Application of a New Restricted Boltzmann Machine to Radar Target Recognition

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Abstract— When facing radar target recognition, the main problems focus on the data representation capability and the robustness to cope with noise. The merits of deep learning such as automatic setting for training and hierarchical extraction of features. Most of existing deep networks are related to Restricted Boltzmann machine (RBM), which has played an important role in deep learning techniques. The models election problem in RBM and its deep architecture is very intractable since both their learning and inference are highly time-consuming. As regular RBM has a restriction between visible units and hidden units, this restriction will cause reduction of the recognition probability when training data samples are degraded by noise. Fuzzy Restricted Boltzmann machine (FRBM) is a new RBM, in which the parameters of collection between visible units and hidden units are replaced by fuzzy number. In this paper, FRBM has been applied to moving airplane radar target data. Tested target contain three categories airplane HRRP data samples. The proposed FRBM can significantly reduce the number of free parameters and the degree of over fitting. Moreover, compared with RBM and traditional classification methods, it has showed better representation capacity and better robustness property when the training data are contaminated by noises.

1. INTRODUCTION

Radar automatic target recognition has played an important role in commercial and military applications, such as facing recognition, traffic monitoring, and national defense. These years, radar technologies have experienced a great development, as well as with mounting demands for target identification, classifying targets with high-resolution radars has been widely used in radar target recognition. The deep learning can approximate very complicated function and achieve a new representation for the distribution of input data. Thus introducing deep learning to Radar Automatic Target Recognition (ATR) is necessary and urgent, there is some research on SAR image [1] representation and recognition, but few researchers have started the work on High Resolution Range Profile (HRRP) and RCS feature.

This paper proposed a deep learning network application in radar target recognition, a new Fuzzy Restricted Boltzmann Machine (FRBM) model [2], basing on HRRP and RCS database. Compared the test results with traditional recognition classifiers, like KNN and SVDD, and also with the regular RBM model [3] it can be seen that the proposed FRBM have higher accuracy on recognition and much more productive process during the recognition. In this stage, they can obtain features in each layer and rebuild the learned features for high performance recognition [4].

The rest of the paper is organized as follows. In Section 2, the preliminaries about RBM and proposed Fuzzy RBM, learning algorithm, and their notations are presented. After that, the outstanding performance of the proposed FRBM model is proved by implementing experiments on above radar detected data in Section 3. Finally, the conclusion and remarks are demonstrated in Section 4.

2. PRELIMINARIES

2.1. Restricted Boltzmann Machine

Restricted Boltzmann Machine (RBM) is a generative stochastic neural network which is invented by Hinton in 1986 [2]. RBM, as illustrated in Figure 1, is a bipartite graph. The RBM has two groups of units, commonly named as the "visible" and "hidden" units respectively [5]. It can learn a probability distribution over its set of visible feature v and hidden feature units h. The network is controlled by the collection weight and bias across the layers. Suppose the network has n and m visible unites and hidden unites respectively in the RBM. Parameter θ contains weight matrix $w_{m\times n}$, visible layer bias $a = a_1, a_2, \dots, a_m$ and hidden layer bias $b = b_1, b_2, \dots, b_n$. These three vector determined how the network represent the input n dimension samples into m dimension features. It can be defined as a long vector $\theta = (W, a, b)$, $E(v, h)$ is the energy function, Z is the normalizing factor named the partition function. The energy function is defined with $\theta = (W, a, b)$. As for a sets of certain vector (v, h), the energy function is defined as follow:

$$E_\theta(v, h, \theta) = -a^T v - b^T v - h^T W v \tag{1}$$

As RBM is an energy-based probabilistic model in which has an energy function $P(v, h)$, which defines its probability distribution as follows:

$$P_\theta(v, h) = \frac{e^{-E(v,h)}}{Z(\theta)}, \quad Z = \sum\nolimits_{v,h} e^{-E(v,h;\theta)} \tag{2}$$

When consulting the recognition problems, we concentrated on the probability distribution of inputs $P_\theta(v)$, also called the likelihood function [7], which can be figured out by computing the marginal distribution of $P(v, h)$ at h.

$$P_\theta(v, h) = \frac{1}{Z(\theta)} \sum\nolimits_h \exp\left[a^T v + b^T v + h^T W v\right] \tag{3}$$

The aim of training RBM is maximum its log-likelihood function

$$\ln L_{\theta,S} = \ln \prod\nolimits_{i=1}^{n_s} P(v^i) \tag{4}$$

Since Hinton introduced Contrastive divergence (CD) learning algorithm, it has become a standard learning approach to train RBMs [8]. It is sufficient for model training because the estimated results can be obtained from several steps of running the chain. In this paper, we use CD-k algorithm to denote the estimation after k-step Gibbs sampling.

