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SAR Target Recognition Using Improved Fuzzy Neural Network

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Abstract: Target recognition in high-resolution synthetic aperture radar (SAR) images is a challenging task, because SAR images have higher ambiguity for different target, which will reduce the correct recognition rate. This paper presents an improved SAR recognition algorithm based on fuzzy neural network (FNN), which deals with the ambiguity SAR target recognition very well. This improved FNN system improves learning algorithm and structure which has fuzzy multi-input and fuzzy multi-output. This paper takes the MSTAR data as the test data in simulation to show that this improved fuzzy neural network obtains a higher correct recognition rate. *Copyright © 2013 IFSA.*

Keywords: Fuzzy neural network, Higher ambiguity, Correct recognition rate, SAR image.

1. Introduction

Radar systems are important sensors because they can detect the remote target day and night, and not affected by fog, clouds and rain. Along with the development of radar technologies, as well as with increasing demands for target identification in radar applications, automatic target recognition (ATR) using synthetic aperture radar (SAR) has become an active research area [1]. The latest theoretical developments in classification methodologies quickly have been applied to the SAR ATR design [2].

However, SAR target recognition is still a tough task due to the high variation of image signatures caused by different target orientations, incidence angles, and resolutions [3]. Generally, target recognition consists of three processes: preprocessing, feature extraction and classification. Feature extraction and classification are two principal steps, which mainly determine the recognition performance of a target recognition algorithm [4].

SAR images are highly sensitive to the target aspect because of shadowing effects, interaction of the signature with the environment, projection of a three-dimensional scene onto a slant plane and other reasons related to the aspect dependence of radar cross-sections. The ability to discriminate between targets in SAR imagery also varies greatly with target aspect [5]. Therefore, using multiple views of a target in different aspects may provide more robust classification performance than only using a single view. Different aspects of same target would have huge dissimilarity, and different targets seem semblable in various aspects. A lot of classifiers have been applied in SAR target recognition and each of them has their own strengths and weaknesses. The correct recognition rate greatly suffers from the illegibility [6].

Fuzzy logic and neural network are complementary technologies, and they can provide us with rich functionality when the two technologies are integrated together. Fuzzy logic was proposed by Zadeh, it has the ability of human thinking for objective world. Fuzzy logic can offers a high level framework for approximate reasoning that can commendably perform the task with uncertainty and imprecise information, and offers requisite control principles [7-8]. Neural network provide nonlinear mapping functionality, self-learning ability and changeable architectures that can easily adapt to contextual input and feedback [9-10]. By integrating the two technologies, the fuzzy neural network (FNN) system is endowed with a twofold advantage. FNN model can provide a fuzzy logic system with the powerful computation and learning capabilities of neural networks, and provide neural networks with "human-like" reasoning capabilities of fuzzy logic systems. Nowadays, a lot of new concepts, such as fuzzy model and innovative architecture about FNN have been developed, and FNN has been widely used in many fields, such as pattern recognition [11-14], modeling, and diagnostics. Takagi-Sugeno fuzzy reasoning model [15] is the most commonly used fuzzy model in fuzzy neural network, it can extract the fuzzy rules and identify the fuzzy parameter directly from the input-output data.

This paper is organized as follows. Section 2 includes a short description of fuzzy neural network. Section 3 illustrates the improved fuzzy neural network proposed in this paper. Section 4 shows the recognition performance of improved FNN for SAR images. The conclusions are given in Section 5.

2. Description of Fuzzy Neural Network Model

2.1. Structure of Fuzzy Neural Network

A fuzzy neural network has four layers including input layer, fuzzy layer, fuzzy inference layer and de-fuzzy layer, Fig. 1 shows the structure of fuzzy neural network.

