A NOVEL RADAR SIGNAL RECOGNITION METHOD BASED ON A DEEP RESTRICTED BOLTZMANN MACHINE

Dongqing Zhou* – Xing Wang – Yuanrong Tian – Rujia Wang

Aeronautics and Astronautics Engineering College, Air Force Engineering University, Shannxi Xi'an, 710038

ARTICLE INFO

***Article history*:**
Received: 28.6.2015.
Received in revised form: 24.10.2015.
Accepted: 26.10.2015.
Keywords:
Radar signal recognition
Deep learning
Restricted Boltzmann machine
RSRDRBM

Abstract:

Radar signal recognition is of great importance in the field of electronic intelligence reconnaissance. To deal with the problem of parameter complexity and agility of multi-function radars in radar signal recognition, a new model called radar signal recognition based on the deep restricted Boltzmann machine (RSRDRBM) is proposed to extract the feature parameters and recognize the radar emitter. This model is composed of multiple restricted Boltzmann machines. A bottom-up hierarchical unsupervised learning is used to obtain the initial parameters, and then the traditional back propagation (BP) algorithm is conducted to fine-tune the network parameters. Softmax algorithm is used to classify the results at last. Simulation and comparison experiments show that the proposed method has the ability of extracting the parameter features and recognizing the radar emitters, and it is characterized with strong robustness as well as highly correct recognition rate.

1 Introduction

Radar signal recognition is a key procedure in electronic support measure system, and it is a fundamental problem in solving threat efficiency evaluation and jamming decision making in modern electronic warfare. Radar signal recognition is widely used in detecting and identifying navigation or aviation radars deployed on ships or airplane in civilian applications [1,2]. Meanwhile, in battlefield surveillance application, radar signal recognition provides an important means to detect targets employing radars, especially those from hostile forces.

The more drastic the modern electronic warfare is, the more high-tec radars are set into use and become dominant [3]. The modulation methods of these radar signals are diverse and complicated. Furthermore, radar signals are overlapped in parameter space, and electromagnetic circumstance becomes denser. As a result, the traditional signal identification methods which are based on five radar parameter features, such as, pulse repetition interval (PRI), direction of arrival (DOA), pulse frequency (PF), pulse width (PW), pulse amplitude (PA), are unsuitable for modern electronic warfare. For this reason, some scholars extract the intra-pulse information to recognize the radar emitter. Lopez-Risueno used atomic decomposition [4] to extract the time-frequency characteristics of signals. Zhang applied the wavelet packet transform method to radar signal recognition [5], and then in [6], the author proposed a novel intra-pulse feature extraction approach which is called resemblance coefficient. Li investigated the abundant information of the cyclostationary signatures to recognize radar signal [7].

* Corresponding author. *E-mail address: zhoudongqing.523@gmail.com.*

These recognition methods based on intra-pulse information achieve better performance of varying degrees than those using conventional methods although the drawbacks of these algorithms are still obvious. Firstly, these algorithms are sensitive to noise. They always get good recognition accuracy results in high SNR (signal to noise ratio), but by decreasing SNR, the recognition accuracy results are decreased. Secondly, these algorithms map the original data from low-dimension space to high-dimension before the feature parameters extraction, which could lose the important information of the original radar emitter data in transformation. These feature extraction methods could affect the recognition accuracy and algorithm stability.

Deep learning has been a new area of machine learning research since 2006. It is about learning multiple levels of representation and abstraction that helps to make sense of data. A series of scholars, workshops and institutions have been devoted to deep learning and its application in signal processing, such as image, sound and document. Hinton develops the original deep belief network (DBN) and deep auto-encoder to solve the image recognition [8]. Collobert investigated a convolutional DBN model to solve the language processing problem [9]. Ranzato proposed a novel approach by using DBN and deep auto-encoder to solve the document indexing and retrieval in [10]. These applications based on deep learning method get better results because of its excellent performance in feature extraction and recognition.

In this paper, a novel recognition model which is called RSRDRBM (radar signal recognition based on deep restricted Boltzmann machine) is proposed to solve the radar signal recognition problem. RSRDRBM is based on deep learning method, and composed of multiple restricted Boltzmann machines. Compared with the previously radar emitter recognition method, the proposed algorithm has three advantages. Firstly, the proposed algorithm extracts the feature parameter from the original radar emitter pulse data and it does not need the feature design stage. It could avoid the information losing in transformation. Secondly, the proposed algorithm uses the multiple hidden layers to extract the feature of the radar signal samples, which makes feature extraction more effective. Thirdly, the proposed algorithm is not sensitive to noise and has the stronger robustness performance.

