A new algorithm of SAR target recognition based on advance deep learning neural network

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Abstract

In order to improve the accuracy of synthetic aperture radar images target recognition, we have proposed a new algorithm of SAR target recognition based on advance Deep Learning neural network. The traditional radar recognition algorithm has many disadvantages, In order to improve the accuracy of synthetic aperture radar images target recognition, the author have proposed a new algorithm of SAR target recognition based on advance Deep Learning neural network. In this paper, the author have got the feature of SAR image through the Refine Lee filter and HOG transformation firstly, and then realized the SAR object segmentation and recognition through the multi-layers RBM machine and GRNN neural network. and then realized the SAR object segmentation and recognition through the multi-layers RBM machine and GRNN neural network, and the learning rate parameter of the multi-layers RBM machine is optimized through the GA algorithm. The simulation results shows that the object recognition rate of the algorithm proposed in this paper can reach 97%, which can improve the performance of the algorithm obviously.

Keywords: Lee, HOG, SAR, Deep Learning, RBM, GA

1 Introduction

The synthetic aperture radar object recognition object recognition technology is very important in the field of SAR image process and pattern recognition, which has a very important commercial value and military value. In order to get a ideal catch a better results of SAR object recognition, the characteristics of data must be in a good class cohesion and the differences between classer.

In the reference Paper 1 and Paper 2, In the first reference, which have the paper has proposed an algorithm of SAR object recognition based on the template matching.matching method. But the SAR image is very sensitive to the change of azimuth angle and attitude angle, which must store a large number of templates in the actual target recognition problem. In the second reference, which had the paper has proposed an algorithm of SAR object recognition based on model, mathematical model, which can extracted the features from the unknown target and find the object through the mathematical model. In the reference paper4 had proposed In the third reference, the paper has proposed a algorithm based on the SVM (Support Vector Machine) method, but most of the traditional methods are based on statistics, But this method is based on statistics, training and recognizing through feature extraction, which cannot work well in actual recognition.

In order to solve this problem, the author have proposed a method of SAR target recognition the author of this paper has proposed a method of SAR target recognition based on advance Deep Learning neural network. Deep Learning neural network is a kind of method, which can extract the data feature in deep layer, and working as the human brain by multi layers neural network. There are a variety of deep learning network, such as Restrict Boltzmann Machine [5] (RBM), Convolutional Neural Networks (CNN) and Auto Encoder [6] (AE), etc. There are a variety of kinds of deep learning network [4], such as RBM (Restrict Boltzmann Machine), AE (Auto Encoder) and CNN (Convolution Neural Networks), etc.

2 Feature extraction

2.1 REFINE LEE FILTER

Due to the limited resolution and coherence of SAR system, there will be speckle noise in the process of synthetic aperture radar imaging, which can reduce the accuracy of target recognition seriously [7]. There are speckle noise in the process of synthetic aperture radar imaging, because of the limited resolution and coherence of SAR system, which can reduce the accuracy of target recognition seriously [5]. The Lee filter is working based on the fully developed speckle noise model, which selects a certain length of window as a local area, and assumes a priori mean and variance can be calculated by the local area. The formulation of Lee Filter is: The Lee Filter formulate on is:

$$g_{ij}' = \bar{g}_{ij} w + g(1-w), \tag{1}$$

where $\bar{g}_{ij}$ is the average pixel gray value of the inner window. The formulation of $\bar{g}_{ij}$ is:

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$$\bar{g}_{ij} = \bar{g}(i,j) = \frac{1}{(2M+1)(2N+1)} \sum_{k=j-M}^{j+M} \sum_{l=i-N}^{i+N} g(k,l) , \qquad (2)$$

and in the different areas of SAR image, we will use different filter, which will use different filter in the different areas of SAR image, the guidelines are as follow:

$$\begin{cases} g_{ij}^{'} = \overline{g}_{ij} & \sigma_{ij} \le c_u \\ g_{ij}^{'} = \overline{g}_{ij} w + g(1-w) & c_u < \sigma_{ij} \le c_{\max} , \\ g_{ij}^{'} = g_{ij} & \sigma_{ij} > c_{\max} \end{cases} \qquad (3)$$

where σ_{ij} is the average variance of the inner window, the formulation is:

$$\sigma_{ij} = \frac{1}{(2M+1)(2N+1)} \sum_{k=j-M}^{j+M} \sum_{l=i-N}^{i+N} \left(g(k,l) - \overline{g_{ij}} \right)^2 . \qquad (4)$$

Here w is the weight function of Lee filter, the its expression is:

$$w = 1 - C_u^2 / C_I^2 . \qquad (5)$$

The influence of speckle noise in SAR image can be reduced greatly through the Refine Lee filter, which is beneficial to extract the characteristic signal with higher precision.

