A Biological Fuzzy Multilayer Perceptron Algorithm

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Abstract—A biologically inspired fuzzy multilayer perceptron is proposed in this paper. The proposed algorithm is established under consideration of biological neuronal structure as well as fuzzy logic operation. We applied this suggested learning algorithm to benchmark problem in neural network such as exclusive OR and 3-bit parity, and to digit image recognition problems. For the comparison between the existing and proposed neural networks, the convergence speed is measured. The result of our simulation indicates that the convergence speed of the proposed learning algorithm is much faster than that of conventional backpropagation algorithm. Furthermore, in the image recognition task, the recognition rate of our learning algorithm is higher than of conventional backpropagation algorithm

Index Terms—Biological Neuron Structure, Antagonistic Interaction, Directionality of Synaptic Transmission, Inhibitory Neuron, Excitatory Neuron, Activated Neuron.

I. INTRODUCTION

The study of brain provides insights at many different levels of analysis - from cognitive behaviors such as problem solving, language production, etc. to molecular structure of a neuron[1]. Our approach is concerned to human neural mechanism in two aspects based on levels of analysis. One is the symbolic processing that programs the knowledge in the brain and can be considered the analysis of functional level[2]. The other is to implement the knowledge at the level of artificial neural structure [3,4,5]. These two methods are melting into a hybrid fuzzy neural network.

The proposed algorithm is modified conventional backpropagation by providing fuzzy logic operations under consideration of physiological study. As well known, the synaptic potential is transmitted if it exceeds the threshold for action potential. The transmission of synaptic potential is modulated in the manner of inhibitory and excitatory actions. The directionality of synapse connectivity's can be feed-forward or feed-backward[6]. These inhibition and excitation mechanism of synapse found in physiological study are implemented with the cooperation of a neural network and a fuzzy logic.

The effectiveness of the hybrid algorithm is tested on benchmark problem such as exclusive OR and 3-bit parity, and to image pattern recognition problems.

II. A BIOLOGICAL FUZZY MULTILAYER LEARNING MODEL

A. Biological Neuron Structure

The transmission of synaptic potential can be classified into inhibition and excitation according to whether it causes post-synaptic neuron excited or inhibited. These inhibitory and excitatory interactions between neurons are antagonistic in some neural structure[7,8]. As shown in Fig (1.A), the sensory neurons in the knee-jerk reflex have both excitatory and inhibitory connections. Stimulating the sensory neurons results in exciting a motor neuron in one pathway and inhibiting a motor neurons modulated by inhibitory interneurons in the other pathway. The effective processing in the active pathway can be achieved by the means of forward inhibition. The feedback inhibition is a self-modulating mechanism. That is, the level of firing of motor neuron shown in Fig. (1.B) is controlled by feedback inhibition of the interneuron[6,9,10].

B. The Neuron Structure by Fuzzy Logic

The fuzzy neuron structure is constructed by the logical connectivity's and operations such as the fuzzy logic AND, OR and NEGATION operations. Each operation is used to capture the functional properties of synaptic transmission described above.

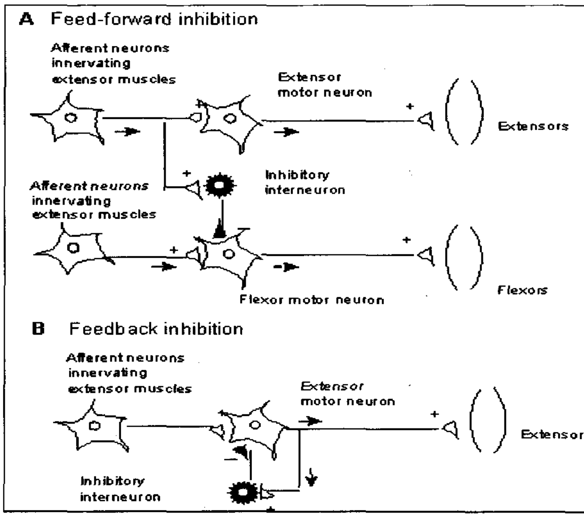

Fig. 1 Inhibition interneuron structure

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The fuzzy logic OR operation is corresponded to the forwardly activated neuronal structure in our algorithm and fuzzy logic AND operation is corresponded to forwardly inhibitory interneuron structure. In addition to the forward synaptic connection the fuzzy logic NEGATION operation is used as a feedback inhibition interneuron structure. For more intuitive understanding, consider a feed-forward excitatory neuronal structure. The net input for a neuron in output layer is calculated by OR operation that summed up weighted inputs. And then the activation of the neuron is determined by comparison with threshold in soma of the neuron. Therefore, the two methods are interconnected in some sense to mimic synaptic mechanism.

