Radar Specific Emitter Recognition Based on DBN Feature Extraction

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Abstract: Deeping learning possesses excellent performance of extracting deep features and processing high-dimensional data, therefore deep belief network is considered to realize radar specific emitter recognition. A radar specific emitter recognition algorithm based on DBN feature extraction is proposed. Firstly, unsupervised extraction of pulse envelope frontier is realized in time-domain by DBN. Then model parameters are supervised fine-tuning to complete the training using labeled data, and radar specific emitters are recognized finally. Compared to traditional algorithm, the advantage of the novel algorithm can adaptively extract deep pulse features and the progress of feature extraction reduce the dependence on human experiences and signal processing technology. The experimental results show that the novel algorithm provides significant performance of pulse envelope feature extraction and higher recognition accuracy for simulation data and measured data. The validity and application value of this algorithm are verified.

1. Introduction

Radar emitter recognition is the process of determining the status and individual of radar emitters through radar signal detection, signal features extraction and analysis. This process is the necessary link of intelligence reconnaissance and battlefield situational awareness, also is the key basis of the threat rating assessment and interference decision. The development of multi-function radar (MFR) makes the radar signal style complex and changeable. The traditional method is based on the characteristic parameters, such as TOA(time of arrival), DOA(angle of arrival), RF(radio frequency), PRI(pulse repeat interval) and PW(pulse width), it is hard to meet the requirement of radar emitter recognition. Recently extraction internal fine features of radar pulses to realize individual recognition is the breakthrough of radar emitter recognition[1].

Radar pulse fine features are mainly produced by additional unintentional modulation of emission...
devices, which mainly includes envelope frontier, phase noise, frequency drift, etc\(^2\). The stable fine features also are known as “fingerprint features” distinguishing different emitter individuals. The “fingerprint features” have the characteristics of testability, universality, uniqueness, independence and so on\(^3\). In [4] ambiguity function of radar emitter signal is extracted to realize specific radar emitter recognition. Unintentional modulation of frequency-domain distribution and band-width on pulse is extracted\(^5\), as well as other transformed features such as bispectrum\(^6,7\), higher order moment\(^8\), Time–Frequency–Energy Distribution Features\(^9\), etc. The above features are extracted artificially, therefore the quality of features seriously rely on expert experience and signal processing technology and the ability to characterize the fine difference in signal is limited in the absence of a priori information. In addition, deep characteristics of radar signals cannot be excavated, which affect recognition accuracy.

Compared to shallow network, deep learning is a deep network structure with multiple hidden layers and has been widely used with its powerful feature presentation since it was put forward\(^10-12\). Particular deep structure of Deep learning can abstract high level representation of sample from low level features without human, which overcomes uncertainty and redundancy of artificial feature extraction\(^13\). In radar emitter recognition, radar operation modes are recognized with deep learning\(^14\), and in [15] a method is proposed based on deep belief network to recognize modulation of radar signals, and in [16] a deep automatic encoder is to used recognize radar emitter. In order to realize specific radar emitter recognition, a new recognition model based on DBN is proposed in this paper. The essential features of initial radar signal are learned directly and autonomously through DBN, that reduces the dependence on prior knowledge and extracts fine difference of different pulse envelopes, therefore distinguish different emitter individuals.

2. Feature of Pulse Envelope

The unintentional modulation of radar signals by radar transmitter is the main basis for specific radar recognition. We focus on pulse envelope distortion feature with advantages of convenient extraction and easy to distinguish, which is the main feature to individual recognition. Ideal pulses are regular rectangular pulse string and figure 1(a) shows an example of ideal pulse signal. Actually, there exists difference in the pulse envelopes of different individual radar, especially in envelop front and back edge and top fluctuation. The above characteristics are stable and unique, and do not vary with radar working state. Even though parameters such as RF, PW, PRI are identical, different individuals can still be distinguished.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Radar pulse signals}
\end{figure}

Figure 1(b) shows the measured pulse with front and back edge distortion. Considering the
instability of back edge of the actual intercepted pulse envelope, we focus our attention to extract envelope front edge feature based on DBN to recognize specific radar emitter. Complex process of artificial extraction of features is therefore replaced, moreover deeper abstract representation is obtained to achieve better recognition effect.