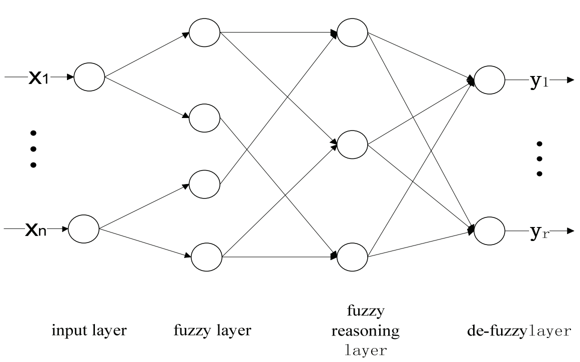


Fig.1. Structure of fuzzy neural network.

Input layer: The input layer nodes which transfer input value to the next layer directly connect with the input vector $X=[x_1\ x_2 \cdots x_k]$, and the number of nodes in this layer is the dimension of *X*.

Fuzzy layer: Each node represents a linguistic variable in this layer and its function is calculating membership $\mu_{A_j^i}(x)$ of each linguistic variable. In this paper, Gauss function is used as the membership function. The gauss membership function is expressed as:

$$\mu_{A_j^i}(x_j) = \exp(-(\frac{x_j - c_j^i}{b_j^i})^2), \tag{1}$$

where A_j^i, which is the i^th^ linguistic variable of x_j - the fuzzy set defined in the universe of discourse, c_j^i is the center value of membership function and b_j^i is the width of membership function.

Fuzzy reasoning layer: Each node in this layer represents a fuzzy rule. It is used to match the fuzzy rules, and calculate the fitness of each rule by product operation or minimal operation, the rules is shown as follows:

$$\omega^i = \mu_{A_1^i}(x_1) * \mu_{A_2^i}(x_2) * \cdots * \mu_{A_k^i}(x_k) \tag{2}$$

De-fuzzy layer: It calculates the total output as:

$$y_i = \sum_{i=1}^{n} \omega^i (p_0^i + p_1^i x_1 + \cdots + p_k^i x_k) / \sum_{i=1}^{n} \omega^i \tag{3}$$

2.2. Learning of Fuzzy Neural Network

Fuzzy neural network design the control system by input/output data and this process is defined as learning process. Gradient descent algorithm is widely used in parameter adjusting process of ordinary neural network for its applicability, as well as in fuzzy neural network. The objective of Gradient descent is using the gradient of weights to update the weights. With the repetitious training of sample, fuzzy rules can be adjusted by the updating weights. The learning algorithm is expressed as follows:

1) Expectation Error

$$e = \frac{1}{2}(y_d - y_c)^2, \tag{4}$$

where y_d is the expected output, y_c is the actual output, *e* is the error between both.

2) Coefficient Updating

$$p_j^i(k) = p_j^i(k-1) - \alpha \frac{\partial e}{\partial p_j^i}, \tag{5}$$

$$\frac{\partial e}{\partial p_j^i} = (y_d - y_c)\omega^i / \sum_{i=1}^{m} \omega^i \cdot x_j , \tag{6}$$

where P_j^i is the coefficient of neural network, α is the learning rate.

3) Parameter Updating

$$c_j^i(k) = c_j^i(k-1) - \alpha \frac{\partial e}{\partial c_j^i} \tag{7}$$

$$b_j^i(k) = b_j^i(k-1) - \alpha \frac{\partial e}{\partial b_j^i} \tag{8}$$

where c_j^i is the center of membership function; b_j^i is the width of membership function.

Parameter training process will finish one time after parameter is updated one time by expressions (5)-(8), then the neural network will finish the training process again and again until the expectation error satisfies the request of precision. The learning algorithm is based on the thinking of BP neural network, and it updates parameter by Gradient descent.

3. The Improved Fuzzy Neural Network

As described in section II, The learning rate and step will not change in the training process of conventional fuzzy neural network, since the majority of training data have high difference from others, and in order to increase learning efficiency, the learning rate and step will mainly satisfy these data. Thus, the conventional FNN cannot accurately recognize some higher ambiguity data. For these data, there have little difference between the distance from it to its own class center and the distance from it to error recognition class center. When these higher ambiguity data are trained by conventional network, they would not be trained adequately and even learned mistakenly for the fast speed of gradient descent which also can induce a concussion in training process. What's more, if the training data is too many as well as the ambiguity data, the conventional FNN will gain a low correct recognition rate. Aiming at these problems, and in order to increase correct recognition rate, this paper proposed an improved fuzzy neural network with improved structure and learning algorithm.

