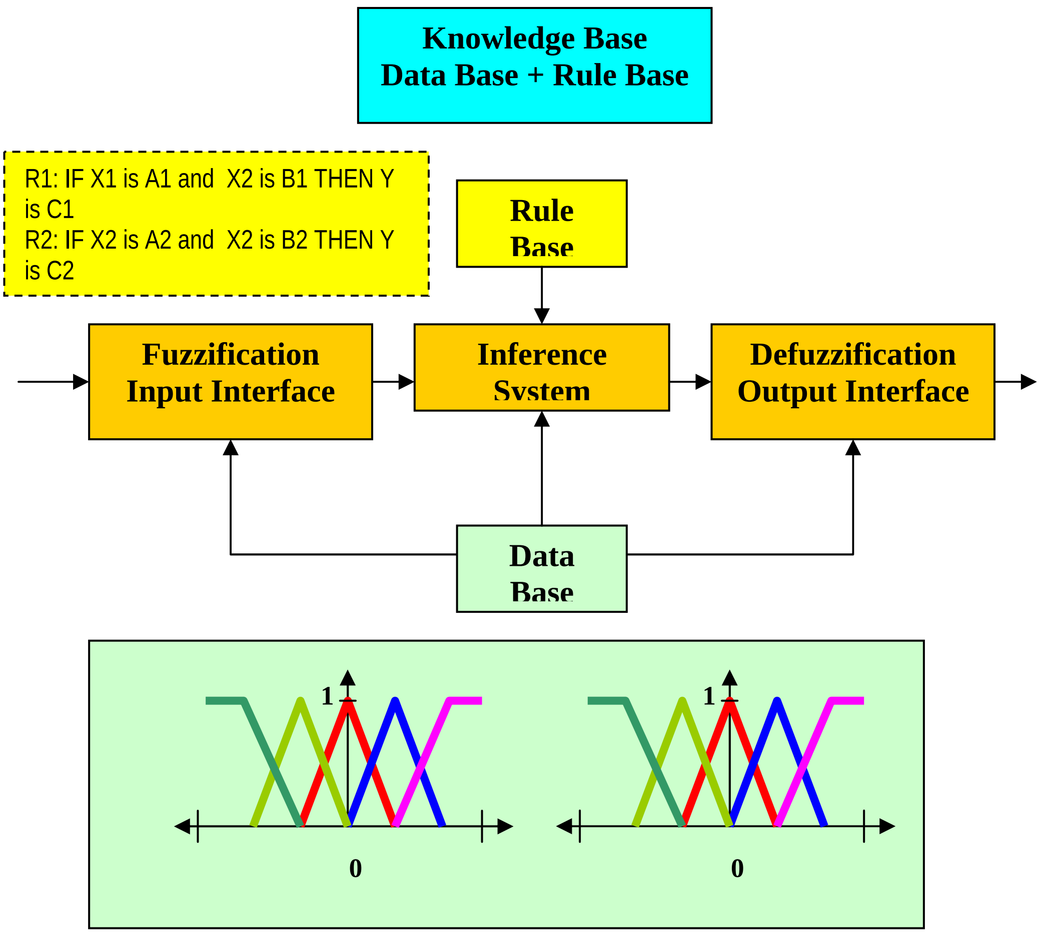

Figure 1. Structure of a linguistic FRBS

In linguistic FRBSs, the KB includes two components, a data base (DB) and a rule base (RB). The RB contains a set of IF-THEN fuzzy rules, which are joined by a rule connective ("OR" operator). Therefore the same input can fire multiple rules concurrently. The DB includes the FSs associated with the linguistic terms of the RB. Each linguistic variable involved in the problem is associated to a fuzzy partition of its domain representing the FSs associated to each of its linguistic terms. The number of FSs in a fuzzy partition can be variable and is called granularity. The determination of this granularity and fuzzy partition is essential in fuzzy modeling.

The inference engine of FRBSs acts in a different way depending of the kind of problem (classification or regression) and the kind of fuzzy rules. It always includes a fuzzification interface that serves as the input to the fuzzy reasoning process, an inference system that infers from the input to several resulting output (FS, class, …) and the defuzzification interface that converts the FSs obtained from the inference process into a crisp action in the case of regression problems, or provide the final class associated to the input pattern in the case of classification problems.

