Radar Working Modes Recognition Based on Discrete Process Neural Network

Xiaoxuan Dong*, Siyi Cheng
Air Force Engineering University, Xi’an 710038, China
*Corresponding author e-mail: legenddxx@163.com, csy_316@163.com

Abstract. Accurate identification of radar operation modes is the important premise of threat level assessment and interference decision. But parameters overlap of PDW between different radar working modes seriously affects the recognition accuracy. A discrete process neural network (DPNN) based on particle swarm optimization (PSO) training is proposed to realize radar working modes recognition. Firstly, radar syntactic modeling method is proposed to extract radar phrases as operation modes character description. Then, the appropriate DPNN structure is built and trained via PSO. Finally, radar working mode recognition of unknown radar phrases is realized by the finished DPNN. Different from traditional machine learning method based on single sampling of radar signals, this method achieve recognition according to accumulation of radar pulse sequence, and make the best use of time series change law of radar signals. The simulation results show that compared with traditional machine learning method, such as LSSVM, BPNN, working modes recognition rate of the novel method increases significantly under the condition of serious parameter overlap.

1. Introduction
The radar working mode recognition is to estimate the internal working state of the radar by prior knowledge and radar signal reconnaissance, which is essential for the threat level assessment, interference decision and radar state prediction. In modern air combat, only obtaining real-time and accurate state information of enemy radar can maximize the survival rate of fighters. With the development of multi-function radar (MFR), radar signal style and working mode are becoming more and more complex with blurry corresponding relationship between them, and the overlapping of signal styles between different working modes is becoming more and more serious. These factors bring challenges to the recognition of radar work pattern. At present, machine learning algorithms are widely used in radar working mode recognition. In [1-3], radar working mode recognition is realized on the basis of neural network and hybrid neural network; [4-6] studies the application of SVM in radar work pattern recognition.

The above algorithms are all sampling of single time radar signals based on instantaneous synchronization, which cannot reflect the timing relationship of radar pulse sequence. Although the recognition effect has been improved to a certain extent, the recognition accuracy is limited when similarity degree is high and parameter overlapping is serious between different signals.

Process neural network (PNN) is a network model with input and weight values that can be time functions. In PNN the time accumulation and spatial aggregation of input functions are realized via
process neurons in hidden layer, and PNN realizes classification by using information of change process of functions. After proposed, PNN algorithm has been widely applied in the fields of time series prediction [7], fault diagnosis [8], detection and recognition [9].

In this paper, discrete process neural network (DPNN) is applied to radar working mode recognition overcoming radar signal parameter overlapping problem. Unlike traditional recognition method based on single time sampling, DPNN realizes recognition of the radar pulse sequence. First, the radar phrase is extracted after the radar pulse sequence is modeled, then the DPNN is constructed, and the particle optimization algorithm (PSO) is used to optimize the network parameters. Finally, the training finished DPNN is used to realize the recognition of radar phrases.

2. Radar Signal Modeling

MFR can adapt to various task requirements under complex battlefield environment of which the signal styles are very flexible and overlapped between different working modes. This makes the modeling method based on pulse level difficult to meet the requirement of MFR working mode recognition. The pulse description words (PDW), a traditional radar signal modeling method, represent the characteristics of the single radar pulse. But for MFR with changeable signal features, it is hard to realize effective distinction of radar working modes based on PDW, and a new method of modeling for radar signals is necessary.

Haykin and Visnevski regard MFR as a random discrete event system [10], and use syntactic rules to model the radar signals dividing the pulse sequence of radar emitter by the hierarchical structure of “word-phrase”. Radar word is the basic unit of radar signal, and radar phrase is a sequence of radar words arranged according to rules. Radar signals are modeled as sentences via radar syntactic modeling, and in different working modes radar will produce different sentences. Therefore recognition of radar working mode is the process of recognition of radar phrases.

Figure 1 shows the hierarchical structure of radar signal. In figure “a” and “b” are different radar words, and the sequence “abaa” is a radar sentence made up of radar words.