3.1. Improved Network Structure

Compared with the conventional network structure, each last output of the improved structure is an ambiguity result on each type, not an accurate judge, so it is a fuzzy multi-input and fuzzy multi-output structure. It is shown as Fig. 2.

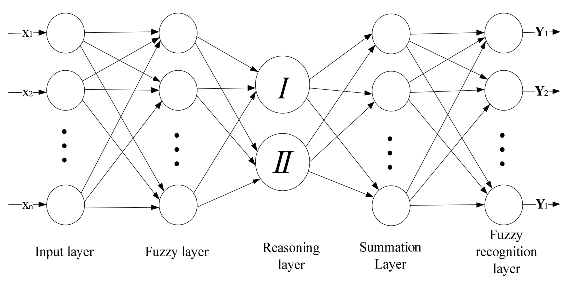


Fig. 2. Structure of improved fuzzy neural network.

Input layer: the number of input variable is *n*, and the corresponding nodes number is *n*.

$$O_a^1 = x_a \qquad a = 1, 2, \cdots, n \tag{9}$$

Fuzzy layer: as described in section II, the improved network will also adopt gauss function as the membership function in this layer.

$$f_{aj} = \exp\left(-\frac{(x_a - c_{aj})^2}{\delta_{aj}^2}\right), j = 1, \cdots, u , \tag{10}$$

where f_{aj} is the membership from x_a to j^{th} neural node, c_{aj} is the center value of membership function, and δ_{aj}^2 is the width of membership function, u is the number of neural nodes in this layer, and the output of j^{th} neural node is expressed as follows:

$$O_j^2 = \exp\left(-\sum_{a=1}^{n} \frac{(x_a - c_{aj})^2}{\delta_{aj}^2}\right), j = 1, \cdots, u \tag{11}$$

Reasoning layer: to gain a better training result on higher ambiguity data, the improved network choose summation ($\sum$) and product ($\prod$) operation as reasoning rule since they have more parameters in training process. The rules are expressed as follows:

$$\begin{aligned} O_{\Sigma}^3 &= w_{11}O_1^2 + w_{12}O_2^2 + \cdots + w_{1u}O_u^2 \\ &= \sum_{j=1}^{u} w_{1j}O_j^2 \end{aligned} , \tag{12}$$

$$\begin{aligned} O_{\Pi}^3 &= w_{21}O_1^2 \cdot w_{22}O_2^2 \cdot \cdots \cdot w_{2u}O_u^2 \\ &= \prod_{j=1}^{u} w_{2j}O_j^2 \end{aligned} , \tag{13}$$

where $w_{kj}, k = 1, 2$ is the weight parameter.

Summation layer: it is used to calculate the summation between output of product node and output of summation node in former layer, this layer is expressed as follows:

$$O_m^4 = \alpha_m O_\Sigma^3 + (1-\alpha_m) O_\Pi^3, m = 1, \cdots, u \quad (14)$$

Fuzzy recognition layer: the output is an ambiguity or probability information which relative to each recognition category. Based on different type data, the last recognition judge can be finished from the ambiguity information by different method. The output is shown as:

$$\begin{aligned} y_i &= \sum_{m=1}^{u} O_m^4 w_{mi} + \theta_i \\ &= \sum_{m=1}^{u} (\alpha_m \prod_{j=1}^{u} w_{1j} O_j^2 + (1-\alpha_m) \prod_{j=1}^{u} w_{2j} O_j^2) w_{mi} \\ &+ \theta_i \end{aligned} \quad (15)$$

