A Real-time Intra-pulse Recognition Method of Radar Signals Based on Restricted Boltzmann Machines

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Abstract. Intra-pulse features extraction of radar is of great research significance in electronic reconnaissance technology. With continuous development and equipment of the new system radar, the characteristics of the modern electromagnetic environment could be summarized as density, complexity and variability, which makes the traditional signal identification methods difficult to achieve the desired effect and determines the recognition must be real-time. Therefore, this paper is devoted to the study a fast method and performance analysis in extracting intra-pulse features of radar emitters in complex electromagnetic environment, especially in low SNR environment, and the experiment process could achieve real-time recognition.

1. Introduction

Intra-pulse modulation recognition aiming at recognizing the intra-pulse modulation type of radar signals plays an important part in modern intercept receivers, which could be used to recognize the signal threat level and choose the optimal algorithm to estimate parameters of the detected signal [1]. Nowadays, signals in various types and widely occupied spectrum are used in new system radar, which makes the modern electromagnetic environment is more complex [2][3]. Therefore, the SNR there is quite low. Besides, real-time is one of the virtue considerations when people access intelligence [4]. Therefore, the problem discussed in this paper is of great research value.

In recent years, scholars have been exploring features of the intra-pulse features of radar signals [5]. Methods such as wavelet packet feature [6], similar coefficient [7] entropy [8] and fractional Fourier transform [9] are purposed, promoting the process of intra-pulse recognition of radar signal. However, when SNR is lower than 5 dB, the recognition accuracy of most algorithms would be serious decline. When SNR is between 2 dB to 5 dB, only a few algorithms could achieve satisfactory effect [10] [11]. Moreover, lots of algorithms involve complex matrix calculations and require several minutes before getting results, which could influence critical decisions making during the urgent events.

To achieve better recognition performance in recognition, ambiguity function (AF) of radar signals is purposed as intra-pulse characteristics [12] [13]. Thus, many dimension reduction algorithms have been applied to extract key information in AF [14] [15]. However, most tradition algorithms are to carry out a large amount of data and the speed drops rapidly with the increase of sampling points, which is contrary to the need of modern intelligence [16]. Consequently, this paper adopts restricted Boltzmann machines (RBM), a stochastic neural network, to extracted features effectively. Firstly, we calculate the AF of the radar signals. Then, singular value decomposition (SVD) is applied on main
ridge section of the AF as denoise method in low SNR. Finally, processed data are input trained RBM and acquire the recognition results.

This paper is organized as followed. Section II elaborates the details of this method, including AF, SVD and RBM. In Section III, simulation experiments verify the validity of this method. Meanwhile, some important data and performance are analyzed. A summary is given in in Section IV.

2. Details of The Recognition Method

2.1. AF Main Ridge Section of Radar Signal

AF of radar signal is 2D correlation function of signal time and frequency, and its essence is a time-frequency distribution function [17]. While recognizing radar signal, AF could not only describe the distinction between characteristics of different radar signals, but also be able to describe the clutter suppression characteristics and measurement accuracy. Since the AF is unique and volume invariant, we could conclude that AF and radar signal are one-to-one correspondence.

The AF of radar signal \( x(t) \) defined as:

\[
\chi(t, \xi) = \int_{-\infty}^{+\infty} x(t - \tau) e^{j2\pi \xi \tau} d\tau
\]

where \( \tau \) denotes the time delay, \( \xi \) denotes the Doppler frequency shift, \(^*\) denotes conjugate, and \( s(t) \) denotes the complex envelope of \( x(t) \).

As for the received radar sampling signal \( x(n) \), \( n = 0, 1, \cdots, N-1 \). According to the equation (1), discrete autocorrelation AF is represented as follows:

\[
A[\eta, \tau] = \sum_{n = 0}^{N-1} x^*[n] x[(n+\tau)] e^{-j \frac{2\pi n \eta}{N}}
\]

where \((\bullet)^*\) represents the cyclic shift, \( \eta \) represents the Doppler frequency shift, and \( \tau \) represents the discrete time delay.