Figure 1. Hierarchical structure of radar signal.

In order to improve the detection gain in actual work, MFR usually launches pulses in a group mode, and in each group the parameters of pulses remain stable, called the coherent processing interval (CPI). In this paper, a CPI pulse group is regarded as a radar word which is represented as: $W = \{w_1, w_2, \ldots, w_L\}$. $w_i$ is the feature description parameter of the CPI, including the parameter information of once measurement of the radar signal. There are several CPI in each radar working mode, and the sequence of CPI constitute the radar phrase of working mode, including the timing relationship changing law of radar signals.

The traditional radar signal PDW is the characteristic description of the instantaneous pulse sampling. The characteristic vector $PDW = [RF, PRI, PW, \ldots]$ is used to characterize the radar's working mode without the ability to express the change of radar signal characteristic. Different from the traditional modeling method with PDW, the radar syntactic modeling method uses radar phrase to represent the radar working mode containing change features of the radar signal. Assuming that a working mode contains $L$ CPI pulse groups, so the radar phrase is represented as $P = W_1, W_2, \ldots, W_L$. The radar phrase $P$ is written as the parameter matrix form, as shown in Eq. (1). In this way, the working mode of radar can be fully expressed in the parameter matrix of the Eq. (1).
Each column in the matrix $P$ represents a radar word, and each row is a sequence of parameters of the radar signal.

### 3. Discrete Process Neural Network Based on PSO

After the syntactic modeling of radar signals, radar phrase $P$ is obtained, and further recognition of radar phrases is necessary. In this paper, a discrete process neural network based on PSO parameter optimization is used to identify radar phrases and determine the current working mode of radar.

#### 3.1. DPNN Structure

Unlike traditional neurons using single time sampling feature vectors as input, the input and weight of process neurons are all time related functions, that is, $(x_1(t), x_2(t), \ldots, x_n(t))$ and $(w_1(t), w_2(t), \ldots, w_n(t))$. Spatial aggregation and time accumulation of input signals are realized in process neurons, which is different from the mapping relationship of the general neuron. The process neuron uses the process information in time-domain of radar signals which output is expressed as:

$$Y = f\left(\sum_{i=1}^{n} x_i(t)w_i(t)dt - \theta\right)$$

Eq. (2) is the output of continuous process neuron, function $f(x)$ is activation function, and $\theta$ is neuron threshold. The input of discrete process neurons is a time series formed by measured values of multiple moments. Unlike the integral form of continuous functions, the time accumulation of discrete time series is convolution form [11]. Discrete neuron output is specifically expressed as:

$$Y = f\left(\sum_{k=1}^{L} x_i(k)w_i(k) - \theta\right)$$

Among them, $x_i(k)$ is the discrete input sequence, $w_i(k)$ is the corresponding sequence of discrete weights. Assuming that the length of $x_i(k)$ and $w_i(k)$ both are $L$, so

$$x_i(k) * w_i(k) = \sum_{l=-\infty}^{\infty} x_i(l)w_i(k-l) = \sum_{l=0}^{L} x_i(l)w_i(k-l)$$

When the $k$ in the Eq. (4) is taken as $L$, $w_i(l) = w_i(L-l)$, so

$$x_i(L) * w_i(L) = \sum_{l=0}^{L} x_i(l)w_i(l)$$

Convolution completes the weighted summation operation of the input sequence to achieve the time accumulation. Therefore the mapping relationship between input and output of neurons is expressed as:

$$Y = f\left(\sum_{i=1}^{n} \sum_{k=1}^{L} x_i(k)w_i(k) - \theta\right)$$
Compared to other time aggregation methods, such as numerical integration method [9], function fitting method [12], convolution method is simple and does not need the orthogonal expansion of the input function; it has a great improvement on the computational complexity improving calculation speed. The problem of non-existence of parse function and uncertainty of base function brought by the fitting are overcome.

In the radar working mode recognition problem, the radar phrase $P$ is used as the input of the DPNN, and the single hidden layer DPNN is constructed as shown in Figure 2.

