# A Radar Target Detection Method Based on RBF Neural Network

Hu Jurong, Wu Tong(✉), Lu Long, and Li Xujie

School of Computer and Information, Hohai University, Nanjing 210098, China

**Abstract.** In recent years radar target detection environment is more and more complex. Traditional CFAR (Constant False Alarm Rate) is a technology in which the radar system discriminates the output signal and noise of the receiver to determine whether the target signal exists under the condition that the False Alarm probability is kept Constant. In order to improve the radar target detection performance, a radar target detection method based on NN (Neural Network) is proposed. In this paper, the radar signal received by a single RBFNN is used for network training, and the probability of detection target is studied by combining the binary detection theory. Simulation results show that the proposed algorithm can effectively improve the radar target detection probability.

**Keywords:** Radar · Constant false alarm rate · Neural network · Target detection

## 1 Introduction

An important task performed by the radar system is target detection [1]. There are various interferences in the target detection environment of radar signals. These interferences include thermal noise inside the receiver antenna and clutter interferences caused by obstacles, wind or rain, sea waves and so on, sometimes there are active interference and passive interference from the enemies. The intensity of clutter and enemies' interference is often much higher than the internal noise level of the radar receiver. Therefore, to extract signals from strong interference, not only a certain signal-to-noise ratio is required, but also constant false-alarm rate (CFAR) [2] on the signal.

Neural network [3, 4] has a distributed structure, which is similar to the human brain, and it has strong robustness and fault tolerance. When we use the neural network to process the disturbed signal, it will guarantee the authenticity of the signal. Neural network is a non-liner model [5, 6], so we can simulate many engineering nonlinear problems through neural network. Using the chaotic characteristics of echo [7], artificial neural network [8] can be used as a clutter simulator to train the single radar echoes which in a targetless state, then use the trained network as a predictor to predict

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the echo received by the radar at the next moment. According to the comparison result of the prediction error of the radar echo signal and the decision threshold [9–11], we can classify the two kinds of interference to complete the target detection. Simulation result shows that the detection probability of this method id better than the traditional cell average CFAR (CA-CFAR) detection method.

## 2 CFAR Target Detection

Define that $r(t)$ is the signal received by the radar receiver, and $r(t)$ is composed of target signal $\mathrm{x_T}(t)$, interference signal $j(t)$ and noise $\mathrm{g}(t)$, $\mathrm{g}(t)$ is a random signal with zero-mean. They are independent of each other, then the signal $r(t)$ can be expressed as:

$$r(t) = \mathrm{x_T}(t) + j(t) + g(t) \tag{1}$$

The simulation model of the target signal $\mathrm{x}(t)$ with radar single scan is:

$$x_T(t) = \frac{\mathrm{K_T}}{\mathrm{R^2(t)}}\cos[\omega_d(t - \frac{2\mathrm{R_0}}{\mathrm{c}} - kT_r) + (\omega_k + \pi b)(t - \frac{2\mathrm{R(t)}}{\mathrm{c}} - kT_r)] \tag{2}$$

$K_T$ is a constant and is determined by factors such as radar transmit power, antenna gain, transmission loss or target cross-sectional area; $\mathrm{R}(t)$ is the instantaneous distance between the radar and the target; $\mathrm{R_0}$ is the distance between the target and the radar when the kth pulse meets the target; $\omega_d$ is Doppler frequency; $\omega_\mathrm{k}$ is frequency increment; c is the speed of light; $T_r$ is pulse repetition period; b is linear FM scan rate.

We take for example that the interference signal $j(t)$ is an FM signal:

$$j(t) = U_i \cos[w_i t + 2\pi K \int_0^t u_f(\tau) d\tau + \varphi] \tag{3}$$

Where $U_i$ represent the amplitude of FM signal; Time-varying functions $u_\mathrm{f}(t)$ represent a stationary random process with zero-mean; And $\varphi$ is a uniform distribution on $[0, 2\pi]$ and independent of $u_\mathrm{f}(t)$; $\omega_i$ is the central frequency of the noise FM signal; $K_f$ is FM slope.

Divide the intercepted signal represented by formula (1) into multiple time series u (k), then construct a binary hypothesis testing:

$$\begin{cases} H_0 : \mathrm{r}_{n,k} = \mathrm{j}_{n,k} + \mathrm{g}_{n,k} \\ H_1 : \mathrm{r}_{n,k} = \mathrm{x}_{n,k} + \mathrm{j}_{n,k} + \mathrm{g}_{n,k} \end{cases} \tag{4}$$

Where $\mathrm{g}_{n,k}$ and $\mathrm{r}_{n,k}$ represent the value of the nth sampling point in the kth time series; $\mathrm{x}_{n,k}$ and $j_{n,k}$ represent signal term and error term respectively. $H_0$ means no target, while $H_1$ means target exists.

