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EDITORIAL

COMPUTATIONAL INTELLIGENCE FOR PATTERN RECOGNITION

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The term *computational intelligence* (CI) was first introduced by Bezdek[2] in 1994. Bezdek says "... A system is computationally intelligent when it: deals with only numerical (low-level) data, has a pattern recognition component, does not use knowledge in the AI 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".

On the other hand, Fogel[8] attempts to summarize CI as "... These technologies of neural, fuzzy and evolutionary systems were brought together under the rubric of Computational Intelligence, a relatively new term offered to generally describe methods of computation that can be used to adapt solutions to new problems and do not rely on explicit human knowledge."

Irrespective of the way CI is defined, its components should have the following characteristics: considerable potential in solving real world problems, ability to learn from experience, capability of self-organizing, and ability of adapting in response to dynamically changing conditions and constraints. To summarize, it should display aspects of intelligent behavior as observed in humans.

In view of these, we assume that the major ingredients of a computational intelligence system are artificial neural networks, fuzzy sets, rough sets, and evolutionary computation. Some other components that may be parts of CI systems are artificial life and immuno computing. It is a synergistic combination of all these components.

In this context, it is worth acknowledging another term, *soft computing*, which is used to refer to a collection of tools containing neural networks, fuzzy logic, evolutionary computation, etc. Soft-computing is defined as a consortium of different computing tools that can exploit our tolerance for imprecision and uncertainty to achieve tractability, robustness and low cost.[18] Often, it attempts to find an approximate solution to a precisely or imprecisely formulated problem.

For the sake of completeness, we say a few words about the major components of CI. Fuzzy logic[6] is mainly concerned with providing a machinery for dealing with imprecision and approximate reasoning. It can model human reasoning ability. Rough sets theory provides a mechanism to deal with a different kind of nonprobabilistic uncertainty.[17] It can be used to find decision rules hidden in a data set. Neurocomputing (NC) deals with learning and curve fitting. It can find the input–output relation hidden in data.[11] A fuzzy system has high knowledge transparency whereas a neural network has high learning abilities. Genetic algorithm (GA) is a stochastic search method that is driven by the Darwinan principle of survival of the fittest.[10] GA finds the solution of an optimization problem. Genetic programming, although is driven by the same principle, searches for a program to solve a given problem.[12]

Often, to solve a fairly complex real world problem a single computational tool of CI may not be adequate. For such cases, integration of more than one tool may be more effective. Neural networks (NNs) attempt to model the way brain computes/works; they have the generic advantages of parallelism, fault tolerance and robustness. Fuzzy logic, on the other hand, can model, to a reasonable extent, the vagueness present in a system and reason or explain occurrences. Thus, a judicious integration of the two approaches may lead to knowledge transparency and learning ability to a system giving the benefits of both paradigms.[13] Sometimes, such an integration may result in some application specific advantages in addition to their generic merits. GAs are parallel stochastic search techniques, which have the capability of both exploration and exploitation. Many fuzzy or neural systems require finding the optimal values of a set of parameters to realize good performance. Therefore, GAs can be inserted into the development path of a fuzzy or neural system to devise a better system for solving a given problem. The integration of two or more CI tools has promises to realize computationally more "intelligent systems" — such integrations have resulted in hybrid systems known as neuro-fuzzy, fuzzy-neural, neuro-genetic, fuzzy-genetic systems and so on.

The knowledge transparency of a neuro-fuzzy system can help us to have a more efficient training scheme where one can avoid learning from scratch by exploiting experts' domain knowledge of qualitative nature, at least, at the linguistic level. In the evolutionary — granular computing paradigm, fuzzy logic provides an essential interface between the environment and the available domain knowledge gathered by suitable genetic operations. The evolutionary mechanism can help to design a fuzzy system that builds up rules and can select various inferencing mechanisms. Similarly, a neural network can be designed to realize the most suitable inference scheme for a given problem.[5,15]

With this introduction to computational intelligence let us consider how it can help to solve pattern recognition problems. Duda and Hart[7] defined pattern recognition (PR) as a field concerned with machine recognition of meaningful regularities in a noisy or complex environment, while according to Bezdek[1] pattern recognition is the search for structure in data. Irrespective of the way PR is defined, it primarily deals with three important tasks: feature analysis, clustering and classification. An image analysis system is also a PR system — most of the tasks related to image analysis can be viewed as one of the three PR tasks. For example, segmentation corresponds to clustering while tasks like pixel modification (enhancement) and characterization of segments can be viewed as feature extraction and analysis.

