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A Study on Radar Emitter Recognition Based on SPDS Neural Network

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Abstract: With the rapid development of new type radar, it's more difficult to recognize radar emitter signal. Trying to improve radar emitter recognition rate and reduce the processing time are the core of the research in this area. A new efficient radar emitter recognizer using Single Parameter Dynamic Search (SPDS) algorithm is proposed in this study. The SPDS algorithm is a modified algorithm of BP network and it only permits one of all parameters in the network to change during each epoch of searching step for parameters which guarantees to carry out the exact one-dimensional search. This algorithm can overcome the giant limits of BP algorithm such as local minimum and long training time. The effectiveness of SPDS algorithm is shown in simulation results. Compared with the classical neural network algorithms, the radar emitter signal can be recognized more accurately with the SPDS algorithm and the learning speed is improved greatly. The recognition rate is close to 100% under the condition of enough training times and uncomplicated data.

Key words: Recognition rate, local minimum, training time, pulse description word

INTRODUCTION

Radar emitter recognition is an important part of radar system. Recognizing radar emitter correctly plays an important role in modern war. After selection and feature extraction, how to analyze the style of radar emitter signal for superior decision-making institution is the main assignment of radar emitter signal recognition (Zhang *et al*., 2009). Traditional methods contain feature parameter matching (Zhang *et al*., 2008), character in pulse analysis, data fusion (Guan *et al*., 2005) and artificial intelligence analysis (Kou and Wang, 2007). Due to the deterioration of electromagnetic environment and noise, radar receivers receive signals with great pollution and interference. The range of some parameter is changed, because of the impact of noise. There are more working modes in modern radar. Correspondingly, there are more combinations of radar signal parameters. It is more difficult to recognize the type of radar emitter, because of electromagnetic environment deterioration, jamming technique and new type radar. Traditional recognition can not be competent for the job (Zhang *et al*., 2009). So the research about this point has been the emphases and exploring the new radar emitter recognition method has the theory and applying meaning.

Back Propagation (BP) neural network is a popular method for classification. BP algorithm is one of the most widely used algorithms at present, but BP algorithm can not be applied in depth to neural network due to its limitation and many disadvantages such as slowness of convergence speed, imperfectness of traditional algorithm, possibility of network paralysis and etc. Especially, BP algorithm is easily trapped into local minimum (Feng *et al*., 2000). To overcome the problem of local minimum, a new algorithm named Single Parameter Dynamic Search (SPDS) algorithm is proposed by some researchers (Wang and Fang, 1997). The SPDS algorithm based on the idea of circulating coordinate in turns is an algorithm of multilayered feedforward neural network, which only permits one of all parameters in the network to change during each epoch of searching for parameters so that guarantees to carry out the exact one-dimensional search. In this study, a method of radar emitter recognition is proposed, which adopts the BP neural network based on SPDS algorithm. The availability is proved by simulation.

BP NEURAL NETWORK

At present, BP neural network is the most useful neural network in many fields (Li *et al*., 2010). There are

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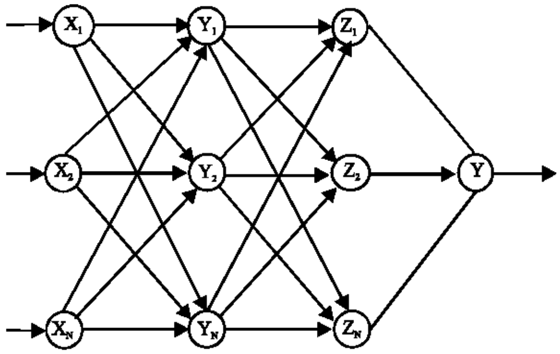

Fig. 1: Structure of BP neural network. Where $\{X_1, X_2, \ldots, X_N\}$ is in the input layer. $\{Z_1, Z_2, \ldots, Z_N\}$ is in the hidden layer and $\{Y_1, Y_2, \ldots, Y_N\}$ is in the output layer

two parts are in BP neural network: positive-going information transition and erroneous opposite-going transition. In the process of positive-going transition, the input information is transited through the input layer, hidden layer to the output layer (Alsaade, 2010). The states of neurons at each layer only affect that of the next layer's. If no anticipated output is obtained at the output layer, the deviation value of the output layer is thus calculated and transited in the reverse direction, returning the deviation signal through the original passage in the network, then revise the weight values of neurons at each layer until the expected target is reached (Qiang-Zhu, 2006). The structure of BP neural network is shown in Fig. 1.