By the N-P criterion, we can define the false alarm probability $P_f$(k) and detection probability $P_d$(k) in the time series u(k):

$$\begin{cases} P_f(\mathrm{k}) = \mathrm{P}\{\mathrm{r}_{n,k} > V|H_0\} \\ P_d(\mathrm{k}) = \mathrm{P}\{\mathrm{r}_{n,k} > V|H_1\} \end{cases} \tag{5}$$

In the observation time, the average false alarm probability is $\overline{\mathrm{P}}_f$ and the average detection probability is $\overline{\mathrm{P}}_d$:

$$\begin{cases} \overline{P_f} = \dfrac{1}{M}\displaystyle\sum_{\mathrm{i}=1}^{\mathrm{M}} P_f(i) \\ \overline{P_d} = \dfrac{1}{M}\displaystyle\sum_{\mathrm{i}=1}^{\mathrm{M}} P_d(i) \end{cases} \tag{6}$$

Assume that the noise in the intercepted signal conforms to the zero-mean Gaussian distribution, and its power is $\delta^2$:

$$g(\mathrm{n}) \sim N(0, \delta^2) \tag{7}$$

Perform n-point discrete-time Fourier transform on formula (3) to get G($f$), the variance can be expressed as:

$$N'\delta^2 = \delta^2 \sum_{n=1}^{N} h_n^2 \tag{8}$$

$|\mathrm{G}(f)|$ is the magnitude of $\mathrm{G}(f)$, and $|\mathrm{G}(f)|$ obeys the Rayleigh distribution with parameter $\lambda = \sqrt{N'/2\delta}$, we can get that:

$$P_f = e^{-\mathrm{V}_1^2/N'\delta^2}, \quad \eta = \sqrt{-N'\delta^2 \ln P_f} \tag{9}$$

Where $P_f$ is false alarm probability and $\eta$ is detection threshold.

According to the false alarm probability formula:

$$P_{fa} = \int_{\eta}^{\infty} p_n(x)dx = 1 - \int_0^{\eta} p_n(x)dx \tag{10}$$

We can get:

$$\int_0^{\eta} p_n(x)dx = 1 - P_{fa} \tag{11}$$

The threshold $\eta$ can be obtained by formula (11), then we can conclude that the thresholds corresponding to different probability density functions can get a constant false alarm probability. That is, as the probability density function transforms, there is a corresponding adaptive threshold.

## 3 Target Detection Based on Neural Network

Assume that the echo signal is described by the following model.

RBF neural network has three layers, its input layer and hidden layer have M and K neurons respectively, and it has only one output neuron. The input and output relationship of the neural network is shown in Fig. 1.

The activation function of the RBF neural network can be represented by the Gaussian function as:

$$R(r_p - c_i) = \exp(-\frac{1}{2\delta_{\mathrm{k}}^2}\left\|\mathrm{r}_p - c_i\right\|^2) \tag{12}$$

Where $\mathrm{r}_p$ is the pth input sample, $c_i$ is the ith center point. $R\left(r_p - c_i\right)$ is a nonlinear mapping that maps the input vector to the hidden layer.

The output of RBF neural network can be represented as:

$$y_j = \sum_{i=1}^{K} w_{ij} \exp(-\frac{1}{2\delta_{\mathrm{k}}^2}\left\|\mathrm{r}_p - c_i\right\|^2) \;\; j = 1, 2, \ldots, \mathrm{n} \tag{13}$$

Where $\omega_{ij}$ is adaptive update through RLS algorithm, $c_i$ is randomly selected from the trained array, K is obtained by the least absolute deviation which found through multiple trials. Besides, $\delta_{\mathrm{k}}^2 = \mathrm{d}^2/\mathrm{K}, \delta_{\mathrm{k}}$ is standard deviation, d is the maximum distance between selected centers.

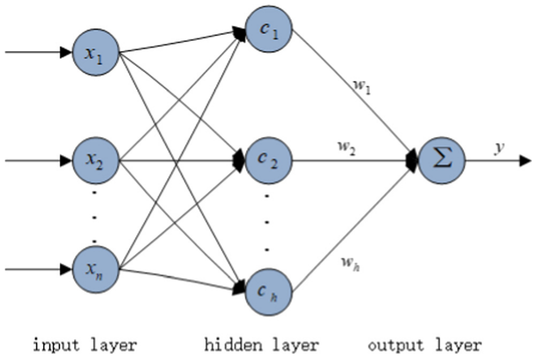



**Fig. 1.** The schematic diagram of neural network

The prediction absolute error can be expressed as:

$$\varepsilon(t) = \left|r(t) - \hat{r}(t)\right| \tag{14}$$

Binary detection:

$$r(t) \in \begin{cases} H_0 & \varepsilon(t) \geq \eta \\ H_1 & \varepsilon(t) < \eta \end{cases} \tag{15}$$

Where $H_0$ means there is no target, and $H_1$ is the hypothesis of the target exists.

