PATTERN RECOGNITION BASED ON THE FUZZY NEURAL NETWORKS

LEHOTSKÝ, M. - OLEJ, V.

Department of Computer Science
Technical University, 031 19 Liptovský Mikuláš
Slovak Republic

Abstract: The paper presents applications of programming systems for the analysis of classical genetic algorithms and new modified genetic algorithms for learning in the neural networks and fuzzy neural networks. Process of learning by classical genetic algorithms and the analysis of pattern recognition by fuzzy neural networks based on the modified genetic algorithms is described.

1. Introduction

Neural networks (NN) and fuzzy neural networks (FNN) can be used for pattern recognition and speech analysis. The important part for using NN and FNN are the learning algorithms. Classical genetic algorithms (CGA) and modified genetic algorithms (MGA) represent an efficient technique based on dynamics of the evolution. In this paper the CGA and MGA for learning the NN and FNN are described.

2. Classical genetic algorithms

Classical genetic algorithms [1-9] can be expressed by the following steps:

1. Initialization : let $t = 0$ and randomly choose M elements from the set of all possible genotypes α for creating the population $\beta(0)$.
2. Selection : reproduce genotypes $A_i \in \beta(t)$ with respect to the fitness μ of the genotype A_i and create the intermediate population β (t); using CGA to produce the new population β (t+1).
3. Variation : crossing and mutation modify the intermediate population β (t).
4. Setting : $t = t + 1$, return to step 2.

The steps selection, crossing and mutation are also called genetic operators (GO).

The CGA changes and modifies the sets of alleles of mutual various genotypes. CGA alternates between selection and variation - the two fundamental processes of the evolution. The evolution is the process changing the generations of the organisms in such way that they are adapting to the environment. The CGA finds a suboptimal solution of this problem, but the experiments show that the convergence is too slow and the weights of the synapsis can be far away from the optimum depending on the initial values. Therefore we propose a modification of the CGA.

3. Pattern recognition by neural networks based on classical genetic algorithms

Let consider the NN on the figure 1. It is composed from the input layer $IN = \{IN_1, IN_2, \ldots, IN_{42}\}$, output layer $OUT = \{OUT_1, OUT_2, \ldots, OUT_{10}\}$ and the hidden layer $H = \{H_1, H_2, \ldots, H_{20}\}$. Neurons are connected as shown in figure 1. Each synapsis represents one gene. The alleles are the weights of the corresponding synapsis. Initialization randomly generates alleles for M organisms. The problem is to determine the weights of the NN on figure 1 to recognize the patterns on figure 2.

The weights of synapsis between the input neuron IN_i and hidden neuron H_j are v_{ij} and the weights of synapsis between the hidden neuron H_i and the output neuron OUT_j are w_{ij}. The input to the neuron IN_i is a_i, the output of the neuron H_i is b_i and the output of the neuron OUT_i is c_i. Then

$$b_i = \begin{cases} 1 & \text{if } \tilde{b}_i > \theta \\ 0 & \text{if } \tilde{b}_i \le \theta \end{cases} \quad \text{where} \quad \tilde{b}_i = \sum_{j=1}^{n} v_{ji} \cdot a_j \qquad (1)$$

and

$$c_i = \begin{cases} 1 & \text{if } \tilde{c}_i > \theta \\ 0 & \text{if } \tilde{c}_i \le \theta \end{cases} \quad \text{where} \quad \tilde{c}_i = \sum_{j=1}^{N} w_{ji} \cdot b_j \qquad (2)$$

and θ is the common threshold for all neurons in the NN.