![Figure 2. Structure of DPNN.](image)

The $n$ parameter sequences $w_i(k)(i=1,2,\cdots,n)$ of the radar phrase $P$ are the $n$ inputs of DPNN. The hidden layer has $m$ discrete process neurons realizing time accumulation of the radar signal sampling sequence. We focus on the neural network with single output neuron which final output is represented as follows:

$$y = g\left(\sum_{i=1}^{m} v_j f \left( \sum_{k=0}^{n} w_i(k) \mu_j(k) - \theta_j \right) - \theta \right)$$  (7)

In (7), $\mu_j(k)$ is the weight sequence between the $i$-th neuron in input layer and the $j$-th neuron in hidden layer; $v_j$ is the weight between hidden layer and output layer; $\theta_j$ and $\theta$ are thresholds of the $j$-th neuron in hidden layer and neuron of output layer respectively; function $f(x)$ and $g(x)$ are the activation functions of neurons in hidden and output layer respectively.

According to the Eq. (7), the error function of DPNN output is defined. When the number of training samples is $S$, the sum squared error (SSE) function of network actual output and expected output is as follows:

$$E = \sum_{s=1}^{S} \left[ g\left(\sum_{i=1}^{m} v_j f \left( \sum_{k=0}^{n} w_i(k) \mu_j(k) - \theta_j \right) - \theta \right) - d_s \right]^2$$  (8)

$d_s$ is the expected output of DPNN when the $s$-th sample is entered.

### 3.2. DPNN Training Based on PSO

After the completion of DPNN construction, it is necessary to further realize the learning of network parameters using training data. Compared with the traditional gradient descent algorithm, the particle swarm optimization (PSO) algorithm which applied widely in the field of parameter optimization, has fast convergence speed, high precision, and is not easy to fall into the local optimal. In view of the advantages of the PSO algorithm, a training method for DPNN based on PSO algorithm is developed in this paper.

After initial value is randomly assigned to the initial particle, PSO algorithm searches out the global optimum by updating the velocity and position of the particle according to the optimal value of the current particle. The specific particle update equations are as follow:
\[ V_i(k+1) = \omega V_i(k) + c_1 r_1 (P_i(k) - X_i(k)) + c_2 r_2 (P_g(k) - X_i(k)) \]  
\[ X_i(k+1) = X_i(k) + V_i(k+1) \]  

The velocity of the \( i \)-th particle is expressed as \( V_i \); \( X_i \) is the position of the \( i \)-th particle; \( P_i \) is individual extreme value of the particle; \( P_g \) is the global extreme value of the particle population, \( c_1 \) and \( c_2 \) are nonnegative constants, called acceleration factor; \( r_1 \) and \( r_2 \) are the random numbers between [0,1], and \( \omega \) called inertia weight. In training, the searching intervals of particle velocity and location are usually restricted in \([-V_{\text{max}}, V_{\text{max}}]\) and \([-X_{\text{max}}, X_{\text{max}}]\).

The DPNN training process based on PSO is as follows:

**Step 1** Particle initialization. Set the number of iterations, population size, particle acceleration factor \( c_i \), inertia weight \( \omega \), error accuracy and initialize velocity and position of particle.

**Step 2** Particle fitness. In the process of parameter optimization of DPNN, the error function of Eq. (8) is used as fitness function and the fitness of each generation of particles is calculated. The \( \mu_j(k) \), \( v_j \) and \( \theta_j \) in fitness function are all parameters that need to be optimized.

**Step 3** Iterative optimization. According to the Eq. (9) and (10), position and speed of the particles are updated and the individual extreme value and the group extreme value are updated via comparing with the updated particles.

**Step 4** When iteration satisfies the termination conditions, stop the iteration and output the optimal position, otherwise return step 3 for next iteration.

### 4. Simulation Analysis

In order to verify the effectiveness of DPNN for radar working mode recognition, the recognition rate of the algorithm is analyzed through comparative simulation.