The rest of the paper is organized as follows. The deep learning method is introduced in section 2. Section 3 gives a description of RSRDRBM model. And then, the experimental results of the proposed algorithm in comparison with another approach are shown in section 4. At last, the conclusions are summarized in Section 5.

2 Deep learning method

The most traditional machine learning methods use a single hidden layer to do nonlinear feature transformation. This model is called shallow learning model in general [11], which maps the input data or feature into a higher feature space to complete the classification or recognition. For example, support vector machines (SVMs), Gaussian mixture models (GMMs) and hidden Markov models (HMMs), are all part of a shallow learning model.

Deep learning is a novel machine learning method which is used to extract the essential feature from the original data by hierarchical architectures. Compared with a traditional feature extraction method, the deep learning model is composed of multiple hidden layers. This multi-layer perceptron could extract feature from the original dataset more effective and doesn't need the feature design stage.

Restricted Boltzmann machine (RBM) is a special model for deep learning method, which can be represented as bipartite graph consisting of a layer of visible units and a layer of hidden units with no visible-visible or hidden-hidden connections. It is essential to train RBMs carefully that could apply deep learning to practical problems successfully.

In a RBM, the joint distribution function $P(v,h;\theta)$ is defined as [12]:

$$P(v,h;\theta)=\frac{1}{Z}\exp(-E(v,h;\theta)) \tag{1}$$

In (1), v and h are visible units and hidden units, respectively. θ represents model parameters. $E(v,h;\theta)$ is the energy function. For a RBM consisting of n visible units v_i and m hidden units h_j, the energy function is defined as:

$$E(v,h)=-\sum_{i=1}^{n}\sum_{j=1}^{m}v_ih_jw_{ij}-\sum_{i=1}^{n}b_iv_i-\sum_{j=1}^{m}a_jh_j \tag{2}$$

where b_i and a_j are the bias terms. The parameter w_{ij} is the symmetric interaction term between visible unit v_i and hidden unit h_j.

The conditional probabilities can be calculated as:

$$P(h_j=1\mid v;\theta)=\sigma(\sum_{i=1}^{n} v_i w_{ij}+a_j) \tag{3}$$

$$P(v_i=1\mid h;\theta)=\sigma(\sum_{j=1}^{m} h_j w_{ij}+b_i) \tag{4}$$

where $\sigma(x)=(1+e^{-x})^{-1}$ [13].
The energy function for Gaussian (visible) -Bernoulli (hidden) RBM is presented as follows:

$$E(v,h;\theta)=-\sum_{i=1}^{n}\sum_{j=1}^{m} v_i h_j w_{ij}+\frac{1}{2}\sum_{i=1}^{n}\left(v_i-b_j\right)^2-\sum_{j=1}^{m} a_j h_j \tag{5}$$

Then, the conditional probabilities are (6) and (7),

$$P(h_j=1\mid v;\theta)=\sigma(\sum_{i=1}^{n} v_i w_{ij}+a_j) \tag{6}$$

$$P(v_i\mid h;\theta)=N(\sum_{j=1}^{m} h_j w_{ij}+b_i,1) \tag{7}$$

where the value of vi is real and satisfies the Gaussian distribution (the mean equals $\sum_{j=1}^{m} h_j w_{ij}+b_i$ and variance equals 1, respectively).
The update rule of the RBM weights uses the gradient of the log likelihood as:

$$\Delta w_{ij}=E_{data}\left(v_i h_j\right)-E_{model}\left(v_i h_j\right) \tag{8}$$

where $E_{data}(v_i h_j)$ is the expectation observed in the training set and $E_{model}(v_i h_j)$ is the expectation defined by the model.

3 RSRDRBM model

3.1 Description of RSRDRBM

In this section, the RSRDRBM model is introduced. This model has two main procedures: a training process and a test process. In the training process, the intercepted original data is divided into several groups in order to decrease the algorithm complexity in pre-processing, after that the parameters in deep neural networks are optimized. In the test process, the test signals are classified into several different kinds with Softmax algorithm.

