

FUZZY CLASSIFIER DESIGN WITH COEVOLUTIONARY ALGORITHMS APPLYING FOR SPEAKER IDENTIFICATION*

The problem of speaker identification is considered in this article. Classification problem «Japanese vowels» from UCI repository is used as source data. This problem was solved with a fuzzy classifier as a classification method that is able to extract cause-and-effect relations from source data. A new method of fuzzy classifier rule base design with coevolutionary algorithms was applied. It is multistep fuzzy classifier design based on multiple repetition of previous fuzzy classifier design with self-tuning coevolutionary algorithms. Computational investigation of fuzzy classifier design with coevolutionary algorithms for different numbers of speakers and for different number of the used fuzzy rules was performed. The proposed method allows getting acceptable classification efficiency for a test sample: from 0.985 for two speakers to 0.786 for nine speakers.

Keywords: fuzzy classifier, coevolutionary algorithm, classification, speaker identification.

Speaker identification is an important related with spoken dialogue system problem. This problem can be formulated as a classification problem. So it is necessary to use special classification methods. One of them is a fuzzy classifier [1]. A fuzzy classifier is a classification algorithm based on fuzzy rules extraction from numerical data. Superiority of this method upon other classification algorithms such as neural networks is provided by fuzzy rules which are linguistic expressions and they are available for humans understanding as cause-and-effect relations. Thus a fuzzy classifier is one of the data mining methods for knowledge discovery.

Fuzzy classifier design can be considered as optimization problem. In this case we need to find the best fuzzy classifier. Fuzzy classifier design includes two problems. The first one is a rule base generating and the second one is membership functions tuning. It should be noted that the first problem is more sophisticated due to huge dimension and discrete variables. So in this paper we present only fuzzy rule base generating problem.

As fuzzy rule base generating is a complicated computational problem, the popular method of its solving is genetic-based machine learning [2; 3]. There are two basic ways for genetic algorithm applying to get fuzzy rule base: Michigan-style and Pittsburgh-style. In Michigan approach [4] chromosomes are individual rules; and a rule set is represented by the entire population. In Pittsburgh method [5] chromosomes are rule sets at whole. The problem in the Michigan approach is the conflict between individual rule fitness and performance of fuzzy rule set. Pittsburgh-style systems require a lot of computational efforts. So a combination of Michigan and Pittsburgh methods is a promising approach. In [6] the hybridization of both approaches by using Michigan method as a mutation operator in Pittsburgh-style algorithm is presented. Another problem with genetic algorithm applying is the algorithm parameters setting. This problem is especially essential for optimization problems with high computational complexity such as fuzzy rule base generating.

There are some methods for GA parameter setting. We suggest special procedure named cooperative-competitive coevolutionary algorithm for this problem solving [7]. A new method of Michigan and Pittsburgh approaches combination for fuzzy classifier rule base design with coevolutionary algorithms was developed in [6].

The next idea is the multistep fuzzy classifier design. After multiple fuzzy classifiers forming we had a set of fuzzy classifiers for each classification problem. The natural step is a collective forming fuzzy rule base using a set of classifiers generated with our approach. It is possible to increase classification efficiency and decrease diversity of classification efficiency using this method. For collective forming of fuzzy classifier cooperate-competitive coevolutionary algorithm can be applied again. Thus we can repeat this procedure more times. So we have formulated a multistep procedure of fuzzy classifier design. We have implemented this method and got results for all classification problems mentioned above. In this paper convergence investigation of multistep fuzzy classifier design is presented. We have observed dynamic features of such parameters as classification performance, standard deviation of classification performance, and number of unique fuzzy rules in a set of classifiers for multistep fuzzy classifier design.

Fuzzy classifier design with coevolutionary algorithms was applied for speaker identification. Classification problem «Japanese vowels» from UCI repository [8] is used as source data. Problem description is distinguishing nine male speakers by their utterances of two Japanese vowels /ae/. We varied number of speakers and number of used fuzzy rules and performed corresponding numerical experiments.