This paper also adapted the CD algorithm. We set the training samples as S, and the $\Delta W, \Delta a, \Delta b$ respectively represent the $\frac{\partial L_s}{\partial W}$, $\frac{\partial L_s}{\partial a}$ and $\frac{\partial L_s}{\partial b}$. The CD-k algorithm is aim to obtain the approximation of $\Delta W, \Delta a, \Delta b$ in one gradient ascent iteration.

2.2. Fuzzy Restricted Boltzmann Machine

The fuzzy RBMs demonstrate an aspect of extending the fuzzy connection between visible and hidden units [9]. In FRBMs, the weight W is regarded as a vector of $\bar{W} = \left[\bar{\bar{W}}_1, \ldots, \bar{\bar{W}}_n\right]^T$ and the fuzzy number $\bar{W}_j$ can be defined as

$$\overline{W_j(\omega)} = \max\left\{1 - \frac{|w - w_j|}{\hat{w_j}}, 0\right\} \tag{5}$$

w_j is the center of the fuzzy number, and the fuzzy number has a width defined as $\hat{w}_j$.

And in this stage, if $\bar{A}$ is a fuzzy set, the α-cut of $\bar{A}$ is represented by $\bar{A}[\alpha]$, defined as follow:

$$\bar{A}[\alpha] = \left\{x \in \Omega | \overline{A(x) \geq \alpha}\right\}, \quad 0 < \alpha \leq 1 \tag{6}$$

The fuzzy function $\bar{f}$ is extended from real-value function $f : Y = f(x, W)$, is defined by

$$\bar{Y} = \bar{f}(x, \bar{W}) \tag{7}$$

The $\bar{Y}$ is the dependent fuzzy output set, W and $\bar{W}$ are parameters in the following Membership function. Based on extension principle, the membership function can be illustrated as

$$\bar{Y}(y) = \sup\left\{\min\left(\bar{W}_1((W_1)), \ldots, \bar{W}_n((W_n))\right) | f(x, W) = y\right\} \tag{8}$$

Since it is infeasible to figure out the membership because of the maximization and minimization of the real-value function is hard to calculate. The α-cut and interval arithmetic is efficient to extend the fuzzy function.

$$\bar{Y}[\alpha] = f\left(x, \bar{W}[\alpha]\right) \tag{9}$$

The intervals $\bar{W}[\alpha]$ can be calculated much more easily.

Compared with the $\theta = (W, a, b)$, FRBM has the fuzzy parameters $\theta = \left(\bar{W}, \bar{a}, \bar{b}\right)$, which has contained the connection weighs and biases. Respectively, the fuzzy energy function can be extended from (1) as follows:

$$\bar{E}\left(v, h, \bar{\theta}\right) = -\bar{a}^T x - \bar{b}^T h - h^T W v \tag{10}$$

Besides, the FRBM has a fuzzy free energy $\bar{F}$, and it changed hidden units and map (1) into the following simpler one:

$$\bar{\mathcal{F}}\left(v, \bar{\theta}\right) = -\log \sum\nolimits_{\bar{h}} e^{-\bar{E}\left(v, \bar{h}, \bar{\theta}\right)} \tag{11}$$

$\bar{\mathcal{F}}$ is extended from crisp free energy function $\mathcal{F}$. In this way, the process of learning optimization can be turned into a fuzzy maximum likelihood problem. Since it is intractable to compute the fuzzy objective function, the Defuzzifying of fuzzy free energy function $\bar{\mathcal{F}}\left(v, \bar{\theta}\right)$ is important [10]. Then, the likelihood function can be defined by the defuzzified fuzzy free energy function. Consequently, the fuzzy optimization problem becomes real-valued problem [11], and conventional optimization approaches can be directly applied to find the optimal solutions. The centroid of fuzzy number $\bar{\mathcal{F}}\left(v, \bar{\theta}\right)$ is denoted by $\mathcal{F}_c\left(v, \bar{\theta}\right)$:

$$\mathcal{F}_c\left(v, \bar{\theta}\right) = \frac{\int \theta \mathcal{F}\left(v, \theta\right) d\theta}{\int \mathcal{F}\left(v, \theta\right) d\theta}, \quad \theta \in \bar{\theta} \tag{12}$$