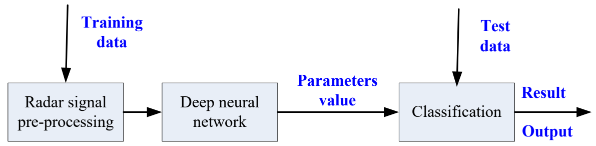

Figure 1. The procedure of RSRDRBM model.

Assume $X=(x_1\ldots\ x_i\ ,\ldots,\ x_m)$ is the dataset to be processed, which consists of m samples and sample $x_i \in R^n$. The deep neural network of RSRDRBM model is composed of multiple RBMs, which extract the feature parameters from the data vector X. The state of the first hidden layer is as follows:

$$h_1=\sigma\left(W_1^T X+b_1\right) \tag{9}$$

where $\sigma(x)=(1+e^{-x})^{-1}$, W_1 and b_1 are the parameters of the network. For the deep l layer neural work, we use greedy algorithm to initialize each layer. The state of i^{th} hidden layer is

$$h_i=1/\left(1+\exp\left(-h_{i-1}\cdot W_i^T+b_i\right)\right) \tag{10}$$

where $h_0=X$, $\forall i\in\{1,2,\cdots\ \ell$.
Then, the back propagation (BP) algorithm is used to fine-tune the network parameters in order to get the global optimum of the weight vector

$$J(W,b)=\left[\frac{1}{m}\sum_{i=1}^{m}\frac{\partial}{\partial W_{ij}^{(l)}}J\left(W,B;x^{(i)},y^{(i)}\right)\right]+\lambda W_{ij}^{(l)} \tag{11}$$

$$\begin{cases}\dfrac{\partial}{\partial W_{ij}^{(l)}}J(W,b)=\left[\dfrac{1}{m}\displaystyle\sum_{i=1}^{m}\dfrac{\partial}{\partial W_{ij}^{(l)}}J\left(W,b;x^{(i)},y^{(i)}\right)\right]+\lambda W_{ij}^{(l)}\\ \dfrac{\partial}{\partial b_i^{(l)}}J(W,b)=\dfrac{1}{m}\displaystyle\sum_{i=1}^{m}\dfrac{\partial}{\partial b_i^{(l)}}J\left(W,b;x^{(i)},y^{(i)}\right)\\ W_{ij}^{(l)}=W_{ij}^{(l)}-\alpha\dfrac{\partial}{\partial W_{ij}^{(l)}}J(W,b)\\ b_i^{(l)}=b_i^{(l)}-\alpha\dfrac{\partial}{\partial W_i^{(l)}}J(W,b)\end{cases} \tag{12}$$

where $J(W,b)$ is the cost function, and α is the step length coefficient.
Softmax regression is used to classify the radar signal after the training process. This model generalizes logistic regression to classification where the class label can take on more than two possible values.

For k classes and m sample data vector $\{(x^{(1)},y^{(1)}), (x^{(2)},y^{(2)}), \ldots (x^{(i)},y^{(i)}), \ldots, (x^{(m)},y^{(m)})\}$, the class label probability is estimated as:

$$p(y^{(i)} = j \mid x^{(i)};\theta) = e^{\theta_j^T x^{(i)}} / \sum_{\ell}^{k} e^{\theta_\ell^T x^{(i)}}, j = 1,2,\cdots \quad (13)$$

where $\sum_{\ell=1}^{k} e^{\theta_\ell^T x^{(i)}}$ is the normalization to make sure that the sum of possibility of sample x belongs to k classes.

At last, the cost function is used to train the parameter θ and it is guaranteed to have a unique solution:

$$J = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=1}^{k}\{y^{(i)} = j\}\log\frac{e^{\theta_j^T x^{(i)}}}{\sum_{\ell=1}^{k} e^{\theta_\ell^T x^{(i)}}}\right] + \frac{\lambda}{2}\sum_{i=1}^{k}\sum_{j}^{n}\theta_{ij}^2 \quad (14)$$

where $\{y^{(i)} = j\} = 1$ if the result j equals label $y^{(i)}$; otherwise, $\{y^{(i)} = j\} = 0$.

