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ON THE COMBINATION OF FUZZY LOGIC AND EVOLUTIONARY COMPUTATION: A SHORT REVIEW AND BIBLIOGRAPHY

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ABSTRACT

In this paper, an evaluation of the current situation regarding to the combination of Fuzzy Logic and Evolutionary Computation is given. This is made by means of a classification in fourteen areas, giving a short introduction to each one of them and presenting a selected bibliography (mainly journal contributions and book's chapters) in these areas. The overview of bibliography is, of course and unfortunately, not complete, but should give a representative account of current focuses of research in the bidirectional integration of Fuzzy Logic and Evolutionary Computation.

1 INTRODUCTION

Recentely, numerous papers and applications combining fuzzy logic (FL) and Evolutionary Computation (EC) have become known, and there is an increasing interest in the integration of these two topics.

The present contribution tries to give a short review of the combination of FL and EC, introducing a classification of the publications in fourteen areas, presenting briefly them and showing selected bibliography in these areas.

Before to introduce the aforementioned areas, a few remarks seem to be necessary.

- The first, regarding to the EC.

  Evolutionary Algorithms (EAs) are search and optimization techniques based on the principles of natural evolution. The important mainstream forms of EAs are: Genetic Algorithms (GAs), Genetic Programming (GP), Evolution Strategies (ES) and Evolutionary Programming (EP). The great majority of contributions are related to the use of GAs and FL, therefore in the following we will use without a lack of generality the term GAs instead of EC, understanding that some references can use either GP, ES or EP.

- The second, is regarding to the selected bibliography.

  It is extracted from our technical report *"A Classified Review on the Combination Fuzzy Logic-Genetic Algorithms Bibliography", Dept. of Computer Science and A.I., University of Granada, Tech.Report 95129, October 1995 (Last version December 1996). Available at the URL address: http://decsai.ugr.es/˜herrera/fl-ga.html.* It classifies and lists 562 references. Although much effort has been devoted to collect as many references as possible, the list is certainly not complete. Anyway, it should give a representative account of the current emphasis in research in the integration of these two topics. This report classifies the bibliography in 15 sections according to the following table. It contains the keywords and the number of papers on each of them. These keywords covers the application of FL based tools to GAs (with the name of fuzzy genetic algorithms) and the different areas of FL and fuzzy set theory where GAs have been applied. The underlying report is continuously being updated.

  In this contribution we consider fourteen areas, we join the table areas 7 and 13 in a global area with the name *Genetic fuzzy rule-based control systems.*

  The selected bibliography collects mainly journal's contributions and book's chapters although some conference's papers are selected either because they are well known and representative of the area or in the absence of other kind of contributions.

1	Fuzzy genetic algorithms	24
2	Fuzzy clustering	14
3	Fuzzy optimization	39
4	Fuzzy neural networks	34
5	Fuzzy relational equations	6
6	Fuzzy expert systems	8
7	Fuzzy classifier systems	33
8	Fuzzy information retrieval and database quering	6
9	Fuzzy decision making, financial, and economic models	10
10	Fuzzy regression analysis	6
11	Fuzzy pattern recognition and image processing	24
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13	Fuzzy logic controllers (Design, Learning, Tuning, Applications)	287
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Table 1. Classification keywords

In the following we describe the aforementioned classification areas and present the selected bibliography.

2 FUZZY GENETIC ALGORITHMS

A Fuzzy Genetic Algorithm (FGA) is considered as a GA that uses fuzzy logic based techniques or fuzzy tools to improve the GA behaviour modeling different GA components.

An FGA may be defined as an ordering sequence of instructions in which some of the instructions or algorithm components may be designed with fuzzy logic based tools, such as, fuzzy operators and fuzzy connectives for designing genetic operators with different properties, fuzzy logic control systems for controlling the GA parameters according to some performance measures, fuzzy stop criteria, representation tasks, etc.

Outstanding references are:

1. Bergman A., Burgard W., and Hemker A. (1994) Adjusting parameters of genetic algorithms by fuzzy control rules. In Becks K. H. and Gallix D. P. (eds) *New Computer Techniques in Physics Research III*, pages 235–240. World Scientific Press, Singapore.

2. Herrera F., Lozano M., and Verdegay J. L. (1995) Tackling fuzzy genetic algorithms. In Winter G., Periaux J., Galán M., and Cuesta P. (eds) *Genetic Algorithms in Engineering and Computer Science*, pages 167–189. John Wiley and Sons, England.

3. Herrera F., Lozano M., and Verdegay J. L. (1995) The use of fuzzy connectives to design real-coded genetic algorithms. *Mathware & Soft Computing* 1(3): 239–251.

4. Herrera F. and Lozano M. (1996) Adaption of genetic algorithm parameters based on fuzzy logic controllers. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 95–125. Physica Verlag.

5. Herrera F., Lozano M., and Verdegay J. L. (1996) Dynamic and heuristic fuzzy connectives based crossover operators for controlling the diversity and convergence of real-coded genetic algorithms. *International Journal of Intelligent Systems 11(12): 1013-1040.* .

6. Herrera F., Lozano M., and Verdegay J. L. (1996) Fuzzy connective based crossover operators to model genetic algorithms population diversity. *Fuzzy Sets and Systems (to appear)* .

7. Lee M. A. and Takagi H. (July 1993) Dynamic control of genetic algorithms using fuzzy logic techniques. In *Proc. Fifth International Conference on Genetic Algorithms (ICGA'93)*, pages 76–83. San Mateo.