The details of the fuzzy classifier design with coevolutionary algorithms are described in Section 2. Investigations of multistep fuzzy classifier design are presented in Section 3. Results of numerical experiments for speaker identification problem are presented in Section 4. Conclusions are listed in Section 5.

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Fuzzy Classifier Design with Coevolutionary Algorithms. A new method of Michigan and Pittsburgh approaches combination for fuzzy classifier rule base design with coevolutionary algorithms was developed in [6]. Fuzzy classifier rule base design consists of two main stages excepting initial population of fuzzy rules forming using a-priori information from a learning sample. At the first stage Michigan method is used for fuzzy rules search with high grade of certainty. At the second stage Pittsburgh method is applied for searching subset of rules with good performance and given number of rules. Constraint for number of rules is used at the second stage of fuzzy classifier design. This method requires less computational efforts than multiobjective optimization for fuzzy rules extraction. Besides this method has some advantages that were showed by numerical experiments.

Another problem with genetic algorithm applying is the algorithm parameters setting. This problem is especially essential for optimization problems with high computational complexity such as fuzzy rule base generating. There are some methods for GA parameter setting. We suggest special procedure named cooperative-competitive coevolutionary algorithm for this problem solving [7]. This method combines ideas of cooperation and competition among subpopulations in the coevolutionary algorithm. We have tested this algorithm for some computationally simple problems for proving its efficiency and then we used it for fuzzy rule base forming. Coevolutionary algorithm for unconstrained optimization is applied at the first stage (Michigan approach) and coevolutionary algorithm for constrained optimization is used at the second stage (Pittsburgh approach).

Michigan-style stage. The chromosomes are fuzzy rules. Chromosome length is equal to the number of attributes; each gene is an index for the corresponding fuzzy number. Fitness function is certainty grade of the fuzzy rule calculated by a learning sample [4]. Genetic algorithm for unconstrained optimization is applied. After generation performing parents and child combined to common array. Different fuzzy rules with the best values of fitness function for each class are selected to the next generation. This new population forming method provides diversity of rules for each class and diversity of classes in population. For each generation classification performance is calculated for population at whole. Population with the best value of classification performance is used for the next stage of fuzzy classifier generating. Cooperative-competitive coevolutionary genetic algorithm for unconstrained optimization is applied.

Pittsburgh-style stage. Chromosomes are the fuzzy rule sets. Chromosome length is equal to the population size for Michigan-style stage. Chromosome genes are binary. Value «1» means using the corresponding rule in the set, value «0» means not using the corresponding rule. Fitness function is classification performance. Constraint for number of rules is used. This value is specified by researcher. The constraint is used because it is better to have small number of rules in the final rule base. Cooperative-competitive coevolutionary genetic algorithm for con-

strained optimization is applied. New generation forming method is standard.

Thus this method of Michigan and Pittsburgh approaches combination for fuzzy classifier rule base generating provides simultaneous advantages of both methods. At Michigan-style stage we get different rules with high values of grade certainty for different classes and at Pittsburgh-style stage we get the rule set with the maximum value of classification performance and necessary number of rules.

As the used rules are fixed and they cannot be changed Pittsburgh-style stage doesn't require a lot of computational resources. Special method of initial population generating provides using of a priori information from a learning sample.

Multistep Fuzzy Classifier Design. The developed method of fuzzy classifier rule base design has been applied for a number of classification machine learning problems from UCI repository [8]:

- Credit (Australia-1) (14 attributes, 2 classes);
- Liver Disorder (6 attributes, 2 classes);
- Iris (4 attributes, 3 classes);
- Yeast (8 attributes, 10 classes);
- Glass Identification (9 attributes, 7 classes);
- Landsat Images (4 attributes, 6 classes).