In order to provide an overview of this type of systems, the generic structure of a linguistic FRBS is shown in Figure 1.

2.2. Evolutionary Algorithms

EAs (Eiben and Smith 2003) are optimization and general purpose search algorithms based on the evolution of a population of solutions, therefore being a part of EC (Foster 2001). These types of models mimic the principles of biological natural evolution, such as natural selection and genetic inheritance. In particular, EAs are the computational reflection of the interplay between the creation of new genetic information and its evaluation and selection. A single individual of a population is affected by other individuals of the population (e.g., by food competition, predators, and mating), as well as by the environment (e.g., by food supply and climate). If the individual performs well in these conditions, then the likelihood of living longer and generate offspring will increase, thus passing its (perturbed) genetic information to those offspring. Additionally, non-deterministic nature of reproduction leads to permanent production of new genetic information and therefore the creation of different offspring.

One of the main reasons for the success of this type of techniques is their ability to exploit the information accumulated about and initially unknown search space in order to bias subsequent searches into useful subspaces, i.e. *their robustness*. This is their key feature, especially in large, complex, and poorly understood search spaces, where classical search tools (enumerative, heuristic, and so on) are inappropriate, offering a valid approach to problems requiring efficient and effective search techniques.

Although there are many possible variants of this basic structure, the fundamental underlying mechanism operates on a population of chromosomes or individuals, representing potential problem solutions encoded into suitable data structures. The evolution consists of three operations: evaluation of individual fitness, formation of a gene pool (intermediate population), and recombination through crossover and/or mutation, as it can be seen in Figure 2.

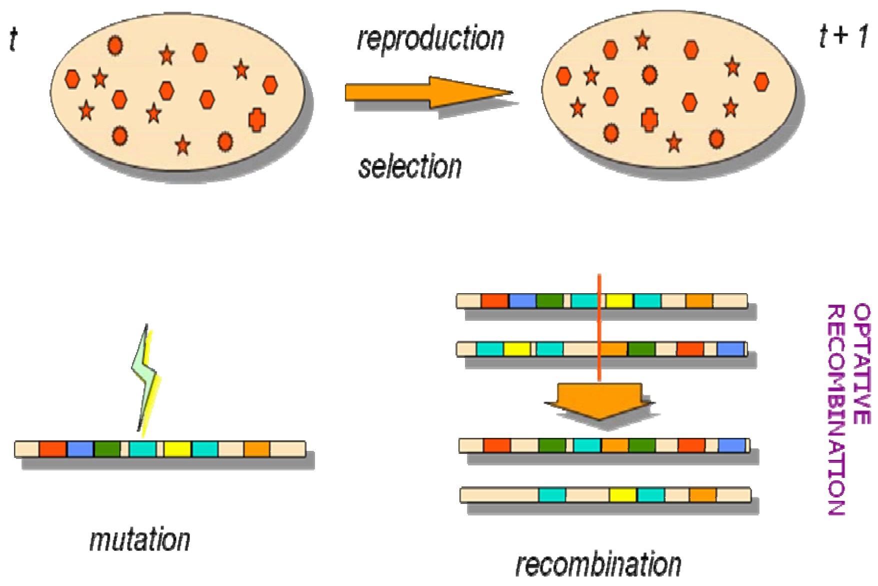

Figure 2. "Ingredients" of an evolutionary algorithm

The way this procedure is carried out, depends on the family of algorithms that are being used. The most well known are genetic algorithms (GAs) (Goldberg 1989), evolution strategies (Schwefel 1995), evolutionary programming (Fogel 1995), genetic programming (Koza 1992, Poli and Langdon 2007), differential evolution (Price et al. 2005), estimation of distributed algorithms (Larrañaga and Lozano 2001), and memetic algorithms (Moscato and Cotta 2003), which combine the evolutionary model with local search for improving the convergence.