CI tools could be very useful for designing effective Pattern Recognition and Image Processing (IP) system.[3,16] We mention here a few illustrative ones. For example, in case of segmentation of satellite images, fuzzy modeling becomes unavoidable. A pixel may correspond to, say, 5×5 sq. m. block on the ground and part of this pixel may correspond to land and the remaining may be water. Thus, for a segmentation algorithm, to get a proper representation of such a pixel, we are compeled to use the concept of fuzzy membership values. Similarly, while designing a classifier, for data falling in the region of overlap of two classes, we need either fuzzy or probabilistic model of output.[3] Neural networks can also play a significant role in designing PR–IP systems. The inherent parallelism of neural network makes it an effective tool for real life recognition systems. Networks like multilayer perceptron, radial-basis function network are well known for their recognition and generalization capability[11] and hence are easy-to-use classifier systems. The robustness of neural networks against component failure makes Hopfield type network a very effective tool for image processing applications.[9] Neural networks can also be very effectively used for feature extraction (implicit and explicit) and feature selection. In fact, NN provides a very interesting paradigm for online feature selection, i.e. the network can be made to select the relevant features while learning the given task.[4,14]

It is almost impossible to think of any real world intelligent decision making system that does involve pattern recognition in some form or other. It is an essential and important part of realizing intelligent systems for solving real world problems. We would like to thank to Prof. H. Bunke who gave us an opportunity to guest edit this special issue on this very important area, *Computational Intelligence for Pattern Recognition*, based on the enhanced version of some selected papers from the *2002 AFSS International Conference on Fuzzy Systems (AFSS 2002), Calcutta*.

Keeping this theme in mind, we shortlisted a set of related papers from the AFSS 2002 proceedings and the authors were asked to submit enhanced versions of their papers. Each of the selected papers were thoroughly reviewed by three to four referees. The revised versions were also re-reviewed as and when required, and finally, we could select eleven papers for this issue. The topics covered by the special issue ranges from bioinformatics, classifier design, image processing, speech analysis, fuzzy and rough sets, design and analysis of neural network algorithms, cellular automata, numeral recognition, stereo matching, clustering algorithms and genetic algorithms. Based on the tools and techniques used, these papers can logically be organized into three groups: neural networks, fuzzy and rough systems and hybrid systems.

Ganguly *et al.* proposed an efficient technique of evolving *Cellular Automata* (*CA*) as an associative memory model. They call the evolved automata, a Generalized Multiple Attractor Cellular Automata (*GMACA*). This can act as a powerful pattern recognizer. They demonstrate that the storage capacity of *GMACA* based associative memory is far better than that of Hopfield net. Detailed analysis of GMACA rules establishes the fact that the rule subspace of the pattern recognizing *CA* lies at the edge of chaos, and it is believed to be capable of executing complex computation.

The next article by Datta and Parui provides a rigorous analysis of a self-organizing neural network model that computes the smallest circle (also called the minimum spanning circle) enclosing a finite set of given points. They prove that the model converges to the desired center of the minimum spanning circle. Authors suggest a suitable neural network architecture for a connectionist implementation of the proposed model. They also compute the time complexity of the algorithm, and discuss its possible extension to higher dimensions.

Navarrete and Solar made an extensive comparison of different eigenspace-based approaches for the recognition of faces. The methods discussed differ primarily in the kind of projection methods that are being used and in the similarity matching criterion employed. This article also presents a detailed comparative study of some of these approaches. Authors consider theoretical aspects as well as experimental results performed on two-face databases.