Based on (12), the probability can be defined as

$$P_c\left(x, \bar{\theta}\right) = \frac{e^{-\mathcal{F}_c\left(v, \bar{\theta}\right)}}{Z}, \quad Z = \sum e^{-\mathcal{F}_c\left(v, \bar{\theta}\right)} \tag{13}$$

The objective function is the negative log-likelihood, demonstrated as follow

$$\mathcal{L}\left(\bar{\theta}, \mathcal{D}\right) = -\sum\nolimits_{x \in \mathcal{D}} \log P_c\left(x, \bar{\theta}\right) \tag{14}$$

In the process of learning FRBM, the defuzzification of fuzzy free energy function is the first step. The α-cuts of the fuzzy function have been proved is the feasible method to calculate the centroid. The α-cut of $\mathcal{F}_c\left(v, \bar{\theta}\right)$ can be defined as:

$$\mathcal{F}\left(v, \bar{\theta}\right)[\alpha] = \mathcal{F}\left(v, \bar{\theta}[\alpha]\right) = \left[\mathcal{F}\left(v, \theta_R\right), \mathcal{F}\left(v, \theta_L\right)\right] \tag{15}$$

According to (15), the approximate centroid can be defined as:

$$\mathcal{F}_c\left(v, \bar{\theta}\right) \approx \frac{1}{2}\left[\mathcal{F}\left(v, \theta_R\right) + \mathcal{F}\left(v, \theta_L\right)\right] \tag{16}$$

where we consider the fuzzy numbers belong to $\alpha = 1$. Then combined with (13), the problem come back to a regular optimization. It can be calculated through the gradient descend-based stochastic maximum likelihood method. After obtaining all the gradients, the CD learning and k-step Gibbs sampling are also used in FRBMsto obtain the approximation of the log-likelihood gradient.

3. EXPERIMENTAL AND RESULTS

The learning and classification capacity of the RBM and FRBM in radar detected targets have been tested on two datasets. One is three types of radar detected airplanes HRRP dataset, and another one is RCS dataset of three types of space moving targets. The training on noisy HRRP dataset is aim to compare the robustness of the two models. Besides, the traditional methods like KNN and SVDD have also been applied to these two datasets to compare with the RBM and FRBM models. The training on RCS dataset is considered to compare the learning capacity of the two models in unsupervised situation.

3.1. Multitarget Dataset Recognition under Supervised Learning

In this part, the experiment of training RBM and FRBM based on radar target HRRP dataset will be discussed. There are three types of airplanes ISAR data as Figure 1 demonstrated, every row shows one type airplane ISAR image.

As the Figure 1 has showed, the training data contains three airplanes HRRP results. The samples covered different pitch attitude of the airplanes. This experiment trained the algorithm