Taking FSK signal as example, we derive the normalized response of the AF and its three views from the FSK signal, which are show in the Fig.1 (a).

![AF and its three views of FSK signal](image-1)

![The envelope of time delay plane of AF from FSK signal](image-2)

Fig.1 AF and envelope of the FSK signal

It is not hard to see that the distribution of AF from FSK signal is concentrated. The main peak is sharp and the edge peak is relatively scattered. Additionally, the AF is complex and the data volume is very large. Therefore, further simplify is needed. This paper compares three views drawing of AF (time delay plane, Doppler plane and time delay-Doppler plane) and chooses one of the most significant and easily extracted in three graphs to represent the characteristics of the signal AF. Synthesizes each kind of situation, the time delay plane of AF from FSK signal can be used to extract
features. In order to simplify calculation, we can adopt the envelope of time delay plane as the further study object, as shown in Fig.1 (b). Similar conclusions can be drawn for other modulation signals mentioned in this paper.

2.2. SVD Denosing

In practice, signals are inevitably encounter noise interference in the process of acquisition and transmission, which caused signal distortion and even beyond recognition. Although the AF has anti-noise performance, the edge peak still would be submerged in noise in low SNR. Thus, to get better recognition performance, noise reduction measures are required. SVD is a nonlinear filtering method with good adaptability [18][19]. This filtering method is not constrained by linear conditions and especially applies for nonlinear non-stationary signals. Using the SVD algorithm based on the characteristic mean, the AF denoising of the received radar signal includes the following steps:

Step 1: The time delay plane signal vector of AF from received noise radar signal is defined to be \( Y = [x(0), x(1), x(2), \ldots x(n-1)] \) and the length of radar signal is \( N \). At first, the \( M \times K \) Hankel matrix is constructed as follows:

\[
X = \begin{bmatrix}
x(0) & x(1) & \cdots & x(M-1) \\
x(1) & x(2) & \cdots & x(M) \\
\vdots & \vdots & \ddots & \vdots \\
x(K-1) & x(K) & \cdots & x(N-1)
\end{bmatrix}
\]

where \( M + K = N + 1 \) and \( K \geq M \).

Meanwhile, define matrix \( S \) as the Hankel matrix of valid signal and matrix \( D \) as the Hankel matrix of noise, which are both \( m \times n \) dimension. Then we can derive that \( XS = D \).

Step 2: Apply SVD to the time delay plane of AF from received noise signal. Define \( U \) as \( n \times n \) dimension unitary matrix and \( V \) as \( m \times m \) dimension unitary matrix. Then, the SVD of the time delay plane of AF from received noise signal is denoted to be

\[
X = U \Sigma V^T
\]

where \( \Sigma \) is a \( m \times n \) dimension diagonal matrix and its diagonal elements \( \sigma_1 \geq \sigma_2 \geq \cdots \sigma_r \geq 0 \) are denoted as the singular value spectrum of the signal matrix \( X \).

Step 3: Threshold control. Use the mean value of eigenvalue as threshold and take the first \( P \) singular values larger than the threshold. We could obtain the singular value matrix as follows:

\[
\Sigma_p = \begin{bmatrix}
\Sigma_1 & 0 \\
0 & 0
\end{bmatrix}
\]

Step 4: Reconstruct the filtered signal matrix. We reconstruct the approximation matrix of the matrix as follows:

\[
X_p = [U_p \quad U_{m-p}] \begin{bmatrix}
\Sigma_p & 0 \\
0 & 0
\end{bmatrix} \begin{bmatrix}
V_p^T \\\nV_{m-p}^T
\end{bmatrix} = U_p \Sigma_p V_p^T
\]

where \( V_p \) represents the right singular vector corresponding to the first \( P \) principal singular values, \( U_p \) represents the left singular vector corresponding to the first \( P \) principal singular values and \( \Sigma_p \) represents the main diagonal matrix corresponding to the first \( P \) main singular values as follows:

\[
\Sigma_p = \begin{bmatrix}
\sigma_1 & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & \sigma_p
\end{bmatrix}
\]