3. Deep Belief Network

Deep belief network (DNB) first proposed by Hinton G E in 2006 is a deep structure superposed by multilayer limited Boltzmann machines. Compared with the traditional shallow network, the deep belief network process is superior to feature extraction and dimension reduction ability, which has been verified in the application of more than 10 years.

As the basic structure of DBN, RBM is a double-layer structure composed of visual and hidden layers. The two layers are fully connected by weight values and each unit in the layer is independent of each other. The concrete structure is shown in Figure 2.

![RBM structure](image)

**Figure 2.** RBM structure.

Assume that the visual layer contains $m$ visual units $v = (v_1, v_2, \cdots, v_m)$ as input to the hidden layer, and the hidden layer contains $n$ hidden units $h = (h_1, h_2, \cdots, h_n)$. $v_i$ and $h_j$ are binary-value variables of 0 or 1, respectively represent status of inactivation and activation of neuronal. $a_i$ and $b_j$ respectively represent bias of the neuronal in visual layer and hidden layer. $w_{ij}$ are Connection weights and $a_i, b_j$ and $w_{ij}$ are uniformly noted parameter $\theta$. The RBM energy function is defined as:

$$E(v,h;\theta) = -\sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} v_i h_j - \sum_{i=1}^{m} a_i v_i - \sum_{j=1}^{n} b_j h_j$$

(1)

After the energy function is indexed and regularized, the joint probability distribution of visual and hidden layers is as follows:

$$p(v,h;\theta) = \frac{\exp(-E(v,h;\theta))}{Z} = \frac{\exp(-E(v,h;\theta))}{\sum_{v,h} \exp(-E(v,h;\theta))}$$

(2)

After further decomposition conditional probability of hidden units and visual units are as follow:

$$p(h_j = 1|v) = \frac{1}{1 + \exp(-a_i - \sum_{j=1}^{n} w_{ij} v_j)}$$

(3)

$$p(v_i = 1|h) = \frac{1}{1 + \exp(-b_j - \sum_{j=1}^{n} w_{ij} h_j)}$$

(4)

When the input visual layer $v$ is known, due to independence of the neurons in the layer, the hidden layer conditional probability is expressed as a multiplicative form $p(h_j|v) = \prod_{i=1}^{m} p(h_j|v_i)$, then a new visual layer $v'$ is reconstructed via calculation of conditional probability $p(v'|h) = \prod_{j=1}^{n} p(v'_j|h)$ based on hidden layer $h$. The RBM training is a process of gradually adjusting the network parameters $\theta$ and
minimizing the reconstruction error of visual layer $v'$ to converge the probability distribution of reconstruction with the input sample data.

4. Specific Radar Emitter Recognition Based on DBN

In view of the powerful feature extraction ability of DBN, learning excellent features autonomously from initial data without requiring excessive intervention, a recognition model based on DBN for specific radar emitter recognition is proposed. Three stages of recognition model are described as below.

Stage 1 Emitter Signal Preprocessing. First, the radiofrequency signal received is down converted to intermediate frequency signal, and then the intermediate frequency signal is enveloped by demodulation. Finally, the discrete data points used as the input of DBN network are obtained by sampling pulse envelope front edge.

Stage 2 DBN Training. First, the sampling data of the pulse envelope is normalized, and then the DBN model with multiple hidden layers is set up, the number of input layer nodes is set according to the dimension of input data. Finally, the training method in second section is used to train the DBN.

Stage 3 Unknown Specific Radar Emitter Recognition. Unknown radar emitter signals are preprocessed as described by step1, and then recognized using the training completed DBN model.

5. Simulation Analysis

5.1 Model parameter setting

In order to verify the effectiveness of the specific radar emitter recognition model based on DBN, simulation analysis is carried out. Due to the randomness of pulse envelope, there is no accurate modeling of pulse envelope in existing literatures. On the basis of analysis of radar signals, we simulate 4 kind of radar pulse frontiers with high similarity. The expression of the specific envelope frontiers are as follows:

Radar I frontier: $y = 1 - e^{-2x}$; Radar II frontier: $y = 1 - e^{-3x}$; Radar III frontier $y = 1 - e^{-x}$; Radar IV frontier $y = 1 - e^{-x^2}$.

In order to get closer to measured signals, random Gauss white noise is added to each envelope generated by simulation. Figure 3 shows the four class of radar signal pulse frontiers. The SNR of the simulated signal is 25dB, the pulse amplitude is 1, the sampling frequency of pulse frontier is 100MHz and the total sampling time is $2\mu s$, so the sampling point of each pulse frontier is 200 points.