The algorithm of BP neural network is as follows: first, the calculation is made through the input layer of the network to the output layer; second, revision and adjustment is made on the connectional weight values and threshold values, namely, make calculation and revision through the output layer to the input layer, then revise weight values connected to the output layer according to the deviations of the output layer until all the requirements are fulfilled (Yang, 2010). The flowchart of BP neural network algorithm is shown in Fig. 2. As shown in the Fig. 2, the algorithmic process of BP neural network is dynamic. The entry of one step is allowed only at the fulfillment of last step, or second analysis is required to find the deviation before entering another step.

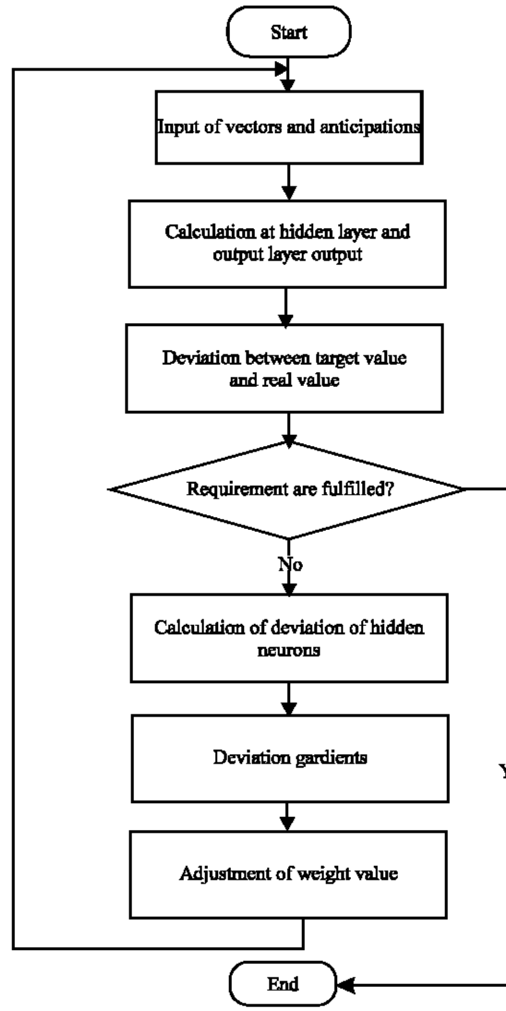

Fig. 2: Flowchart of the algorithm of BP network

SPDS ALGORITHM

Derivation of neural network based on SPDS algorithm: Following calculation steps of SPDS algorithm are to be introduced for application in three-layered neural network.

Let I be the number of input layer units, H be the number of hidden layer units, O be the number of output layer units, K be the number of pattern, the vector $P_{k,i}^{(1)}$ be the output of kth pattern in ith input neuron, $r_{k,i}^{(1)}$ be the sum of input from kth pattern in ith hidden neuron and threshold of ith hidden neuron, $P_{k,i}^{(2)}$ be the output of kth pattern in ith hidden neuron, $r_{k,i}^{(2)}$ be the sum of intput from kth pattern in ith output neuron and threshold of ith output neuron, $y_{k,i}$ be the output of kth pattern in ith output neuron, $w_{j,i}^{(1)}$ be the weight connecting ith input neuron to jth hidden neuron, $h_i^{(1)}$ be the threshold of ith hidden neuron, $w_{j,i}^{(2)}$ be the weight connecting ith hidden neuron to jth output neuron, $h_i^{(2)}$ be the threshold of ith output neuron, $T_{k,i}$ be the teaching signal of kth pattern in ith output neuron. Aimed at 4 different kinds of parameters as above, the 4 corresponding objective functions used in one-dimensional search are to be introduced in following section.

