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A Neural Fuzzy Learning Algorithm Using Neuron Structure

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Abstract

In this paper, a method for the improvement of learning speed and convergence rate was proposed applied it to physiological neural structure with the advantages of artificial neural networks and fuzzy theory to physiological neuron structure. To compare the proposed method with conventional the single layer perceptron algorithm, we applied these algorithms to 3 bit parity problem and pattern recognition containing noise.

The simulation result indicated that our learning algorithm reduces the possibility of local minima more than the conventional single layer perceptron does. Furthermore we show that our learning algorithm guarantees the convergence.

Keywords:Neural Network, Agonistic Neuron, Antagonistic Neuron, Physiological Neuron, Fuzzy Logic

1 Introduction

We imitate human's brain in two ways: one is a symbolic processing of artificial intelligence which programs the knowledge in brain according to functions. The other is the artificial intelligence intended to implement the neural structure achieved from physiological analysis. Among them, a symbolic processing artificial intelligence is the approach of the level of functions - called fuzzy logic in other word. And the other one is considered as the approach of level of physiology.

We analysed an excited neuron in the physiological structure and classify inhibited neurons into a forward inhibitory neuron and a backward inhibitory neuron.

And fuzzy logic has a merit of induction, and is composed of fuzzy set theory and fuzzy logic operation. There are fuzzy AND, fuzzy OR, and fuzzy NEGATION in the conventional fuzzy logic operation[1,2,3].

Therefore, we define the proposition that the forward inhibitory neuron is fuzzy logical-AND organization and the backward inhibitory neuron is fuzzy logical-NEGATION organization.

We define a fuzzy OR structure by analyzing the excitatory neuron in the physiological neuron organization

The learning algorithm which combines the merits of fuzzy logic with the neural networks based on physiological organization is proposed in this paper. To compare the proposed learning algorithm with the conventional single layer fuzzy algorithm, we applied these algorithms to 3 bit parity problem and pattern recognition containing noise.

2. A Neural Fuzzy Learning Based On A Physiological Neuron Structure

2.1 Physiological Neuron structure

The organization structure of physiological is composed of excitatory neurons and inhibitory interneurons, which are each activated by agonistic neurons and inactivated by antagonistic neurons.

An agonistic neuron is the one that directs to forward and antagonistic neuron does to backward.

Inhibition can be classified into antagonistic inhibition, forward inhibition and backward inhibition. Antagonistic inhibition makes on inhibitory synapse through an interneuron which controls the antagonistic neuron. Forward inhibition is inhibited without previous excitation of an antagonistic neuron. Backward inhibition is inhibited backwards in case that on inhibited interneuron acts upon the cell which activated itself[8].

The physiological neuron is shown in Fig. 1.

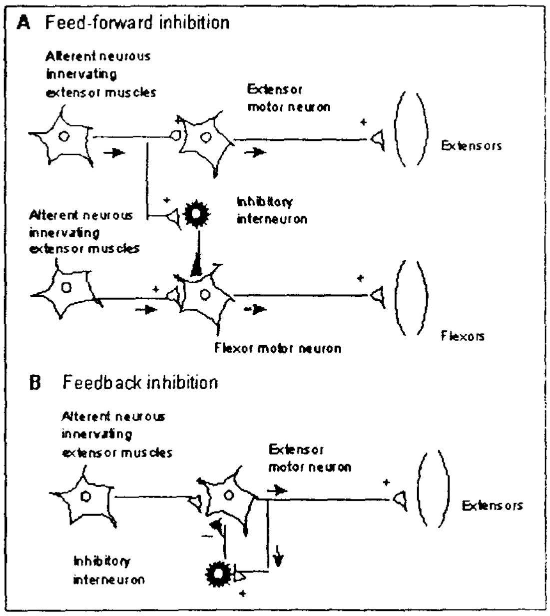

Fig. 1. Physiological neuron structure

2.2 A Physiological Learning Model

We defined a fuzzy OR structure by analyzing excitatory neuron in the physiological neuron organization.

We also defined a fuzzy AND structure by classifying the inhibitory neuron structure as the forward inhibitory neuron structure and the backward inhibitory neuron structure. The interneuron is defined as fuzzy NEGATION.

The proposed learning structure is shown in Fig. 2.

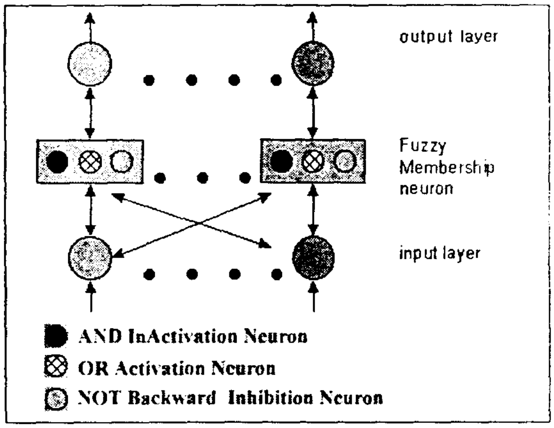

Fig. 2 Physiological Neuron Structure Learning Model

2.3 A Neural Fuzzy Learning Algorithm

The learning steps are classified as the forward step and the backward step in the proposed neural fuzzy algorithm. The actual output values are calculated through the fuzzy neuron membership function in the forward steps. The initial weight range is established by [8].

We used fuzzy logic operator Max & Min instead of sigmoid function, with these operators, Max operator can be used if target value is '1' or Min operator if '0'.

The weight was adjusted by dividing each neuron into excitatory neuron and inhibitory neuron in accordance with the fuzzy neuron membership function in the backward steps.