To sum up, the singular value can reflect the information of both the noise and the time delay plane of AF. Among them, most of the singular values reflect the signal information, which are mainly in the previous singular values. While a few parts reflect the noise, which are mainly in the singular value of almost zero. Thus by solving the first singular values, zeroing other singular values, and then
reconstructing the approximation matrix, we can filter the noise in the time delay plane of AF from the radar signal. Taking FSK signal as example, the denoising effect is illustrated in Fig.2.

In Fig.2 (a), we set blue line represents the pure valid signal, green line represents the signal and the additive white Gaussian noise (SNR=-2dB), and the red line represents the signal after SVD filter. It is obvious that the signal after SVD filter are much more similar with the original signal.

2.3. RBM Clustering Algorithm
This paper adopts RBM as the method to extract image shape features and achieve clustering. RBM, a neural network model based on energy function, was firstly proposed by Hinton based on Boltzmann Machine (BM) to deal with gradient diffusion in deep neural networks (DNN)[20]. With further study, RBM is now wildly used in all sorts of situations, such as dimension reduction, classification, regression, collaborative filtering, feature learning, etc.

The typical model of RBM is shown in Fig.2 (b). Its structure is relatively simple. There are only two layers, of which one is visible layer and another is hidden layer. Both layers contain several random neurons. Their output states are only to be inactive and active. The specific states of the neurons refer to the probabilistic statistical rules. Neurons inside the layer are connectionless, and neurons between the layer are full connections. Therefore, the activated states of neurons in the hidden layer are independent on condition that states of neurons in the visible layer are given and vice versa.

As shown in Fig.2(b), \( v \) denotes the visible layer, \( h \) denotes the hidden layer, \( a \) denotes visible layer neuron bias, \( b \) denotes hidden layer neuron bias and \( w \) denotes the weight matrix. We could conclude that the RBM model is determined by the three parameters of the model \( \theta = \{w,a,b\} \).

The process could be described as follows:

Firstly, the energy function and joint probability function between visible layer vector \( v \) and hidden layer vector \( h \) are shown in equation 8 and 9 respectively.

\[
E(v,h) = -\sum_{i=1}^{n_v} a_i v_i - \sum_{j=1}^{n_h} b_j h_j - \sum_{i \in n_v, j \in n_h} v_i h_j w_{ij}
\]

\[
p(v,h) = \frac{1}{Z} e^{-E(v,h)}
\]
where $Z = \sum_{h} \exp(-E(v,h))$ represents normalization factor.

If we replace the visible vector $v$ by input vector $x$, then the probability distribution function for $x$ can be expressed as follows:

$$P(x) = \sum_{h} p(x,h) = \sum_{h} e^{-E(x,h)}$$

Then we get the derivation for the logarithm of equation 10:

$$-\frac{\partial \log P(x)}{\partial \theta} = \frac{\partial F(x)}{\partial \theta} - \sum_{h} p(x) \frac{\partial F(x)}{\partial \theta}$$

$$F(x) = -\log \sum_{h} e^{-E(x,h)}$$

The RBM reaches the steady state when the system energy is minimized. From formula above, to minimize the energy function $E(v,h)$, we should minimize $F(x)$, which means maximize $P(x)$. Therefore, we could take $-P(x)$ as loss function.

There are many ways to solve RBM model parameters. This paper adopts Gibbs sampling and contrastive divergence (CD) algorithm, which replacing the previous iterations with one iteration [21][22].

