Soft Computing and Image Analysis : Features, Relevance and Hybridization

Sankar K. Pal, Ashish Ghosh, and Malay K. Kundu

Machine Intelligence Unit
Indian Statistical Institute
203 B. T. Road, Calcutta 700035, INDIA.
{*E-mail :*} {*sankar,ash,malay*}*@isical.ac.in*

Abstract. The relevance of integrating the merits of different soft computing tools for designing efficient image processing and analysis systems is explained. The feasibility of such systems and different ways of integration, so far made, are described. Scope for further research and development is outlined. An extensive bibliography is also provided.

1 Motivation

Soft computing is a consortium of methodologies which work synergetically and provides, in one form or another, flexible information processing capabilities for handling real life ambiguous situations. Its aim is to tolerate the imprecision, uncertainty, approximate reasoning and partial truth in order to achieve tractability, robustness, low solution cost, and close resemblance with human like decision making. In other words, it provides the foundation of the conception and design of high machine IQ (MIQ) systems, and therefore forms the basis for future generation computing systems. At this juncture, fuzzy logic (FL), artificial neural networks (ANN) and genetic algorithms (GA) are the three principal components where FL provides algorithms for dealing with imprecision and uncertainty, and computing with words, ANN the machinery for learning and adaptation; and GA is used for optimization and searching [1,2].

The present chapter deals with the relevance and feasibility of soft computing tools in the area of image processing, analysis and recognition. The techniques of image processing [3,4] stem from two principal applications namely, improvement of pictorial information for human interpretation and processing of scene data for automatic machine perception. The different tasks involved in the process include enhancement, filtering, noise reduction, segmentation, contour extraction, skeleton extraction etc. Their ultimate aim is to make understanding, recognition and interpretation of the images from the processed information available from the image pattern.

In an image analysis system, uncertainties can arise at any phase resulting from incomplete or imprecise input information, ambiguity or vagueness in input images, ill-defined and/or overlapping boundaries among the classes

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or regions, and indefiniteness in defining/extracting features and relations among them. Any decision taken at a particular stage will have an impact on the subsequent stages. It is therefore required for an image analysis system to have sufficient provision for representing the uncertainties involved at every stage, so that the ultimate output (results) of the system can be associated with the least uncertainty.

The utility of fuzzy set theory [5]-[8] in handling uncertainty [9]-[10], arising from deficiencies of information available from a situation (as mentioned above) in image processing and recognition problems, has adequately been addressed in the literature [6,11]. This theory provides an approximate, yet effective and more flexible means of describing the behavior of systems which are too complex or too ill-defined to admit precise mathematical analysis by classical methods and tools. Since the theory of fuzzy sets is a generalization of classical set theory, it has greater flexibility to capture faithfully the various aspects of incompleteness or imperfection (i.e., deficiencies) in information of a situation. This theory is also reputed to mimic human reasoning process for decision making. Research in the area of fuzzy image processing and analysis grew up based on the realization that the basic concepts of image characteristics e.g, regions, edges, relation among them, and the notion of belonging of a pixel to a class do not lend themselves to precise definition.

Again, for the above mentioned system, one desires to achieve robustness of the system with respect to random noise and failure of components, and to obtain output in real time. Moreover, a system can be made artificially intelligent if it is able to emulate some aspects of human information processing system. Artificial neural network *(ANN)* [12]-[17] based approaches are attempts to achieve these goals. The architecture of the network depends on the goal one is trying to achieve. The massive connectivity among the neurons usually makes the system fault tolerant (with respect to noise and component failure) while the parallel processing capability enables the system to produce output in real time. One may also note that, most of the image analysis operations are co-operative in nature and the tasks of recognition mostly need formulation of complex decision regions. ANN models have the capability of achieving these properties. All these characteristics, therefore, suggest that image processing and recognition problems can be considered as prospective candidates for neural network implementation.

It is well known that the methods developed for image processing and recognition are usually problem dependent. Moreover, many tasks involved in the process of analyzing/identifying a pattern need appropriate parameter selection and efficient search in complex spaces in order to obtain optimal solutions. This makes the process not only computationally intensive, but also leads to a possibility of losing the exact solution.