8. Pedrycz W. and Reformat M. (1996) Genetic optimization with fuzzy coding. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 51–67. Physica Verlag.

9. Serapião A. B. S., Rocha A. F., Rebello M. P., and Pedrycz W. (1996) Towards a theory of genetic systems. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 68–94. Physica Verlag.

10. Xu H. Y. and Vukovich G. (October 1993) A fuzzy genetic algorithm with effective search and optimization. In *Proc. International Joint Conference on Neural Networks (IJCNN'93)*, pages 2967–2970. Nagoya.

3 FUZZY CLUSTERING

Clustering plays a key role in searching for structures in data. Given a finite set of data, X, the problem of clustering in X is to find several cluster centers that can properly characterize relevant classes of X. In classical cluster analysis, these classes are required to form a partition of X such that the degree of association is strong for data within blocks of the partition and weak for data in different blocks. However, this requirement is too strong in many practical applications, and it is thus desirable to replace it with a weaker requirement. When the requirement of a crisp partition of X is replaced with a weaker requirement of a *fuzzy partition* or a *fuzzy pseudopartition* on X, the emerged problem area is refered as *fuzzy clustering.*

GAs may be used for a global search of the space of possible data partitions given a choice of the number of clusters or classes in the data, for determining the number of clusters, etc.

The following four references show these applications.

1. Bezdek J. C. and Hathaway R. J. (June 1994) Optimization of fuzzy clustering criteria using genetic algorithms. In *Proc. First IEEE Conference on Evolutionary Computation (EC-IEEE'94)*, pages 589–594. Orlando.

2. Hall L. O., Bezdek J. C., Boggavarpu S., and Bensaid A. (1994) Genetic fuzzy clustering. In *Proc. North American Fuzzy Information Processing Society Biannual Conference (NAFIPS'94)*, pages 411–415. San Antonio.

3. Srikanth R., George R., Warsi N., Prabhu D., Petry F. E., and Buckles B. P. (1995) A variable-length genetic algorithm for clustering and classification. *Pattern Recognition Letters* 16: 789–800.

4. Yuan B., Klir G. J., and Swan-Stone J. F. (March 1995) Evolutionary fuzzy C-Means clustering algorithm. In *Proc. Fourth IEEE International Conference on Fuzzy Systems (FUZZ-IEEE'95)*, pages 2221–2226. Yokohama.

4 FUZZY OPTIMIZATION

Fuzzy optimization deals with how to find a best point under some fuzzy goals and restrictions given as linguistic terms or fuzzy sets.

GAs have been used for solving different fuzzy optimization problems. This is the case for instance of fuzzy flowshop scheduling problems, vehicle routing problems with fuzzy due-time, fuzzy mixed integer programming applied to resource distribution, interactive fuzzy satisfycing method for multiobjective 0-1, fuzzy optimal reliability design problems, job-shop scheduling problem with fuzzy processing time, fuzzy optimization of distribution networks, etc.

Outstanding references are:

1. Buckley J. J. and Hayashi Y. (1994) Fuzzy genetic algorithm and applications. *Fuzzy Sets and Systems* 61(2): 129–136.
2. Castillo L. and González A. (1996) Fuzzy optimization of distribution networks by using genetic algorithms. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 641–657. Physica Verlag.
3. Cheng R., Gen M., and Tozawa T. (1995) Vehicle routing problem with fuzzy due-time using genetic algorithms. *Japanese Journal of Fuzzy Theory and Systems* 7(5): 665–679.
4. Cheng R. and Gen M. (1996) Fuzzy vehicle routing and scheduling problem using genetic algorithms. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 683–709. Physica Verlag.
5. Herrera F., Lozano M., and Verdegay J. L. (1994) Applying genetic algorithms in fuzzy optimization problems. *Fuzzy Systems and Artificial Intelligence* 3(1): 39–52.
6. Ishibuchi H., Yamamoto N., Murata T., and Tanaka H. (1994) Genetic algorithms and neighborhood search algorithms for fuzzy flowshop scheduling problems. *Fuzzy Sets and Systems* 67: 81–100.
7. Mizunuma H. and Watada J. (1995) Fuzzy mixed integer programming based on genetic algorithm and its application to resource distribution. *Japanese Journal of Fuzzy Theory and Systems* 7(1): 97–117.
8. Sakawa M., Kato K., Sunada H., and Enda Y. (1995) An interactive fuzzy satisficing method for multiobjective 0-1 programming problems through revised genetic algorithm. *Japanese Journal of Fuzzy Theory and Systems* 7(2): 233–245.
9. Sakawa M. and Shibano T. (1996) Interactive fuzzy programming for multiobjective 0-1 programming problems through genetic algorithms with double strings. In Ruan D. (ed) *Fuzzy Logic Foundations and Industrial Applications*, pages 113–128. Kluwer Academic Press, Boston.

10. Sasaki M., Yokota T., and Gen M. (1995) A method for solving fuzzy optimal reliability design problem by genetic algorithm. *Japanese Journal of Fuzzy Theory and Systems* 7(5): 681–694.

11. Tsujimura Y., Gen M., and Kubota E. (1995) Solving job-shop scheduling problem with fuzzy processing time using genetic algorithm. *Japanese Journal of Fuzzy Theory and Systems* 7(5): 695–707.

12. Wong K. P. and Wong S. Y. W. (February 1996) Combined genetic algorithm/simulated annealing/fuzzy set approach to short-term generation scheduling with take-or-pay fuel contract. *IEEE Transactions on Power Systems* 11(1): 128–135.