3.2. Improved Learning Algorithm

As described in the improved network structure, four kinds of parameters should be trained, that are the mean c_{aj} and variance δ_{aj}^2 of membership function, the weight w_{kj} in reasoning layer, the weight w_{mi} in fuzzy recognition layer. The improved learning algorithm is shown as follows:

$$\begin{aligned} c_{aj}(n+1) - c_{aj}(n) &= -\eta(n) \Delta c_{aj}(n) \\ \eta(n) &= (4/3)^\lambda \eta(n-1) \\ \lambda &= (sign[\Delta c_{aj}(n) \cdot \Delta c_{aj}(n-1)] - 1)/2 \end{aligned} \quad (16)$$

$$\begin{aligned} \delta_{aj}(n+1) - \delta_{aj}(n) &= -\eta(n) \Delta \delta_{aj}(n) \\ \eta(n) &= (4/3)^\lambda \eta(n-1) \\ \lambda &= (sign[\Delta \delta_{aj}(n) \cdot \Delta \delta_{aj}(n-1)] - 1)/2 \end{aligned} \quad (17)$$

$$\begin{aligned} w_{kj}(n+1) - w_{kj}(n) &= -\eta(n) \Delta w_{kj}(n) \\ \eta(n) &= (4/3)^\lambda \eta(n-1) \\ \lambda &= (sign[\Delta w_{kj}(n) \cdot \Delta w_{kj}(n-1)] - 1)/2 \end{aligned} \quad (18)$$

$$\begin{aligned} w_{mi}(n+1) - w_{mi}(n) &= -\eta(n) \Delta w_{mi}(n) \\ \eta(n) &= (4/3)^\lambda \eta(n-1) \\ \lambda &= (sign[\Delta w_{im}(n) \cdot \Delta w_{im}(n-1)] - 1)/2 \end{aligned} \quad (19)$$

It is shown that the learning rate will change by the change of positive and negative of dynamic variable from expressions (16)-(19). With an opposite change of gradient, the learning rate will decrease by 25 %, this can effectively control the concussion produced by training process.

The concrete updating process of parameter δ_{aj}^2 is shown as follows:

$$\delta_{aj}(n+1) - \delta_{aj}(n) = -\eta(n) \cdot \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial \delta_{aj}(n)} \quad (20)$$

It is shown that the updating process needs to solve the partial derivative of variable in denominator from expressions (20). Owing to this process, the computational complexity would be increased and the learning efficiency would be decreased. Aiming at the problem, this paper regards the reciprocal of δ_{aj} as an independent variable and uses the reciprocal to finish training process. The reciprocal is denoted by b_{aj}, and the membership function becomes as follows:

$$f_{aj} = \exp(-(x_a - c_{aj})^2 b_{aj}^2) \quad (21)$$

Then the updating process of parameter c_{aj} and b_{aj} become as follows:

$$c_{aj}(n+1) - c_{aj}(n) = -\eta(n) \cdot \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial c_{aj}(n)} \quad (22)$$

$$b_{aj}(n+1) - b_{aj}(n) = -\eta(n) \cdot \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial b_{aj}(n)} \quad (23)$$

As the above analysis, in expression (20), δ_{aj} has a third power and a concussion will be induced when δ_{aj} become smaller in training process. However, in expression (23), parameter b_{aj} does not appear in the reciprocal and just has a third power. Thus, the computational complexity will be decreased and a concussion will be controlled effectively when δ_{aj} become smaller.

4. Simulation Results

The MSTAR (three types of ground vehicles in the moving and stationary target acquisition and recognition) data is a standard dataset in the SAR ATR community, allowing researchers to fairly test and compare their ATR algorithms. A variety of feature extraction algorithms have been used in SAR target recognition. This paper takes the Hu moment invariants as the SAR target feature [16]. The geometry moment is written as

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y) dx dy, \quad (24)$$

where $f(x,y)$ are two dimensionality random functions. Its center moment is

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y), \quad (25)$$

where $\bar{x} = \frac{m_{10}}{m_{00}}, \bar{y} = \frac{m_{01}}{m_{00}}$.