Genetic algorithms (GAs) [18]-[20], another biologically inspired technology, are randomized search and optimization techniques guided by the principles of natural evolution and natural genetics. They are efficient, adaptive and robust search processes, producing near optimal solutions and have a large amount of implicit parallelism. Therefore, the application of genetic algorithms for solving certain problems of image processing/pattern recognition, which need optimization of computational requirements, robust, fast and approximate solution, appears to be appropriate and natural [21]. Note that this component of soft computing is relatively much newer than the other two.

As mentioned before, the components FL, ANN and GA in soft computing paradigm, are complementary, rather than competitive. Based on this concept, researchers have started to use them in combination rather than individually for achieving more advantages. Among these hybrid systems, the most visible one, at this moment, is based on neuro-fuzzy computing. Here the merits of both FL and ANN are being integrated in order to achieve both generic and application specific merits. Other such integrated systems, those are being investigated, include fuzzy-genetic, neuro-genetic and neuro-fuzzy-genetic systems.

The rest of this chapter is organized as follows. In Section 2, the relevance of fuzzy set theoretic methods for image analysis and recognition is described. The relevance of neural network based techniques in this context is described in Section 3. In Section 4 we discuss the issues of applying GAs for image processing problems. Various integrations of the soft computing tools such as neuro-fuzzy, fuzzy-genetic, neuro-genetic and neuro-fuzzy-genetic approaches for designing efficient hybrid systems are discussed in Section 5. Concluding remarks can be found in Section 6.

2 Relevance of fuzzy set theory in image processing

Fuzzy sets were introduced in 1965 by Zadeh [5] as a new way to represent vagueness in everyday life. They are generalizations of conventional (crisp) set theory. Conventional sets contain objects that satisfy precise properties required for membership. Fuzzy sets, on the other hand, contain objects that satisfy imprecisely defined properties to varying degrees. A fuzzy set A of the universe X is defined as a collection of ordered pairs

$$A = \{(\mu_A(x), x),\ \forall x \in X\} \tag{1}$$

where $\mu_A(x)$ $(0 \leq \mu_A(x) \leq 1)$ gives the degree of belonging of the element x to the set A or the degree of possession of an imprecise property represented by A. Since the theory of fuzzy sets is a generalization of classical one, it has greater flexibility to capture faithfully the various aspects of incompleteness or imperfection in information of a situation. The flexibility of fuzzy set theory is associated with the elasticity property of the concept of its membership function. The grade of membership is a measure of the compatibility of an object with the concept represented by a fuzzy set. The higher the value of membership, the lesser will be the amount (or extent) to which the concept represented by a set needs to be stretched to fit an object. Different aspects of fuzzy set theory including membership functions, basic operations and uncertainty measures can be found in [7]-[10]. Here we explain some of the uncertainties which one often encounters while designing an image processing system and the relevance of fuzzy set theory in handling them.

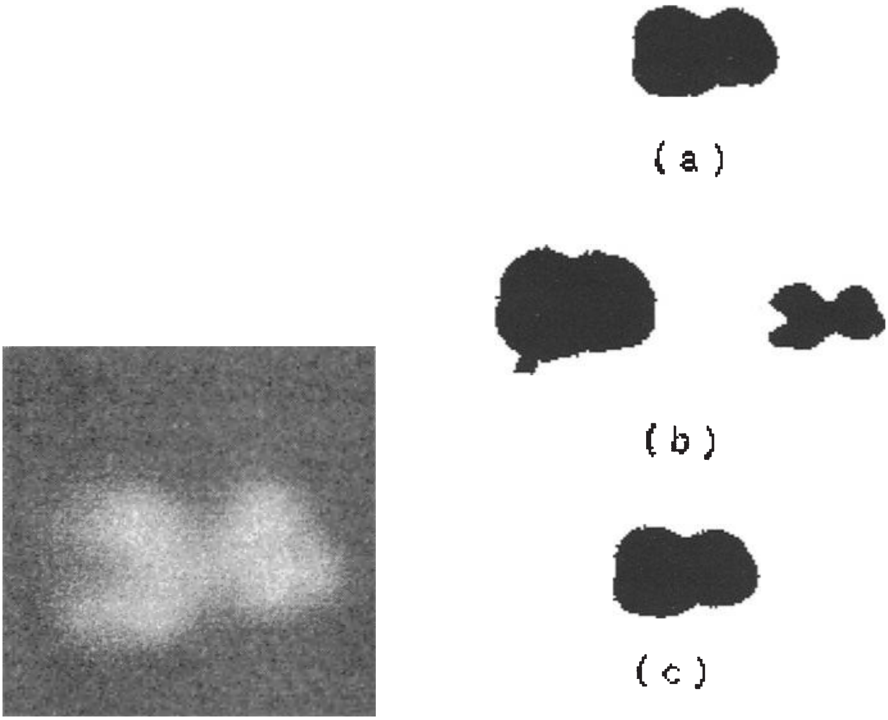
Let us consider the problem of processing and recognition of a graytone image. A gray tone image possesses ambiguity within each pixel because of the possible multi-valued levels of brightness. This uncertainty is due to inherent vagueness rather than randomness. If the gray levels are scaled to lie in the range [0, 1], we can regard the gray level of a pixel as its degree of belonging (membership) in the set of high-valued ('bright') pixels; thus a gray tone image can be viewed as a fuzzy set. Regions, features, primitives, properties, and relations among them which are not crisply defined can similarly be regarded as fuzzy subsets [22,23]. Basic principles and operations of image processing in the light of fuzzy set theory are available in [7,9].