The flowchart of the method of predicting and detecting targets based on neural network is shown in Fig. 2:

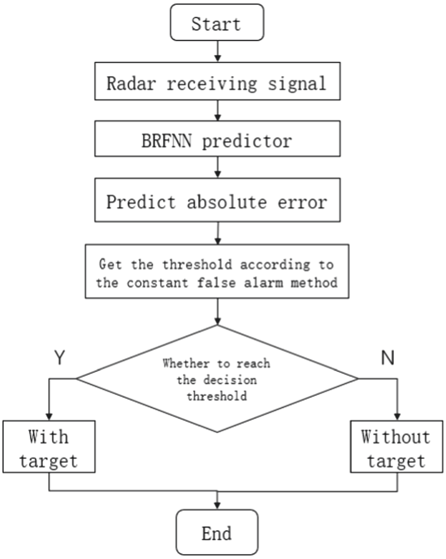



**Fig. 2.** The flowchart of the method of predicting and detecting targets based on neural network

The specific three steps of the detection method based on neural network target detection:

The first step: Determine the training sample set, and train the parameters of the neural network;
The second step: Use the single-step prediction method to predict the clutter state of the next moment;
The third step: Obtain the detection threshold according to the constant false alarm rate method, then compare the prediction absolute error with the detection threshold to get the target detection result.

# 4 Simulation

This experiment uses FM signal as the interference signal, collect two sets of FM signal data, with 2000 training samples and 2000 test samples. The Doppler frequency is 80 Hz, and the length of the time-series is 64 and 128 respectively. Perform network training to get the RBF predictor, then pass the signal $r(t)$ which obtained by the radar receiver through the RBF predictor. Use the simulation to compare the effects of different signal-to-noise ratios on the ability of neural network target detection.

## 4.1 The Influence of Sampling Frequency on the Mean Square Error of Neural Network Training

In order to study the influence of sampling frequency on the mean square error of neural network training, we will try to find the best sampling frequency through a large number of experiments. Assuming that the interference signal is an FM signal, the neural network parameter $c_i$ is randomly selected from the trained array, parameter K is obtained through multiple experiments to find the smallest prediction absolute error, $\delta_k^2$ is calculated by the formula $\delta_k^2 = d^2/K$. Then selected a set of FM interference data with a sequence length of 64 to train the RBF network, and the time length is 30 s. When the sampling frequency is set to 2 Hz, 3 Hz, 4 Hz, the mean square error that varies with the number of samples can be obtained, as shown in Fig. 3.

According to Fig. 3, we can get that when the sampling frequency is 2 Hz and 3 Hz respectively, as the number of samples increases, the mean square error gradually decreases, gradually approaching a certain order of magnitude $10^{-16}$ and $10^{-17}$ respectively. When the sampling frequency is 4 Hz, at the beginning, as the number of samples increase, the mean square error gradually decreases but still large. When the number of samples reaches a certain value, the mean square error tends to increase for a short time. This is because the sample data has great randomness. If the sample is too small, the training requirements cannot be met, and the prediction model cannot fully reflect the distribution characteristics of the interference signal. Similarly, if there are too many samples, the mean square error of the sampling frequency of 4 Hz in Fig. 3

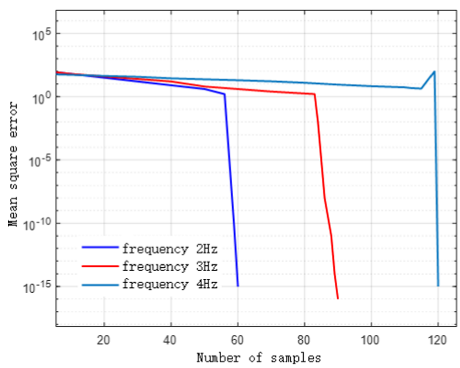
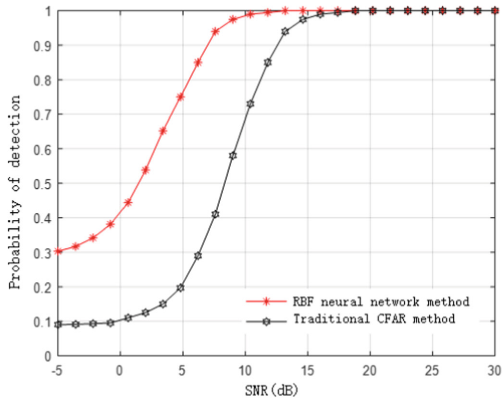



