POSITION PAPER

Hybrid Intelligent Systems for Pattern Recognition

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Abstract:

We describe in this paper a general overview of the analysis and design of hybrid intelligent systems for pattern recognition applications. Hybrid intelligent systems can be developed by a careful combination of several soft-computing techniques. The combination of soft computing techniques has to take advantage of the capabilities of each technique in solving part of the pattern recognition problem. We review the problems of face, fingerprint and voice recognition and their solution using hybrid intelligent systems. Recognition rates achieved with the hybrid approaches are comparable with the best approaches known for solving these recognition problems.

Keywords: *soft computing, intelligent systems, algorithms, fuzzy logic, neural networks*

1. Introduction

We describe in this paper, new methods for intelligent pattern recognition using soft computing techniques. Soft Computing (SC) consists of several computing paradigms, including fuzzy logic, neural networks, and genetic algorithms, which can be used to create powerful hybrid intelligent systems. Combining SC techniques, we can build powerful hybrid intelligent systems that can use the advantages that each technique offers. We consider in this paper "intelligent pattern recognition" as the use of SC techniques to solve pattern recognition problems in real-world applications. We consider in particular the problems of face, fingerprint and voice recognition. We also consider the problem of recognizing a person by integrating the information given by the face, fingerprint and voice of the person.

As a prelude, we provide a brief overview of the existing methodologies for solving pattern recognition problems. We then describe our own approach in dealing with these problems. Our particular point of view is that face recognition, fingerprint recognition and voice identification are problems that can not be considered apart because they are intrinsically related in real-world applications. We show that face recognition can be achieved by using modular neural networks and fuzzy logic. Genetic algorithms can also be use to optimize the architecture of the face recognition system. Fingerprint recognition can also be achieved by applying modular neural networks and fuzzy logic in a similar way as in the method for face recognition. Finally, voice recognition can be achieved by applying neural networks, fuzzy logic, and genetic algorithms. We will illustrate each of these recognition problems and its solutions in real world situations. In each application of the SC techniques to solve a real-world pattern recognition problem, we show that the intelligent approach proves to be more efficient and accurate that traditional approaches.

Traditionally, pattern recognition problems mentioned above, have been solved by using classical statistical methods and models, which lack, in some cases, the accuracy and efficiency needed in real-world applications. Traditional methods include the use of statistical models and simple information systems. We instead, consider more general modeling methods, which include fuzzy logic and neural networks. We also use genetic algorithms for the optimization of the fuzzy systems and neural networks. A proper combination of these methodologies will result in a hybrid intelligent system that will solve efficiently and accurately a specific pattern recognition problem.

Fuzzy logic is an area of soft computing that enables a computer system to reason with uncertainty (Castillo & Melin 2001). 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 (Zadeh, 1965). 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. Fuzzy expert systems, for example, have been applied with some success to problems of decision, control, diagnosis and classification, just because they can manage the complex expert reasoning involved in these areas of application. The main disadvantage of fuzzy systems is that they can't adapt to changing situations. For this reason, it is a good idea to combine fuzzy logic with neural networks or genetic algorithms, because either one of these last two methodologies could give adaptability to the fuzzy system (Melin & Castillo 2002). On the other hand, the knowledge that is used to build these fuzzy rules is uncertain. Such uncertainty leads to rules whose antecedents or consequents are uncertain, which translates into uncertain antecedent or consequent membership functions (Karnik & Mendel 1998). Type-1 fuzzy systems, like the ones mentioned above, whose membership functions are type-1 fuzzy sets, are unable to directly handle such uncertainties. We also consider here, type-2 fuzzy systems, in which the antecedent or consequent membership functions are type-2 fuzzy sets (Mendel, 2001). Such sets are fuzzy sets whose membership grades themselves are type-1 fuzzy sets; they are very useful in circumstances where it is difficult to determine an exact membership function for a fuzzy set. Another way to handle this higher degree of uncertainty is to use intuitionistic fuzzy logic

(Atanassov, 1999), which can also be considered as a generalization of type-1 fuzzy logic. In intuitionistic fuzzy logic the uncertainty in describing fuzzy sets is modeled by using at the same time the membership function and the non-membership function of a set (assuming that they are not complementary).