![Figure 3. Radar pulse envelope frontier.](image-url)
For DBN hidden layer and node settings, the recognition results of multiple experiments are shown in Table 1.

Table 1. Effect of DBN structure on recognition rate.

| DBN structure       | Recognition rate |
|---------------------|------------------|
| 200-150-100-50      | 55%              |
| 200-150-100         | 99.8%            |
| 200-150-50          | 97.9%            |
| 200-150             | 99.2%            |

The results show that when the DBN layer number is too deep or node number decreases too much, the recognition effect will decrease. According to the experimental results, the 3 level DBN model is adopted. As the number of sampling points for the signal is 200, the number of bottom RBM input nodes is set at 200, and the other layer node number is reduced in turn, set to 200-150-100. The learning rate and momentum parameter of DBN have great influence on the recognition results. After many experiments, the learning rate is 0.1 and the momentum parameter is 0.1.

5.2 Envelope feature extraction

In order to verify the feature extraction effect of the DBN model for emitter data, compare the output characteristics of the initial data and the first hidden layer and the second hidden layer. In order to facilitate comparison, the data are processed by feature visualization via reducing high-dimensional data to 3D images with PCA algorithm. Figure 4 shows the results of dimensionality reduction of the initial time-domain sampled data, in which overlap of 4 radar signal sampling data is serious. It is difficult to distinguish the radar individuals effectively only by analyzing the initial data.

Figure 4. Initial data feature visualization

Figure 5 shows the results of dimensionality reduction of the first hidden layer of DBN. It shows that the same kind of radar signals are gathered together, and the different radar signals are effectively separated with only a small number of data points overlap. Figure 6 shows the results of dimensionality reduction after features extraction of second hidden layer. Compared with the first layer feature extraction results, the aggregation degree of similar signals in Figure 6 is more compact, and different classes of data points are more distinguishable without overlap. From the first, second
hidden layer feature extraction results, it can be seen that the DBN model can extract more effective features of initial signals autonomously.

![Figure 5. First hidden layer feature](image1)

![Figure 6. Second hidden layer feature](image2)

5.3 Contrast simulation

The DBN based recognition model is simulated comparing with the ambiguity function slice algorithm\(^4\) and bispectrum algorithm, PCA-SVM, LDA-SVM, OLPP-BP algorithms. Among them, the ambiguity function slice and bispectrum are individual features of emitter signal extracted artificially, PCA, LDA and OLPP are three commonly used dimensionality reduction algorithms. 1000 training data are generated by each radar, a total of 4000. Then 4000 test data adding random noise are generated, and the SNR is 20dB, 15dB and 10dB respectively. The results of the recognition rate comparison are shown in Table 2.

| SNR    | 20dB | 15dB | 10dB |
|--------|------|------|------|
| DBN algorithm | 98.8% | 91.57% | 79.7% |
| Ambiguity function slice\(^4\) | 89.58% | 78.3% | 69.1% |
| Selective bispectrum\(^6\) | 87.6% | 76.4% | 70.5% |
| PCA-SVM | 86.08% | 72.12% | 63.47% |
| LDA-SVM | 89.9% | 70.65% | 53.03% |
| OLPP-BP | 93.45% | 84.95% | 73.18% |

Through the comparison of the recognition rate of the above algorithms, we can see that the DBN recognition model has the best recognition effect in each SNR environment, and the recognition rate is 98.8% when the SNR is 20dB, 5% higher than the supervised OLPP dimensionality reduction algorithm. The deep features of initial radar signals extracted by DBN are more effective compared with the ambiguity function slice feature and dimension reduction algorithm.
6. Conclusion

Aiming at the problem of specific radar emitter identification, a recognition method based on DBN feature extraction is proposed in this paper. From the individual difference of the envelope frontier of radar, the unsupervised features are extracted with DBN after sampling of the envelope frontier in time-domain. Then, the parameters of network are supervised adjusted by the labeled data. Finally, the classification is realized by the training finished model. The proposed method overcomes the complexity of artificial feature extraction and extracts the deep features of radar signal directly in time-domain. The simulation results of simulated and measured signals show that the recognition rate of the proposed method is higher than that of the traditional method, and the validity of the method is verified.

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