Then, it is feasible to get the first four moment, they are shown as follows:

$$\begin{aligned}
&\mu_{00} = m_{00} = \mu \\
&\mu_{01} = \mu_{10} = 0 \\
&\mu_{20} = m_{20} - \mu\bar{x}^2 \\
&\mu_{11} = m_{11} - \mu\bar{x}\bar{y} \\
&\mu_{02} = m_{02} - \mu\bar{y}^2 \\
&\mu_{12} = m_{12} - m_{02}\bar{x} - 2m_{11}\bar{y} + 2\mu\overline{xy}^2 \\
&\mu_{03} = m_{12} - 3m_{02}\bar{y} + 2\mu\bar{y}^3 \\
&\mu_{21} = m_{21} - m_{02}\bar{y} + 2m_{11}\bar{x} + 2\mu\bar{x}^2\bar{y} \\
&\mu_{30} = m_{30} - 3m_{20}\bar{x} + 2\mu\bar{x}^3
\end{aligned} \quad (26)$$

The normalized central moment is

$$\eta_{pq} = \mu_{pq} / \mu_{00}^r \quad (27)$$

where $r = (p+q+2)/2$, $p+q = 2,3,\cdots\cdots$.

The Hu moment invariants can be expressed as follows:

$$\phi_1 = \eta_{20} + \eta_{02} \quad (28)$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (29)$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (30)$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (31)$$

$$\begin{aligned}
\phi_5 = &(\eta_{30}+\eta_{12})(\eta_{30}-3\eta_{12}) \,|\, (\eta_{30}+\eta_{12})^2 \\
&-3(\eta_{21}+\eta_{03})^2 \,|\, + (3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03}) \\
&|\, 3(\eta_{30}+\eta_{12})^2 - (\eta_{21}-\eta_{03})^2 \,|
\end{aligned} \quad (32)$$

$$\begin{aligned}
\phi_6 = &(\eta_{20}+\eta_{02}) \,|\, (\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2 \,| \\
&+ 4\eta_{11} \,|\, (\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03}) \,|
\end{aligned} \quad (33)$$

$$\begin{aligned}
\phi_7 = &(\eta_{30}+\eta_{12})(3\eta_{12}-\eta_{30}) \,|\, (\eta_{30}+\eta_{12})^2 \\
&-3(\eta_{21}+\eta_{03})^2 \,| + (3\eta_{12}-\eta_{30})(\eta_{21}+\eta_{03}) \\
&|\, 3(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2 \,|
\end{aligned} \quad (34)$$

The four moment invariants which are obtained from the affine transformation are expressed as [17]

$$I_1 = \frac{\mu_{20}\mu_{02} - \mu_{11}^2}{\mu_{00}^4} \quad (35)$$

$$\begin{aligned}
I_2 = &(\mu_{03}^2\mu_{30}^2 - 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} + 4\mu_{30}\mu_{12}^3 \\
&+4\mu_{21}^3\mu_{03} - 3\mu_{21}^2\mu_{12}^2) / \mu_{00}^{10}
\end{aligned} \quad (36)$$

$$\begin{aligned}
I_3 = &(\mu_{20}(\mu_{21}\mu_{03} - \mu_{12}^2) - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12}) \\
&+\mu_{02}(\mu_{30}\mu_{12} - \mu_{21}^2)) / \mu_{00}^7
\end{aligned} \quad (37)$$

$$\begin{aligned}
I_4 = &(\mu_{20}^3\mu_{03}^2 - 6\mu_{20}^2\mu_{11}\mu_{12}\mu_{03} - 6\mu_{20}^2\mu_{02}\mu_{21}\mu_{03} \\
&+9\mu_{20}^2\mu_{02}\mu_{12}^2 + 12\mu_{20}\mu_{11}^2\mu_{21}\mu_{03} + 6\mu_{20}\mu_{11}\mu_{30}\mu_{03} \\
&-18\mu_{20}\mu_{11}\mu_{02}\mu_{21}\mu_{12} - 8\mu_{11}^3\mu_{03}\mu_{30} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} \\
&+9\mu_{20}\mu_{02}^2\mu_{21}^2 + 12\mu_{11}^2\mu_{02}\mu_{30}\mu_{12} - 6\mu_{11}\mu_{02}^2\mu_{21}\mu_{03} \\
&+\mu_{02}^2\mu_{03}^2) / \mu_{00}^{11}
\end{aligned} \quad (38)$$