2.2 HOG TRANSFORMATION

The feature extraction of Histogram of Oriented Gradient is based on the Gradient direction and edge density distribution of the shape of the target image appearance [8]. [6]. The HOG method will divide the SAR image into small connected regions firstly, which is called Unit Cell. And then calculate and collect the gradient of each pixel or the direction histogram of edge. Finally, combine all the histogram and constitute a feature descriptor. The main steps of HOG feature extraction are as follows:

a) *Gamma compression*

We can reduce the influence of illumination by Gamma compression, the formulation is:

$$I(x,y) = I(x,y)^{gamma} . \qquad (6)$$

b) *Image gradient*

We can reduce the influence of illumination further by capturing the edge of SAR image. The edge of SAR can be calculated through the gradient of image.

The gradient of each pixel(x,y) is

$$G_x(x,y) = I(x+1,y) - I(x-1,y) , \qquad (7)$$

$$G_y(x,y) = I(x,y+1) - I(x,y-1) , \qquad (8)$$

$$\theta(x,y) = \tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)} \right) . \qquad (9)$$

c) *Construction of gradient direction histogram*

The HOG can provide a code for the local image region through the Construction of gradient direction histogram.

d) *The normalized gradient histogram*

Normalization can compress the light, shadow and edge further.

3 A new deep learning neural network

In the deep learning algorithms, RBM machine is easy to realize, which can overcome the problem of the multi-layer network training more effectively. So, in this paper, we will focus on the deep learning algorithms based on the RBM machine [7-9].

3.1 RESTRICTED BOLTZMANN MACHINE

RBM machine is not only a probability model, but also a kind of energy model, the RBM contains a hidden layer and a visible layer. The hidden layer and visible layer is connected through a two-way connection between layers, while there are no interconnection between each unit in the same layer. The basic structure of RBM is shown in figure1.

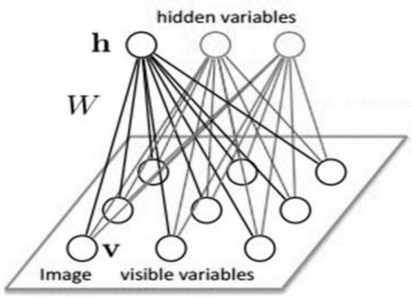

FIGURE 1 The structure of RBM

So, RBM machine can be expressed as the follow formulation:

So, the RBM machine in deep learning neural network can be expressed as the follow formulation:

$$E(v,h) = -\sum_{i \in v} a_i v_i - \sum_{i \in h} b_i h_i - \sum_{i,j} v_i h_i w_{ij} , \qquad (10)$$

where w_{ij} is the connection weight matrix. This network can give each visible and hidden vector a probability:

$$p(v,h) = \frac{1}{Z} e^{-E(v,h)} , \qquad (11)$$

where Z is a partition function, its expression is:

$$Z = \sum_{v,h} e^{-E(v,h)} . \qquad (12)$$

The logarithmic gradient of weight in formula 2 can be expressed as the follow formula:

$$\frac{\partial \log p(v,h)}{\partial w_{ij}} = \langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{\mathrm{model}} , \qquad (13)$$

where $\langle v_i h_j \rangle_{data}$ is the meaning of data, $\langle v_i h_j \rangle_{model}$ is meaning of model. So we can get the RBM learning rules from the gradient formula 13.

$$\Delta w_{ij} = \varepsilon\left(\langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{model}\right). \tag{14}$$

For the data expectation, due to the matter that there is no direct connection between the hidden layer units, we can get an unbiased samples of data distribution. For a given random training image v, the probability of hidden unit will be set 1 in binary:

$$p\left(h_j = 1 \mid v\right) = \sigma\left(b_j + \sum_i v_i w_{ij}\right). \tag{15}$$

In a same reason, the probability of visible unit will be set 1 in binary.

$$p\left(v_i = 1 \mid h\right) = \sigma\left(a_i + \sum_j h_j w_{ij}\right), \tag{16}$$

where $\sigma\left(x\right) = \dfrac{1}{\left(1 + e^{-x}\right)}$.

We can realize the forward transform like the neural network, and calculate all the state through calculation.