2.4. Procedures of Intra-pulse Recognition

According to the comprehensive analysis above, the complete procedure of intra-pulse recognition is as follows:

Step1: Train the RBM in advance and save the weight matrix.
Step2: Normal sampling. Obtain the discrete signal by normal sample of the received signals.
Step3: Oversampling. Resample the discrete signal so that all the resampled signals have fixed length.
Step4: Calculate the AF of the resampled signal and extract the time-delay plane.
Step5: Denoising the time-delay plane of AF by SVD.
Step6: Extract the feature and cluster via trained RBM model.

The system map is shown in Fig.3 (a).

![System Map](image)

(a) The system map of recognition method

![AF Model](image)

(b) AF model of six kinds of radar signals

Fig.3 The experiment simulation

3. Simulation and Result Analysis

Nowadays, the recognition of radar signals with different parameters is still a problem, especially when the signals are in the same modulation. For this problem, the two-level recognition system is taken into consideration. For hybrid signals with different modulations and different parameters, the first level completes the recognition of radar signals with different modulations and the second level completes the recognition of the same modulated radar signals with different parameters.
This paper selects six kinds of radar signals as study objects, including LFM, SFM, VFM, BPSK, QPSK and FSK. We simulated the AF of these signals and finished the recognition experiments. The simulation results of AF for different modulated radar signals are shown in Fig.3 (b).

In Fig.3(b), each kind of radar signal has its own unique features, which provides the theoretical basis for recognition experiment. Nevertheless, many features would be drowned out by noise along with the decrease of SNR, so the SNR should be taken into account when training RBM network.

In order to illustrate and analyze the research result clearly, three experiments were conducted, in which the first two experiments are for the first level and the last experiment is for the second level.

3.1. Recognition of Radar Signals with Different Modulation in Low SNR

This experiment tests performance in the first level, which completes the recognition of different modulated radar signals in low SNR.

In this experiment, the pulse width of the radar signal is 0.5 and the sampling rate is 600. Base on the modeling AF data of six kinds of radar signals with SNR equaling -5dB to 5dB, the modulation type is recognized by means of RBM network. The RBM network built in the first level is assigned as RBM1. In RBM1, the sample size of the training data is 600. The specific parameter settings of RBM1 are shown in the tableⅠ.

| Visible Layer Neurons | Hidden Layer Neurons | Iterations | Learning Rate |
|-----------------------|----------------------|------------|---------------|
| 300                   | 200                  | 20         | 0.06          |

In order to study the effect of SNR for this algorithm, the testing data includes six different modulated radar signals in different SNR. The sample size of the testing data is 100. The recognition results are stated in tableⅡ.

| SNR   | Precision | Recall | F1-score |
|-------|-----------|--------|----------|
| 0dB   | 1.00      | 0.99   | 0.99     |
| -1dB  | 1.00      | 0.99   | 0.99     |
| -2dB  | 0.99      | 0.98   | 0.99     |
| -3dB  | 0.97      | 0.97   | 0.97     |
| -4dB  | 0.90      | 0.90   | 0.90     |
| -5dB  | 0.74      | 0.71   | 0.71     |

According to the tableⅡ, this method could achieve 90% when SNR is -4dB, which shows that it could have good performance in low SNR and verified that the first level could complete the recognition of radar signals with different modulations.

3.2. Recognition of Radar Signals with the Same Modulation in First Level

On the basis of experimentⅠ, a more detailed argumentation to the two-level recognition system would be expounded below.

Firstly, we must verify that radar signals with same modulation and different parameters would be recognized as the same kind in the first level. In this system, the RBMⅠ is used as the neural network in the first level. We select FSK, BPSK and LFM as study objects. For each kind of modulated signal, we simulated the radar signals with different parameter (different coding or different modulation rate) with SNR equaling -4dB to 5dB. These data are exactly testing data and are recognized by RBMⅠ. The different parameters and recognition results are respectively shown in the tableⅢ and table Ⅳ.

Because signals in the same modulation and different parameter should be recognized as the same type, the labels of signal 1, 2 and 3 are all equals to 3, the labels of signal 4, 5 and 6 are all equals to 1 and the labels of signal 7, 8 and 9 are all equals to 0.
From Table IV, we could conclude that there are nearly no error detection probability and small leak detection probability in recognizing radar signals with the same modulation and different parameters.