This paper takes the moment invariants as the feature to SAR target recognition, which is

$$X = [\phi_1 \; \phi_2 \; \phi_3 \; \phi_4 \; \phi_5 \; \phi_6 \; \phi_7 \; I_1 \; I_2 \; I_3 \; I_4 \; \mu \; Var]',$$

where μ, Var is the mean and variance of the two dimensionality random functions.

This paper builds a simulation recognition system for MSTAR image, its structure is shown as Fig. 3.

This paper uses 1286 images for simulation, these images are from 15° and 17° aspects of three targets (T72, BMPZ, BTR7O). Simulation system random chooses 1000 images as the training data and other 286 images as test data. The simulation has taken iteration training in 100 times by using the learning algorithm which is detailed in part 3. The iteration learning curve is shown as Fig. 4, which shows the iterative result of normal learning and improved learning algorithm.

It can be found that the improved learning algorithm can contribute less error and more stable in iterative procedure. And the recognition result is shown as Fig. 5.

Table 1 shows the difference recognition results of some illegibility SAR images between conventional and improved FNN.

For the table, it is shown that the correct recognition rate has been increased in the improved FNN. The FNN recognition can contribute 84.7 % for the MSTAR and the improved FNN recognition can get 93.4 %.

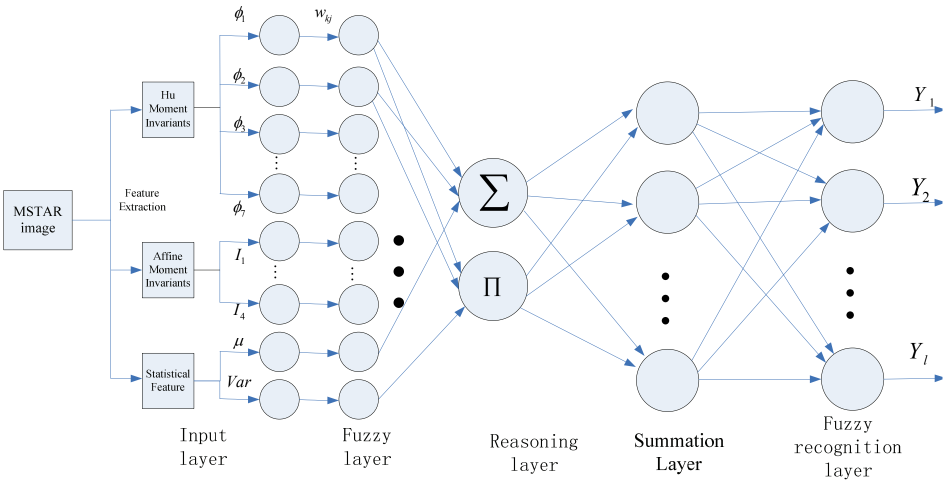
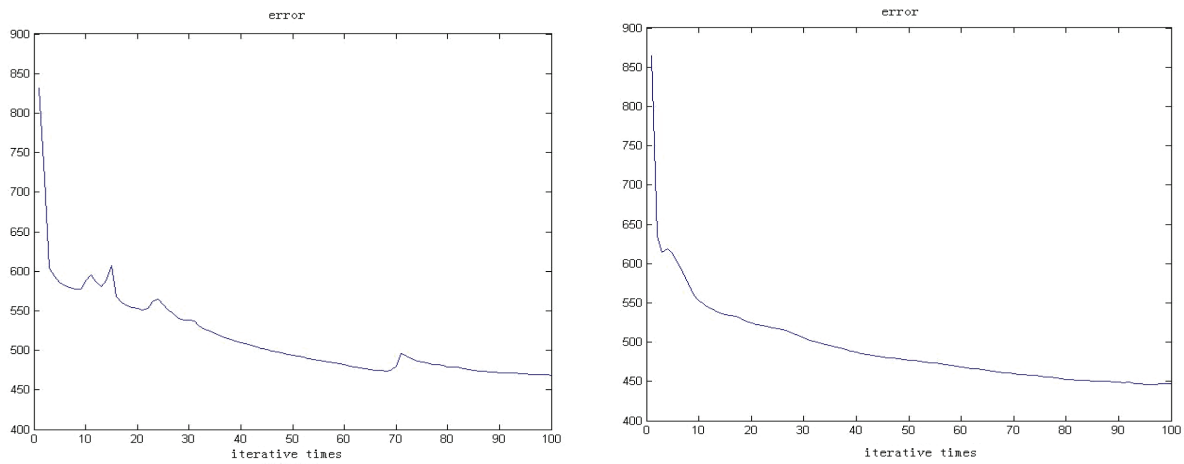