3.2 RBM TRAINING BASED ON OPTIMIZE GA

From the 14th formula, we can know that the weight updating between unit v_i and h_j is composed by data expectation and model expectation. Due to the large memory consumption, the computation time of model expectation $\langle v_i h_j \rangle_{model}$ will increase exponentially in the number of units. In the reference paper 12, the author had proposed a training algorithm of Contrastive Divergence, which is using k step Gibbs samples to replace the mode expectation $\langle v_i h_j \rangle_{model}$, its expression as shown below:

$$\Delta w_{ij} \approx \varepsilon\left(\langle v_i h_j \rangle_{data} - \sum_{k=1}^{N} \langle v_i h_j \rangle_k\right), \tag{17}$$

where ε is the learning rate.

But this algorithm has a disadvantage of local optimal problems. The RBM training The RBM training step is a multidimensional optimization problem, in order to which will obtain the global optimal value, we must use the genetic algorithm. Through the genetic algorithm. But the traditional GA algorithm has two problems, premature and slow convergence. Such as the premature and the slow convergence.

In this paper, the author has proposed a new GA algorithm in order to obtain the global optimal value. The parameter of weight, a and b can be expressed as follow:

$$\Delta w_{ij} \approx \varepsilon_{opt}\left(\langle v_i h_j \rangle_{data} - \sum_{k=1}^{N} \langle v_i h_j \rangle_k\right), \tag{18}$$

$$\Delta a_i \approx \varepsilon_{opt}\left(\langle v_i \rangle_{data} - \sum_{k=1}^{N} \langle v_i \rangle_k\right), \tag{19}$$

$$\Delta b_j \approx \varepsilon_{opt}\left(\langle h_j \rangle_{data} - \sum_{k=1}^{N} \langle h_j \rangle_k\right), \tag{20}$$

where ε_{opt} is the learning rate after optimization.

Compared the traditional GA algorithm, there are two main difference in the new GA algorithm.

Real number encoding

As we know, there is binary encoding in the traditional GA algorithm, in this paper, we use the Real number encoding in order to obtain larger space searching and higher calculation precision.

Adaptive adjustment

In order to avoid the local convergence, we will use Adaptive adjustment crossover probability and mutation probability. The expression is shown as below:

$$P_c = \frac{1}{1 + e^{\left(-k_1 \Delta f\right)}}, \tag{21}$$

$$P_m = 1 - \frac{1}{1 + e^{\left(-k_2 \Delta f\right)}}. \tag{22}$$

According to the above steps, the advance GA algorithm can adjust the crossover probability and mutation probability adaptively based on the actual situation of chromosome.

3.3 GENERALIZED REGRESSION NEURAL NETWORK

3.3.1 GRNN network

The generalized regression neural network, (GRNN) is a kind of neural network, which is building on the nonparametric kernel regression [10], and calculating the probability density function of the dependent and independent variables through the samples. The structure of GRNN is shown in figure 2, the network contains four layer: input layer, model layer, summation layer and output layer.

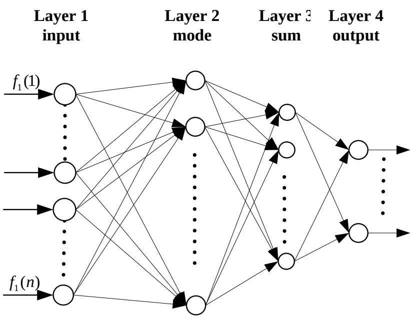

FIGURE 2 The structure of GRNN

The performance of GRNN is mainly depending on the smooth factor δ .The number of neurons in the input layer is equal to the learning samples dimension. Each neurons corresponds to a different learning samples. The transfer function of model layer is:

$$P_i = e^{\left(-\frac{(X-X_i)^T(X-X_i)}{2\delta^2}\right)}, i=1,2,...,n, \tag{23}$$

where X_i is the X is the input variables, X_i is the learning samples of neurons.

Learning samples of neurons, X is the input variables. The Summation layer contains two kinds of neurons, the corresponding transfer function is:

$$S_A = \sum_{i=1}^{n} P_i \,. \tag{24}$$

The output of neurons in the output layer is calculated by the different results from the Summation layer:

$$y_j = \frac{S_{Nj}}{S_{Aj}}, j=1,2,...,k \,. \tag{25}$$

So when we have selected the learning samples, the structure and weight of GRNN will be completely determined. The GRNN training is more faster than the BP or RBF training.