III. BIOLOGICAL FUZZY MULTILAYER PERCEPTRON ALGORITHM

A. Linear Activation Function

In BP, the equation that computes delta value is represented as follows:

$$\delta = error * f(net) * (1 - f(net)) \quad (1)$$

If the value of $f(net)$ is between 0.0 and 0.25, $f(net)*(1-f(net))$ is very approximated to $f(net)$. If the value of $f(net)$ is between 0.25 and 0.75, $f(net)*(1-f(net))$ is approximately 0.25. And if the value of $f(net)$ is between 0.75 and 1.0, $f(net)*(1-f(net))$ is approximated to $1-f(net)$. Therefore, the expression of delta evaluation is modified as follows:

$$\delta = error * f(net), \ where \ \ 0.0 \le f(net) < 0.25 \quad (2a)$$

$$\delta = error * 0.25, \ where \ \ 0.25 \le f(net) \le 0.75 \quad (2b)$$

$$\delta = error * (1-(net)), \ where \ \ 0.75 < f(net) \le 1.0 \quad (2c)$$

According to the above expression, activation function need not be differential and continuous. The suggested linear activation function is represented as follows:

$$f(net) = 1.0, \ where \quad 5.0 < net \quad (3a)$$

$$f(net) = 0.1 * x + 0.5, \ where \ \ -5.0 \le net \le 5.0 \quad (3b)$$

$$f(net) = 0.0, \ where \quad net < -5.0 \quad (3c)$$

The formulation of the linear activation function is as follows:

$$f(net) = \left(\frac{1}{(range*2)}\right) * net + 0.5 \quad (4)$$

Where the range means monotonically increasing interval except for interval between 0.0 and 1.0 of the value of the f(net).

Therefore, the output of a neuron is given by

$$Y = f\left(\frac{1}{(range*2)}\right) * (\sum_{i=1}^{m} w_i * x_i - \theta) + 0.5 \quad (5a)$$

where w_i is a weight for an input x_i, θ is a constant "threshold" and Y is a result of the linear activation function given by

$$Y = f\left(\frac{1}{(range*2)}\right) * net + 0.5 \quad (5b)$$

B. Fuzzy Logic Operation

We provide the conditions and fuzzy logic operation for linear activation functions with continuous inputs for later use. The results are the extension of well-known facts for boolean function. We assume $x \in [0,1]$ and associated two parameters, X^{Min} and X^{Max}, to each x. if $f(x) < X^{Min}$ then, we regard f(x) as "inhibitory interneuron" and if $f(x) > X^{\max}$, as "activated neuron". And if $X^{Min} \le f(x) \le X^{Max}$ then, we regard x as "exciting neuron".

Therefore, antagonistic step is composed of exciting neuron, activated neuron and forward inhibitory interneuron.

1) Fuzzy OR operation using feed-forward activated neuron

If the net is over 5.0 in the proposed linear activation function, the neuron is activated to the feed-forward. Therefore, feed-forward activated neuron is calculated by the OR membership function of fuzzy logic. The proposed equation is as follows :

$$f(net) = Max[Max(x), \varepsilon_1] \quad (6a)$$

where ε_1 is the interneuron with maximum criteria. The proposed biological fuzzy backpropagation algorithm is constructed according to the fuzzy-logic rule-based system.

2) Fuzzy AND operation using feed-forward inhibitory neuron

If the net is less than -5.0, the feed-forward neuron is inhibited. Therefore, feed-forward inhibitory interneuron is calculated by the AND membership function of fuzzy logic. The equation is as follows :

$$f(net) = Min[Min(x), \varepsilon_2] \quad (6b)$$

where ε_2 is the interneuron with minimum criteria.

3) Exciting neuron

If the net is between -5.0 and 5.0. The neuron is in an exciting state. Therefore, the proposed linear activation function is as follows.

$$f(net) = 0.1 * net + 0.5 \tag{6c}$$

4) Fuzzy NEGATION operation using feedback interneuron

The feedback inhibition is defined $\bar{x}$ where $\bar{x}$ = 1 - x. Thus, we can express the NEGATION $\bar{x}$ by the following transformation:

$$f(x) \to 1 - f(x) \tag{7a}$$

The self-modulation step is computing feedback interneurons, delta's and weights. In this step, feedback interneuron process on the neurons activating themselves only when $f(net)$ is between 0.75 and 1.0. So the equation 2(c) in section 2.1 can be represented as follows:

$$\delta = error * feedback\_inhibition\_interneuron \tag{7b}$$
$$where \ 0.75 < f(net) \le 1.0$$

C. The problem of setting the initial weight value and the changing amount of weight value

One problem in BP is that the convergence to optimal minima is sensitively dependent on initial weight values. Thus, a good choice for the initial weight values of the multilayered neural network is very helpful to converge to desired minima. However, the wrong selection of the weight values can cause a problem that is known as 'premature saturation'. That is, the networks fall in the situation where instantaneous sum of squared error remains almost unchanged for some period during leaning[10,11].