5 FUZZY NEURAL NETWORKS

Neural networks have been recognized as an important tool for constructing membership functions, operations on membership functions, fuzzy inference rules, and other context-dependent entities in fuzzy set theory.

On other hand, attempts have been made to develop alternative neural networks, more attuned to the various procedures of approximate reasoning. These alternative neural networks are usually referred to as *fuzzy neural networks*. The following features, or some of them, distinguish fuzzy neural networks from their classical counterparts: inputs are fuzzy numbers, outputs are fuzzy numbers, weights are fuzzy numbers, weighted inputs of each neuron are not aggregated by summation, but by some other aggregation operation. A deviation from classical neural networks in any of these features requires a properly modified learning algorithm to be developed.

GAs may be used for designing an overall good architecture of fuzzy neural networks and fuzzy neural networks, for determining an optimal set of link weightd, for participating in hybrid learning algorithms, etc.

Outstanding references are:

1. Buckley J. J., Reilly K. D., and Penmetcha K. V. (1996) Backpropagation and genetic algorithms for training fuzzy neural nets. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 505–532. Physica Verlag.

2. Figueiredo M. and Gomide F. (1996) Evolving neurofuzzy networks for basic behaviors and a recategorization approach for their condition. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 533–552. Physica Verlag.

3. Fukuda T. and Shibata T. (1994) Fuzzy-neuro-GA based intelligent robotics. In Zurada J. M., Marks II R. J., and Robinson C. J. (eds) *Computational Intelligence Imitating Life*, pages 352–363. IEEE Press, New York.

4. Hanebeck U. and Schmidt G. K. (1996) Genetic optimization of fuzzy networks. *Fuzzy Sets and Systems* 79: 59–68.

5. Ishigami H., Fukuda T., Shibata T., and Arai F. (May 1995) Structure optimization of fuzzy neural networks by genetic algorithm. *Fuzzy Sets and Systems* 71(3): 257–264.

6. Lehotsky M., Olej V., and Chmumy J. (1995) Pattern recognition based on the fuzzy neural networks and their learning by modified genetic algorithms. *Neural Network World* 5(1): 91–97.

7. Pal S. K. and Bhandari D. (1995) Genetic algorithms with fuzzy fitness function for object extraction using cellular networks. *Fuzzy Sets and Systems* 65(2): 129–139.

8. Schaffer J. D. (1994) Combinations of genetic algorithms and neural networks or fuzzy systems. In Zurada J. M., Marks II R. J., and Robinson C. J. (eds) *Computational Intelligence Imitating Life*, pages 371–382. IEEE Press, New York.

9. Xue H. (1994) *Applications of Genetic Algorithms in Optimization of Fuzzy-Associative Memory Based Controllers*. PhD thesis, University of New Mexico, CAD Laboratory for Intelligent and Robotic Systems. Department of EECE.

10. Zhang L., Li Y., and Chen H. (March 1996) A new global optimizing algorithm for fuzzy neural netowrks. *International Journal of Electronics* 80(3): 393–403.

6 FUZZY RELATIONAL EQUATIONS

The notion of fuzzy relational equations is associated with the concept of composition of binary relations. This operation involves exactly the same combinations of matrix entries as in the regular matrix multiplication. However, the multiplications and additions that are applied to these combinations in the matrix multiplication are replaced with other operations. These alternative operations represent, in each given context, the appropriate operations of fuzzy set intersection and union, respectively. Fuzzy relational equations have been intensively exploited in many areas of applications of fuzzy sets.

GAs may be used either for finding approximate solutions to a system of fuzzy relational equations or for learning in relational structures.

Two references related to the aforementioned applications are:

1. Negoita M. G., Fagarasan F., and Agapie A. (September 1994) Applications of genetic algorithms in solving fuzzy relational equations. In *Proc. Second European Conference on Intelligent Techniques and Soft Computing (EUFIT'94)*, pages 1126–1129. Aachen.

2. Pedrycz W. (1995) Genetic algorithms for learning in fuzzy relational structures. *Fuzzy Sets and Systems* 69(1): 37–52.

7 FUZZY EXPERT SYSTEMS

An expert system is a computer-based system that emulates the reasoning process of a human expert within a specific domain of knowledge. In fuzzy expert systems, the knowledge is usually represented by a set of fuzzy production rules, which connect antecedents with consequent, premises with conclusions, or conditions with actions.

GAs can solve two basical problems of the knowledge base, the knowledge base buliding and the knowledge filtering.

Two references related to this topic are:

1. Perneel C., Themlin J. M., Renders J. M., and Acheroy M. (1995) Optimization of fuzzy expert systems using genetic algorithms and neural networks. *IEEE Transactions on Fuzzy Systems* 3(3): 300–312.

2. Zhang L., Wang L., Zang Y., Seki H., and Itoh H. (March 1995) On rule checking and learning in an acupuncture diagnosis fuzzy expert system by genetic algorithm. In *Proc. Fourth IEEE International Conference on Fuzzy Systems (FUZZ-IEEE'95)*, pages 455–460. Yokohama.

8 FUZZY INFORMATION RETRIEVAL

Information retrieval may be defined as the problem of the selection of documentary information from storage in response to search questions. The motivation of the application of fuzzy set theory to the design of databases and information storage and retrieval systems lies in the need to handle imprecise information. The database that can accommodate imprecise information can store and manipulate not only precise facts, but also subjective expert opinions, judgments, and values that can be specified in linguistic terms.