**Fig. 3.** Mean square error curve under different sampling frequencies

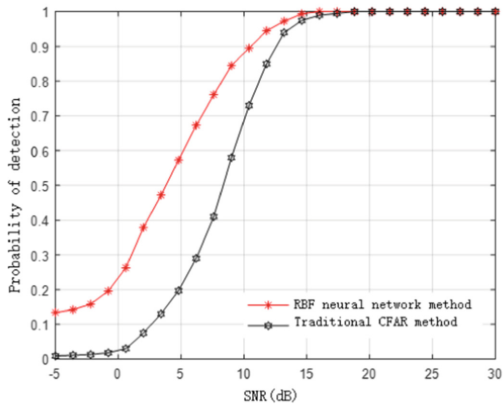
will become larger in a short time, and cannot achieve better prediction. Therefore, a large number of simulation experiments are needed to find that the sampling frequency is 3 Hz, the number of training samples is moderate, and the mean square error is also approaching 0.

## 4.2 Target Detection Based on RBF Neural Network

Use FM signal as interference signal to study the two cases where the length of the data sequence is 128 and 256 in a single scan, under the condition that the false alarm probability $P_f = 10^{-13}$, $f_d = 120$ Hz, and the sampling frequency is 3 Hz. Pass the signal through the RBF network predictor for simulation experiment, then compare the prediction result with the traditional CFAR detection performance. The target detection probability of the signal-to-noise ratio (SNR) of different sequence lengths is shown in the Fig. 4.




(a) The sequence length is 128




(b) The sequence length is 256

**Fig. 4.** Target detection probability curves of different sequence lengths

It can be seen from Fig. 4(a)–(b) that when the SNR is low, the detection performance of the method based on neural network is better than the traditional CFAR method in the FM interference environment. As the SNR increases, the detection probability continues to increase. When the SNR increases to 6, the detection probability can reach more than 90%. When the signal-to-noise ratio is low, the detection probability of the longer sequence length is low. As the SNR increases, the detection probability of the two methods continues to increase, and eventually approach 1.

## 5 Conclusion

We studied the target detection method based on neural network and the constant false alarm target detection method through theory and simulation. And we take the FM signal as the interference signal, and study to use the prediction method based on neural network to predict the modulated interference signal. The simulation result shows that this method can effectively improve the radar's detection probability of the target under the modulation interference environment, and the detection performance is better than the traditional CFAR method.

## References

1. Li, J., Stoica, P.: MIMO Radar Signal Processing. Wiley, Hoboken (2009)
2. Nagle, D.T., Saniie, J.: Performance analysis of linearly combined order statistic CFAR detectors. IEEE Trans. Aerosp. Electron. Syst. **31**, 522–533 (1995)
3. Xing, H., Xu, W.: The neural networks method for detecting weak signals under chaotic background. Acta Phys. Sin. **56**(7), 3771–3776 (2007)
4. Si, W., Tong, N., Wang, Q.: Weak targets detection research under sea clutter background. J. Signal Process. **01**, 106–111 (2014)
5. Harpham, C., Dawson, C.W.: The effect of different basis function on a radial basis function network for time series prediction: a comparative study. Neurocomputing **69**, 2161–2170 (2006)
6. Hennessey, G., Leung, H., Yip, P.C.: Sea-clutter modeling using a radial-basis-function neural network. IEEE J. Oceanic Eng. **26**(3), 358–372 (2001)
7. Xie, N., Leung, H., Chan, H.: A multiple-model prediction approach for sea clutter modeling. IEEE Trans. Geosci. Remote Sens. **41**(6), 1491–1502 (2003)
8. Haykin, S., Thomson, D.J.: Signal detection in a non-stationary environment reformulated as an adaptive pattern classification problem. Proc. IEEE **86**(11), 2325–2344 (1998)
9. Zheng, H., Xing, H., Xu, W.: Detection of weak signal embedded in chaotic background using echo state network. J. Signal Process. **03**, 336–345 (2015)
10. Zhao, F.: Detection and Extraction of Weak Target in Sea Clutter Based on RBF. Jilin University, Changchun (2013)
11. Zheng, K., Zhu, X., Wang, H.: Suppression effects analysis of DRFM jamming on radar CFAR detection. Electron. Inf. Warfare Technol. (01), (2016)
12. Wang, J., Hou, R.: CFAR detection algorithm of electronic reconnaissance system in frequency domain. Shipboard Electron. Countermeas. **40**(2), 60–63 (2017)