Cho, in his article on bioinformatics, explores the utility of various features in conjunction with different classifiers for classification of gene expression profiles of acute leukemia. He makes an extensive comparative study to find the promising feature selection methods and machine learning algorithms for gene expression classification. The gene information from a patient's marrow expressed by DNA microarray, which is either the acute myeloid leukemia or acute lymphoblastic leukemia, is used to predict the cancer class. Various feature selection criteria including Pearson's correlation coefficient, cosine coefficient, information gain, mutual information have been used. He used a wide spectrum of classifiers such as backpropagation neural network, self-organizing map, support vector machine, decision tree and k-nearest neighbor. His experimental results indicate that the combination of backpropagation neural network and Pearson's correlation coefficient produces the best recognition rate on the test data.

Character recognition is still an important problem to researchers. In the next article a new approach to recognition of handprinted Bangla (an Indian script) numerals is proposed by Bhattacharya *et al.* To extract a vector skeleton from a binary numeral image, they proposed a modified topology adaptive self-organizing neural network. A set of topological and structural features like loops, junctions, positions of terminal nodes are used along with a decision tree to classify handwritten numerals into smaller subgroups. Then for each subgroup a multilayer perceptron network is trained to uniquely classify the numerals belonging to this subgroup. Sufficient experimental investigation suggests that the scheme is quite robust with respect to noise.

Although, it is easy to analyze, the rough set theory built on a partition induced by an equivalence relation may not provide a realistic view of relationships between elements in the real-world applications. Intan and Mukaidono, in their article, proposed a generalized model of rough sets in which coverings of, or nonequivalence relations on, the universe can be considered to represent a more realistic model instead of a partition. Authors introduce a weak fuzzy similarity to represent a relationship between two elements of data in real-world applications. Coverings of the universe is provided by fuzzy conditional probability relations. They provide generalized concepts of rough approximations and rough membership functions based on the coverings of the universe. Such a generalization can be viewed as a kind of fuzzy rough set.

Noise often creates a problem in stereo matching. The article by Kumar and Chatterji describes a stereo matching method in the setting of fuzzy sets theory. In this article, similarity measures based on fuzzy relations are used for stereo matching. The strength of the relationship of fuzzified data of two windows in the left and right images of a stereo image pair is determined using suitable fuzzy aggregation operators. However, if there are occluded pixels in the corresponding windows, these measures fail to establish an appropriate correspondence. For this, another stereo matching algorithm based on fuzzy relation is used. This algorithm uses the weighted normalized cross correlation of the intensity data in the left and the right windows. Experimental results with various real stereo images demonstrate the superiority of these algorithms over the nonfuzzy normalized cross-correlation method.

Dimitriadou *et al.* in their article present a voting scheme for combining several fuzzy partitions. It gives a partial solution to one of the cluster validation problems, finding a better partition by combining several partitions. It can help to select the appropriate clustering method for a given data set. Experiments show that the voting algorithm finds structurally stable results. Several cluster validity indexes are used to demonstrate the effectiveness of the voting scheme.

Tran and Wagner presented a new approach to speaker verification based on fuzzy set theory. Most of the current methods use the *claimed speaker's score* and a threshold value for acceptance and rejection of a speaker. Authors view this score as a fuzzy membership function. They proposed fuzzy entropy and fuzzy c-means membership scores that relate to the likelihood function. Their noise clustering method provides an effective modification to several methods, which can overcome some of the problems of ratio-type scores and greatly reduce the false acceptance rate. Experimental results with various corpus demonstrate the superiority of the algorithm over the conventional methods.

The article by Lin *et al.* describes techniques for speech segmentation and enhancement in the presence of noise. This is a neuro-fuzzy system. They proposed a new word boundary detection algorithm using a neural fuzzy network (called adaptive time frequency (ATF) based self-constructing neural fuzzy inference network (SONFIN)) for identifying islands of word signals in a fixed noise-level environment. Another new refined time-frequency (RTF) based recurrent self-organizing neural fuzzy inference network (RSONFIN), where the background noise level varies during recording, is also proposed. The ATF and RTF parameters can extract useful frequency information by adaptively choosing proper bands of the mel-scale frequency bank. Due to the self-learning ability of the networks, the proposed algorithms avoid the need of empirically determining thresholds and ambiguous rules. The RTF-based RSONFIN algorithm is quite robust against variation of the background noise level. Their experimental results show that the proposed algorithms could achieve higher recognition rate than several commonly used word boundary detection algorithms.