GAs are used for designing models for optimization of queries in a fuzzy information retrieval system.

Two references related to this topic are:

1. Kraft D. H., Petry F. E., Buckles B. P., and Sadasivan T. (1995) Applying genetic algorithms to information retrieval systems via relevance feedback. In Bosc P. and Kacprzyk J. (eds) *Fuzziness in DataBase Management Systems*, pages 330–344. Physica-Verlag Heidelberg, Germany.
2. Sanchez E., Miyano H., and Brachet J. P. (July 1995) Optimization of fuzzy queries with genetic algorithms. application to a data base of patents in biomedical engineering. In *Proc. Sixth International Fuzzy Systems Association World Congress (IFSA'95)*, volume 2, pages 293–296. Sao Paulo.

9 FUZZY DECISION MAKING, FINANCIAL, AND ECONOMIC MODELS

Decision making is the study of how decisions are actually made and how they can be made better or more successfully. Fuzzy set theory has been widely used in the field of decision making. For the most part, the application consisted on fuzzifications of the classical theories of decision making. Also it is used for modelling some financial and economic problems.

GAs may be used for cooperating in the design and resolution of these models.

The following references show three specific applications to these fields.

1. Goonatilake S., Campbell J. A., and Ahmad N. (1995) Genetic-fuzzy systems for financial decision making. In Furuhashi T. (ed) *Advances in Fuzzy Logic, Neural Networks and Genetic Algorithms. Proc. 1994 IEEE/Nagoya-University World Wide Wisepersons. Selected papers. LNAI 1011*, pages 202–223. Springer-Verlag, Berlin.

2. Loia V. and Scandizzo S. (September 1995) Qualitative selection strategies in genetic-based evolutionary economic models. In *Proc. Third International Symposium on Uncertainly Modeling and Analysis and Annual Conference of the North American Fuzzy Information Processing Society (ISUMA-NAFIPS'95)*, pages 333–338. Maryland.

3. Rubinson T. C. and Geotsi G. M. (July 1996) Estimation of subjective preferences using fuzzy logic and genetic algorithms. In *Proc. Sixth International Conference on Information Processing and Management of Uncertainty in Knowledge Based Systems (IPMU'96)*, pages 781–786. Granada.

10 FUZZY REGRESSION ANALYSIS

Regression analysis is an area of statistics that deals with the investigation of the dependence of a variable upon one or more other variables. Two distinct motivations, fuzzy relation seems intuitively more realistic and the nature of data which in some applications are inherently fuzzy, lead to two types of fuzzy regression analysis. One involves fuzzy parameters and crisp data, while the other one involves crisp parameters and fuzzy data.

GAs may be used for solving the underlying optimization problems.

The following reference show an example of the application of GAs to fuzzy regression analysis.

1. Yabuchi Y., Watada J., and Tatsumi K. (1994) Fuzzy regression anaysis of data with error. *Japanese Journal of Fuzzy Theory and Systems* 6(6): 673–685.

11 FUZZY PATTERN RECOGNITION AND IMAGE PROCESSING

There are various aspects of image processing and analysis problems where the theory of fuzzy sets has been applied: as generalizations of classical membership-roster methods, generalizations of classical syntactic methods, providing image ambiguity/information measures and quantitative evaluation, computing fuzzy geometrical properties, etc.

In handling uncertainty in pattern analysis, GAs may be helpful in determining the appropriate membership functions, rules and parameter space, and in providing a reasonably suitable solution. For this purpose, a suitable fuzzy fitness function needs to be defined depending on the problem.

The following four selected references deal with some of the aforementioned applications:

1. Albert J., Ferri F., Domingo J., and Vicens M. (1990) An approach to natural scene segmentation by means of genetic algorithms with fuzzy data. In Pérez de la Blanca N., SanFeliu A., and Vidal E. (eds) *Fourth National Symposium in Pattern Recognition and Image Analysis (Selected Papers)*, pages 97–112. World Scientific Publishers Co. Inc., Singapore.

2. Ankenbrandt C. A., Buckles B. P., and Petry F. E. (1990) Scene recognition using genetic algorithms with semantic nets. *Pattern Recognition Letters* 11(4): 285–293.

3. Bhandari D., Pal S. K., and Kundu M. K. (March 1993) Image enhancement incorporating fuzzy fitness function in genetic algorithms. In *Proc. Second IEEE International Conference on Fuzzy Systems (FUZZ-IEEE'93)*, volume 2, pages 1408–1413. San Francisco.

4. Lee Y. G., Lee J. H., and Hsueh Y. C. (November 1995) Genetic-based fuzzy hit-or-miss texture spectrum for texture analysis. *Electronics Letters* 31(23): 1986–1988.

12 FUZZY CLASSIFICATION - CONCEPT LEARNING

Fuzzy classification sytems based on fuzzy logic are capable of dealing with cognitive uncertainties such as the vagueness and ambiguity involved in classification problems. In a fuzzy classification system, a case or an object can be classifed by applying (mainly) a set of fuzzy rules based on the linguistic values of its attributes.

GAs are used in a fuzzy classification system for learning fuzzy rules, membership functions, fuzzy partitions, etc.

Outstanding references are:

1. González A., Pérez R., and Verdegay J. L. (1994) Learning the structure of a fuzzy rule: A genetic approach. *Fuzzy Systems and Artifical Intelligence* 3(1): 57–70.