Uncertainty in an image pattern may be explained in terms of grayness ambiguity or spatial (geometrical) ambiguity or both. Grayness ambiguity means 'indefiniteness' in deciding whether a pixel is white or black. Spatial ambiguity refers to 'indefiniteness' in the shape and geometry of a region within the image. For example, grayness ambiguity measures are reflected by index of fuzziness [24] and entropy [25]-[27], whereas spatial ambiguity measures are represented by fuzzy geometrical properties [28]-[34].

Conventional approaches to image analysis and recognition [3,4] consist of segmenting the image into meaningful regions, extracting their edges and skeletons, computing various features (e.g., area, perimeter, centroid etc.) and primitives (e.g., line, corner, curve etc.) of and relationships among the regions, and finally, developing decision rules and grammars for describing, interpreting and/or classifying the image and its sub-regions. In a conventional system each of these operations involves crisp decisions (i.e., yes or no, black or white, 0 or 1) to make regions, features, primitives, properties, relations and interpretations crisp.

Since the regions in an image are not always crisply defined, uncertainty can arise within every phase of the aforesaid tasks. Any decision made at a particular stage will have an impact on all the following stages. An image recognition system should have sufficient provision for representing and manipulating the uncertainties involved at every processing stage; i.e., in defining image regions, features and relations among them, so that the system retains as much of the 'information content' of the data as possible. If this is done, the ultimate output (result) of the system will possess minimal uncertainty (and unlike conventional systems, it may not be biased or affected as much by the decision at the previous stages).

For example, consider the problem of object extraction from an image (Fig. 1A). Here, the question is 'how can one define exactly the target or object region in the image when its boundary is ill-defined?' Any hard thresholding made for the extraction of the object will propagate the associated uncertainty to subsequent stages (e.g., thinning, skeleton extraction, primitive selection, etc.) and this might, in turn, affect feature analysis and recognition. Fig. 1(a-c) shows different fuzzy segmented versions of Fig. 1A to avoid this problem. The different outputs correspond to different ambiguity values (or decision levels) [29].



A

Fig. 1. Fuzzy segmentation of blurred chromosome

A similar case arises with the task of skeletonization, contour detection and primitive extraction of a region. Thus, it is convenient, natural and appropriate to avoid committing ourselves to a specific (hard) decision (e.g., segmentation, edge detection and skeletonization), by allowing the segments or skeletons or contours to be fuzzy subsets of the image, the subsets being characterized by the possibility (degree) to which each pixel belongs to them. Prewitt [22] first suggested that the results of image segmentation should be fuzzy subsets, rather than ordinary subsets. Similarly, while describing relations among different components and features or classifying the sub-regions it is necessary to make the decision-making algorithms flexible by providing soft decisions.

In short, gray information is expensive and informative. Once it is thrown away, there is no way to get it back. Therefore, one should try to retain this information as long as possible throughout the decision making tasks for its full use. When it is required to make a crisp decision at the highest level one can always throw away or ignore this information.

Some of the areas of image analysis where the theory of fuzzy sets has been adequately applied are :

i : computation of fuzzy geometric properties and shapes [23], [29]-[34],

ii : fuzzy segmentation [6,7], [29]-[31], [35]-[39],

iii : evaluation of image quality [7], [40,41],

iv : image operations like thinning and edge detection [7,28], [42]-[44],

v : fuzzy primitives extraction (or features) from fuzzy edges and segmented regions [45].