Input: $x^{(0)}$ is a training sample from the training distribution for the RBM;
ϵ is the learning rate for updating the parameters;
W^L and W^R are the visible-hidden connection weight matrix;
b^L and b^R are the bias vectors for input units;
c^L and c^R are the bias vectors for hidden units;
Output: The updated parameters in the RBM: W^L, b^L, c^L, W^R, b^R, c^R.
For all hidden units i do
Compute $P_L\left(h_i^{L(0)}=1|x^{(0)}\right)$ and $P_R\left(h_i^{R(0)}=1|x^{(0)}\right)$
Sample $h_i^{L(0)}\in\{0,1\}$ from $P_L\left(h_i^{L(0)}|x^{(0)}\right)$;
Sample $h_i^{R(0)}\in\{0,1\}$ from $P_R\left(h_i^{R(0)}|x^{(0)}\right)$;
End for
For all visible units j do
Compute $P_L\left(x_j^{L(1)}=1|h^{\mathrm{L}(0)}\right)$ and $P_R\left(x_j^{R(1)}=1|h^{\mathrm{R}(0)}\right)$
Sample $x_j^{L(1)}\in\{0,1\}$ from $P_L\left(x_j^{L(1)}|h^{\mathrm{L}(0)}\right)$;
Sample $x_j^{R(1)}\in\{0,1\}$ from $P_R\left(x_j^{R(1)}|h^{R(0)}\right)$;
End for
For all hidden units i do
Compute $P_L\left(h_i^{L(1)}=1|x^{\mathrm{L}(1)}\right)$ and $P_R\left(h_i^{R(1)}=1|x^{\mathrm{R}(1)}\right)$
Sample $h_i^{L(1)}\in\{0,1\}$ from $P_L\left(h_i^{L(1)}|x^{\mathrm{L}(1)}\right)$;
Sample $h_i^{R(1)}\in\{0,1\}$ from $P_R\left(h_i^{R(1)}|x^{R(1)}\right)$;
End for
$W^L=W^L+\epsilon\left(x^{(0)}\times P_L\left(h^{L(0)}=1|x^{(0)}\right)-x^{L(1)}\times P_L\left(h^{L(1)}=1|x^{\mathrm{L}(1)}\right)\right)$;
$b^L=b^L+\epsilon\left(x^{(0)}-x^{L(1)}\right)$;
$c^L=c^L+\epsilon\left(P_L\left(h^{L(0)}=1|x^{(0)}\right)-P_L\left(h^{L(1)}=1|x^{L(1)}\right)\right)$;
$W^R=W^R+\epsilon\left(x^{(0)}\times P_R\left(h^{R(0)}=1|x^{(0)}\right)-x^{R(1)}\times P_R\left(h^{R(1)}=1|x^{\mathrm{R}(1)}\right)\right)$;
$b^R=b^R+\epsilon\left(x^{(0)}-x^{R(1)}\right)$;
$c^L=c^R+\epsilon\left(P_R\left(h^{R(0)}=1|x^{(0)}\right)-P_R\left(h^{R(1)}=1|x^{\mathrm{R}(1)}\right)\right)$;
Output W^Lb^L, c^LW^R, b^Rc^R.

under supervised learning to verify and compare the classification capacity of FRBM with RBM model and other traditional radar target recognition classifier model like KNN and SVDD.

The FRBM and RBM model selected training data through batches and the batches are created randomly through the 39000 data points HRRP data sequence. The 39000 long datasets are combined with three types of airplanes datasets and mixed up randomly. There are 300 epochs, and each of the epochs contains 1000 batches. The training samples are randomly mixed with the three types of airplanes datasets and the algorithm denoted to learn the datasets and classifier the three airplane with the right labels. In the experiments, the FRBM and RBM model are set with 20 visible units and 100 hidden units and the learning algorithm is CD-1. The weight cost is 0.0002, and initialization of biases b and c are zero values. The learning rates for updating W, b and c are set to be 0.2. The average recognition accuracy in 20 times experiments of RBM model and FRBM model have been shown in Table 1.

Table 1: RBM and FRBM recognition result on three airplanes HRRP in supervised learning.

Algorithm Model	RBM	FRBM
Average Accuracy	89.1%	94.3%

It can be seen that among 20 times experiments, the FRBM has got 94.3% on average accuracy while the RBM has about 89.1% accuracy on average in the same conditions. Three Airplanes HRRP Supervised learning.

Besides of that, the line graphs of recognition accuracy in learning process of two models are demonstrated in Figure 2.