2. González A. and Pérez R. (February 1995) Completeness and consistency conditions for learning fuzzy rules. Fuzzy Sets and Systems, To appear.

3. Ishibuchi H., Nozaki K., Yamamoto N., and Tanaka H. (1994) Construction of fuzzy classification systems with rectangular fuzzy rules using genetic algorithms. *Fuzzy Sets and Systems* 65: 237–253.

4. Ishibuchi H., Nozaki K., Yamamoto N., and Tanaka H. (1994) Performance evaluation of a GA-based method for selecting fuzzy classification rules. *Transactions Inst. Electron. Inf. Commun. Eng.* 10: 1409–1411.

5. Ishibuchi H., Nozaki K., Yamamoto N., and Tanaka H. (1995) Selecting fuzzy if-then rules by genetic algorithm for classification problems using genetic algorithms. *IEEE Transactions on Fuzzy Systems* 3(3): 260–270

6. Ishibuchi H. and Murata T. (1996) A genetic-algorithms-based fuzzy partition method for pattern classification problems. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 555–578. Physica Verlag.

7. Janikov C. Z. (1996) A Genetic Algorithm Method for Optimizing Fuzzy Decision Trees. *Information Sciences* 89: 275-296.

8. Yuan Y. and Zhuang H. (1996) A genetic algorithms for generating fuzzy classification rules. *Fuzzy Sets and Systems* 84: 1–19.

13 GENETIC FUZZY RULE BASED CONTROL SYSTEMS

Fuzzy rule based systems have been shown to be an important tool for modelling complex systems in which, due to the complexity or the imprecision, classical tools are unsuccessful. The experience of skilled operators and the knowledge of control engineers are expressed qualitatively by a set of fuzzy control rules. *Fuzzy logic controllers* (FLCs) constitute knowledge-based systems that include fuzzy rules and fuzzy membership functions to manage adequately human knowledge. The *FLC knowledge base* (KB) is comprised of two components, a *data base* (DB), containing the definition of the fuzzy partitions or fuzzy rule membership functions, and a *Rule Base* (RB), constituted by the collection of fuzzy control rules representing the expert knowledge. The definition of fuzzy rules and fuzzy membership functions is one of the key questions when designing FLCs. Some efforts have been made to obtain an improvement on system performance by incorporating learning mechanisms to modify the rules and/or membership functions of the KB.

GAs have demonstrated to be a powerful tool for automating the definition of the KB, since adaptive control, learning, and self-organization may be considered in a lot of cases as optimization or search processes. Their adavantages have extended the use of GAs in the development of a wide range of approaches for designing FLCs over the last few years. In particular, the application to the design, learning and tuning of KBs has produced quite promising results. These approaches can receive the general name of *Genetic Fuzzy Systems* (GFSs).

We must remark that we can also understand a GFS as an approach for learning fuzzy rules for classification systems, although we have prefered to distinguish between FLCs and fuzzy classification systems, and to introduce the GFSs in this section in order to not become diluted the few references in fuzzy classification into the big set of references in FLCs. On other hand, we also must understand the GFSs as the application of GAs to any fuzzy system being the fuzzy rule based systems a particular case although the most extended, this is the reason of calling this section as *genetic fuzzy rule based control systems.*

EAs, specially GAs in the great majority of the cases, are applied to modify/learn the DB and/or the RB. In this classification we distinguish two different groups of genetic fuzzy rule based control systems:

1. Genetic definition (learning) of the fuzzy logic controller data base, or in short called *genetic tuning processes.*

2. Genetic learning of the fuzzy logic controller rule bases or knowledge bases.

Different approaches have been proposed for genetic learning processes (for learning RB or KB). The main problem in these applications consists of finding a "comfortable" representation in the sense that it might be capable both of gathering the problem's characteristics and representing the potential solutions. Three genetic learning approaches have been proposed:

The Michigan approach: The chromosomes are individual rules and a rule set is represented by the entire population. The collection of rules are modified over time via interaction with the environment. This model maintains the population of classifiers with credit assignment, rule discovery and genetic operations applied at the level of the individual rule.

The Pittsburgh approach: Each chromosome encodes a whole RB or KB. Crossover serves to provide a new combination of rules and mutation provides new rules. In some cases, variable-length rule bases are used, employing modified genetic operators for dealing with these variable-length and position independent genomes.

Iterative Rule Learning approach: In the latter model, as in the Michigan one, each chromosome in the population represents a single rule, but contrary to the latter, only the best individual is considered as the solution, discarding the remaining chromosomes in the population. Therefore, in the iterative model, the GA provides a partial solution to the problem of learning. In order to obtain a set of rules, which will be a true solution to the problem, the GA has to be placed within an iterative scheme similar to the following:

1. Use a GA to obtain a rule for the system.
2. Incorporate the rule into the final set of rules.
3. Penalize this rule.
4. If the set of rules obtained till now is adequate to represent the examples in the training set, the system ends up returning the set of rules as the solution. Otherwise return to step 1.

The main difference with respect to the Michigan approach is that the fitness of each chromosome is computed individually, without taking into account cooperation with other ones. This reduces substantially the search space, because in each sequence of iterations only one rule is searched.

The structure used for classifying the references include the following subsections: one for genetic tuning processes, three for the genetic learning processes according to the three aforementioned representation approaches, and a final section that will include reviews, other approaches and unclassified papers that do not belong to our collection and can not be classified.