Having formed multiple fuzzy classifiers design we had a set of fuzzy classifiers for each problem. Although classification efficiency diversity is acceptable, the problem is there exist a small number of repetitive fuzzy rules in a set of fuzzy classifiers (see Table 1). There is feasible number of rules in brackets.

A natural step for fuzzy rule repeatability increasing is a collective design fuzzy rule base using a set of classifiers generated with our approach. In this case Pittsburgh-style stage of fuzzy classifier forming is performed again. A set of fuzzy rule base is analog of fuzzy rule base generated after Michigan-style stage. We also use constraint for feasible number of rules. For collective forming of fuzzy classifier cooperate-competitive coevolutionary algorithm can be applied again. Thus we can repeat this procedure some more times. So we got multistep procedure of fuzzy classifier design. We can use threshold value of classification performance increasing, standard deviation decreasing, or number of unique rules decreasing as a stopping criterion for our multistep procedure. The action sequence for multistep fuzzy classifier forming is the following:

- 1) Select start fuzzy rules with a special procedure (repeat n times);
- 2) Perform one-step fuzzy classifier forming (repeat n times);
- 3) Form from n fuzzy classifiers initial population for the next iteration;
- 4) If stopping criterion is true end else go to position 2).

Using multistep procedure fuzzy rule repeatability must increase and classification efficiency diversity must decrease. Besides it is possible to increase classification performance. We have implemented this method and approved our forecasts.

Some statistical investigations were performed for all problems. For each problem maximum, average, and minimum classification performance values (correctly classified part of test sample), standard deviation of classification performance, and number of unique rules at 10 bases are presented in Tables 1–7.

There are a feasible number of rules in brackets. Stopping criterion is average classification performance increasing less than 0,005 or standard deviation equals to 0. For some cases we have performed one or two steps additionally for equal step number providing for the same problem.

We can see that a number of unique rules and standard deviation of classification performance decreases for each step of fuzzy classifier design. Also classification per-

formance increases for all problems using multistep fuzzy classifier design.

For the first two problems comparison with alternative classification methods has been performed. These algorithms are Bayesian approach, multilayer perceptron, boosting [9], bagging [10], random subspace method (RSM) [11], and cooperative coevolution ensemble learning (CCEL) [12; 13]. It should be noted that base algorithms for bagging, boosting, RSM, and CCEL are not fuzzy classifiers; they are conventional classification methods. Performance value is a part of test sample that is classified correctly with an algorithm. The classification performance comparison with alternative algorithms for Credit (Australia-1) and Liver Disorder problems is presented in Table 8.

Table 1

Results of Numerical Experiments for One-step Fuzzy Classifier Forming

Parameter	Problem					
	1	2	3	4	5	6
Maximum performance	0,827 (10)	0,666 (10)	0,908 (3)	0,573 (20)	0,737 (20)	0,838 (10)
	0,861 (20)	0,682 (15)	0,951 (4)	0,586 (30)	0,781 (30)	0,847 (15)
	0,873 (30)	0,692 (30)	0,971 (5)	0,593 (60)		0,849 (20)
Average performance	0,870 (10)	0,687 (10)	0,947 (3)	0,598 (20)	0,757 (20)	0,849 (10)
	0,890 (20)	0,710 (15)	0,973 (4)	0,606 (30)	0,827 (30)	0,857 (15)
	0,891 (30)	0,725 (20)	0,987 (5)	0,626 (60)		0,857 (20)
Minimum performance	0,758 (10)	0,632 (10)	0,767 (3)	0,540 (20)	0,706 (20)	0,821 (10)
	0,841 (20)	0,655 (15)	0,900 (4)	0,555 (30)	0,757 (30)	0,836 (15)
	0,854 (30)	0,655 (20)	0,940 (5)	0,542 (60)		0,835 (20)
Standard deviation	0,02482(10)	0,01500(10)	0,05643(3)	0,01801(20)	0,01388(20)	0,00783(10)
	0,01231(20)	0,01669(15)	0,02623(4)	0,01710(30)	0,01831(30)	0,00416(15)
	0,01035(30)	0,01731(20)	0,01303(5)	0,02207(60)		0,00546(20)
Number of unique rules at 10 bases	100 (10)	85 (10)	12 (3)	200 (20)	196 (20)	68 (10)
	200 (20)	136 (15)	20 (4)	300 (30)	290 (30)	91 (15)
	300 (30)	183 (20)	27 (5)	560 (60)		156 (25)
			30 (6)			