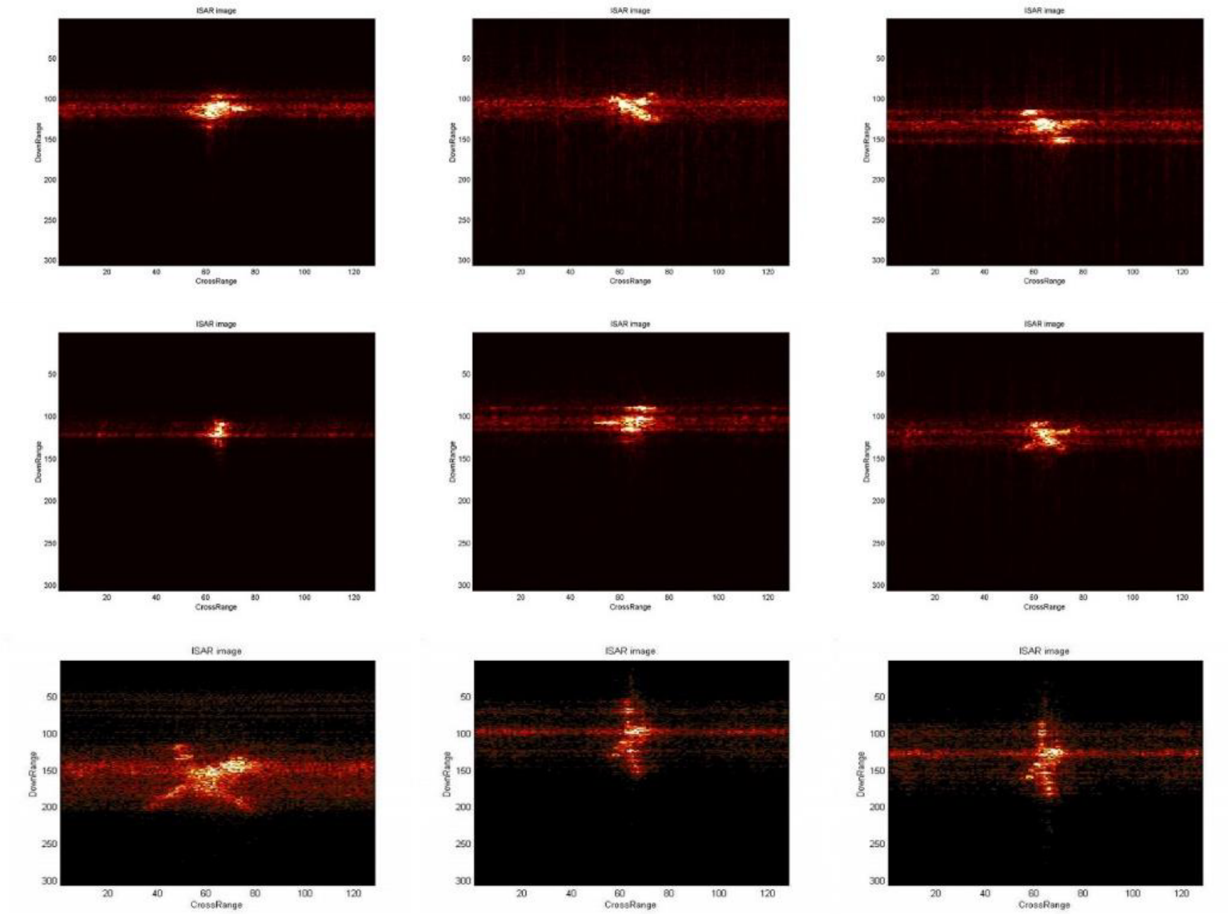

Figure 1: Three types of airplanes ISAR image data.

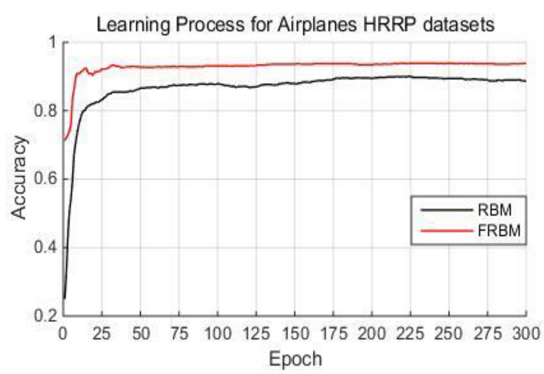

Figure 2: Learning process for RBM and FRBM on three airplanes HRRP datasets.

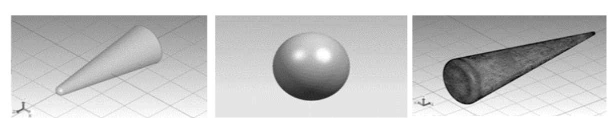

Figure 3: Three targets simulation model.

Compared with RBM model, the FRBM model stayed in stable recognition accuracy in fewer Gibbs steps (FRBM got stable accuracy in 50 epochs while RBM got stable after training with 125 epochs). In contrast, the training samples are also denoted to KNN and SVDD classifier and the recognition results are showed in the Table 2. It is easy to find that the RBM and FRBM model has achieved higher accuracy in the experiment.

As a conclude, FRBM has more power representation capability and learning productivity than RBM in HRRP datasets experiment. The fuzzy relationship between visible and hidden units can be considered as the contribution of this result, which reduce the computation amount of the collection weight and biases among hidden units and visible units.

Table 2: Recognition results on three airplanes HRRP datasets in supervised learning.