Therefore the structure is the following:

- Genetic tuning processes
- Genetic learning processes: Michigan approach
- Genetic learning processes: Pittsburgh approach
- Genetic learning processes: Iterative Rule Learning approach
- Genetic fuzzy rule based control systems: reviews, other approaches and unclassified papers

Outstanding references are:

Genetic tuning processes

1. Filipic B. and Juricic D. (1996) A genetic algorithm to support learning fuzzy control rules from examples. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 403–418. Physica Verlag.
2. Glorennec P-Y. (1997) Co-ordination between autonomous robots. *International Journal of Approximate Reasoning (to appear)* .
3. Karr C. L. (February 1991) Genetic algorithms for fuzzy controllers. *AI Expert* 6(2): 26–33.
4. Karr C. L. and Gentry E. J. (February 1993) Fuzzy control of pH using genetic algorithms. *IEEE Transactions on Fuzzy Systems* 1(1): 46–53.
5. Karr C. L. (1996) Designing precise fuzzy systems with genetic algorithms. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 331–348. Physica Verlag.
6. Herrera F., Lozano M., and Verdegay J. L. (1995) Tuning fuzzy logic controllers by genetic algorithms. *International Journal of Approximate Reasoning* 12(3): 293–315.

7. Surmann H. (1996) Genetic optimizing of fuzzy rule-based systems. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 389–402. Physica Verlag.

Genetic learning processes: Michigan approach

1. Bonarini A. (1996) Evolutionary learning of fuzzy rules: Competition and cooperation. In Pedrycz W. (ed) *Fuzzy Modeling: Paradigms and Practice*, pages 265–283. Kluwer Academic Press, Norwell.
2. Bonarini A. (1996) Delayed reinforcement, fuzzy q-learning and fuzzy logic controllers. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 447–466. Physica Verlag.
3. Bonarini A., Basso F. (1997) Learning to compose fuzzy behaviors for autonomous agents. *International Journal of Approximate Reasoning (to appear)* .
4. Furuhashi T., Nakaoka K., Morikawa K., and Uchikawa Y. (1994) An acquisition of control knowledge using multiple fuzzy classifier system. *Japanese Journal of Fuzzy Theory and Systems* 6(3): 603-609.
5. Furuhashi T., Nakaoka K., Morikawa K., Maeda H., and Uchikawa Y. (1995) A study on knowledge finding using fuzzy classifier system. *Japanese Journal of Fuzzy Theory and Systems* 7(4): 555–567.
6. Furuhashi T., Nakaoka K., and Uchikawa Y. (1996) A study on fuzzy classifier systems for finding control knowledge of multi-input systems. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 489–502. Physica Verlag.
7. Geyer-Schulz A. (1993) Fuzzy classifier systems. In Lowen R. and Roubens M. (eds) *Fuzzy Logic: State of the Art*, pages 345–354. Kluwer Academic Publishers, Dordretch.
8. Geyer-Schulz A. (1995) *Fuzzy Rule-Based Expert Systems and Genetic Machine Learning*. Physica-Verlag, Heidelberg.
9. Geyer-Schulz A. (1995) On the specification of fuzzy data in management. In Bandemer H. (ed) *Mathematical Research: Modelling Uncertain Data*, pages 105–110. Akademie Verlag.
10. Parodi A. and Bonelli P. (July 1993) A new approach to fuzzy classifier system. In *Proc. Fifth International Conference on Genetic Algorithms (ICGA'93)*, pages 223–230. San Mateo.

11. Valenzuela-Rendón M. (July 1991) The fuzzy classifier system: A classifier system for continuously varing variables. In *Proc. Fourth International Conference on Genetic Algorithms (ICGA'91)*, pages 346–353. San Diego.

Genetic learning processes: Pittsburgh approach

1. Carse B., Fogarty T. C., and Munro A. (1996) Evolving temporal fuzzy rule-bases for distributed routing control in telecommunication networks. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 467–488. Physica Verlag.

2. Carse B., Fogarty T. C., and Munro A. (1996) Evolving fuzzy rule based controllers using genetic algorithms. *Fuzzy Sets and Systems* 80: 273–294.

3. Cooper M. G. (July 1995) Evolving a rule based fuzzy controller. *Simulation* 65(1): 67–72.

4. Fukuda T., Hasegawa Y., and Shimojima K. (1995) Structure organization of hierarchical fuzzy model using by genetic algorithm. *Japanese Journal of Fuzzy Theory and Systems* 7(5): 631–643.

5. Heider H., Tryba V., and Mühlenfeld E. (1995) Automatic design of fuzzy systems by genetic algorithms. In Bouchon-Meunier B., Yager R. R., and Zadeh L. A. (eds) *Fuzzy Logic and Soft Computing*, pages 21–28. World Scientific.

6. Heider H. and Drabe T. (1997) A cascaded genetic algorithm for improving fuzzy system design. *International Journal of Approximate Reasoning (to appear)* .

7. Homaifar A. and McCormick V. E. (1995) Simultaneous design of membership functions and rule sets for fuzzy controllers using genetic algorithms. *IEEE Transactions on Fuzzy Systems* 3(2): 129–139.

8. Karr C. L. (March 1991) Applying genetics to fuzzy logic. *AI Expert* 6(3): 38–43.

9. Krishnakumar K., Gonsalves P., Satyadas A., and Zacharias G. (1995) Hybrid fuzzy logic flight controller systhesis via pilot modeling. *AIAA Journal of Guidance, Control and Dynamics* 18:5 1098-1105.