Neural networks are computational models with learning (or adaptive) characteristics that model the human brain (Jang, Sun & Mizutani, 1997). Generally speaking, biological natural neural networks consist of neurons and connections between them, and this is modeled by a graph with nodes and arcs to form the computational neural network. This graph along with a computational algorithm to specify the learning capabilities of the system is what makes the neural network a powerful methodology to simulate intelligent or expert behavior (Miller, Sutton & Werbos, 1995). Neural networks can be classified in supervised and unsupervised. The main difference is that in the case of the supervised neural networks the learning algorithm uses input-output training data to model the dynamic system, on the other hand, in the case of unsupervised neural networks only the input data is given. In the case of an unsupervised network, the input data is used to make representative clusters of all the data. It has been shown, that neural networks are universal approximators, in the sense that they can model any general function to a specified accuracy and for this reason neural networks have been applied to problems of system identification, control, diagnosis, time series prediction, and pattern recognition. We also describe the basic concepts, theory and algorithms of modular and ensemble neural networks. We will also give particular attention to the problem of response integration, which is very important because response integration is responsible for combining all the outputs of the modules. Basically, a modular or ensemble neural network uses several monolithic neural networks to solve a specific problem. The basic idea is that combining the results of several simple neural networks we will achieve a better overall result in terms of accuracy and also learning can be done faster. For pattern recognition problems, which have great complexity and are defined over high dimensional spaces, modular neural networks are a great alternative for achieving the level of accuracy and efficiency needed for real-time applications.

Genetic algorithms and evolutionary methods are optimization methodologies based on principles of nature (Jang, Sun & Mizutani, 1997). Both methodologies can also be viewed as searching algorithms because they explore a space using heuristics inspired by nature. Genetic algorithms are based on the ideas of evolution and the biological process that occur at the DNA level (Michalewicz, 1996). Basically, a genetic algorithm uses a population of individuals, which are modified by using genetic operators in such a way as to eventually obtain the fittest individual (Man, Tang & Kwong, 1999). Any optimization problem has to be represented by using chromosomes, which are a codified representation of the real values of the variables in the problem (Mitchell, 1998). Both, genetic algorithms and evolutionary methods can be used to optimize a general objective function. As genetic algorithms are based on the ideas of natural evolution, we can use this methodology to evolve a neural network or a fuzzy system for a particular application. The problem of finding the best architecture of a neural network is very important because there are no theoretical results on this, and in many cases we are forced to trial and error unless we use a genetic algorithm to automate this process. A similar thing occurs in finding out the optimal number of rules and membership functions of a fuzzy system for a particular application, and here a genetic algorithm can also help us avoid time consuming trial and error. In this case, we use genetic algorithms to optimize the architecture of pattern recognition systems.

2. Problem Formulation

We consider in this paper the pattern recognition problems of face, fingerprint and voice recognition. Although the methods that are described can also be used for other type of pattern recognition problems, we concentrate here on the problems mentioned above. Pattern recognition, in many cases, requires that we perform a previous step of clustering the data to facilitate the use of the recognition methods. For this reason, we describe in detail methods of clustering data. We also describe the new hybrid intelligent approaches for achieving pattern recognition of the problems mentioned above.

We perform clustering with intelligent techniques, like fuzzy logic and neural networks. Cluster analysis is a technique for grouping data and finding structures in data (Yager & Filev, 1994). The most common application of clustering methods is to partition a data set into clusters or classes, where similar data are assigned to the same cluster whereas dissimilar data should belong to different clusters. In real-world applications there is very often no clear boundary between clusters so that fuzzy clustering is often a good alternative to use (Bezdek, 1981). Membership degrees between zero and one are used in fuzzy clustering instead of crisp assignments of the data to clusters. Pattern recognition techniques can be classified into two broad categories: unsupervised techniques and supervised techniques. An unsupervised technique does not use a given set of unclassified data points, whereas a supervised technique uses a data set with known classifications. These two types of techniques are complementary. For example, unsupervised clustering can be used to produce classification information needed by a supervised pattern recognition technique.

The new approach for face recognition combines modular neural networks with a fuzzy logic method for response integration. We use a new architecture for modular neural networks for achieving pattern recognition in the particular case of human faces. Also, the method for achieving response integration is based on the fuzzy Sugeno integral. Response integration is required to combine the outputs of all the modules in the modular network. We have applied the new approach for face recognition with a real database of faces from students and professors of our institution. Recognition rates with the modular approach were compared against the monolithic single neural network approach, to measure the improvement. The results of the new modular neural network approach gives excellent performance overall and also in comparison with the monolithic approach (Melin, Acosta, Felix, 2003).