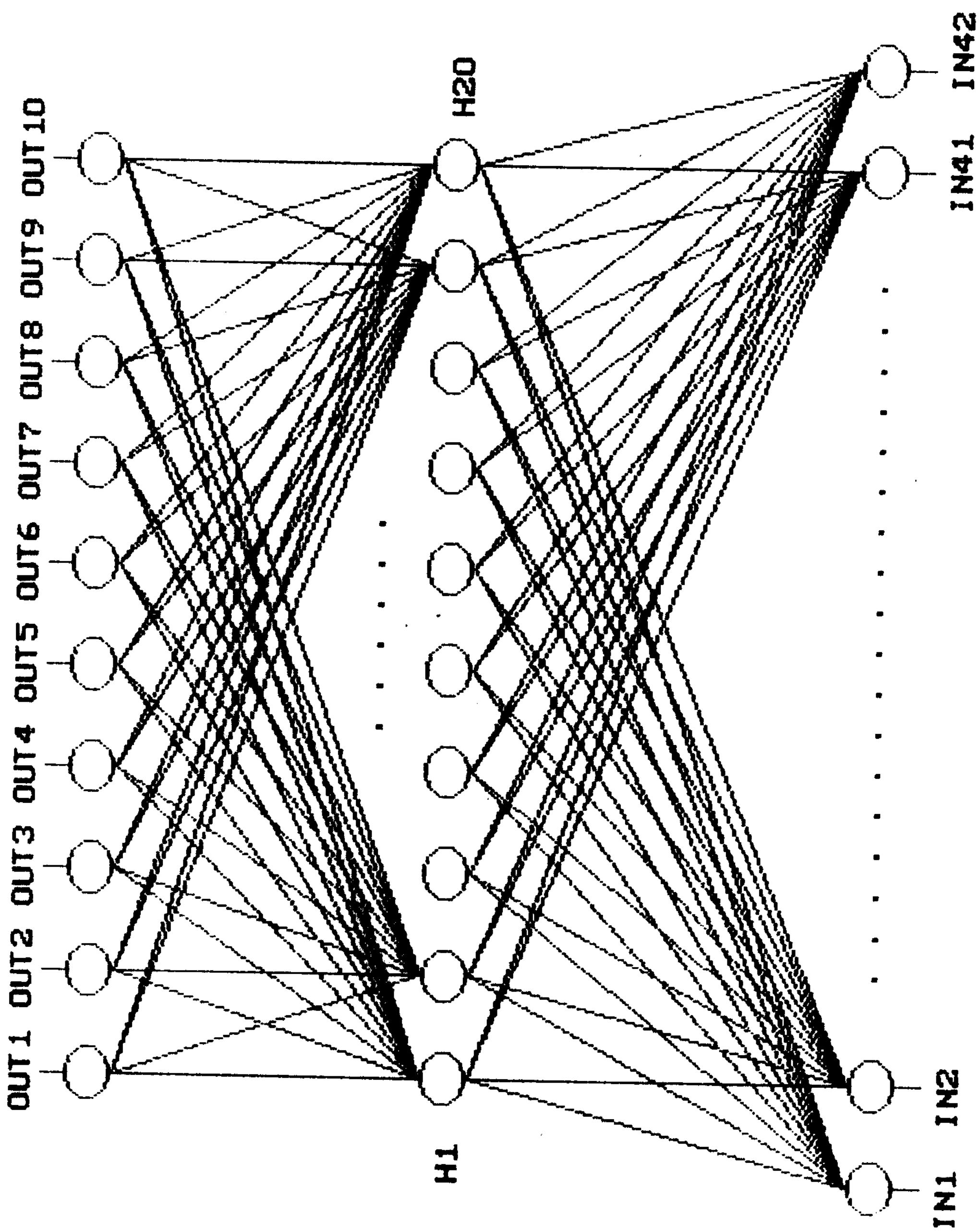

Fig.1. Neural network

.XXXX. X....X X...XX X.XX.X XX...X X....X .XXXX.	...X.. ..XX.. .X.X.. ...X.. ...X.. ...X.. .XXXXX	.XXXX. X....X .....X ...XX. .XX... X..... XXXXXX	.XXXX. X....X .....X .XXXX. .....X X....X .XXXX.	....X. ...XX. ..X.X. .X..X. XXXXXX ....X. ....X.
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Fig.2. Input patterns for neural network

The fitness μ is determined in our experiments as the number of mutually different responses of the NN between all possible couples of inputting patterns. The maximum is therefore

$$\left[\begin{matrix}10\\2\end{matrix}\right] = 45.$$

The input parameters of the NN and the CGA are the following:

- cardinality of the population $N = 60$;
- probability of the crossing $PC = 0.6$;
- probabilty of the mutation $PM = 0.001$;
- threshold $TH = 0.5$.