10. Krishnakumar K. and Satyadas A. (1995) Evolving multiple fuzzy models and its application to an aircraft control problem. In Periaux J., Winter G., Galán M., and Cuesta P. (eds) *Genetic Algorithms in Engineering and Computer Science*, pages 305–320. John Wiley and Sons.

11. Lee M. A. and Takagi H. (March 1993) Integrating design stages of fuzzy systems using genetic algorithms. In *Proc. Second IEEE International Conference on Fuzzy Systems (FUZZ-IEEE'93)*, volume 2, pages 612–617. San Francisco.

12. Lee M. A. and Takagi H. (1996) Hybrid genetic-fuzzy systems for intelligent systems design. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 226–250. Physica Verlag.

13. Leitch D. (1996) Genetic algorithms for the evolution of behaviours in robotic. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 306–328. Physica Verlag.

14. Li Y. and Ng K. C. (1996) Uniform approach to model-based fuzzy control system design and structural optimization. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 129–151. Physica Verlag.

15. Magdalena L. and Monasterio-Huelin F. (1997) A fuzzy logic controller with learning through the evolution of its knowledge base. *International Journal of Approximate Reasoning (to appear)* .

16. Magdalena L. (1997) Adapting the gain of an FLC with genetic algorithms. *International Journal of Approximate Reasoning (to appear)* .

17. Nomura H., Hayashi I., and Wakami N. (1993) A self-tuning method of simplified fuzzy reasoning by genetic algorithm. In Kandel A. and Langholz G. (eds) *Fuzzy Control and Systems*, pages 338–353.

18. Pham D. T. and Karaboga D. (1991) Optimum design of fuzzy logic controllers using genetic algorithms. *Journal of Systems Engineering* 1(2): 114–118.

19. Renhou L. and Yi Z. (1996) Fuzzy logic controller based on genetic algorithms. *Fuzzy Sets and Systems* 83: 1–10.

20. Satyadas A. and Krishnakumar K. (1996) EFM-based controllers for space station attitude control: Application and analysis. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 152–171. Physica Verlag.

21. Shibata T. and Fukuda T. (1994) Coordination in evolutionary multi-agent-robotic system using fuzzy and genetic algorithm. *Control Engineering Practice* 2(1): 103–111.

22. Shijojima K., Fukuda T., and Hasegawa Y. (May 1995) Self-tuning fuzzy modeling with adaptive membership function, rules, and hierachical structure based on genetic algorithm. *Fuzzy Sets and Systems* 71(3): 295–309.

23. Shijojima K., Kubota N., and Fukuda T. (1996) Virus evolutionary genetic algorithm for fuzzy controller optimization. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 369–388. Physica Verlag.

24. Tarng Y. S., Yeh Z. M., and Nian C. Y. (1996) Genetic synthesis of fuzzy logic controllers in turning. *Fuzzy Sets and Systems* 83: 301–310.

25. Thrift P. (July 1991) Fuzzy logic synthesis with genetic algorithms. In *Proc. Fourth International Conference on Genetic Algorithms (ICGA'91)*, pages 509–513. San Diego.

26. Wong C. C. and Feng S. M. (1995) Switching-type fuzzy controller design by genetic algorithms. *Fuzzy Sets and Systems* 74: 175–185.

Genetic learning processes: Iterative Rule Learning approach

1. Cordón O. and Herrera F. (1996) A hybrid genetic algorithm-evolution strategy process for learning fuzzy logic controller knowledge bases. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 251–278. Physica Verlag.

2. Cordón O. and Herrera F. (1997) Identification of linguistic fuzzy models by means of genetic algorithms. In Driankov D., Hellendoorn H., and Palm R. (eds) *Fuzzy Identification: A User's Handbook (to appear)*. Springer-Verlag, Berlin.

3. Cordón O. and Herrera F. (1997) A three-stage evolutionary process for learning descriptive and approximative fuzzy logic controller knowledge bases from examples. *International Journal of Approximate Reasoning (to appear)* .

4. González A. and Pérez R. (1996) A learning system of fuzzy control rules based on genetic algorithms. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 202–225. Physica Verlag.

5. González A. and Herrera F. (1997) Multi-stage genetic fuzzy systems based on the iterative rule learning approach. *Mathware & Soft Computing (to appear)*

6. Herrera F., Lozano M., and Verdegay J. L. (1995) Generating fuzzy rules from examples using genetic algorithms. In Bouchon-Meunier B., Yager R. R., and Zadeh L. A. (eds) *Fuzzy Logic and Soft Computing*, pages 11–20. World Scientific.

7. Ramalho M. F. and Scharf E. M. (1996) The application of fuzzy logic techniques and genetic algorithms for connection admission control in ATM networks. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 615–640. Physica Verlag.

Genetic fuzzy rule based control systems: reviews, other approaches and unclassified references

* Reviews

1. Cordón O. and Herrera F. (1995) A general study on genetic fuzzy systems. In Periaux J., Winter G., Galán M., and Cuesta P. (eds) *Genetic Algorithms in Engineering and Computer Science*, pages 33–57. John Wiley and Sons.

2. Cordón O., Herrera F., Herrera-Viedma E., and Lozano M. (1996) Genetic algorithms and fuzzy logic in control processes. *Archives of Control Science* 5(1–2): 135–168.

3. Magdalena L. and Velasco J. R. (1996) Fuzzy rules-based controllers that learn by evolving their knowledge base. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 172–201. Physica Verlag.