The new approach for fingerprint recognition combines modular neural networks with a fuzzy logic method for response integration. We describe a new architecture for modular neural networks for achieving pattern recognition in the particular case of human fingerprints. Also, the method for achieving response integration is based on the fuzzy Sugeno integral. Response integration is required to combine the outputs of all the modules in the modular network. We have applied the new approach for fingerprint recognition with a real database of fingerprints obtained from students of our institution (Melin, Mancilla, Gonzalez, Bravo, 2004).

We also consider the use of neural networks, fuzzy logic and genetic algorithms for voice recognition. In particular, we consider the case of speaker recognition by analyzing the sound signals with the help of intelligent techniques, such as the neural networks and fuzzy systems. We use the neural networks for analyzing the sound signal of an unknown speaker, and after this first step, a set of type-2 fuzzy rules is used for decision making. We need to use fuzzy logic due to the uncertainty of the decision process. We also use genetic algorithms to optimize the architecture of the neural networks. We illustrate our approach with a sample of sound signals from real speakers in our institution (Melin, Gonzalez, Martinez, 2004).

Finally, we consider new approach for human recognition using as information the face, fingerprint, and voice of a person. We have described above the use of intelligent techniques for achieving face recognition, fingerprint recognition, and voice identification. Now we can consider the integration of these three biometric measures to improve the accuracy of human recognition. The new approach consists in a modular architecture that contains three basic modules: face, fingerprint, and voice. The final decision is based on the results of the three modules and uses fuzzy logic to take into account the uncertainty of the outputs of the modules.

3. Basics of Soft Computing Techniques

We summarize the basic concepts of soft computing in this section. We briefly describe the main techniques of Soft Computing, which are fuzzy logic, neural networks, and genetic algorithms.

3.1 Type-1 Fuzzy Logic

Since research on fuzzy set theory has been underway for over 30 years now, it is practically impossible to cover all aspects of current developments in this area (Zadeh, 1975). Therefore, the main goal of this section is to provide an introduction to and a summary of the basic concepts and operations that are relevant to the study of type-1 fuzzy sets. The definition of linguistic variables and linguistic values and how to use them is important in type-1 fuzzy rules, which are an efficient tool for quantitative modeling of words or sentences in a natural or artificial language. By interpreting fuzzy rules as fuzzy relations, we can consider different schemes of fuzzy reasoning, where inference procedures based on the concept of the compositional rule of inference are used to derive conclusions from a set of fuzzy rules and known facts. Fuzzy rules and fuzzy reasoning are the basic components of fuzzy inference systems, which are the most important modeling tool, based on fuzzy set theory. The "fuzzy inference system" is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning (Jang, Sun & Mizutani, 1997). It has found successful applications in a wide variety of fields, such as automatic control, data classification, decision analysis, expert systems, time series prediction, robotics, and pattern recognition (Jamshidi, 1997). Because of its multidisciplinary nature, the fuzzy inference system is known by numerous other names, such as "fuzzy expert system" (Kandel, 1992), "fuzzy model" (Sugeno & Kang, 1988), "fuzzy associative memory" (Kosko, 1992), and simply "fuzzy system".

3.2 Intuitionistic and Type-2 Fuzzy Logic

Two relatively new areas in fuzzy logic are type-2 fuzzy logic systems and intuitionistic fuzzy logic. Basically, a type-2 fuzzy set is a set in which we also have uncertainty about the membership function (Mendel, 2001). Of course, type-2 fuzzy systems consist of fuzzy if-then rules, which contain type-2 fuzzy sets. We can say that type-2 fuzzy logic is a generalization of conventional fuzzy logic (type-1) in the sense that uncertainty is not only limited to the linguistic variables but also is present in the definition of the membership functions. On the other hand, intuitionistic fuzzy sets can also be considered as an extension of type-1 fuzzy sets, in the sense that intuitionistic fuzzy sets not only use the membership function, but also a non-membership function to represent the uncertainty of belonging to a fuzzy set (Atanassov, 1999), (Szmidt & Kacprzyk, 2002). Both type-2 fuzzy sets and intuitionistic fuzzy sets can be used to convey the uncertainty in designing intelligent systems for real-world applications.

