A Novel Radar Signal Recognition Method based on Deep Learning

Dongqing Zhou, Xing Wang, Yuanrong Tian, Ruijia Wang
Aeronautics and Astronautics Engineering College, Air Force Engineering University, Shannxi Xi'an, 710038

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 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 machine. A bottom-up hierarchical unsupervised learning is used to obtain the initial parameters, and then the traditional BP algorithm is conducted to fine-tune the network parameters, softmax is used to classify the results at last. Simulation and comparison experiment show that the proposed method has the ability of extracting the parameter features and recognizing the radar emitters, and it has strong robustness as well as high correct recognition rate.
Keywords: Radar signal recognition, Deep learning, Restricted Boltzman machine, RSRDRBM

1 Introdution

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]. Meanwhile, in battlefield surveillance application, radar signal recognition provides an important means to detect targets employing radars, especially those from hostile forces.

More drastic as modern electronic warfare being, more high-tec radars are set into use and become dominant[2]. The modulation methods of these radar signals are diverse and complicated. Further more, radar signals are overlapped in parameter space, and electromagnetic circumstance becomes more density. 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 to the modern electronic warfare. For this reason, some scholars extract the intra-pulse information to recognize the radar emitter. Lopez-Risueno uses atomic decomposition[3] to extract the time-frequency characteristics of signals. Zhang applies the wavelet packet transform method to radar signal recognition[4], and then in [5], the author proposes a novel intrapulse feature extraction approach which called resemblance coefficient. Li investigates the abundant information of the cyclostationary signatures to recognize radar signal[6]. Although these proposed algorithms achieve better performance of varying degrees than conventional methods, the drawbacks are still obvious. Firstly, the algorithms are sensitive to noise. They always get good recognition accuracy results in high SNR, on the contrary, the recognition accuracy results decrease with the SNR decreasing. 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 transforming. These feature extraction methods could affect the recognition accuracy and algorithm stability.

Deep learning is a new area of machine learning research since 2006 [7]. It is about learning multiple levels of representation and abstraction that help to make sense of data. A series of scholars, workshops

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and institutions have been devoted to deep learning and its application in signal processing, such as image, sound, video, and document. Hinton develops the original DBN and deep auto-encoder to solve the image recognition [7], and then he proposes a modified DBN where the top-layer model uses a third-order Boltzmann machine in 3-D object recognition [8]. In [9], Collobert and Weston investigate a convolutional DBN model to simultaneously solve language processing problem. Ranzato proposes a novel approach by using DBN and deep auto-encoder to solve the document indexing and retrieval in [10].

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 machine. This neural network model could extract the feature in original data, so it could get better recognition accuracy and algorithm stability.

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 alogrithm in comparison with other approach are shown in section 4. At last, the conclusions are summarized in section 5.

2 Deep Learning Method

Most machine learning and signal processing technology have exploited shallow-structured architectures which contain a single layer of nonlinear feature transformations [11]. For example, Gaussian mixture models (GMMs), hidden Markov models (HMMs), conditional random fields (CRFs), maximum entropy(MaxEnt) models, support vector machines (SVMs) and multi-layer perceptron (MLP) neural network with a single hidden layer including extreme learning machine. These shallow learning models is a simple architecture which only contains one layer for transforming. It often maps the input signals or features into a higher feature space to complete the classification or recognition.

Deep learning is a novel machine learning method which is based on unsupervised feature learning and hierarchical architectures. The goal of it is to exploit the pattern analysis or classification, and the essence of it is to compute hierarchical features or representations of the observational data. Compared with traditional feature extraction method, deep learning could extract the efficacious feature from the original dataset, it doesn't need the feature design stage. What's more, deep learning focuses on the model structure which is composed of multiple hidden layers built by non-linear function composition. Multi-layer perceptron with many hidden layers are used to extract internal representation and build the feature matrix from rich sensory inputs.

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 $P(\mathrm{v,h};\theta)$ over the visible units v, hidden units h and model parameters θ, is defined in terms of an energy function $E(\mathrm{v,h};\theta)$ of

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

For a RBM consisting of n visible units v_i and m hidden units h_j, the energy function is defined as

$$E(v,h)=-\sum_{i=1}^{n}\sum_{j=1}^{m}v_i h_j w_{ij}-\sum_{i=1}^{n}b_i v_i-\sum_{j=1}^{m}a_j h_j \qquad (2)$$

where w_{ij} is the symmetric interaction term between visible unit v_i and hidden unit h_j, b^i and a^j are the bias terms.

The conditional probabilities can be calculated as

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

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

where $\sigma(x)=(1+e^{-x})^{-1}$[12].