3 Relevance of neural networks in image processing

Artificial neural network *(ANN)* models [12]-[17] try to emulate the biological neural network/nervous system with electronic circuitry. *ANN* models have been studied for many years with the hope of achieving human-like performance (artificially), particularly in the field of image analysis, by capturing the key ingredients responsible for the remarkable capabilities of the human nervous system. Note that these models are extreme simplification of the actual human nervous system.

*ANN*s are designated by the network topology, connection strength between pairs of neurons (called weights), node characteristics and the status updating rules. Node characteristics mainly specify the primitive types of operations it can perform, like summing the weighted inputs coming to it and then amplifying it or doing some fuzzy aggregation operations. The updating rules may be for weights and/or states of the processing elements (neurons). Normally an objective function is defined which represents the complete status of the network and the set of minima of it corresponds to the set of stable states of the network. Since there are interactions among the neurons the collective computational property inherently reduces the computational task and makes the system fault tolerant. Thus *ANN* models are also suitable for tasks where collective decision making is required.

Some of the popular networks are Hopfield Net (HN), Multilayer Perceptron (MLP), Self-Organizing Feature Map (SOFM), Learning Vector Quantization (LVQ), Radial Basis Function (RBF) Network, Cellular Neural Network (CNN) and Adaptive Resonance Theory (ART) network.

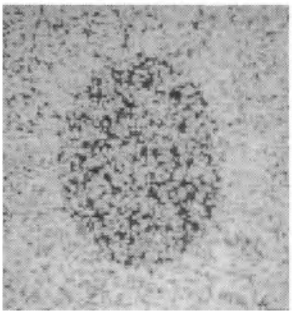
Neural network based systems are usually reputed to enjoy the following major characteristics :

- *adaptivity*- adjusting the connection strengths to new data/information,

- *speed*- due to massively parallel architecture,
- *robustness*- to missing, confusing, ill-defined/noisy data,
- *ruggedness*- to failure of components,
- *optimality*- as regards error rates in performance.

For any image analysis or recognition system, one desires to achieve the above mentioned characteristics. Moreover, there exists some direct analogy between the working principles of many image processing/analysis tasks and neural network models. For example, the processing and analysis in the spatial domain mainly employ simple arithmetic operations at each pixel site in parallel. These operations usually involve information of neighboring pixels (co-operative processing) in order to reduce the local ambiguity and to attain global consistency. An objective measure is required (representing the overall status of the system), the optimum of which represents the desired goal. The system thus involves collective decisions. On the other hand, we notice that neural network models are also based on parallel and distributed working principles (all neurons work in parallel and independently). The operations performed at each processor site are also simpler and independent of the others. The overall status of a neural network can also be measured.

Let us consider, in particular, the case of pixel classification. A pixel is normally classified into different classes depending on its gray value, positional information and contextual information (collected from the neighbors). Pixels at different sites can be classified independently. The mathematical operations needed for this task are also simple. A neural network architecture in which a single neuron is assigned to a pixel and is connected to its neighbors can therefore be applied for this task. The neurons operate in parallel and are independent of each other. The local interconnections provide the contextual information (which can be adaptive or dynamic also) for classification. An outcome of pixel classification based on this principle is illustrated in Fig. 2 where a Hopfield type net is used for extracting the object region from a noisy input [52].



Noisy input

Extracted object

Fig. 2. Object extraction by Hopfield network

Again, the task of recognition in a real-life problem involves searching a complex decision space. This becomes more complicated particularly when there is no a priori information on class distribution. Neural network based systems use adaptive learning procedures, learn from examples and attempt to find a useful relation between input and output, however complex it may be, for decision-making. Neural networks are also reputed to model complex non-linear boundaries and to discover important underlying regularities in the task domain. These characteristics demand that methods are needed for constructing and refining neural network models for various recognition tasks. For example, consider the case of supervised classification. Here each pattern is characterized by a number of features. Different features usually have different amounts of weight in characterizing the classes. A collective decision, taking into account all the features, is made for assignment of class labels to an input. A multi-layer perceptron in which the input layer has neurons equal to the number of features and the output layer has neurons equal to the number of classes, can therefore be used to tackle this classification problem. Here the importance of different features will automatically be encoded in the connecting links during training. The non-linear decision boundaries are modeled and class labels are assigned by taking collective decisions.