3.3 Supervised Learning Neural Networks

The basic concepts, notation, and learning algorithms for supervised neural networks are of great use for solving pattern recognition problems. The main methods that can be considered here consist of the following: backpropagation for feedforward networks, radial basis networks, adaptive neuro-fuzzy inference systems (ANFIS) and applications. A brief review of the basic concepts of neural networks and the basic backpropagation learning algorithm is very important. Second, we give a brief description of the momentum and adaptive momentum learning algorithms. Third, we give a brief review of the radial basis neural networks. The adaptive neuro-fuzzy inference system (ANFIS) methodology (Melin & Castillo 2002) is also an important alternative for solving many problems. We consider this material necessary to understand the new methods for pattern recognition that will be integrating these models with other soft computing methods.

3.4 Unsupervised Learning Neural Networks

Unsupervised networks are useful for analyzing data without having the desired outputs; in this case, the neural networks evolve to capture density characteristics of a data phase. The main methods are: competitive learning networks, Kohonen self-organizing networks, learning vector quantization, and Hopfield networks (Kohonen, 1990). When no external teacher or critic's instruction is available, only input vectors can be used for learning. Such an approach is learning without supervision, or what is commonly referred to as unsupervised learning. An unsupervised learning system evolves to extract features or regularities in presented patterns, without being told what outputs or classes associated with the input patterns are desired. In other words, the learning system detects or categorizes persistent features without any feedback from the environment. Thus unsupervised learning is frequently employed for data clustering, feature extraction, and similarity detection.

Unsupervised learning Neural Networks attempt to learn to respond to different input patterns with different parts of the network. The network is often trained to strengthen firing to respond to frequently occuring patterns, thereby leading to the so-called synonym probability estimators. In this manner, the network develops certain internal representations for encoding input patterns.

3.5 Modular Neural Networks

The basic concepts, theory and algorithms of modular and ensemble neural networks are very important in solving problems of high complexity. Of particular attention is the problem of response integration, which is very important because response integration is responsible for combining all the outputs of the modules. Basically, a modular or ensemble neural network uses several monolithic neural networks to solve a specific problem. The basic idea is that combining the results of several simple neural networks we will achieve a better overall result in terms of accuracy and also learning can be done faster (Sharkey, 1999). For pattern recognition problems, which have great complexity and are defined over high dimensional spaces, modular neural networks are a great alternative for achieving the level of accuracy and efficiency needed for real-time applications (Lu & Ito, 1999). These models will serve as a basis for the modular architectures that will be proposed for specific pattern recognition problems.

The results of the different applications involving Modular Neural Networks (MNN) 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 backpropagation NN (Fu, Lee, Chiang, & Pao, 2001). Indeed, to constrain the network topology on connectivity, increases the learning capacity of NN and allow us to apply them to large-scale problems (Happel & Murre, 1994). This is highly confirmed by the experience carried out by (Barna & Kaski, 1990), which shows that a random pruning of connections before any learning improves significantly the network's performance. Also, we can note that (Feldman, 1989) and (Jacobs, 1991) argue that a complex behavior requires bringing together several different kinds of knowledge and processing, which is, of course, not possible without structure (modularity).

3.6 Evolutionary Computing for Architecture Optimization

Evolutionary algorithms, which are basic search methodologies, can be used for modelling and simulation of complex non-linear dynamical systems. Since these techniques can be considered as general purpose optimization methodologies, we can use them to find the mathematical model which minimizes the fitting errors for a specific problem (Goldberg, 1989). On the other hand, we can also use any of these techniques for simulation if we exploit their efficient search capabilities to find the appropriate parameter values for a specific mathematical model. We also can consider the application of genetic algorithms to the problem of finding the best neural network or fuzzy system for a particular problem (Man, Tang, & Kwong, 1999). We can use a genetic algorithm to optimize the weights or the architecture of a neural network for a particular application. Alternatively, we can use a genetic algorithm to optimize the number of rules or the membership functions of a fuzzy system for a specific problem. These are two important application of genetic algorithms, which can be used in to design intelligent systems for pattern recognition in real world applications.

3.7 Clustering with Intelligent Techniques

Cluster analysis is a technique for grouping data and finding structures in data. The most common application of clustering methods is to partition a data set into clusters or classes, where similar data are assigned to the same cluster whereas dissimilar data should belong to different clusters. In real-world applications there is very often no clear boundary between clusters so that fuzzy clustering is often a good alternative to use (Bezdek, 1981). Membership degrees between zero and one are used in fuzzy clustering instead of crisp assignments of the data to clusters.