Table 2

Results of Multistep Fuzzy Classifier Design for Credit (Australia-1)

Parameter	1 st iteration	2 nd iteration	3 rd iteration
Maximum performance	0,870 (10)	0,891 (10)	0,891 (10)
	0,890 (20)	0,919 (20)	0,919 (20)
	0,891 (30)	0,926 (30)	0,928 (30)
Average performance	0,827 (10)	0,888 (10)	0,891 (10)
	0,861 (20)	0,918 (20)	0,919 (20)
	0,873 (30)	0,924 (30)	0,926 (30)
Minimum performance	0,758 (10)	0,886 (10)	0,891 (10)
	0,841 (20)	0,910 (20)	0,919 (20)
	0,854 (30)	0,922 (30)	0,925 (30)
Standard deviation	0,02482 (10)	0,00174 (10)	0,00000 (10)
	0,01231 (20)	0,00269 (20)	0,00000 (20)
	0,01035 (30)	0,00171 (30)	0,00127 (30)
Number of unique rules at 10 bases	100 (10)	25 (10)	17 (10)
	200 (20)	51 (20)	40 (20)
	300 (30)	99 (30)	76 (30)

Table 3

Results of Multistep Fuzzy Classifier Design for Liver Disorder

Parameter	1 st iteration	2 nd iteration	3 rd iteration	4 th iteration
Maximum performance	0,687 (10)	0,713 (10)	0,716 (10)	0,716 (10)
	0,710 (15)	0,739 (15)	0,739 (15)	0,742 (15)
	0,725 (20)	0,757 (20)	0,757 (20)	0,757 (20)
Average performance	0,666 (10)	0,705 (10)	0,714 (10)	0,716 (10)
	0,682 (15)	0,731 (15)	0,735 (15)	0,738 (15)
	0,692 (20)	0,748 (20)	0,754 (20)	0,755 (20)
Minimum performance	0,632 (10)	0,699 (10)	0,710 (10)	0,716 (10)
	0,655 (15)	0,719 (15)	0,728 (15)	0,733 (15)
	0,655 (20)	0,739 (20)	0,751 (20)	0,751 (20)
Standard deviation	0,01731 (10)	0,00449 (10)	0,00229 (10)	0,00000 (10)
	0,01669 (15)	0,00608 (15)	0,00411 (20)	0,00280 (15)
	0,01500 (20)	0,00554 (20)	0,00229 (20)	0,00246 (20)
Number of unique rules at 10 bases	85 (10)	55 (10)	20 (10)	13 (10)
	136 (15)	68 (20)	46 (15)	31 (15)
	183 (20)	80 (20)	53 (20)	45 (20)