Based on the GRNN formula of the four network layers, the GRNN network output can be expressed as the follow:

$$\overline{Y} = \frac{\sum_{i=1}^{n} Y_i \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\delta^2}\right]}{\sum_{i=1}^{n} \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\delta^2}\right]} \tag{26}$$

3.3.2 DBM network based on RBM and GRNN

According to the above chapters, this paper has proposed a new kind of Deep Learning neural network, its whole structure as shown in the figure below:

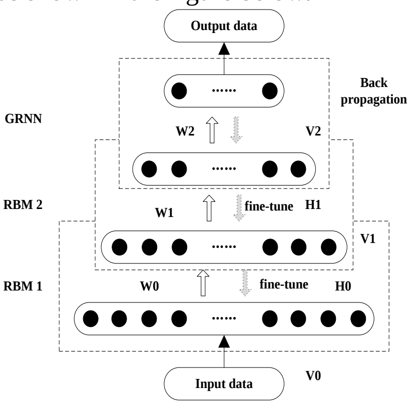

FIGURE 4 structure of new Deep Learning neural network

In figure3, we can see that the training step of new Deep Learning neural network can divide into two steps:

The first step: Finding a best learning rate by the advance GA optimization. And then training each layer of network without supervision, ensure the feature vector can preserve the feature information as much as possible when map to different feature space.

The second step: The GRNN network will receive the feature vector from the RBM as its input feature vector, and train the classifier with supervision.

Each RBM layer network can ensure its own weight to the optimum when mapping and feedback the error information to the each RBM layers in order to fine-tuning the entire network.

The above is the whole deep learning of the neural network training process.

3.3.3 SAR image segmentation based on new deep learning neural network

The main structure of the new SAR image segmentation is show in figure4.

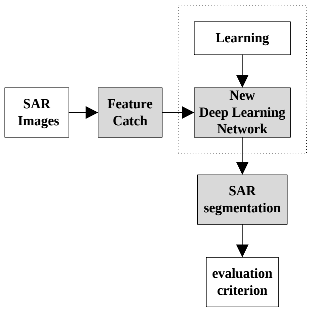

FIGURE 4 Main structure of the new SAR segmentation

The SAR image segmentation algorithm can divided into five steps:

1).Input the SAR image;

2).Feature extraction of SAR image;

3).Training and recognition of SAR image according to the figure3;

4).SAR image target segmentation;

5).The experimental results analysis and evaluation;

This paper will test the target recognition rate and algorithm consuming as the performance evaluation.

4 Simulation and analysis

4.1 THE RESOURCE OF SAR IMAGE

For the effectiveness of the image target recognition, all the test SAR image in this paper is from Sandia National Laboratories [11, 16], the testing SAR image is shown as bellow:

Sandia operates a Sandia plane with the ku band (15 GHz) of synthetic aperture radar, the SAR image data is collected in the range of 2 to 15 km.

FIGURE 5 SAR Resource

4.2 FEATURE EXTRACTION BASED ON LEE FILTER AND HOG TRANSFORM

First, the SAR image will input the Refine Lee filter, after this step, we can get the result as follow:

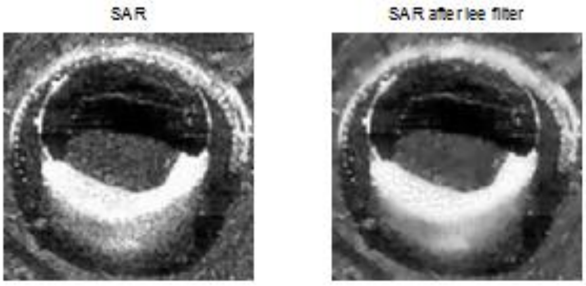

FIGURE 6 Refine-Lee filter

According to the simulation results in the figure 6, the gray value of SAR image will become more uniform and smooth, and the speckle noise will reduce. Target becomes clearer.

After filter, we will extract the SAR feature by HOG transformation, the parameter of HOG algorithm is that:

Divide each CELL colour gradient into a 9-dimenision amplitude weighted vector from the range of 1~180 degrees. The size of each CELL is 8*8 pixels matrix, the offset of CELL pixel is 8. We can obtain the HOG features after HOG transformation: Figure7 HOG features of SAR image.

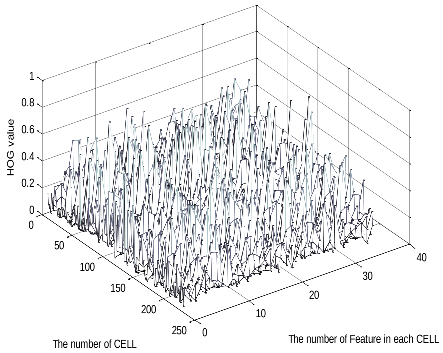

FIGURE 7 The HOG feature of SAR image

In Figure7, the X coordinates express the number of CELL, Y coordinates express the number of feature vector of each CELL.