In short, neural networks are natural collective decision makers having resistance to noise, tolerance to distorted images/patterns (ability to generalize), superior ability to recognize partially degraded images, and potential for parallel processing.

Major areas of image analysis in which neural networks have been applied in order to exploit the computational power, and to make robust decisions are :

i : image compression [46]-[48],
ii : image segmentation [49]-[60],
iii : image filtering/edge detection [61,62],
iv : image restoration [63]-[66]
v : scene analysis/recognition/vision [67]-[72],
vi : text processing [73].

4 Relevance of genetic algorithms for image processing

Genetic Algorithms (GAs) [18]-[20] are adaptive computational procedures modeled on the mechanics of natural genetic systems. They express their ability by efficiently exploiting the historical information to speculate on new offspring with expected improved performance [18]. GAs are executed iteratively on a set of coded solutions, called *population,* with three basic operators : *selection/reproduction, crossover* and *mutation.* They use only the payoff (objective function) information and probabilistic transition rules for moving to the next iteration. They are different from most of the normal optimization and search procedures in four ways:

- GAs work with the coding of the parameter set, not with the parameter themselves.
- GAs work simultaneously with multiple points, and not a single point.
- GAs search via sampling (a blind search) using only the payoff information.
- GAs search using stochastic operators, not deterministic rules.

Since a GA works simultaneously on a set of coded solutions it has very little chance to get stuck at local optima when used as an optimization technique. It does not need any sort of auxiliary information, like derivative of the optimizing function. The resolution of the possible search space is controlled by operating on coded (possible) solutions and not on the solutions themselves. Further this search space need not be continuous.

GAs typically consist of the following components:

- a population of binary strings or coded possible solutions (biologically referred to as chromosomes),
- a mechanism to encode a possible solution (mostly as a binary string),
- objective function and associated fitness evaluation techniques,
- selection/reproduction procedure,
- genetic operators (crossover and mutation), and
- probabilities to perform genetic operations.

As mentioned earlier, methodologies developed for image processing and pattern recognition are usually problem dependent. Moreover, many tasks involved in these processes need appropriate parameter selection and efficient search in complex spaces in order to obtain optimal solutions.

For example, let us consider the problem of image segmentation which refers to the grouping of different parts of an image that have *similar* image characteristics [74]. The segmentation problem is characterized by several factors, which make the parameter selection process difficult as discussed below.

First, most of the powerful segmentation techniques available today contain numerous control parameters which must be adjusted to obtain the optimal performance. The size of the parameter search space in these systems can be prohibitively large, unless it is traversed in an highly efficient manner.

Second, the parameters within most segmentation algorithms typically interact in a complex, non-linear fashion, which makes it difficult or impossible to model the parameters' behavior in an algorithmic or rule based fashion. Thus, the multidimensional objective function defined using various parameter combinations cannot generally be modeled analytically.

Third, since variation between images causes changes in the segmentation results, the objective function that represents segmentation quality varies from image to image. To search a technique that works in the parameter space to optimize the objective function must be able to adapt to these variations between images.

Finally, the definition of the objective function itself can be subject of debate because there is no single, universally accepted measure of segmented image. In general, several measures are used which are sensitive to different image characteristics and features.

Hence, a tremendous need exists to apply an adaptive technique that can efficiently search the complex space of possible parameter combinations and locate the values which may yield optimal results. Considering the general applicability of the approach, it should not be strongly dependent on a particular application domain nor should it have to rely on very detailed knowledge pertinent to the selected segmentation algorithm. Thus GAs, which are designed to efficiently locate an approximate global maximum in a search space, should be a good tool for this problem.

Similarly, let us consider another problem called contrast enhancement by gray level modification. Here the problem is to select an appropriate transformation/mapping function (operator) for obtaining a desired output. Usually, a suitable non-linear functional mapping is used to perform this task. Now for a given image, it is difficult to select a functional form which will be best suited without requiring the prior knowledge of image statistics. Even if we are given the image statistics it is possible only to estimate approximately the function required for enhancement.

Since we do not know the exact function that will be suited for a given image, it seems appealing and convenient to use one general form with different parameters; and apply an adaptive technique that can efficiently search the complex space of possible parameter combinations and locate the values which yield optimal results. Once again, GAs seem to be a feasible alternative for this task. This is illustrated in Fig. 3 where GAs are used to determine the optimal enhancement function out of four different functional forms (Fig. 3A). The optimal one (Fig. 3B) is seen to be of composite form. This is supported by the enhanced image output (Fig. 3C) also [75].