Algorithm	Recognition Accuracy
KNN	82.3%
SVDD	85.7%
RBM	88.9%
FRBM	94.3%

3.2. Multi-target Dataset Recognition under Unsupervised Learning

Automatic learning and recognition space moving target from its similar flying objects is always the core of military radar target recognition, and most of the recognition situation of space moving target is unsupervised learning. In this experiment, unsupervised learning has been carried out for the FRBM and RBM model on space moving targets RCS datasets. There are three types of targets simulation models have been demonstrated in Figure 2. From the left to right, there are cone-shaped target 1, Spherical target and cone-shaped target 2 in turns.

The algorithm aims to classify the cone-shaped target 1 from the Spherical target and cone-shaped target 2.

It should be noticed is that in this experiment, the training dataset of targets RCS is only 1600 points length which contains three types of targets in different angle of pitch. The angle of pitch ranges from 0°, 5°, 10°, 20°. In this stage, the numbers of training samples are limited. From the Table 3, it is reasonable to find that the FRBM and RBM outperforms the regular classifier models. Besides the FRBM has showed greater learning and representation capacity as its probability is increased with 4.4% by relaxing restrictions on the relationships between cross-layer units.

Table 3: Recognition results on three space moving targets RCS datasets.

Algorithm	Recognition Accuracy
KNN	76.4%
SVDD	80.7%
RBM	86.2%
FRBM	90.6%

3.3. Noisy Target Dataset Recognition

In order to exam the robustness of the FRBM model, this paper replaced the training samples with noisy training samples. The FRBM and RBM are respectively trained with noisy above HRRP samples which have been separately added with Salt & Pepper (S&P) noise and Gaussian noise at 20 dB, 10 dB and 5 dB are illustrated in the Table 4.

Table 4: RBM and FRBM HRRP data recognition in noisy intervention.

SNR	Accuracy of RBM	Accuracy of FRBM
S&P	82.6%	93.8%
20 dB	818%	93.3%
10 dB	773%	91.7%
5 dB	71.4%	89.5%

The FRBM has showed the greater capacity of robustness than RBM through the Table 4. It can be seen that in the Salt & Pepper noise, the recognition accuracy of FRBM has kept a stable recognition accuracy, but the RBM model has showed a slight drop on recognition accuracy. In the aspect of the capacity of the resistance of Gaussian noise, RBM has experienced a prominent descent on recognition accuracy with the increase of SNR of the noise, while the FRBM has also demonstrated the great robustness of noise.

4. CONCLUSION

This paper proposed a FRBM model to improve the representation capability in radar multi-targets recognition and robustness in noisy situation recognition. These advantages can be concluded as the fuzzy numbers replace the regular connection weighs and biases between visible and hidden units. These structure extended the input and its high dimensional representation features through relaxing the random variable which denoted to the relationship of visible units and hidden units. Therefore, the FRBM has more powerful representation capability than the regular RBM. On the other hand, the robustness of the FRBM is also more powerful than the RBM model. These merits attribute to the fuzziness of the FRBM model.

This paper examined the FRBM and RBM model in supervised and unsupervised methods. The recognition and representation capability of the proposed model have been verified in the experiments carried on radar target HRRP airplanes classification and radar RCS space moving targets classification. The powerful robustness of the FRBM model is also examined on HRRP airplanes dataset with different levels of noises. From those experiments, it can be concluded that the representation capability of proposed FRBM is better than the RBM. Besides of that, the FRBM also shows out more powerful robustness that is necessary to address the noisy problem in the applications of radar target unsupervised learning and automatic recognition.

The application to the radar target priority recognition, such as model construction and learning process productivity are still unsolved problems in these experiments. For the model selection problem, how to decide the number of hidden units and how many hidden layers in deep architectures is always hard to determine, which impact the performance ability of dimensional features representation and the training time of the learning process. For the learning process productivity problem, the computational cost of training their deep architectures are so high that needs to be speed up in some more efficient optimization approaches to apply in real radar target recognition within few recognition time. After proving the FRBM and RBM can be pertinently improved to be applied in radar target recognition and classification especially in the field of airplanes and space moving targets recognition situation, with small size of samples and noise interference, the corresponding learning algorithm such as fuzzy multi-layers RBM and fuzzy deep belief networks can be concerned in the future experiment to verity the automatic recognition of radar target.

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