3.2 Radar signal recognition algorithm based on RSRDRBM

RSRDRBM neural network model is composed of the input layer, hidden layer and output layer. For the recognition algorithm based on RSRDRBM model in this paper, we consider three RBM layers in the hidden layer and the number of neuron in these layers are 1000, 500 and 100. The number of neuron in Softmax regression is set to 8 owing to 8 radar signals. The flowchart is shown in Figure 2 and detail steps are presented as follows.

Step 1: Data pre-processing. This step randomly transforms the original radar signal pulse into p data vectors, each vector having q data. The preprocessing could increase the decidability of the data vector, while decreasing the complexity of the model.

Step 2: Parameters optimization. This step uses multiple hidden layers to train the radar signals. The parameter setting is the key point in this step which is divided into two parts: first, the weight W_i of each hidden layer is tuned though the unsupervised learning so that the state of tuned layer is the input of the next hidden layer. Second, the supervised BP algorithm is conducted to fine-tune the whole network parameters. Meanwhile, the momentum parameter is introduced to prevent the data overfitting.

Step 3: Classification. This step uses Softmax regression to classify the tested radar signals and output the recognition result.

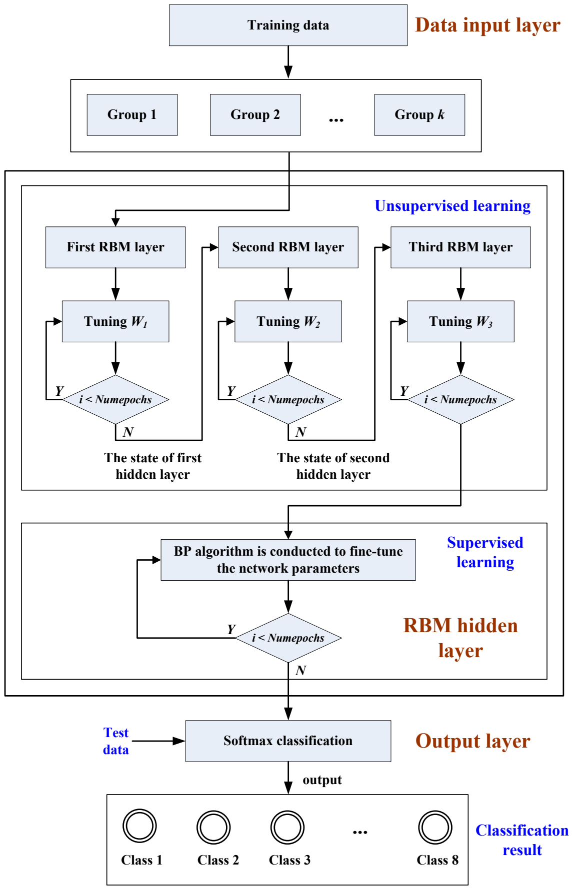

Figure 2. The flowchart of RSRDRBM algorithm.

4 Experiment result

In our experiment, 8 different radar signals [14] are used to test the proposed algorithm. These signals are continuous wave (CW), phase-shift keying (PSK), differential phase-shift keying (DPSK), frequency-shift keying (FSK), simple pulse (SP) and pulse compression. The pulse compression signal contains linear frequency modulation (LFM), non-linear frequency modulation (NFLM), and a phase encoding (PE) signal. The modulating slope of LFM is 1, the NLFM is modulated by a sinusoidal function, and PE uses 13 barker codes. We assume that noise accompanying a radar signal is white Gaussian noise, the learning rate and the momentum parameters are set to 0.1 and 0.001, respectively.

We generate 600 radar sample pulses with -20 dB, -15 dB, -10 dB, -5 dB, 0 dB, 5 dB, 10 dB and 15 dB SNR separately. 500 radar sample pulses are used to train data vector while other 100 samples are used to test the algorithm. Three algorithms, which use bispectrum cascade feature (BC) [14], rough set theory (RS) and time-frequency atom features (TFA), are adopted to compare with RSRDRBM.The whole radar signal recognition correct rate is defined as:

$$P_r = \frac{N_r^1 + N_r^2 + \cdots}{N^1 + N^2 + \cdots} \tag{15}$$

Each radar signal recognition correct rate is defined as:

$$P_r^i = \frac{N_r^i}{N^i} \qquad i = 1, \cdots \tag{16}$$

where P_r is the whole radar signal recognition correct rate, P^i_r is the i^{th} radar signal recognition correct rate, N^i_r is the correct recognition number of the i^{th} radar signal, N^i is the total number of the i^{th} radar signal.