Because of the aforesaid characteristics, GAs are successfully being applied in different facets of image processing/analysis [75]-[84].

5 Integration of the Soft Computing Tools

In this section we describe some of the ways how the various soft computing tools can be made to work synergetically (not competitively) to build efficient hybrid systems [2] for pattern recognition in general and image processing, in particular.

5.1 Neuro-fuzzy systems

As mentioned before, fuzzy set theory provides an approximate but effective and flexible way of representing, manipulating and utilizing vaguely-defined data and information, and of describing the behaviors of systems which are

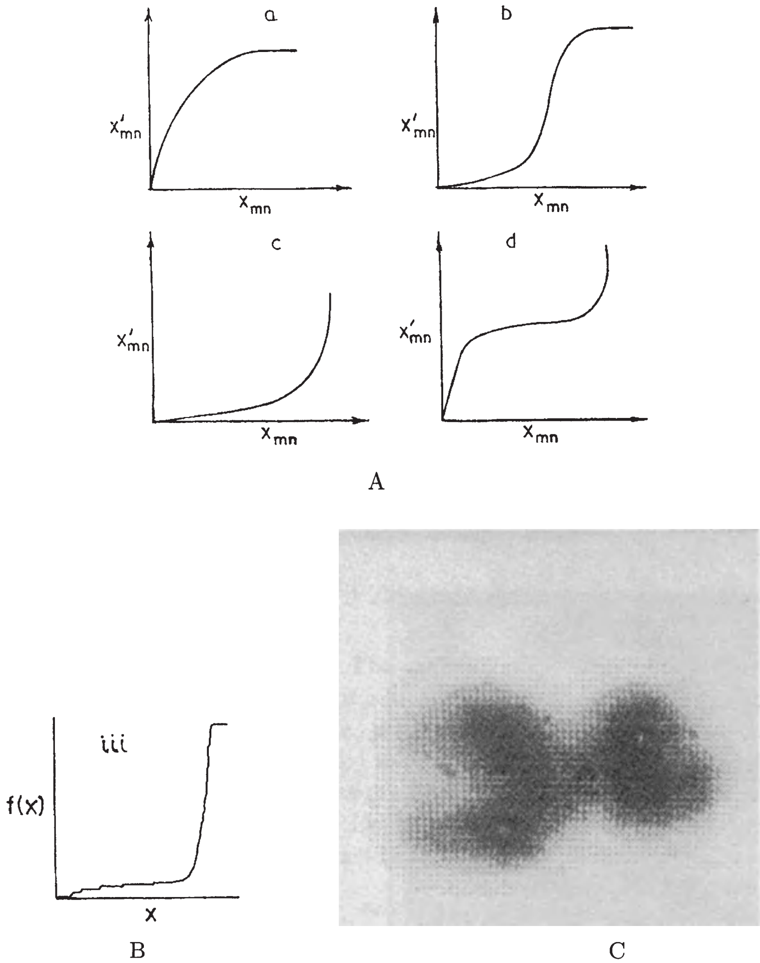


Fig. 3. Image enhancement by genetic algorithms

too complex or too ill-defined to admit of precise mathematical analysis by classical methods and tools. Successful use of fuzzy logic to create many commercial products has been made in Japan. This, in turn, has increased interest among engineers, researchers and company executives to understand and explore further this technology. Though the approach tries to model the human thought process in a decision-making system, it has no relation with the architecture of the human neural information processing system, nor does it take into consideration the information storage technique of human beings, and some times it is computationally intensive.

Human intelligence and discriminating power, on the other hand, are mainly attributed to the massively connected network of biological neurons in the human brain. Artificial neural networks are the attempts to emulate electronically the architecture and information representation scheme of the said biological neural networks. The collective computational abilities of the densely interconnected nodes or processors may provide a material technique, at least to a great extent, for solving highly complex real life problems in a manner such as a human being does.