Velayutham *et al.* propose an evolvable subsethood product fuzzy neural inference system (ESuPFuNIS). This is a neuro-fuzzy-genetic system. ESuPFuNIS model employs only fuzzy weights, and accepts both numeric and linguistic inputs. Consequently, all numeric inputs are fuzzified using a feature specific fuzzifier. The network uses product aggregation operator and generates outputs using volume defuzzification. The original SuPFuNIS used gradient descent to learn the parameters, while ESuPFuNIS uses genetic algorithms for learning. The genetic learning results in a significant improvement in classification accuracy and rule economy. They used real-coded genetic algorithms. For all data sets considered, the GA based classifier performs better than its gradient descent counterpart in terms of classification accuracy as well as size of the rule base.

To summarize, the eleven papers included in the special issue cover all major facets of CI and they encompass a wide spectrum of applications containing cancer classification, speech analysis, speaker verification, character recognition and face recognition.

Before we conclude, once again we wish to thank Prof. H. Bunke, for facilitating this special issue of the *International Journal of Pattern Recognition and Artificial Intelligence.* We express our sincere gratitude to all referees without whose help and cooperation this special issue would not have been a reality. Finally, we thank all authors who submitted their papers for this issue.

References

1. J. C. Bezdek, *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum Press, NY, 1981.
2. J. C. Bezdek, "What is computational intelligence?" *Computational Intelligence: Imitating Life*, eds. J. Zurada, R. Marks and C. Robinson, Piscataway, IEEE Press, 1994, pp. 1–12.
3. J. C. Bezdek, J. M. Keller, R. Krishnapuram and N. R. Pal, *Fuzzy Models and Algorithms for Pattern Recognition and Image Processing*, Kluwer Academic, 1999.
4. D. Chakraborty and N. R. Pal, "Integrated feature analysis and fuzzy rule based system identification in a neuro-fuzzy paradigm," *IEEE Trans. Syst. Man Cybern.* **B31** (2001) 391–400.
5. S. Chakraborty, K. Pal and N. R. Pal, "A neuro-fuzzy framework for inferencing," *Neural Nets.* **15** (2002) 247–261.

6. D. Dubois and H. Prade, *Fundamentals of Fuzzy Sets*, Kluwer Academic, 2000.
7. R. O. Duda, P. E. Hart and D. G. Stork, *Pattern Classification*, Wiley, NY, 2000.
8. D. Fogel, Review of "Computational intelligence: imitating life," *IEEE Trans. Neural Networks* **6** (1995) 1562–1565.
9. A. Ghosh, N. R. Pal and S. K. Pal, "Modeling of component failure in neural networks for robustness evaluation: an application to object extraction," *IEEE Trans. Neural Nets.* **6** (1995) 648–656.
10. D. E. Goldberg, *Genetic Algorithms: Search, Optimization and Machine Learning*, Addison-Wesley, NY, 1989.
11. S. Haykin, *Neural Networks — A Comprehensive Foundation*, Macmillan College, Proc. Con. Inc., NY, 1999.
12. J. R. Koza, *Genetic Programming: On the Programming of Computer by Means of Natural Selection*, Cambridge, MIT Press, 1992.
13. C. T. Lin and C. S. G. Lee, *Neural Fuzzy Systems: A Neural-Fuzzy Synergism to Intelligent Systems*, Prentice-Hall, Englewood Cliffs, NJ, May, 1996.
14. N. R. Pal and K. Chintalapudi, "A connectionist system for feature selection," *Neural Parall. Sci. Comput.* **5** (1997) 359–381.
15. K. Pal, N. R. Pal and J. M. Keller, "Some neural net realizations of fuzzy reasoning," *Int. J. Intell. Syst.* **13** (1998) 859–886.
16. N. R. Pal, *Pattern Recognition in Soft Computing Paradigm*, FLSI Vol. 2, World Scientific, 2001.
17. Z. Pawlak, "Rough sets," *Int. J. Comput. Inform. Sci.* **11** (1982) 341–356.
18. L. A. Zadeh, "Fuzzy logic and soft computing: issues, contention and perspectives," *Proc. 3rd Int. Conf. Fuzzy Logic, Neural Nets and Soft Computing, IIZUKA*, Japan, 1994, pp. 1–2.