Pattern recognition techniques can be classified into two broad categories: unsupervised techniques and supervised techniques. An unsupervised technique does not use a given set of unclassified data points, whereas a supervised technique uses a data set with known classifications. These two types of techniques are complementary. For example, unsupervised clustering can be used to produce classification information needed by a supervised pattern recognition technique.

Unsupervised clustering is motivated by the need of finding interesting patterns or groupings in a given data set. For example, in voting analysis one may want to collect data about a group of voters (e.g. through a survey or interviews) and analyze these data to find interesting groupings of voters. The result of such an analysis can be used to plan the strategies of a particular candidate in an election (Yager & Filev, 1994).

In the area of pattern recognition and image processing, unsupervised clustering is often used to perform the task of "segmenting" the images (i.e., partitioning pixels of an image into regions that correspond to different objects or different faces of objects in the images). This is because image segmentation can be considered as a kind of data clustering problem where each datum is described by a set of image features of a pixel.

4. Hybrid Models for Pattern Recognition

We describe in this section the hybrid models proposed for different pattern recognition problems. In particular, we consider the face, fingerprint, voice and human recognition problems.

4.1 Face Recognition with Modular Neural Networks and Fuzzy Measures

The new approach for face recognition combines modular neural networks with a fuzzy logic method for response integration. A new architecture for modular neural networks for achieving pattern recognition in the particular case of human faces is proposed (Melin & Castillo 2005). Also, the method for achieving response integration is based on the fuzzy Sugeno integral (Yager, 1993). Response integration is required to combine the outputs of all the modules in the modular network. We have applied the new approach for face recognition with a real database of faces from students and professors of our institution. Recognition rates with the modular approach were compared against the monolithic single neural network approach, to measure the improvement. The results of the new modular neural network approach gives excellent performance overall and also in comparison with the monolithic approach.

Automatic face detection and recognition has been a difficult problem in the field of computer vision for several years (Rao & Ballard, 1995) (Reisfeld, 1994). Although humans perform this task in an effortless manner, the underlying computations within the human visual system are of tremendous complexity (Akamatsu, Saski, Fukamachi, Masui, & Suenaga, 1992). The seemingly trivial task of finding and recognizing faces is the result of millions of years of evolution and we are far from fully understanding how the human brain performs it. Furthermore, the ability to find faces visually in a scene and recognize them is critical for humans in their everyday activities. Consequently, the automation of this task would be useful for many applications including security, surveillance, affective computing, speech recognition assistance, video compression and animation. However, to this date, no complete solution has been proposed that allows the automatic recognition of faces in real images.

4.2 Fingerprint Recognition with Modular Neural Networks and Fuzzy Measures

The new approach for fingerprint recognition combines modular neural networks with a fuzzy logic method for response integration (Melin & Castillo 2005). A new architecture for modular neural networks for achieving pattern recognition in the particular case of human fingerprints is proposed. Also, the method for achieving response integration is based on the fuzzy Sugeno integral. Response integration is required to combine the outputs of all the modules in the modular network. We have applied the new approach for finger-print recognition with a real database of fingerprints obtained from students of our institution (Melin Mancilla, Gonzalez, Bravo, 2004).

Among all the biometric techniques, fingerprint-based identification is the oldest method, which has been successfully used in numerous applications. Everyone is known to have unique, immutable fingerprints. A fingerprint is made of a series of ridges and furrows on the surface of the finger. The uniqueness of a fingerprint can be determined by the pattern of ridges and furrows as well as the minutiae points. Minutiae points are local ridge characteristics that occur at either a ridge bifurcation or a ridge ending. Fingerprint matching techniques can be placed into two categories: minutiae-based and correlation based. Minutiae-based techniques first find minutiae points and then map their relative placement on the finger. However, there are some difficulties when using this approach. It is difficult to extract the minutiae points accurately when the fingerprint is of low quality. Also this method does not take into account the global pattern of ridges and furrows. The correlation-based method is able to over-come some of the difficulties of the minutiae-based approach. However, it has some of its own shortcomings. Correlation-based techniques require the precise location of a registration point and are affected by image trans-lation and rotation.