It, therefore, appears that integration of the merits of these two technologies can provide more intelligent systems (in terms of parallelism, fault tolerance, adaptivity and uncertainty management) to handle real life recognition problems. These promises have motivated a large number of researchers to exploit these modern concepts for solving real world problems, leading to the development of a new paradigm called neuro-fuzzy computing [85]. Besides the generic advantages of parallelism, fault-tolerance and uncertainty handling, the neuro-fuzzy paradigm some times provides some application specific advantages. This includes, for example, utilizing an MLP, that is usually used under supervised mode, as an unsupervised classifier [55] or incorporating fuzzy linguistic variables at the input of the MLP for enhancing its performance as well as the application domain [86,87].

The hybridization, so far made, can be broadly classified in two categories: a neural network equipped with the capability of handling fuzzy information (termed fuzzy-neural network FNN) to augment its application domain, and a fuzzy system augmented by neural networks to enhance some of its characteristics like flexibility, speed, learning and adaptability (termed neural-fuzzy system NFS). The most visible soft computing hybrid systems, at this moment, are the neuro-fuzzy systems. Some of the attempts made to apply this hybrid technique in image processing problems are available in [9,55,57], [85]-[91]. As an illustration, consider Fig. 4 where different corrupted finger prints of a particular class (whorl) are seen to be correctly labeled by neuro-fuzzy classification. Here different fuzzy geometrical properties [23,30] of images are considered as input feature to an MLP.

5.2 Genetic-fuzzy system

Apart from the usual merits of parallelism and robustness, GAs are found sometimes essential to support fuzzy logic based systems, for enhancing the efficacy. This may help overcoming some of the limitations of fuzzy set theory, specifically to reduce the *"subjective"* nature of fuzzy membership functions. For example, the tuning of fuzzy membership functions with GAs can be done [2,87]. Note that the other way of integration, i.e., incorporating the concept of fuzziness into GAs has not yet been tried seriously.

5.3 Neuro-genetic systems

Synthesis of artificial neural network architectures can be done using GAs, as an example of another kind of integration between ANN and GAs under

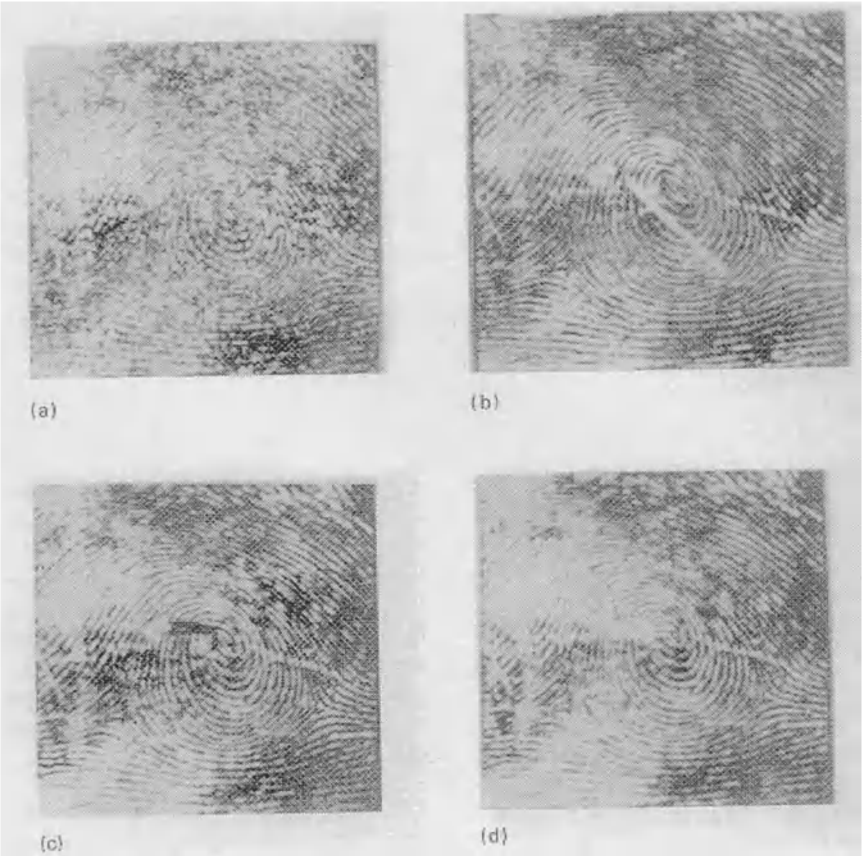


Fig. 4. Corrupted finger prints

the framework of soft computing. Such an integration may help designing optimum ANN architectures with appropriate parameter sets. Methods for designing neural network architectures using GAs are primarily divided into two parts. In one part the GA replaces the learning method to find appropriate connection weights of some predefined architecture [92]-[95]. In another part, GAs are used to find the architecture (connectivity) itself and it is then evaluated using some learning algorithms [76,92], [95]-[97].