The error function can be represented as:

$$E=\sum_{j=1}^{N}\sum_{k=1}^{K}\left(y_{k,j}-T_{k,j}\right)^2 \quad (1)$$

Then the activation function is given by:

$$g(x)=\frac{1}{1+e^{-\lambda x}} \quad (2)$$

The flowchart of SPDS algorithm is shown as Fig. 3.

As shown in Fig. 3, the SPDS algorithm consists of 4 steps as follow:

- **Step 1:** Adjustment of threshold in output layer

For $1\le i\le O$, adjust $h_i^{(2)}$, since $h_i^{(2)}$ is the unique parameter permitted to change, consider the functions:

$$f_1=\sum_{k=1}^{K}(y_{k,i}-T_{k,i})^2 \quad (3)$$

$$y_{k,i}^{(2)}=g\left(r_{k,i}^{(2)}\right) \quad (4)$$

$$r_{k,i}^{(2)}=\left(r_{k,I}^{(2)}-h_i^{(2)}\right)+h_i^{(2)} \quad (5)$$

Let item $(r_{k,i}^{(2)}-h_i^{(2)})$ in Eq. 5 be the constant R_x with the only relevance to k, item $h_i^{(2)}$ in Eq. 5 be variable x, namely:

$$R_k=r_{k,i}^{(2)}-h_i^{(2)} \quad (6)$$

$$r_{k,i}^{(2)}=R_k+x \quad (7)$$

$$f_1(x)=\sum_{k=1}^{K}\left(g(R_k+x)-T_{k,i}\right)^2 \quad (8)$$

Compute x_0 that satisfies $f_1(x_0)=\min f_1(x)$, $x\in R$, then x_0 is the updated $h_i^{(2)}$, meanwhile, adjust $r_{k,i}^{(2)}$ and $y_{k,i}$ according to the x_0, where $1\le k\le K$.

- **Step 2:** Adjustment of weight connecting hidden layer to output layer

For $1\le i\le O$, $1\le j\le H$, adjust $w_{i,j}^{(2)}$, since $w_{i,j}^{(2)}$ is the unique parameter permitted to change, consider the function:

$$f_2(x)=\sum_{k=1}^{K}\left(y_{k,i}-T_{k,i}\right)^2 \quad (9)$$

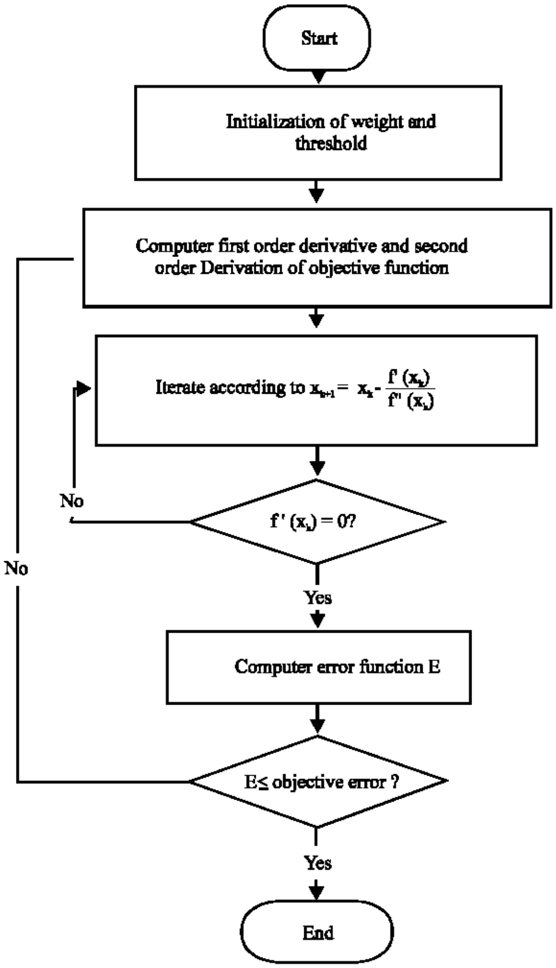

Fig. 3: Flowchart of SPDS algorithm

By similar procedure with step 1, Eq. 9 would then be:

$$f_2(x)=\sum_{k=1}^{K}\left(g\left(R_k^{(2)}+R_k^{(1)}x\right)-T_{k,i}\right)^2 \quad (10)$$

$$r_{k,j}^{(2)}=r_{k,j}^{(2)}-P_{k,j}^{(2)}W_{i,j}^{(2)}+P_{k,j}^{(2)}w_{i,j}^{(2)}=R_k^{(2)}+R_k^{(1)}x \quad (11)$$

$$R_k^{(2)}=r_{k,j}^{(2)}-P_{k,j}^{(2)}w_{i,j}^{(2)} \quad (12)$$

$$R_k^{(1)}=P_{k,j}^{(2)} \quad (13)$$

Compute x_0 that satisfies $f_2(x_0)=\min f_2(x)$, $x\in R$, then x_0 is the updated $w_{i,j}^{(2)}$, meanwhile, adjust $r_{k,i}^{(2)}$ and $y_{k,i}$ according to the x_0, where $1\le k\le K$.

- **Step 3:** Adjustment of threshold in hidden layer

For $1\le i\le H$, adjust $h_i^{(1)}$, since $h_i^{(1)}$ is the unique parameter permitted to change, consider the functions:

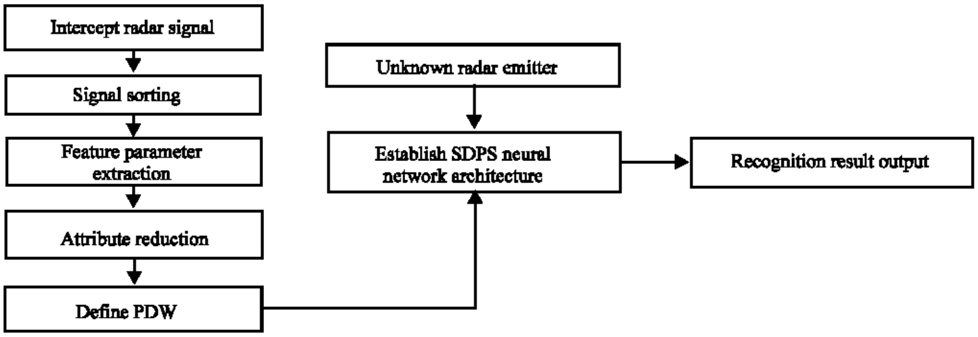

Fig. 4: Radar emitter recognition based on SPDS algorithm

$$f_3 = \sum_{j=1}^{O}\sum_{k=1}^{K}\left(y_{k,i} - T_{k,j}\right)^2 \tag{14}$$

By similar procedure with step 2, Eq. (14) would be:

$$f_3(x) = \sum_{j=1}^{0}\sum_{k=1}^{K}\left(g(L_{k,j} + g(M_k + x)w_{j,i}^{(2)}) - T_{k,j}\right)^2 \tag{15}$$

$$L_{k,j}^{(2)} = r_{k,j}^{(2)} - P_{k,i}^{(2)}\, w_{j,i}^{(2)} \tag{16}$$

$$P_{k,i}^{(2)} = g(r_{k,i}^{(1)}) \tag{17}$$

$$r_{k,j}^{(1)} = r_{k,I}^{(1)} - h_i^{(1)} + h_i^{(1)} = M_k + x \tag{18}$$

Compute x_0 that satisfies $f_3(x_0) = \min f_3(x)$, $x \in R$, then x_0 is the updated $h_i^{(1)}$, meanwhile, adjust $r_{k,j}^{(2)}$, $y_{k,j}$, $r_{k,i}^{(1)}$ and $P_{k,i}^{(2)}$, according to the x_0, where $1 \le j \le O$, $1 \le k \le K$.