Fig. 3. MSTAR image recognition system structure.



(a) (b)

Fig. 4. Error curve, (a) error curve of conventional learning algorithm, (b) error curve of improved learning algorithm.

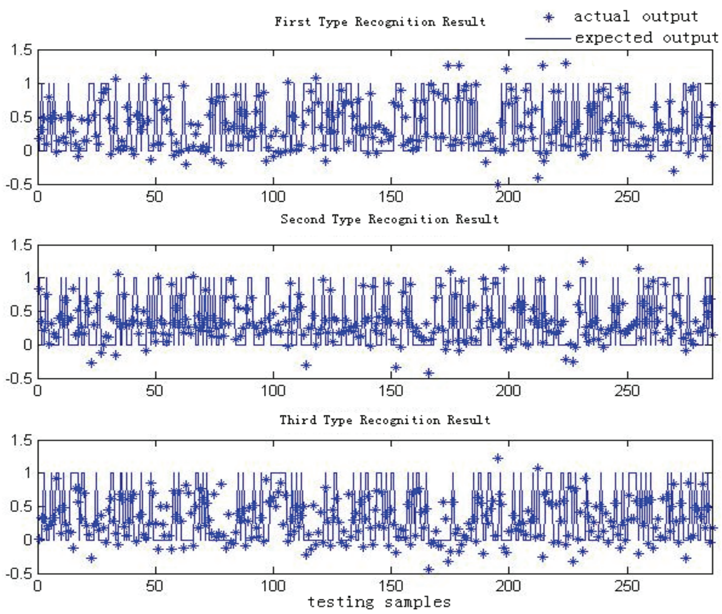


Fig. 5. Actual output and expected output of testing sample.

Table 1. Recognition results of some illegibility SAR images.

	Conventional FNN output	Improved FNN			Actual output
		Probability of 1st type	Probability of 2nd type	Probability of 3rd type	
1	[0 0 1]	0.528038	-0.01213	0.476288	[1 0 0]
2	[0 1 0]	-0.10639	0.545774	0.547673	[0 0 1]
3	[1 0 0]	0.511021	0.53006	-0.04534	[0 1 0]
4	[0 0 1]	0.47564	0.005308	0.525628	[1 0 0]
5	[0 1 0]	0.035892	0.426995	0.535446	[0 0 1]
6	[0 0 1]	0.430008	0.182494	0.385733	[1 0 0]
7	[1 0 0]	0.401752	0.151182	0.460472	[0 0 1]
8	[0 1 0]	0.365494	0.339978	0.292665	[1 0 0]

5. Conclusions

This paper proposes an improved fuzzy neural network for SAR image recognition, and the proposed network includes an improved structure and learning algorithm. At the last layer of improved structure, the output is fuzzy information which contains the probability on each type. The improved learning algorithm modifies the learning rate and parameters. This paper uses the MSTAR SAR images data for simulation, and the results verify that the improved FNN recognition can contribute higher recognition rate than conventional FNN, especially in illegibility images data.

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