5.4 Neuro-fuzzy-genetic systems

GAs have also been used recently [79] with fuzzy fitness function for classification of objects and background by cellular neural networks. The grayness and spatial ambiguity measures have been used as the basis of the fitness function. This sort of combination can be termed as *neuro-fuzzy-genetic* integration. Although some literature on this category exists [98] in other fields, more research articles are yet to come on image processing. Another important example of integrating FL, ANN and GAs is shown in Fig. 5. Here different parameters (e.g., membership function for low (L), medium (M) and high (H), and the input, the connection weights & biases of ANN, and the boundary of output classes or decision) of a neural network are adjusted by GAs for its optimal performance.

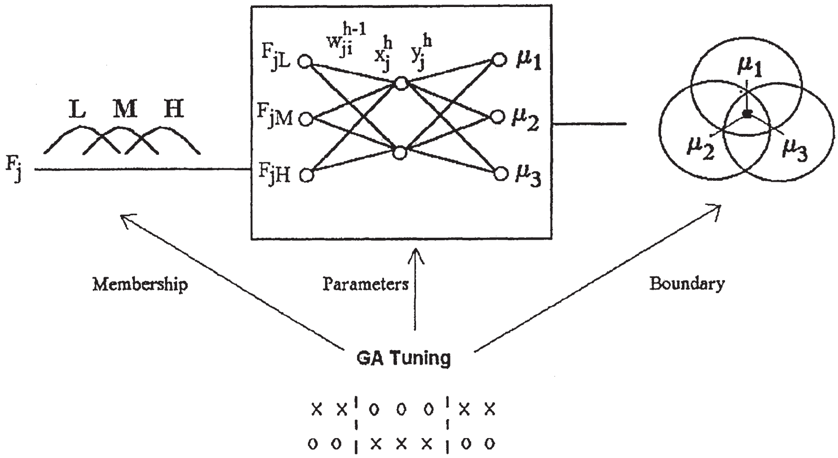


Fig. 5. Neuro-fuzzy-genetic system

5.5 Other hybridization

More recently, the theory of rough sets has emerged as another major mathematical approach for managing uncertainty that arises from inexact, noisy, or incomplete information. It is turning out to be methodologically significant to the domains of artificial intelligence and cognitive sciences, especially in the representation of and reasoning with and/or imprecise knowledge, data classification, data analysis, machine learning and knowledge discovery. The theory is also proving to be of substantial importance in many areas of applications. Various ways of integrating rough sets and fuzzy sets for designing new computing paradigm for decision making are available in [99]. An attempt in encoding domain knowledge in a fuzzy MLP for faster convergence and better performance is recently reported in [100]. However, the literature in image processing seems to be poor, at present.

6 Conclusions

We have discussed on some of the recent aspects of soft computing paradigm, its primary constituting tools, and their relevance to image processing and analysis. Although, FL, ANN and GAs are considered here as the primary components, other tools like rough sets, chaos, fractals will soon find their position in the primary list. As the significance of fuzzy set theory to image processing problems is adequately established since early seventies, we have given here sufficient references for the convenience of readers. Research in artificial neural networks both in theory and applications is in full swing and has reached almost its peak stage. This is evident through publications of several journals, special issues and books. GAs, on the other hand, is relatively new subject of research. Scientists are gradually getting motivated towards this field.

Research is going on extensively towards developing various hybrid systems involving the merits of the individual technology synergetically. Hybridization should ensure that it provides application specific merits, besides the generic advantages. The role of rough sets in this framework will be evident in the not distant future.

It may be noted that soft computing can be viewed as the key ingredient of real world computing (RWC), which is capable of distributed representation of information, massively parallel processing, and learning and adaptability in order to achieve flexibility in information processing. Therefore the growth of information technology in terms of computing power ranges from conventional computing (whose kernel is data processing), fifth generation computing systems (whose kernel is knowledge based information processing) to RWC (whose kernel is flexible information processing).

Thus, as it stands, the soft computing research, particularly the issue of hybridization, will not only continue to remain in the forefront line for the coming years, but also will play a key role in the development of future technology including sixth generation computing systems.

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