#### 4.1. Radar Signal Parameter Distribution

In this paper, four radar working modes are selected in the reconnaissance database, and two significant characteristic parameters PRI and PW are extracted from radar CPI pulse group to form radar words. A radar word \( W_i \) is written as \( W_i = [\text{PRI}_i, \text{PW}_i]^T \). A continuous sampling of 4 radar words in the pulse sequence form a radar phrase of this working mode, which is expressed as

\[ P = [W_1, W_2, W_3, W_4] = \begin{bmatrix} \text{PRI}_1 & \text{PRI}_2 & \text{PRI}_3 & \text{PRI}_4 \\ \text{PW}_1 & \text{PW}_2 & \text{PW}_3 & \text{PW}_4 \end{bmatrix} \]  

The distribution of the specific parameters of the radar phrase, as shown in Figure 3, (a) and (b) show the distribution and change characteristics of the two parameters of PRI and PW respectively in a radar phrase. It can be seen that the parameters of different working modes are overlapped in different degrees under all radar words. The (c) shows parameter overlapping situation of the third radar word. It can be seen that the radar word parameters between 1, 3 and 4 are overlapped seriously, which causes difficulty to distinguish and identify the radar working mode effectively in recognition if only rely on a single radar word.
4.2. Model Parameter Setting.
According to the four radar operating modes, 100 signal samples of each radar working mode are selected as the training data sets of DPNN from the reconnaissance database, and then 200 samples are selected as the identification performance test data sets. There may be large differences in the parameters between different radar words, it is necessary to preprocess the data set before training and recognition. Linear normalization method is used to standardize the parameters of different radar words to the unified form. The specific expressions are as follows:

\[
PRI' = \frac{PRI - PRI_{\text{min}}}{PRI_{\text{max}} - PRI_{\text{min}}}, \quad PW' = \frac{PW - PW_{\text{min}}}{PW_{\text{max}} - PW_{\text{min}}}
\] (12)

In the setting of DPNN model parameters, the two parameter sequences of radar phrase are selected as the input of the DPNN, so the structure of DPNN is 2-5-1, which is the network structure composed of two input neurons, 5 hidden neurons and single output neurons. In particle optimization, particle population size \(n = 50\), particle velocity range \([-1, 1]\), particle position range \([-10, 10]\), acceleration factor \(c_1 = c_2 = 1.5\).

4.3. Comparison of Recognition Rate.
400 selected radar signal samples are used to train DPNN, and the optimal weights sequence is obtained through PSO algorithm. After training, the DPNN is used to recognize test data to verify the recognition performance for radar working mode. Considering the influence of the measurement error on the recognition performance of the test sample, in the experiment, recognition rate of different degrees of parameter measurement error is simulated. The error of the parameter measurement is increased from 0% to 30% in simulation. The recognition rate is calculated under different errors and the recognition rate-measurement error curves are drawn as shown in Fig 4.

In the simulation, we first analyzes the recognition rate based on single radar word with using the traditional BP neural network and LSSVM algorithm [5] to identify the above four radar words respectively. The recognition results of each radar word of BPNN and LSSVM are shown in Fig 4 (a) and (b) respectively. It can be seen that the recognition effect under the third radar word is the most undesirable, which is because the overlapping of parameters in radar word 3 is the most serious, resulting in a rapid decline of the recognition rate. Fig 4(a) shows that when the parameter measurement error is 5%, the recognition rate is reduced to less than 70%. Because the parameter overlap in radar word 1 is less, the recognition result of radar word 1 is better than that of other radar words. It can be seen from the simulation that the recognition rate based on single radar word is low under the influence of overlapping parameters, and the recognition rate decreases obviously with the increase of parameter measurement error, so it is hard to identify the radar working mode by only single radar word effectively. Although the recognition effect may be better in particular cases, the
The overall recognition confidence is not high. Fig 4(c) shows the comparison between the DPNN algorithm and the average recognition rate of BPNN and LSSVM.