Table 4

Results of Multistep Fuzzy Classifier Design for Yeast

Parameter	1 st iteration	2 nd iteration	3 rd iteration	4 th iteration
Maximum performance	0,598 (20)	0,609 (20)	0,617 (20)	0,621 (20)
	0,606 (30)	0,641 (30)	0,651 (30)	0,651 (30)
	0,626 (60)	0,674 (60)	0,676 (60)	0,678 (60)
Average performance	0,573 (20)	0,605 (20)	0,614 (20)	0,618 (20)
	0,586 (30)	0,633 (30)	0,647 (30)	0,649 (30)
	0,593 (60)	0,668 (60)	0,672 (60)	0,675 (60)
Minimum performance	0,540 (20)	0,602 (20)	0,610 (20)	0,617 (20)
	0,555 (30)	0,625 (30)	0,640 (30)	0,647 (30)
	0,542 (60)	0,662 (60)	0,667 (60)	0,672 (60)
Standard deviation	0,01801 (20)	0,00241 (20)	0,00246 (20)	0,00198 (20)
	0,01710 (30)	0,00431 (30)	0,00339 (30)	0,00123 (30)
	0,02207 (60)	0,00429 (60)	0,00241 (60)	0,00215 (60)
Number of unique rules at 10 bases	200 (10)	97 (20)	55 (20)	46 (20)
	300 (30)	142 (30)	93 (30)	75 (30)
	560 (60)	263 (60)	205 (60)	165 (60)

Table 5

Results of Multistep Fuzzy Classifier Design for Landsat Images

Parameter	1 st iteration	2 nd iteration	3 rd iteration	4 th iteration
Maximum performance	0,849 (10)	0,851 (10)	0,853 (10)	0,853 (10)
	0,857 (15)	0,861 (15)	0,862 (15)	0,862 (15)
	0,857 (20)	0,864 (20)	0,866 (25)	0,866 (25)
Average performance	0,838 (10)	0,850 (10)	0,852 (10)	0,852 (10)
	0,847 (15)	0,859 (15)	0,860 (15)	0,862 (15)
	0,849 (20)	0,863 (20)	0,865 (25)	0,866 (25)
Minimum performance	0,821 (10)	0,848 (10)	0,851 (10)	0,852 (10)
	0,836 (15)	0,856 (15)	0,857 (15)	0,861 (15)
	0,835 (20)	0,862 (20)	0,863 (25)	0,865 (25)
Standard deviation	0,00783 (10)	0,00107 (10)	0,00036 (10)	0,00014 (10)
	0,00416 (15)	0,00144 (15)	0,00148 (15)	0,00037 (15)
	0,00546 (20)	0,00090 (20)	0,00097 (25)	0,00034 (25)
Number of unique rules at 10 bases	68 (10)	38 (10)	23 (10)	15 (10)
	91 (15)	63 (15)	46 (15)	33 (15)
	156 (25)	100 (25)	72 (25)	56 (25)

Table 6

Results of Multistep Fuzzy Classifier Design for Iris

Parameter	1 st iteration	2 nd iteration
Maximum performance	0,947 (3)	0,980 (3)
	0,973 (4)	0,980 (4)
	0,987 (5)	0,987 (5)
	0,987 (6)	0,993 (6)
Average performance	0,908 (3)	0,980 (3)
	0,951 (4)	0,980 (4)
	0,971 (5)	0,987 (5)
	0,975 (6)	0,993 (6)
Minimum performance	0,767 (3)	0,980 (3)
	0,900 (4)	0,980 (4)
	0,940 (5)	0,987 (5)
	0,933 (6)	0,993 (6)
Standard deviation	0,05643 (3)	0,00000 (3)
	0,02623 (4)	0,00000 (4)
	0,01303 (5)	0,00000 (5)
	0,01073 (6)	0,00000 (6)
Number of unique rules at 10 bases	12 (3)	5 (3)
	20 (4)	15 (4)
	27 (5)	13 (5)
	30 (6)	18 (6)