The basic idea of the new approach is to divide a human fingerprint in to three different regions: the top, the middle and the bottom. Each of these regions is assigned to one module of the neural network. In this way, the modular neural network has three different modules, one for each of the regions of the human fingerprint. At the end, the final decision of fingerprint recognition is done by an integration module, which has to take into account the results of each of the modules. In our approach, the integration module uses the fuzzy Sugeno integral to combine the outputs of the three modules (Yager, 1993). The fuzzy Sugeno integral allows the integration of responses from the three modules of the top, middle and bottom of a human specific fingerprint. Other approaches in the literature use other types of integration modules, like voting methods, majority methods, and neural networks.

4.3 Voice Recognition with Neural Networks, Fuzzy Logic and Genetic Algorithms

The use of neural networks, fuzzy logic and genetic algorithms for voice recognition is also described. In particular, we consider the case of speaker recognition by analyzing the sound signals with the help of intelligent techniques, such as the neural networks and fuzzy systems. We use the neural networks for analyzing the sound signal of an unknown human speaker, and after this first step, a set of type-2 fuzzy rules is used for decision making. We need to use fuzzy logic due to the uncertainty of the decision process (Melin & Castillo 2005). We also use genetic algorithms to optimize the architecture of the neural networks. We illustrate our approach with a sample of sound signals from real speakers in our institution (Melin Gonzalez, Martinez, 2004).

Speaker recognition, which can be classified into identification and verification, is the process of automatically recognizing who is speaking on the basis of individual information included in speech waves (Furui, 1994). This technique makes it possible to use the speaker's voice to verify their identity and control access to services such as voice dialing, banking by telephone, telephone shopping, database access services, information services, voice mail, security control for confidential information areas, and remote access to computers (Rosenberg and Soong, 1991).

4.4 Human Recognition Using Face, Fingerprint and Voice

A new approach for human recognition using as information the face, fingerprint, and voice of a person is described (Melin & Castillo 2005). The use of intelligent techniques for achieving face recognition, fingerprint recognition, and voice identification was previously considered. Now we are considering the integration of these three biometric measures to improve the accuracy of human recognition. The new approach will integrate the information from three main modules, one for each of the three biometric measures. The new approach consists in a modular architecture that contains three basic modules: face, fingerprint, and voice. The final decision is based on the results of the three modules and uses fuzzy logic to take into account the uncertainty of the outputs of the modules.

Our proposed approach for human recognition consists in integrating the information of the three main biometric parts of the person: the voice, the face, and the fingerprint. Basically, we have an independent system for recognizing a person from each of its biometric information (voice, face, and fingerprint), and at the end we have an integration unit to make a final decision based on the results from each of the modules.

5. Conclusions

In light of the results of our proposed modular approach, we have to notice that using the modular approach for human face pattern recognition is a good alternative with respect to existing methods, in particular, monolithic, gating or voting methods. As future research work, we propose the study of methods for pre-processing the data, like principal components analysis, eigenfaces, or any other method that may improve the performance of the system. Other future work includes considering different methods of fuzzy response integration, or considering evolving the number of layers and nodes of the neural network modules. Also, we have to notice that using the modular approach for human fingerprint pattern recognition is a good alternative with respect to existing methods, in particular, monolithic, gating or voting methods. As future research work, we propose the study of methods for pre-processing the data, like principal components analysis, eigenvalues, or any other method that may improve the performance of the system. We described an intelligent approach for pattern recognition for the case of speaker identification. We first described the use of monolithic neural networks for voice recognition. We then described a modular neural network approach with type-2 fuzzy logic. The results are very good for the monolithic neural network approach, and excellent for the modular neural network approach. We still have to make more tests with different words and levels of noise.

We also considered an intelligent approach for integrating the results of face, fingerprint and voice recognition. The proposed approach consists in the use of a fuzzy system to implement the decision unit of the hierarchical architecture of human recognition. The fuzzy system consists of a set of fuzzy rules, which take into account the decisions of the individual modules of face, fingerprint and voice. The output of the fuzzy rules is the final identification of the person based on the input values of the three modules. We have achieved excellent results with this fuzzy logic approach for integrating the decisions of face, fingerprint and voice.

In conclusion, we can say that using hybrid intelligent systems in pattern recognition problems is a good alternative in achieving good accuracy and efficiency in the recognition process.

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