The proposed algorithm as follows:

Step 1 : Initialize Logic_value, Logic_weight, and Logic_mark

- Logic_weight : $W_{AND_{ij}} = 1,\ W_{OR_{ij}} = 1,\ W_{NT_{ij}} = 1$
- Logic_value : $V_{AND_{ij}} = \frac{1}{I},\ V_{OR_{ij}} = 1,\ V_{NT_{ij}} = -1$
- Logic_mark : $ON_{AND_{ij}} = 1,\ ON_{OR_{ij}} = 1,\ ON_{NT_{ij}} = 1$

where $W_{AND_{ij}}$: forward inhibitory operation

$W_{OR_{ij}}$: forward excitory operation

$W_{NT_{ij}}$: backward inhibitory operation

Step 2 : Read input pattern

Step 3 : Select target bit j for input pattern

Step 4 : Calculate and normalize Synapse_value from 0 to 1

- $Synapse_{ij} = Synapse_{ij} + (ON_{AND_{ij}} \times x_{pi} \times V_{AND_{ij}} \times W_{AND_{ij}})$

$+ (ON_{OR_{ij}} \times x_{pi} \times V_{ON_{ij}} \times W_{OR_{ij}})$

$\text{if}(Synapse_{ij} > 1.0)\ Synapse_{ij} = Synapse_{ij} + V_{NT_{ij}}$

Step 5 : Determine Soma_value for output value

- $\text{if}(target_{pj} = 1.0) Soma_j = \bigvee(Synapse_{ij});$

$\text{if}(target_{pj} = 0.0) Soma_j = \bigwedge(Synapse_{ij});$

$at\ \ 1 \le p \le P,\ \ P: Number\ of\ pattern$

$\bigvee$: Fuzzy MAX operation

$\bigwedge$: Fuzzy MIN operation

Step 6 : Update Logic_weight and Logic_mark value

$\text{if}((W_{AND_{ij}} \le 1.0)\text{and}(ON_{AND_{ij}}) = 1)$

$$W_{AND_{ij}} = W_{AND_{ij}} + \beta \times error_{ij} \times \frac{x_{\pi}}{insize}$$

$ON_{AND_{ij}} = 1$

$\text{if}((W_{AND_{ij}} \le 1.0)\text{and}(ON_{AND_{ij}}) = 1)$

$W_{AND_{ij}} = W_{AND_{ij}} - 1.0,\ ON_{AND_{ij}} = 0$

$\text{if}((W_{OR_{ij}} \le 1.0)\text{and}(ON_{OR_{ij}}) = 1)$

$$W_{OR_{ij}} = W_{OR_{ij}} + \beta \times error_{ij} \times \frac{x_{\pi}}{insize}$$

$ON_{OR_{ij}} = 1$

$\text{if}(W_{OR_{ij}} > 1.0)\ W_{OR_{ij}} = W_{OR_{ij}} - 1.0,\ ON_{OR_{ij}} = 1$

$at\ \ \beta$: Learning rate, $insize$: Gravity Center

Step 7 : Repeat step 3, until it process all target bits

Step 8 : Repeat step 2, until it process all input patterns

3. Experimental Results

It was implemented on the IBM/Pentium-II 200Mhz using Delphi. The test data was the 3 bit parity using the benchmark in neural network, recognition of pattern containing noise. We fixed error criteria value to 0.05.

3.1 Benchmark Test

We set initial learning rate at 0.5 in our algorithm. In the our proposed algorithm, we set up the range of initial weight by [8].

In the proposed algorithm, we set up the range of initial weight at [0,1]. Table 1 is the summary of learning results as compared Epoch and TSS (Total Sum of Square). In the our proposed algorithm, the network was converged on 3 bit parity. Therefore, we showed that the proposed algorithm guarantees the convergence.

Table 1. Learning step number

3 bit parity	Neural Fuzzy Learning Algorithm
Epoch Number	100
TSS	0.02745

3.2 Recognition of Pattern Containing Noise

Training patterns consisted of 16 * 16 array. Training pattern is the same as Fig.3. Table 2 shows the recognition rate containing noise pattern. And our algorithm reduced the possibility of local minima and guarantees the convergence.

Therefore, the neural fuzzy learning algorithm using physiological neuron structure has greater stability and classification compared to the conventional single layer perceptron.

Table 2. shows recognition rate for noise pattern.

Table 2. Recognition rate for noise pattern

Noised Test Pattern	Recognition Rate
10 %	100 %
20 %	100 %
30 %	100 %

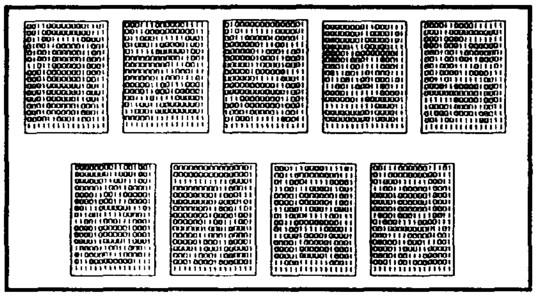

Fig. 3 Training pattern

4. Conclusions

The study and application of fusion fuzzy theory with logic and inference and neural network with learning ability have been actually achieving according to expansion of automatic system and information processing, etc.

We proposed the neural fuzzy learning algorithm on the theoretical basis of fuzzy logic and physiological neural network.

The proposed algorithm is the learning method which contains logic operations to imitate the structure of human brains.

This algorithm combines the learning ability which is the merit of artificial neural network with the manipulating human's obscure expression which is the merit of fuzzy logic. And the proposed algorithm shows the possibility of the application to the real world besides benchmark test in neural network by single layer structure.

In the future study direction, the author will develop the novel fuzzy neuron learning and recognition algorithm and apply to the handwritten digit recognition.

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