Table 7

Results of Multistep Fuzzy Classifier Design for Glass Identification

Parameter	1 st iteration	2 nd iteration	3 rd iteration	4 th iteration	5 th iteration
Maximum performance	0,757 (20)	0,836 (20)	0,846 (20)	0,850 (20)	0,850 (20)
	0,827 (30)	0,874 (30)	0,888 (30)	0,888 (30)	0,888 (30)
Average performance	0,737 (20)	0,824 (20)	0,838 (20)	0,846 (20)	0,850 (20)
	0,781 (30)	0,861 (30)	0,880 (30)	0,886 (30)	0,886 (30)
Minimum performance	0,706 (20)	0,813 (20)	0,827 (20)	0,841 (20)	0,850 (20)
	0,757 (30)	0,827 (30)	0,874 (30)	0,883 (30)	0,883 (30)
Standard deviation	0,01388 (20)	0,00737 (20)	0,00630 (20)	0,00409 (20)	0,00000 (20)
	0,01831 (30)	0,01354 (30)	0,00471 (30)	0,00246 (30)	0,00246 (30)
Number of unique rules at 10 bases	196 (20)	121 (20)	81 (20)	55 (20)	40 (20)
	290 (30)	181 (30)	107 (30)	86 (30)	66 (30)

Table 8

The Classification Performance Comparing for Different Algorithms

Algorithm	Credit (Australia-1)	Liver Disorder
Multistep fuzzy classifier design	0,928	0,757
One-step fuzzy classifier design	0,891	0,725
Bayesian approach	0,847	0,629
Multilayer perception	0,833	0,693
Boosting	0,760	0,656
Bagging	0,847	0,630
Random subspace method	0,852	0,632
Cooperative coevolution ensemble learning	0,866	0,644

Speaker Identification Problem Solving. The problem «Japanese Vowels» [8] description is to distinguish nine male speakers by their utterances of two Japanese vowels /ae/. Nine male speakers uttered two Japanese vowels /ae/ successively. For each utterance, with the analysis parameters described below, 12-degree linear prediction analysis was applied to obtain a discrete-time series with 12 LPC cepstrum coefficients.

This means that one utterance by a speaker forms a time series whose length is in the range 7-29 and each point of a time series is of 12 features (12 coefficients). The number of the time series is 640 in total. We used one set of 270 time series for training and the other set of 370

time series for testing. For fuzzy classifier applying we use average means of each coefficients in time series.

In numerical experiments we increased number of speakers (number of classes) sequentially from 2 to 9 and we varied a number of used fuzzy rules. For each combination of parameters (speakers number and number of used fuzzy rules) we performed 20 algorithm runs for statistical investigation. Effectiveness parameter is correctly classified part of test sample.

Results of numerical experiments are presented in Table 9. You can see the average and maximum values of effectiveness parameter for each combination of parameters.

Results of Speaker Identification Problem Solving

Speaker number	60 rules	100 rules	200 rules	300 rules	400 rules	500 rules	600 rules
2 (average)	0,842	0,877	0,930	0,942	0,943	0,948	0,952
2 (maximum)	0,924	0,924	0,969	0,985	0,985	0,985	0,985
3 (average)	0,570	0,660	0,768	0,822	0,845	0,868	0,872
3 (maximum)	0,649	0,720	0,837	0,876	0,896	0,916	0,916
4 (average)	0,625	0,664	0,762	0,806	0,821	0,842	0,856
4 (maximum)	0,736	0,745	0,827	0,872	0,891	0,909	0,900
5 (average)	0,555	0,622	0,730	0,782	0,813	0,827	0,827
5 (maximum)	0,640	0,705	0,827	0,827	0,885	0,885	0,878
6 (average)	0,591	0,689	0,777	0,828	0,844	0,839	0,865
6 (maximum)	0,662	0,791	0,846	0,902	0,895	0,902	0,908
7 (average)	0,501	0,605	0,733	0,791	0,809	0,830	0,845
7 (maximum)	0,620	0,655	0,803	0,857	0,867	0,882	0,887
8 (average)	0,467	0,558	0,689	0,746	0,761	0,776	0,790
8 (maximum)	0,517	0,620	0,735	0,779	0,814	0,810	0,830
9 (average)	0,399	0,515	0,649	0,685	0,724	0,742	0,755
9 (maximum)	0,481	0,559	0,700	0,732	0,786	0,786	0,786