4. Velasco J. R. and Magdalena L. (1995) Genetic algorithms in fuzzy control systems. In Periaux J., Winter G., Galán M., and Cuesta P. (eds) *Genetic Algorithms in Engineering and Computer Science*, pages 141–165. John Wiley and Sons, England.

* Other approaches

5. Glorennec P. Y. (1996) Constrained optimization of FIS using an evolutionary method. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 349–368. Physica Verlag.

6. Hoffman F. and Pfister G. (1996) Learning of a fuzzy control rule base using messy genetic algorithms. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 279–305. Physica Verlag.

7. Hoffman F. and Pfister G. (1997) Evolutionary design of a fuzzy knowledge base for a mobile robot. *International Journal of Approximate Reasoning (to appear)* .

8. Kacprzyk J. (1996) Genetic algorithms in multistage fuzzy control. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 579–598. Physica Verlag.

9. Kim J. and Zeigler B. P. (June 1996) Hierarchical distributed genetic algorithms: A fuzzy logic controller design application. *IEEE Expert* 11(3): 76–84.

10. Kim J., Moon Y., and Zeigler B. P. (August 1996) Designing fuzzy logic controllers using multiresolutional search paradigm. *IEEE Transactions on Fuzzy Systems* 4(3): 213–226.

11. Park D., Kandel A., and Langholz G. (January 1994) Genetic-based new fuzzy reasoning models with application to fuzzy control. *IEEE Transactions on Systems, Man and Cybernetics* 24(1): 39–47.

12. Schröder M., Klawonn F., and Kruse R. (1996) Sequential optimization of multidimensional controllers using genetic algorithms and fuzzy situations. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 419–444. Physica Verlag.

* Unclassified references

13. Karr C. L. (1993) Adaptive process control with fuzzy logic and genetic algorithms. *Sci. Comput. Autom.* 9(10): 23–30 .

14. Karr C. L., Sharma S. K., Hatcher W. J., and Harper T. R. (1993) Fuzzy control of an exothermic chemical reaction using genetic algorithms. *Engineering Applications of Artificial Intelligence* 6(6): 575–582.

15. Linkens D. A. and Okola H. (1992) Real time acquistion of fuzzy rules using genetic algorithms. In Verbruggen H. B. and Rodd M. G. (eds) *Artificial Intelligence in Real-Time Control 1992*, volume 17, pages 335–339. Pergamon Press Ltd., Oxford.

16. Linkens D. A. and Nyongesa H. O. (1995) Genetic algorithms for fuzzy control. *Control Theory and Applications (UK)* 142(3): 177–185.

17. Subudhi B. and Swain A. K. (August 1995) Genetic algorithm based fuzzy logic controller for real time liquid level control. *Journal Inst. Engineering* 76: 96–100.

18. Wiggins R. (1992) Docking a truck: A genetic fuzzy approach. *AI Expert* 7(5): 28–35

19. Wu J. C. and Liu T. S. (June 1995) Fuzzy control of ryder-motorcycle system using genetic algorithm and auto-tuning. *Mechatronics* 5(4): 441–455.

14 FUZZY LOGIC MISCELLANEOUS

The purpose of this section is to mention some additional references on application areas of fuzzy set theory, which are not covered in previous sections.

Outstanding references are:

1. del Castillo D., Gasos J., and García-Alegre M. C. (1993) Genetic processing of the sensorial information. *Sens. Actuators A. Phys.* 37(2): 255–259.

2. George R. and Srikanth R. (1996) Data summarization using genetic algorithms and fuzzy logic. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 599–612. Physica Verlag.

3. Geyer-Schulz A. (1996) The MIT beer distribution game revisited: Genetic machine learning and managerial behavior in a dynamic decision making experiment. In Herrera F. and Verdegay J. (eds) *Genetic Algorithms and Soft Computing*, pages 658–682. Physica Verlag.

4. Loskiewicz-Buczak A. and Uhrig R. E. (1995) Information fussion by fuzzy set operation and genetic algorithm. *Simulation* 65(1): 51–66.

5. Ozawa J. and Yamada K. (1995) Data linguistic expression method using genetic algorithms. *Japanese Journal of Fuzzy Theory and Systems* 7(5): 645–663.

6. Williams T. (May 1995) Fuzzy, neural and genetic methods train to overcome complexity. *Computer Design* 34(5): 59–76.

15 FUZZY LOGIC - GENETIC ALGORITHMS FRAMEWORK

The purpose of this last section is to mention four additional references. Two of them are technical reports that collect bibliography on the combination of GAs and FL, and the other two are two edited books that present a collection of papers dealing with the topic.

1. Alander J. T. (November 1996) An indexed bibliography of genetic algorithms and fuzzy logic. Technical Report 94-1-FUZZY, University of Vaasa, Department of Information Technology and Industrial Management, University of Vaasa, P.O. Box 700, FIN-65101 Vaasa, Finland.

2. Cordón, O., Herrera, F., Lozano, M. (December 1996) A Classified Review on the Combination Fuzzy Logic-Genetic Algorirhtms Bibliography, Technical Report DECSAI-95129, Dept. of Computer Science and A.I., University of Granada, Granada, Spain.

3. Herrera F. and Verdegay J. L. (1996) *Genetic Algorithms and Soft Computing.* Physica Verlag.

4. Sanchez E., Shibata T., and Zadeh L. A. (1997) *Genetic Algorithms and Fuzzy Logic Systems. Soft Computing Perspectives.* World Scientific.