As shown in Figure 3, it is the comparison experiment of recognition performance in different SNR obtained from the model RSRDRBM against BCF, RS, TFA algorithms.

From an overall perspective, the RSRDRBM shows the best performance against other models. In detail, when SNR>5dB, the recognition probability of RSRDRBM is 100% and better than others which have a neck-to-neck performance; When SNR decreases to -10 dB, model RS, and TFAF show significant performance degradation and the performance of BCF decreases slightly, while RSRDRBM still retains its perfect performance; When SNR is lower than -10dB, the performance of RSRDRBM starts to decrease, but it is still better than the others.

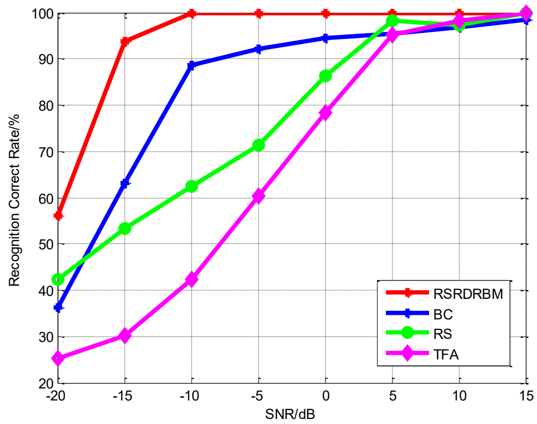

Figure 3. The recognition performance of different algorithms.

The reason why RSRDRBM shows such a good performance is that it adopts a multi-hidden layer RBM based on a deep neural network model to do data analysis and feature extraction of radar emitter signals, which reserve the basic features of original data. Moreover, this model is not sensitive to the noise and it has a strong robustness.

In Figure 4 there are recognition results of different radar signals obtained from RSRDRBM. When SNR > -10 dB, RSRDRBM has a recognition probability of 100% for all the tested radar emitter signals; when SNR < -10dB, the recognition performance of RSRDRBM starts to decrease, and the degree of decrease differs under different kinds of radar emitter signals. When SNR = -15dB, the recognition rate of RSRDRBM is no less than 90% for signal CW, PSK, DPSK, FSK, PE, and LFM, followed by NLFM and SP. When SNR=-20dB, the recognition rates of signal CW, PSK, DPSK, FSK range from 70% to 80%, and that of signal SP, NLFM, and PE range from 40% to 50%, unfortunately, the recognition rate of signal LFM is below 20%.

In order to further analyze the recognition ability of RSRDRBM on different kinds of radar emitters, we show the recognition results and confusion matrix of them on Table 1 and Table 2. Seen from Table 1 and Table 2, there exists misclassification between signals SP, LFM, NLFM, and PE when SNR = -15 dB, because the noise affects the modulation characteristics of SP a lot. When SNR = -20 dB, all other signals have the probability of being misclassified as SP, which is why the modulation characteristics of SP gets less obvious with an increase in noise level.

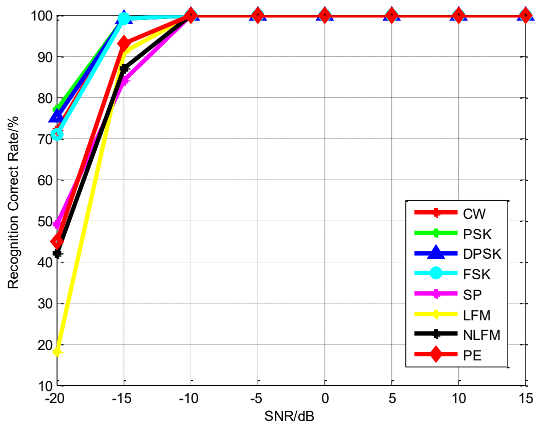

Figure 4. The recognition performance of different radar signal in RSRDRBM algorithm..