It is because the change of the weight value to the special learning pattern is consistent with that of the other patterns, and then it causes little change in the weight value. It's possible to speed up the learning time by controlling the changing amount of connection weight value according to the target value. Therefore, the weight W is changed according to the following rules:

$$\Delta W(t+1) = \eta * \frac{(\partial e)}{\partial W} + \alpha * \Delta W(t) \tag{8}$$

where t indexes the presentation number, η and α is a learning constant, a momentum constant, and e for error, respectively. And $\frac{(\partial e)}{\partial W}$ can be calculated as follows:

1. $if \quad Target \ge 0.5 \quad and \quad W \ge 0 \; then$

$$\frac{\partial e}{\partial W} = \frac{\partial\left\{\frac{(T - Y^{Min})}{2}\right\}}{\partial W} = \frac{\partial\left\{\frac{(T - Y^{Min})}{2}\right\}}{\partial Y^{Min}} * \left(\frac{\partial Y^{Min}}{\partial Net^{Min}}\right) * \left(\frac{\partial Net^{Min}}{\partial W}\right)$$
$$= -(T - Y^{Min}) * Y^{Min} * (1 - Y^{Min}) * X^{Min}$$
$$= -\partial^{Min} * X^{Min} \tag{9a}$$

where Y^{Min} is the minimum output of the current layer, X^{Min} is the minimum output of the precedent layer.

2. $if \quad Target \ge 0.5 \quad and \quad W < 0, \; then$

$$\frac{\partial e}{\partial W} = -\partial^{Min} * X^{Max} \tag{9b}$$

3. $if \quad Target < 0.5 \quad and \quad W \ge 0, \; then$

$$\frac{\partial e}{\partial W} = \frac{\partial\left\{\frac{(T - Y^{Max})}{2}\right\}}{\partial W} = \frac{\partial\left\{\frac{(T - Y^{Max})}{2}\right\}}{\partial Y^{Max}} * \left(\frac{\partial Y^{Max}}{\partial Net^{Max}}\right) * \left(\frac{\partial Net^{Max}}{\partial W}\right)$$
$$= -(T - Y^{Max}) * Y^{Min} * (1 - Y^{Max}) * X^{Max}$$
$$= -\partial^{Max} * X^{Max} \tag{9c}$$

4. $if \quad Target < 0.5 \quad and \quad W < 0, \; then$

$$\frac{\partial e}{\partial W} = -\partial^{Max} * X^{Min} \tag{9d}$$

In the above, ∂^{Max} and ∂^{Min} are determined as follows:

i) ∂^{Max}

1) $0.0 < Y^{Max} < 0.25, then$

$$\partial^{Max} = error * Y^{Max} \tag{10a}$$

2) $0.25 \le Y^{Max} \le 0.70, then$

$$\partial^{Max} = error * 0.25 \tag{10b}$$

3) $0.70 < Y^{Max} < 1.0, then$

$$\partial^{Max} = error * (1 - Y^{Max}) \tag{10c}$$

ii) ∂^{Min}

1) $0.0 < Y^{Min} < 0.25, then$

$$\partial^{Min} = error * Y^{Min} \tag{10d}$$

2) $0.25 \le Y^{Min} \le 0.70, then$

$$\partial^{Min} = error * 0.25 \tag{10e}$$

3) $0.70 < Y^{Min} < 1.0, then$

$$\partial^{Min} = error * (1 - Y^{Min}) \tag{10f}$$

IV. SIMULATION

The proposed learning algorithm had been implemented in the IBM/586 using Visual C language. The algorithm was tested on benchmark problem in neural network such as exclusive OR and 3-bit parity, and on digit image recognition problems.

A. Exclusive OR and 3-bit parity problem

In conventional backpropagation algorithm, when the weights were initialized, the range of weight was between [-0.5,0.5] or [-1,1]. In this range, both conventional backpropagation algorithms are all converged. However, in the range of weight [-4.0,4.0], low convergence rate is shown in conventional backpropagation algorithm. That means our algorithm is more robust for setting initial weight values and less affected by the range of initial weight values. The convergence rate is shown in Table 1. Here, the learning rate was set to 0.5 and momentum, 0.9. Table 2 provides a summary of learning results as comparing to the BP algorithm in epoch and total sum of square (TSS). The results are shown that the proposed algorithm is much better in the tasks.