In section A and B, we have done two experiments for the first level. The results show that BRM1 has effective generalization performance and high precision. On the one hand, it could distinguish the different modulation of radar signals into different classes. On the other hand, it could also put the same modulated radar signals with different parameters in the same class, which is a good preparation for the signals recognition in the second level.

3.3. Recognition of Radar Signals with the Same Modulation in Second Level

Based on the first two experiments, a more detailed argumentation to the second level recognition system is described below.

| Modulation | Parameter | Value |
|------------|-----------|-------|
| LFM        | Modulation rate | 0.2   |
|            |            | 0.3   |
|            |            | 0.4   |
| BPSK       | Coding    | 15-bit M sequence: [1 1 1 1 0 1 0 1 1 0 0 1 0 0 0] |
|            | Coding    | 7-bit L sequence: [1 1 0 1 0 0 0] |
| FSK        | Coding    | 13-bit barker code: [1 1 1 1 1 0 0 1 1 0 1 0 1] |

The second level would complete the recognition of the same modulated radar signals with different parameters, which input form the first level. In this experiment, we select the data used in experiment B as study object. We built a new RBM network called RBM2, which is trained by the modeling AF data of radar signals with one specific modulation and different parameters in the SNR equaling -5dB to 5dB. Take LFM signals as example, the training data for RBM would be the LFM signals with different modulation rates in the SNR equaling -5dB to 5dB and the sample size of the training data is 900. The testing data would be the LFM signals with modulation rates are 0.2, 0.3 and 0.4 and the sample size of the testing data is 300. The specific parameter settings of RBM2 are shown in Table V.

| Visible Layer Neurons | Hidden Layer Neurons | Iterations | Learning Rate |
|-----------------------|----------------------|------------|---------------|
| 300                   | 600                  | 20         | 0.06          |

It is worth noting that because signals in the same modulation and different parameters should be recognized into different classes, the labels of these three kinds of signals are equals to 1, 2 and 3. The final recognition results are shown in Table VI.

According to the results, the RBM2 could achieve quite high precision when the SNR is -2dB and above. Although there exists probability of error detection and leak detection, the performance is relatively good in recognizing radar signals with different modulations and different parameters.

| Modulation | SNR | Precision | Recall | F1-score |
|------------|-----|-----------|--------|----------|
| LFM        | 0dB | 0.91      | 0.91   | 0.91     |
|            | -2dB| 0.80      | 0.79   | 0.78     |
|            | -4dB| 0.75      | 0.76   | 0.75     |
3.4. System Analysis

By combining all the analysis above, the comprehensive map of the two-level recognition system is shown in Fig.4.

This system guaranteed high recognition rate in low SNR. More specifically, over 80 percent of the testing radar signals with different modulations and different parameters are correctly recognized via this system.

| Modulation | 0dB  | -2dB | -4dB |
|------------|------|------|------|
| BPSK       | 0.98 | 0.95 | 0.71 |
| FSK        | 0.97 | 0.87 | 0.59 |

Fig.4 Recognition system function structure

The experiment also proves that the system has advantages of good real-time performance. Most calculated amount is in training the RBM network, which could finish in regular time. Actually, the real recognition process only requires a small amount of calculation compared with traditional recognition method.

Besides, since the RBM network could be stacked into Deep Belief Network (DBN) and transformed into auto-encoder, this method has a good extending capacity when the processing data is huge and complex.

4. Conclusion

This paper improves the intra-pulse recognition method based on existing AF recognition methods and builds up a two-level recognition system using RBM network construction, which could realize real-time recognition of the radar signals with different modulations and different parameters under very low SNR (when the SNR is -2dB, the recognition precision is over 80%). Additionally, this system possesses strong flexibility and expandability. This method provides reference for the development of modern intra-pulse radar signals recognition technology.

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