

Chapter 2

Background and Theory

In this chapter a brief overview of the basic concepts used in this research work is presented.

2.1 Human Recognition

Establishing the identity of an individual is very important in our society. The primordial task of any identity management system is the ability to determine or validate the identity of its users prior to granting them access to the resources protected by the system. Usually, passwords and ID cards have been used to validate the identity of an individual intending to access the services offered by an application or area. However, such mechanisms for user authentication have several limitations. For example, the passwords can be divulged to unauthorized users and the ID cards can be forged or stolen. An alternative is the use of biometric systems. Biometrics is the science of establishing the identity of an individual based on the inherent physical or behavioral traits associated with the person [1]. Biometric systems utilize fingerprints, iris, face, hand geometry, palm print, ear, voice, signature, among others, in order to recognize exactly a person [2].

2.2 Artificial Neural Network

Neural networks (NNs) can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [3, 4]. The term of non-optimized trainings is used when the architecture of a conventional neural network, an ensemble neural network or a modular neural network, is established randomly or by trial and error, i.e. a method to find an optimal architecture is not used. Some parameters of this kind of neural networks can be the

number of hidden layers, the number of neurons for each hidden layer, the learning algorithm, number of epoch, among others [5–7]. This kind of NNS has two phases; the training phase (learning phase) and the testing phase. Depending of the information given in the training phase, the output performance is affected [8].

2.2.1 *Modular Neural Networks*

The concept of modularity is an extension of the principle of divide and conquer, the problem should be divided into smaller sub problems that are solved by experts (sub modules) and their partial solutions should be integrated to produce a final solution [9]. The results of the different applications involving Modular Neural Networks (MNNs) lead to the general evidence that the use of modular neural networks implies a significant learning improvement comparatively to a single NN and especially to the back-propagation NNs. Each neural network works independently in its own domain. Each of the neural networks is built and trained for a specific task [10, 11]. In this research work, modular neural networks are used, where each database or dataset is learned by a neural network of this kind, taking the advantage provided by the modularity.

2.3 Granular Computing

The term of Granular computing was introduced in 1997 [12, 13] and has been studied in different areas such as; computational intelligence, artificial intelligence, data mining, social networks among others [14–16]. For example in [17], the privacy protection in social network data based on granular computing is considered. In that work, the granulation consists of grouping individuals with the same combination of attribute values into a common pool or information granule [18].

The main difference between granular computing and data clustering techniques is that the second ones offer a way of finding relationships between datasets and grouping data into classes. A basic task of granular computing is to build a hierarchical model for a complex system or problem [13, 19]. The basic ingredients of granular computing are granules, a web of granules, and granular structures. A granule can be interpreted as one of the numerous small particles forming a larger unit [19–24]. At least three basic properties of granules are needed: internal properties reflecting the interaction of elements inside a granule, external properties revealing its interaction with other granules and, contextual properties showing the relative existence of a granule in a particular environment. A complex problem is represented as a web of granules, in which a granule may itself be a web of smaller granules. The granule structures represent the internal structures of a compound

granule. The structures are determined by its element granules in terms of their composition, organization, and relationships. Each element granule is simply considered as a single point when studying the structure of a compound granule. From the viewpoint of element granules, the internal structures of a compound granule are indeed their collective structures. Each granule in the family captures and represents a particular and local aspect of the problem [25–29]. In this research work, a granulation approach is used in 2 levels. In the first level, a granulation of a dataset or database is performed and the information is learned using modular neural networks and, in the second level also this approach is used when the responses of the modular neural networks are combined.

2.4 Fuzzy Logic

Fuzzy logic is an area of soft computing that enables a computer system to reason with uncertainty [30]. A fuzzy inference system consists of a set of if-then rules defined over fuzzy sets. Fuzzy sets generalize the concept of a traditional set by allowing the membership degree to be any value between 0 and 1 [31]. This corresponds, in the real world to many situations, where it is difficult to decide in an unambiguous manner if something belongs or not to a specific class [11]. Fuzzy logic is a useful tool for modeling complex systems and deriving useful fuzzy relations or rules [32]. However, it is often difficult for human experts to define the fuzzy sets and fuzzy rules used by these systems [33]. The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules, a database (or dictionary) which defines the membership functions used in the rules, and a reasoning mechanism that performs the inference procedure [34].

2.4.1 Type-2 Fuzzy Logic

The concept of a type-2 fuzzy set was introduced as an extension of the concept of an ordinary fuzzy set (henceforth now called a “type-1 fuzzy set”). A type-2 fuzzy set is characterized by a fuzzy membership function, i.e., the membership grade for each element of this set is a fuzzy set in $[0,1]$, unlike a type-1 set where the membership grade is a crisp number in $[0,1]$. Such sets can be used in situations where there is uncertainty about the membership grades themselves, e.g., an uncertainty in the shape of the membership function or in some of its parameters. Consider the transition from ordinary sets to fuzzy sets. When we cannot determine the membership of an element in a set as 0 or 1, we use fuzzy sets of type-1. Similarly, when the situation is so fuzzy that we have trouble determining the membership grade even as a crisp number in $[0,1]$, we use fuzzy sets of type-2 [8, 35–37]. Uncertainty in the primary memberships of a type-2 fuzzy set, $\tilde{A}$, consists

of a bounded region that we call the “footprint of uncertainty” (FOU). Mathematically, it is the union of all primary membership functions [38–41].

In this book, type-1 and type-2 fuzzy logic are used, because both types of fuzzy logic are a good option to perform the combination of responses when modular neural networks are used and, because the type of fuzzy logic used must depend basing on the complexity of the problem to be solved for this reason both types of fuzzy logic are considered. The optimization of type of fuzzy logic and their parameters are optimized to focus on the needs of each case or problem.

2.5 Genetic Algorithms

A Genetic Algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the “fitness” [42, 43]. Genetic Algorithms (GAs) are nondeterministic methods that use crossover and mutation operators for deriving offspring. GAs work by maintaining a constant-sized population of candidate solutions known as individuals (chromosomes) [44–46]. Competent genetic algorithms can efficiently address problems in which the order of the linkage is limited to some small number k , called order- k separable problems. The class of problems with high-order linkage cannot be addressed efficiently in general. However, specific subclasses of this class can be addressed efficiently if there is some form of structure that can be exploited. A prominent case is given by the class of hierarchical problems [47].

2.5.1 Hierarchical Genetic Algorithms

Introduced in [48], a Hierarchical genetic algorithm (HGA) is a particular type of genetic algorithm. Its structure is more flexible than the conventional GA. The basic idea under a hierarchical genetic algorithm is that for some complex systems, which cannot be easily represented, this type of GA can be a better choice. The complicated chromosomes may provide a good new way to solve the problem and have demonstrated to achieve better results in complex problems than the conventional genetic algorithms [49, 50]. The hierarchical genetic algorithms have genes dominated by other genes, this means than depending of the value of the major genes or control genes will be the behavior of the rest of the genes [51]. This kind of genetic algorithm is used in this research work because, it allows the activation or deactivation of genes (parametric genes) depending on the behavior of the control genes. This advantage is exploited in the proposed method in the optimizations performed, where the number of sub modules or sub granules (when the optimization of modular neural network architectures is performed) and the type of fuzzy logic

(when the optimization of fuzzy inference systems parameters is performed) are control genes.

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