The energy function for Gaussian(visible)-Bernoulli(hidden) RBM is presented

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

Then, the corresponding conditional probabilities are

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

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

where v_i takes real values and follows Gaussian distribution with mean $\sum_{j=1}^{m}h_j w_{ij}+b_i$ and variance 1.

We derive the update rule of the RBM weights by taking the gradient of the log likelihood log$p$(v; θ) as follow

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

where $E_{\text{data}}(v_i h_j)$ is the expectation observed in the training set and $E_{\text{model}}(v_i h_j)$ is that same expectation under the distribution defined by the model. But $E_{\text{model}}(v_i h_j)$ is intractable to compute so the contrastive divergence (CD) approximation to the gradient is used where $E_{\text{model}}(v_i h_j)$ is replaced by running the Gibbs sampler initialized at the data for one full step.[13]

3 RSRDRBM Model

3.1 Description of RSRDRBM

In this section, the RSRDRBM model is introduced. This model has two main procedures: training process and 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, then the parameters in the deep neural networks are optimized. In the test process, the test signals are classified into several different kinds by softmax algorithm.

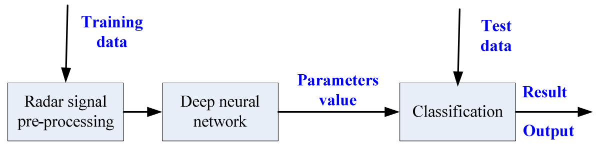

Fig. 1 The procedure of RSRDRBM model

For the pre-processed data vector $X=(x_1,\ldots, x_i,\ldots,x_m)$ with m samples, where 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 follow

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

where $\sigma(x)=1/(1+e^{-x})$, W_1 and b_1 are the parameters of the network. For the l layers deep neural work, we use greedy algorithm to initialize each layer. The state of ith 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, BP algorithm is used to fine-tune the network parameters in order to get the global optimum of weight vector.

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

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

where $J(W,b)$ is the cost function, α is the step l ength coefficient.

Softmax regression is used to classify the radar signal after the training process. This model

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generalizes logisitic regression to classification where the class label can take on more than two possible values.

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

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

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

At last, the cost function is used to train the parameter θ and 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 input layer, hidden layer and output layer. For the recognition algorithm based on RSRDRBM model in this paper, we consider three RBM layers in 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 fig.2 and detail steps are presented as flows.

Step1: Data pre-processing. This step randomly transforms the original radar signal pulse into p data vectors, each vector has q data. The preprocessing could increase the decidability of the data vector, while decreasing the complexity of the model.

Step2: parameter optimization. This step uses multiple hidden layers to train the radar signals. The parameter setting is the key points in this step which is divided into two parts: first, the weight W_i of each hidden layer is tuned though the unsupervised learning, 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.

Step3: Classification. This step uses softmax regression to classify the tested radar signals and output the recognition result.

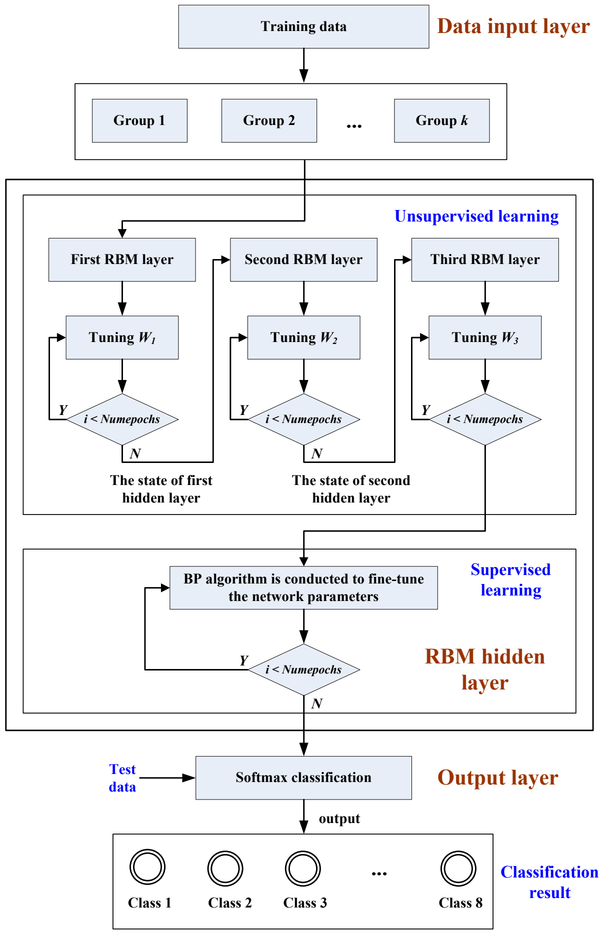

Fig.2 The flowchart of RSRDRBM algorithm

3 Experiment Result

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

We generate 600 radar sample pulses with -20dB, -15dB, -10dB, -5dB, 0dB, 5dB, 10dB and 15dB SNR separately. 500 radar sample pulses are used to train data vector while other 100 sample are used to test the algorithm. Three algorithms, which use bispectrum cascade feature (BC)[14], rough set theory (RS)[15] and time-frequency atom features (TFA)[16], are adopted to compare with RSRDRBM.