- **Step 4:** Adjustment of weight connecting input layer to hidden layer

For $1 \le m \le I$, $1 \le n \le H$, adjust $w_{n,m}^{(1)}$, since $w_{n,m}^{(1)}$ is the unique parameter permitted to change, consider the functions:

$$f_4 = \sum_{j=1}^{O}\sum_{k=1}^{K}\left(y_{k,j} - T_{k,j}\right)^2 \tag{19}$$

By similar procedure with step 3, Eq. (19) would then be:

$$f_4(x) = \sum_{j=1}^{O}\sum_{k=1}^{K}\left(g\left(L_{k,j} + g\left(M_k^{(2)} + M_k^{(1)}x\right)w_{j,n}^{(2)}\right) - T_{k,j}\right)^2 \tag{20}$$

$$r_{k,m}^{(1)} = r_{k,m}^{(1)} - P_{k,m}^{(1)}\, W_{n,m}^{(1)} + P_{k,m}^{(1)}\, w_{n,m}^{(1)} = M_k^{(2)} + M_k^{(1)}\, x \tag{21}$$

$$M_k^{(2)} = r_{k,m}^{(1)} - P_{k,m}^{(1)}\, w_{n,m}^{(1)} \tag{22}$$

$$M_k^{(1)} = P_{k,m}^{(1)} \tag{23}$$

Compute x_0 that satisfies $f_3(x_0) = \min f_3(x)$, $x \in R$, then x_0 is the updated $w_{n,m}^{(1)}$, meanwhile, adjust $r_{k,n}^{(1)}$, $y_{k,j}$, $r_{k,j}^{(2)}$ and $P_{k,n}^{(2)}$ according to the x_0, where $1 \le j \le O$, $1 \le k \le K$.

The objective error functions $f_1(x)$, $f_2(x)$, $f_3(x)$ and $f_4(x)$ as above are one-dimensional functions with infinite-order derivative. On this basis first order derivative and second order derivative of error functions are necessary to be derived, which contributes to using the Newton iteration method to improve the convergent speed of training network furthermore. As initial value point is located nearby extremum point, which satisfies the condition of using Newton iteration method, Newton iteration method can be applied to one-dimensional search. Newton iteration formula is given by:

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)} \tag{24}$$

The model of SPDS neural network: After the electronic reconnaissance system achieves to intercept radar signal, the corresponding radar parameters can be measured by frequency measurement receiver and direction-finding receiver. These parameters such as Radio Frequency (RF), Direction of Arrival (DOA) of pulse signal, Time of Arrival (TOA) of pulse signal, Pulse Width (PW), Pulse Amplitude (PA) and etc compose Pulse Description Words (PDW). Then the architecture of neural network can be established by PDW. The process of radar emitter recognition based on SPDS neural network is described by Fig. 4.

ANALYSIS OF COMPUTERIZED SIMULATION RESULTS

In this study, data sets of 3 different types of radar signal from reference (Guan *et al*., 2005) are used in building the radar emitter initialized information table as shown in Table 1.

After imperfect feature parameters of radar signal as above are reduced according to availability of data, the

Table 1: Initialized parameter of radar signal

Type	1	1	2	2	3	3
Radio frequency (GHz)	0.81~0.85	0.88~0.905	9.325~9.41	9.325~9.41	2~4	2~4
Peak power (MW)	0.18~0.35	0.18~0.35	0.012	0.012	1.2	1.2
Pulse repetition frequency (kHz)	0.2~0.8	0.6~0.88	0.8	2.5	1	0.5
Pulse width (m sec)	0.004~0.00	0.004~0.00	0.0005	0.0009	0.0013	0.0026
Antenna rotate rate (r min^{-1})	-	-	19.8~24.2	19.8~24.2	-	-

Table 2: Data index scope of input vector

Radar type	RF	PP	PRF	PW
Type 1	[0.81 0.85]	[0.18 0.35]	[0.2 0.8]	[0.004 0.005]
Type 1	[0.88 0.905]	[0.18 0.35]	[0.6 0.88]	[0.004 0.005]
Type2	[9.325 9.415]	[0.011 0.013]	[0.7 0.9]	[0.0004 0.0006]
Type2	[9.325 9.415]	[0.011 0.013]	[2.4 2.6]	[0.0008 0.0010]
Type3	[2 4]	[1.1 1.3]	[0.9 1.1]	[0.0012 0.0014]
Type3	[2 4]	[1.1 1.3]	[0.4 0.6]	[0.0025 0.0027]

Correspondingly, output vector T = (0 1; 1 0; 1 1)

attribute of antenna rotate rate is evidently unnecessary. Thus PDW= (RF, PP, PRF, PW), where RF denotes Radio Frequency, PP denotes Peak Power, PRF denotes Pulse Repetition Frequency, PW denotes Pulse Width.