The first result of our work is multistep fuzzy classifier design convergence investigations. Having generated some fuzzy classifiers we are able to construct more effective classifier from previous classifiers using cooperative-competitive coevolutionary algorithm again. Using this method semantically similar fuzzy classifiers are generated. The approach of multistep fuzzy classifier forming has the following features:

- 1) This method improves classification performance without increasing number of rules.
- 2) This method reduces diversity of performance values for multiple algorithm runs, i.e. the method has higher statistical stability.
- 3) The method reduces a number of unique fuzzy rules for multiple algorithm runs.
- 4) Corresponding to features 1–3 trends slow down for increasing of step number. So we can conclude that multistep procedure of fuzzy classifier design has convergence property.
- 5) The method is more effective for more complicated classification problems (more attributes and classes).

Fuzzy classifier design methods comparison with alternative classification methods by performance value demonstrates that both fuzzy classifier forming methods have either the same efficiency as present-day classification algorithms or even they are more efficient.

Next result is speaker identification problem solving using multistep fuzzy classifier design. The proposed method allows getting acceptable classification efficiency for a test sample: from 0.985 for two speakers to 0.786 for nine speakers. Also we can see that for increasing the speaker number it is necessary to increase a number of the used fuzzy rules for getting appropriate results. But per-

manent increasing of the used fuzzy rules is not good idea because from the defined number of fuzzy rules classification effectiveness doesn't increase or even can decrease.

We can see that for some cases speaker number increasing allows increasing the effectiveness parameter. It depends on speaker features. If we add a speaker with voice audiometric features that will differ very much in comparison with that previous speakers, it allows effectiveness parameter increasing.

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ПРИМЕНЕНИЕ МЕТОДА ФОРМИРОВАНИЯ НЕЧЕТКОГО КЛАССИФИКАТОРА САМОНАСТРАИВАЮЩИМИСЯ КОЭВОЛЮЦИОННЫМИ АЛГОРИТМАМИ В ЗАДАЧЕ РАСПОЗНАВАНИЯ ГОВОРЯЩЕГО

Рассматривается задача распознавания говорящего. В качестве исходных данных взята задача «Японские гласные» из UCI репозитория. Эта задача была решена с использованием нечеткого классификатора как метода классификации, способного извлекать причинно-следственные закономерности из исходных данных. Был применён новый метод формирования нечеткого классификатора, самонастраивающимися коэволюционными алгоритмами, а именно многошаговый метод формирования нечеткого классификатора, основанный на многократном повторении ранее разработанного метода формирования нечеткого классификатора. Были проведены численные исследования метода формирования нечеткого классификатора для различного числа говорящих и различного числа используемых нечетких правил. Метод показал приемлемую эффективность на тестовой выборке: от 0,985 для двух говорящих до 0,786 для девяти.

Ключевые слова: нечеткий классификатор, коэволюционный алгоритм, классификация, распознавание говорящего.

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APPLICATION OF NEURO-FUZZY SYSTEMS IN BANK SCORING PROBLEMS*

As the generation of a neuro-fuzzy model from scratch by hand is complex and time consuming process, evolutionary computations are used for this. By virtue of genetic algorithms, the development of neuro-fuzzy systems is simplified and becomes automatic. The proposed scheme is applied to well-known Australian and German Credit Approval problems. Comparison of different algorithms is given.

Keywords: neuro-fuzzy modeling, evolutionary calculations, fuzzy systems, neural networks.

Neuro-fuzzy modeling is applied to soft computing paradigm. It combines the advantages of neural networks and fuzzy rule based systems.

While fuzzy systems implement effective approximate reasoning in uncertain environment, neural networks provide efficient learning algorithms from data. Meanwhile, neuro-fuzzy systems chiefly represent a knowledge base

with fuzzy rules and membership functions where neural network algorithms such are used for parameters learning.

Typically, the learning phase of neuro-fuzzy modeling consists of two stages. The first one is an unsupervised mode where any clustering algorithm could be applied for determination of initial size of rule base, i. e. number of rules.

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