![Figure 4. Recognition rate of different radar words and different algorithms.](image)

The red and black curves in (c) are the average of the four radar word recognition rate curves in (a) and (b), representing the overall confidence of the BPNN and LSSVM algorithms based on single radar word recognition. Blue curve is the recognition rate curve of the radar phrase \( P \) composed of four radar words by the DPNN. The simulation results show that the DPNN algorithm has significantly improved the recognition rate of radar working mode compared with the traditional recognition algorithm. This is because the traditional algorithm is based on a single radar word, only using the single sampling information of the radar signal, cannot overcome reduction of recognition rate caused by overlapping of parameters. The DPNN algorithm is based on radar phrases which preserve pulse sequence changing information. Even if there is overlap of parameters between radar words, excellent recognition performance can be achieved by radar phrases.

5. Conclusion
In this paper, the application of the DPNN in radar working mode recognition is studied in view of the decline of recognition rate caused by overlapping of parameters. Firstly, the radar phrase is extracted via the radar signal syntactic modeling, then the DPNN is constructed and the PSO algorithm is used to optimize the network parameters. Finally, the trained network is used to identify the unknown radar phrases. The simulation results show that the recognition rates of the traditional BPNN and LSSVM algorithms are low when the parameter overlapping is serious, however the DPNN algorithm proposed in this paper can effectively improve the recognition rate under the same error, and the recognition rate is 97% when the parameter measurement error is 10%.

References
[1] C.M. Lin, Y.M. Chen, C.S. Hsueh, A self-organizing interval type-2 fuzzy neural network for radar emitter identification, J. International Journal of Fuzzy System, 2014, 16 (1): 20-30.
[2] Z.Q. Wu, G.Y. Zhang, S Chang, Radar emitter recognition based on neural network and information fusion, J. Electronic Information Warfare Technology, 2015, 30 (6): 1-4.
[3] B. Zhu, W. Jin, Radar emitter signal recognition based on EMD and neural network, J. Journal of Computers, 2012, 7 (6): 1413-1420.
[4] Q. Guo, P. Nan, X. Zhang, et al, Recognition of radar emitter signals based on SVD and AF main ridge slice, J. Journal of Communications & Networks, 2015, 17 (5): 491-498.
[5] Y.B. Wang, S.Y. Cheng, Y.P. Zhou, et al, A parameter optimized LSSVM method for operation modes recognition of airborne fire control radar, J. Journal of Air Force Engineering University (Natural Science Edition), 2017, 18 (3): 49-53.
[6] Y. Lin, X.C. Xu, Z.C. Wang, New Individual Identification Method of Radiation Source Signal Based on Entropy Feature and SVM, J. Journal of Harbin Institute of Technology (New Series), 2014, 21 (1): 99-101.
[7] X.H. Liu, X. Lv, R.Z. QI, Time series prediction model based on wavelet and process neural network, J. Electronic Design Engineering, 2016, 24 (1): 9-11,15.

[8] B. Wang, S.H. Xu, Fault diagnosis of pumping unit based on semi-supervised competitive learning process neural network, J. Information and Control, 2014, 43 (2): 235-240.

[9] Z.G. Liu, S.H. Xu, P.C. Li, et al, Indicator Diagram Recognition Based on Extreme Learning Discrete Process Neural Networks, J. Information and Control, 2016, 45 (5): 627-633.

[10] Visnevski, N., Krishnamurthy, V., Haykin, S, Multi-function radar emitter modeling: a stochastic discrete event system approach, J. Proceedings of the 42nd IEEE Conference on Decision and Control, Maui, Hawaii, USA, December 2003, pp. 6295-6300.

[11] S.S Zhong, D. Lei, G. Ding, Convolution Sum Discrete Process Neural Network and Its Application in Aeroengine Exhausted Gas Temperature Prediction, J. Acta Aeronautica et Astronautica Sinica, 2012, 33 (3): 438-445.

[12] Z.G. Liu, S.H. Xu, P.C. Li, An extreme learning process neural networks based on particle swarm optimization, J. Journal of East China Normal University, 2016, 4: 86-95.