Extraction of pattern data and establishment of evaluating index: Extraction of training pattern data: 200 groups of random PDW data limited scope are extracted from each type of radar signal and the total groups of data are 600.

Assume input vector P = PDW, data index scope of each type is required as Table 2.

Extraction of testing pattern data: Testing pattern is extracted by adding Gaussian white noise on the basis of training pattern. The evaluating indexes consist of 3 parts as following:

- Training error
- Iteration number
- Recognition rate of testing set 1, testing set 2 and testing set 3 in presence of Gaussian white noise

RESULTS AND DISCUSSION

In order to speed up convergent procedure by improving the training way, LM algorithm and One Step Secant algorithm in MATLAB neural network toolbox are necessary to be applied to BP neural network. Implement recognition for the same pattern by using traditional BP algorithm, LM algorithm, One Step Secant algorithm and SPDS algorithm that is proposed in this paper and the average recognition rate is shown in Table 3.

As shown in Table 3, in the same training, SPDS algorithm needs less iterations to achieve a higher recognition rate and the output mean square error of SPDS is less than other methods. The computerized running results of SPDS algorithm is shown in Table 4.

Table 3: Recognition rate of radar emitter based on different algorithms

Algorithm evaluating indux	BP	LM	One Step secant	SPDS
Group of training pattern	600	600	600	600
Iteration number	20793	5	72	361
Output mean square error	0.001	0.001	0.001	0.0006
Group of testing pattern	600	600	600	600
Recognition of set 1	84.15%	94.25%	89.45%	100%
Recognition of set 2	79.05%	78.0%	66.9%	99.85%
Recognition of set 3	75.6%	88.25%	91.4%	100%

Table 4: The quantization analysis of computerized running results of SPDS algorithm

Iteration No.	Training Error	Recognition of Testing Set 1 (%)	Recognition of Testing Set 2 (%)	Recognition of Testing Set 3 (%)
275	20.780560	97.56	98.46	92.24
280	9.6684720	98.01	97.47	95.86
285	4.6781590	98.35	96.95	98.55
290	2.4442600	98.99	97.58	99.40
304	0.9141164	99.34	96.99	99.41
310	0.2195941	100.00	98.09	100.00
315	0.1688742	100.00	98.21	100.00
321	0.1117011	100.00	98.73	100.00
330	0.0319741	100.00	99.31	100.00
347	0.0086426	100.00	99.64	100.00
361	0.00060080	100.00	99.75	100.00
380	0.00004080	100.00	99.95	100.00

As shown in Table 4, the iteration number affects recognition rates and training error sharply. As shown in Table 4, when the iteration number is close to 300, the high recognition rate is obtained. The recognition rate is even close to 100% under the condition of enough iterations and uncomplicated data. Compared with the result processed by BP algorithm to the same pattern, SPDS algorithm has higher recognition rate and faster convergent speed significantly. SPDS algorithm can overcomes the problems of local minimum and long training time, which are the giant limits of BP algorithm. The SPDS neural network is robust to the noise. In a word, compared with BP algorithm, SPDS algorithm can obtain higher recognition rate by less computational complexity in the condition of uncomplicated data and noise.

CONCLUSIONS

SPDS algorithm positively improves BP algorithm and it would not be trapped into local minimum. Meanwhile, computational complexity of SPDS algorithm is significantly less than the gradient descent algorithm. In general, radar emitter signals can be exactly recognized by the SPDS neural network.

By comparing the testing result, it is found that the radar emitter signal can be recognized more accurately with the SPDS neural network and the learning speed is improved greatly. The recognition rate is close to 100% under the condition of enough training times. In addition, neural network based on SPDS algorithm is more robust than neural network based on BP algorithm. Compared with BP algorithm, SPDS algorithm can obtain higher recognition rate by less computational complexity in the condition of uncomplicated data and noise.

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