Table 1 The comparison of convergence rate according to initial weight value

Conventional BP		
Initial weight range	Application problem	
	XOR	3 bit Parity
[-0.5, 0.5]	100%	100%
[-1.0, 1.0]	100%	100%
[-4.0, 4.0]	68%	63%
Biological Fuzzy Multilayer Perceptron		
Initial weight range	Application problem	
	XOR	3 bit Parity
[-0.5, 0.5]	100%	100%
[-1.0, 1.0]	100%	100%
[-4.0, 4.0]	94%	90%

Table 2 The comparison of epoch number, TSS

CONVENTIONAL BP		
Experiment	Epoch No.	TSS
XOR	308	0.038505
3 bit Parity	966	0.039962
BIOLOGICAL FUZZY MULTILAYER PERCEPTRON		
Experiment	Epoch No.	TSS
XOR	43	0.012413
3 bit Parity	129	0.020093

B. Digit image Recognition

The digit image consisted of 7 * 7 array. When learning rate and momentum were set up to 0.5 and 0.75 respectively, the proposed algorithm produced the best convergence rate. As shown in table 3, the performance of our algorithm was better than that of conventional backpropagation in convergence speed as well as in recognition rate.

Table 3 The comparison of epoch no. in digit image recognition task

Digit image recognition	Epoch	Recognition Rate
backpropagation	1702	91%
proposed algorithm	1023	96%

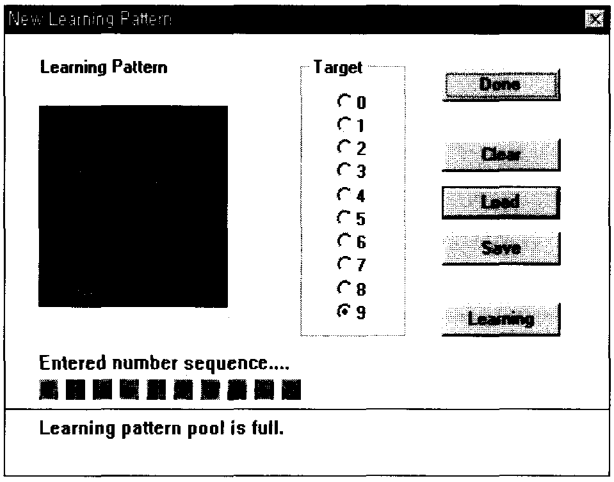

Fig. 2 The proposed learning recognizer

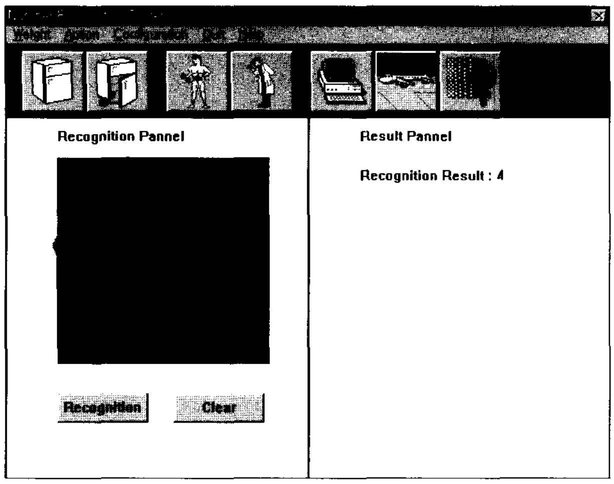

Fig. 3 Recognition result for number '4'

V. CONCLUSION

In this paper we constructed a hybrid neural net based on physiological structure of synaptic mechanism. One of the approaches in our study is related to the fuzzy logic that may model the synaptic mechanism at the functional level. The other is related to the neural network that provides the structure of our model at the different level of analysis. Each method is used to establish the biologically inspired model. We have shown that the fuzzy logic operations and artificial neural networks were used to capture the antagonistic inhibition and self-modulating inhibition, which may be a way to control synaptic interaction between neurons.

The main advantage of the hybrid model is that it can let the multilayer networks process information more efficiently. The conventional BP algorithm could be got stuck because of premature saturation that affects little change on error value. This network paralysis can be overcome by fusioning with other methods such as a fuzzy logic in our study. Typically, the neural structure in our brain is not simple. That is, we do not argue that the brain has the same computational and functional mechanism to our algorithm. However, the interweaving the analysis at the different level, as well as methods can provide more efficient ways to process information.

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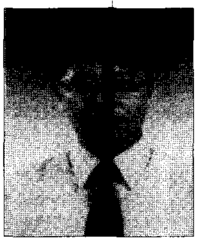

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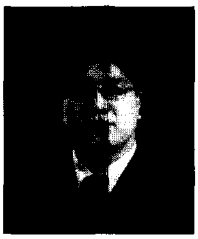

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