4.3 THE SIMULATION OF NEW DEEP LEARNING NETWORK

4.3.1 Simulation parameter

If the parameter setting of RBM model is not appropriate, some specific data sets and RBM will hard to model through the data distribution. So it is very important to ensure the RBM parameters.

The simulation parameters in this experiment are shown in table 1.

TABLE 1 simulation parameter

	Parameter	**value**
1	The sample number of SAR resource	100
2	The initial value of RBM learning rate	0.001
3	The number of the first hidden layer of RBM	200
4	The number of the second hidden layer of RBM	100

4.3.2 Optimization of RBM learning rate

Before the training, we will use the advance GA algorithm to optimize the RBM learning rate, the optimization objective function is:

$$fitness = DL_{error}(k), \tag{27}$$

where DL_{error} is the training error of different learning rate. The optimization process as shown in the figure below:

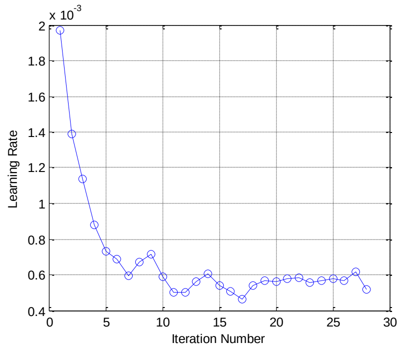

FIGURE 8 Optimization process of RBM learning rate

The simulation results shows that after improved GA algorithm, we can get the best learning rate 0.00052.

After simulation, the SAR target segmentation is shown in below.

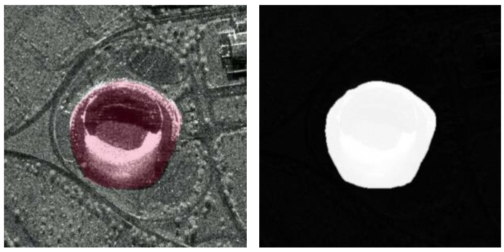

FIGURE 9 SAR recognition and segmentation

From the simulation result in Figure 9, the new deep learning neural network recognition can obtain a better recognition and segmentation performance.

4.4 SIMULATION CONCLUSION ANALYSIS

In order to reflect the performance of new deep learning neural network, here we use other algorithm to compare. In this paper, Here we will compare with the methods of traditional deep learning neural network recognition algorithm, support vector machine recognition algorithm [13, 17] and multi-scale SOM neural network recognition algorithm [14] SAR recognition algorithm, And 100 SAR test samples will be tested. The Simulation results of four segmentation algorithm is shown in the figure below:

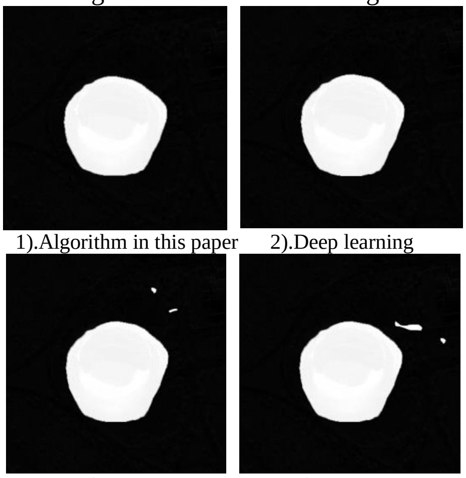

FIGURE 10 Four segmentation algorithm simulation Result

From Figure 10 shows that the algorithm in this paper can obtain a complete target area, and the rest of the several algorithms have regional deformation or goal interference factors. Table 2 shows the recognition accuracy and running time.

TABLE 2 Difference of four algorithms

	algorithms	**recognition accuracy**	**running time**
1	Algorithm in this paper	97%	210s
2	Traditional Deep learning	93%	95s
3	SVM	91%	80s
4	Multi-SOM	90%	120s

According to the simulation results in table 2, The recognition accuracy of the new kind of deep learning recognition algorithm can reach 97%, which performance is better than the rest of the three algorithms, and the recognition accuracy of normal multi-scale SOM neural network recognition algorithm is barely 90%. For the simulation time, because of the hybrid network of RBM and GRNN, the simulation time is longer than other algorithms.

5 Conclusion

In this paper, the author has proposed a new algorithm of synthetic aperture radar images target recognition, which is based on the cascade RBM and GRNN hybrid neural network. The experiment results show that this method has a very high target recognition accuracy, which is an very effective method for the synthetic aperture radar images target recognition.

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