The whole radar signal recognition correct rat e is defined as:

$$P_r = \frac{N_r^1 + N_r^2 + \cdots + N_r^8}{N^1 + N^2 + \cdots + N^8} \tag{15}$$

The each radar signal recognition correct rate is defined as::

$$P_r^i = \frac{N_r^i}{N^i} \qquad i = 1, \cdots, 8 \tag{16}$$

Where P_r is the whole radar signal recognition correct rate, $P^i{}_r$ is the ith radar signal recognition correct rate, $N^i{}_r$ is the correct recognition number of the ith radar signal, N^i is the total number of the ith radar signal.

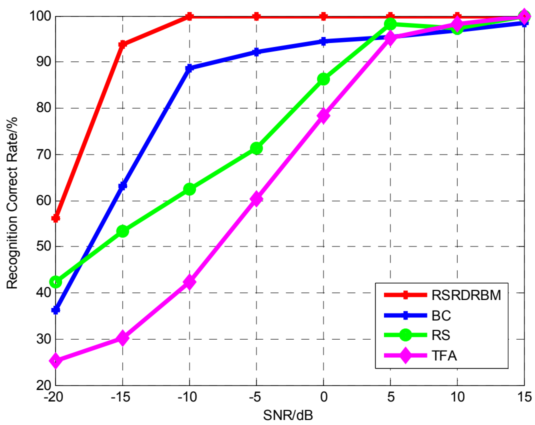

Fig.3 The recognition performance of different algorithms

As shown in Fig.3, it is the comparison experiment of recognition performance in different SNR obtained from model RSRDRBM against BCF, RS, TFA algorithms. From an overall perspective, RSRDRBM shows the best performance against other models. In detail, when SNR>5dB, the recognition probability of RSRDRBM is 100% and better than the others, which have a neck-to-neck performance; When SNR decreases to -10dB, model RS, and TFAF show significant performance degradation and the performance of BCF decreases slightly, while RSRDRBM still has a perfect performance; When SNR is lower than -10dB, the performance of RSRDRBM starts to decrease, but still better than the others. The reason RSRDRBM shows such a good performance is that it adopts a multi-hidden layer RBM based 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.

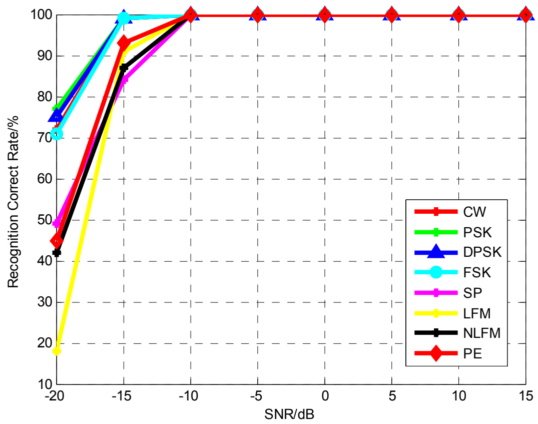

Fig.4 The recognition performance of different radar signal in RSRDRBM algorithm

Fig.4 is the recognition results of different radar signals obtained from RSRDRBM. When SNR>-10dB, 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 ranges from 40% to 50%, unfortunately, the recognition rate of signal LFM is below 20%.

In order to further analysis 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.

Table.1 Confusion matrix in -15dB 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 -20dB 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

Seen from Table1 and Table2, there exists come confusion between signal SP, LFM, NLFM, and PE when SNR=-15dB, that's because the noise effects the modulation characteristics of SP a lot. When SNR=-20dB, all the other signals have the probability of being misclassified as SP for that the modulation characteristics of SP gets less obvious with the increase of noise. In addition, the confusion between PSK, NLFM and FSK is high for that there is some similarity in their modulation type.

4 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 do classification and recognition task. It does a training process layer by layer firstly, then fine-tunes the parameters in the whole networks by 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 RNS environment. It shows that this model has powerful recognition ability and strong robustness. But the high computational complexity is one of its shortcoming, and the number of hidden layers is a open questions to be discussed and analyzed. Therefore, it is also one of our future works to analyze radar signals with deep learning.

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