Table 1. Confusion matrix in -15 dB SNR

	CW	PSK	DPSK	FSK	SP	LFM	NLFM	PE
CW	99	0	0	0	0	1	0	0
PSK	0	99	0	0	0	0	1	0
DPSK	0	0	99	0	0	1	0	0
FSK	0	0	0	99	0	1	0	0
SP	0	1	0	3	84	5	4	3
LFM	0	0	0	0	4	91	3	2
NLFM	0	1	3	1	4	4	87	0
PE	1	0	0	0	1	2	3	93

Table 2. Confusion matrix in -20 dB SNR

	CW	PSK	DPSK	FSK	SP	LFM	NLFM	PE
CW	72	9	3	1	2	3	7	3
PSK	0	77	1	0	10	2	6	4
DPSK	1	1	75	3	9	3	4	4
FSK	3	6	3	71	10	0	7	0
SP	3	7	6	3	49	8	21	3
LFM	4	5	6	7	32	18	22	6
NLFM	6	7	7	5	21	5	42	7
PE	0	10	6	3	15	5	16	45

In addition, the confusion between PSK, NLFM and FSK is high as there is some similarity in their modulation type

5 Conclusion

This paper takes the advantage of the powerful feature extraction ability of deep neural network to do radar signal recognition task, and proposes a radar signal recognition model based on deep restricted Boltzmann machine (RSRDRBM). RSRDRBM can extract the discriminative feature from the radar signals to carry out classification and recognition task. It does a training process layer by layer firstly, and then it fine-tunes the parameters in the whole networks with BP algorithms, and recognizes radar signals at last. The experiment on several kinds of radar signals proves the efficiency of the RSRDRBM model, especially on low SNR environment. It shows that this model has a powerful recognition ability and strong robustness. But the high computational complexity is one of its shortcomings, and the number of hidden layers is an issue to be discussed and analyzed. Therefore, this open question will be answered in our future works dealing with radar signals with deep learning.

References

[1] Liu J., Lee, J.P.Y, Li L, et al.: *Online Clustering Algorithms for Radar Emitter Classification*, IEEE Transactions on Pattern Analysis & Machine Intelligence, 27 (2005), 8, 1185-1196.

[2] Yan M, Wang L.: *Weighted Kalman filter phase unwrapping algorithm based on inSAR image*. Engineering Review, 33 (2013), 3, 227-231.

[3] Visnevski, N., Krishnamurthy, V., Wang, A., Haykin, S.: *Syntactic modeling and signal processing of multifunction radars: a stochastic context-free grammar approach*,

Proceedings of the IEEE. 95 (2007), 5, 1000–1025.

[4] Lopez-Risueno, G.: *Atomic decomposition - based radar complex signal interception*, IEEE Proceedings Radar Sonar & Navigation, 150 (2003), 4, 323-331.

[5] Jin, W., Zhang, G., Hu, L.: *Radar Emitter Signal Recognition Using Wavelet Packet Transform and Support Vector Machines,* Journal of Southwest Jiaotong University, 14 (2006), 1, 115-22.

[6] Zhang, G., Jin, W., Hu, L. et al.: *Resemblance Coefficient Based Feature Selection Algorithm for Radar Emitter Signals,* Chinese Journal of Electronics. 21 (2005), 6, 337-341.

[7] Li, L., Ji, H.: *Radar emitter recognition based on cyclostationary signatures and sequential iterative least-square estimation,* Expert Systems with Applications, 38 (2011), 3, 2140–2147.

[8] Hinton, G. E., Osindero, S., Yw. T. *A fast learning algorithm for deep belief nets,* Neural Computation, 18 (2006), 7, 2006.

[9] Collobert, R., Weston, J.: *A unified architecture for natural language processing: Deep neural networks with multitask learning,* Proceedings of. ICML, 2008.

[10] Lecun, Y., Chopra, S, Ranzato, M., et al.: *Energy - Based Models in Document Recognition and Computer Vision*, Proceedings of the Ninth International Conference on Document Analysis and Recognition - Volume 01. IEEE Computer Society, 2007, 337-341.

[11] Deng, L.: *A tutorial survey of architectures, algorithms, and applications for deep learning,* Apsipa Transactions on Signal & Information Processing, 2014, 3.

[12] Yu, D., Deng, L.: *Deep learning and its applications to signal and information processing,* IEEE Signal Processing Magazine, 28 (2011), 1, 145 - 154.

[13] Bengio, Y.: *Learning Deep Architectures for AI,* Foundations & Trends03 in Machine Learning, 2009, 2.

[14] Wang, S., Zhang, D., Bi, D.: *Research on recognizing the radar signal using bispectrum cascade feature,* Journal of Xidian University. 39(2012), 2, 127-132.