As the table 1 shows the CGA applied on this NN does not converge to the suboptimal solution as the experiments show. The table 1 contains maximum values (max.μ) reached in the population and the number of the genotypes having this value.

Table 1. The evolution by classical genetic algorithm for classsical neural network

GO / N	Selection		Crossing		Mutation	
	max.μ	number	max.μ	number	max.μ	number
10	13	30	6	30	6	30
20	28	30	18	30	16	30
30	22	30	13	30	13	30
40	25	30	14	30	13	30
50	26	30	15	30	16	30
60	23	30	21	30	19	30
70	6	30	6	30	6	30
80	36	30	35	30	29	30

4. Pattern recognition by fuzzy neural networks based on classical genetic algorithms

Neural network learned by CGA cannot solve the problem of pattern recognition as was shown in the previos part. Therefore we proposed FNN which has the same topology as NN on figure 1 but the outputs are computed as fuzzy and not as classical by the following way:

$$c_i = \begin{cases} 1 & \text{if } \tilde{c}_i > \theta \\ 0 & \text{if } \tilde{c}_i \leq \theta \end{cases} \quad \text{where} \quad \tilde{c}_i = \max_j \left(\min\left(w_{ji}, b_j\right)\right) \qquad (3)$$

The input parameters of the FNN and the CGA are the following:

- cardinality of the population $N = 60$;
- probability of the crossing $PC = 0.6$;
- probabilty of the mutation $PM = 0.001$;
- threshold $TH = 0.5$.

As the table 2 shows the performance of this FNN is better than of the NN on figure 1 but is still not satisfactory.

Table 2. The evolution by classical genetic algorithm for fuzzy neural network

GO / N	Selection		Crossing		Mutation	
	max.μ	number	max.μ	number	max.μ	number
10	12	39	1	40	1	40
20	15	41	8	41	8	41
30	10	41	8	41	5	41
40	17	42	17	42	13	42
50	15	42	14	42	14	42
60	26	42	21	42	18	42
70	10	41	2	42	2	42
80	14	42	15	42	15	42

5. Pattern recognition by fuzzy neural networks based on modified genetic algorithms

The MGA also starts with random initial values of alleles. The selection step is replaced by sorting and choosing the best organisms for the following evolution depending on their fitness. These organisms are then randomly crossed 4 times in one population. The mutation operator is the same as in the CGA.

The convergence of the CGA is too slow for practical purposes also for FNN. Therefore it seems to be necessary to modify the CGA. The selection in CGA is too random and the syntetical crossing is needed. The steps selection and crossing are substituted by one step selected crossing expressed by the following way:

1. Each genotype is crossed with n genotypes from the population of size N.
2. From n.N genotypes N individuals with best fitness are chosen for the next population.
3. The mutation for the population is applied as in the CGA.

4. Repeat the steps 1-3 until the desired results is obtained.

The input parameters of the FNN and the MGA are the following:

- cardinality of the population N = 20;
- probabilty of the mutation PM = 0.01;
- threshold TH = 0.5.

For our experiments we have chosen the values n=4. As the following table 3 shows the convergence is obtained after about 80 generations to the solution.

Table 3. The evolution by modified genetic algorithm for fuzzy neural network

GO / N	Crossing		Mutation	
	max.μ	number	max.μ	number
10	13	41	1	42
20	20	41	12	41
30	20	41	14	41
40	20	41	15	41
50	13	42	5	42
60	20	42	9	42
70	13	42	7	42
80	1	45	1	45

6. Conclusion

The analysis of the CGA and MGA and pattern recognition by NN and FNN in programming language TURBO PASCAL at microcomputer IBM PC was realized. The MGA presented in this contribution replacing selection and random crossing by choosing the best organisms and multiple crossing in one generation speeds up the convergence of the learning and reaches better solution. Therefore it is better than the CGA for pattern recognition and speech analysis by NN.

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