2.3. Neural Networks

ANNs (Haykin 2009; Bishop 1995; Ripley 1996, Rojas 1996; Jain 1996) are one of the core components of CI. These systems, originally inspired by the functionality of biological neural networks, can learn complex functional relations by generalizing from a limited amount of training data. They can be used to build black-box models of nonlinear systems that require no detailed information about the structure; they are multivariable static and dynamic systems and can be trained by using input-output data observed on the system.

They are typically composed of several interconnected processing units, or 'neurons' which can have a number of inputs and outputs. In mathematical terms, an ANN can be seen as a directed graph $G(N, A, \psi)$ where each node of the N set implements a neuron model, A denotes the connections (also called arcs or synapses) between the neurons, and ψ represents the learning rule whereby neurons are able to adjust the strengths of their interconnections. The number and type of neurons and the set of possible interconnections between them define the *architecture or topology* of the neural network.

In a nutshell, the working mechanism of this system is as follows: a neuron receives its inputs from an external source or from other neurons in the network, and it then undertakes some processing on this input and sends the results as an output. In the simplest case, the neuron model, i.e. the underlying function of a neuron or activation function, is computed as a weighted sum of the incoming signals (inputs) transformed by a (typically nonlinear) static transfer function.

Learning in ANN's is typically accomplished in a supervised way by using examples to adjust the connection weights (Hush and Horne 1993). It is often formulated as the minimization of a loss function such as the entropy or the total mean square error between the actual output and the desired output summed over all available data. A gradient descent-based optimization algorithm such as BackPropagation (BP) (Rumelhart and McClelland 1986) can then be used to adjust connection weights in the ANN iteratively in order to minimize the error. The essence of a learning algorithm is the learning rule, i.e., a weight-updating rule which determines how connection weights are changed.

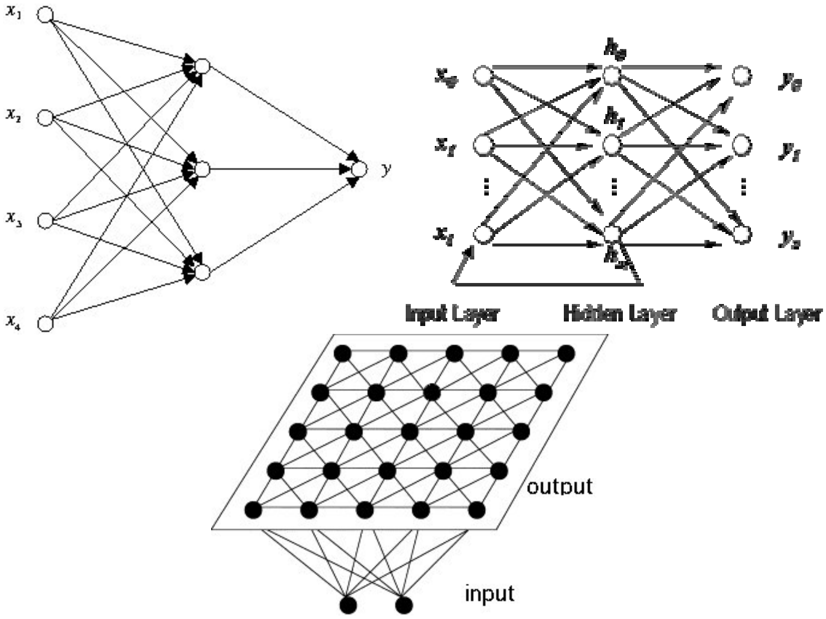

Figure 3. Examples of three representations for ANNs. At the left side an MLP is depicted; at the center, we show a recurrent neural network; finally, at the right side we may observe a Self-Organizing Map.

Out of this general idea, a great number of different models have been appearing in the literature over the last forty years. They differ in aspects like architecture, e.g. layered (feedforward), total interconnection, recurrent (feedback), learning approach, e.g. supervised, unsupervised, reinforcement, kind of neurons (and correspondingly, type of activation function). To name some of the most relevant ANNs that can be found in the specialized literature, we should remark: multilayered perceptrons (MLP); Radial Basis Function networks (RBF); Stochastic Machines, like Boltzmann Machines; Recurrent networks, like Erlang-networks; and Competitive Learning models, like Self-Organizing Maps and ARTMAP; a couple of examples of their representation are shown in Figure 3. See some of the general references above for details.

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