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APPLICATION OF WAVELET TRANSFORM AND NEURAL NETWORK TO TARGET RECOGNITION OF MMW RADIOMETER *

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Abstract The target signal of millimeter wave (MMW) radiometer was decomposed to a series of projections in orthogonal subspaces by wavelet transform. The features of MMW radiometer in each orthogonal subspace were analyzed and characterized by neural network. In addition, the results of simulation show that the target recognition method developed by this paper is effective when the SNR is low.

Key words wavelet transform, MMW radiometer signal, feature extraction, classification, neural network.

Introduction

The MMW passive detector (radiometer) detects targets by using the difference in the MMW radiating energy between target object and background. Since the difference in the MMW radiating rate between metal object and background is big and the passive detector can overcome the flicker effect of the active radar in close quarter, the MMW radiometer is adapted for detecting the metal target in close quarter.

With the development of modern war, the detector is required to detect the existence, position, moving orbit as well as the classification of targets. The traditional MMW radiometer extracts features of pulse duration, area, amplitude and the maximum slope of the signal wave, then recognizes targets through the template matching. The method is simple to realize, but it isn't good at anti-noise performance. When the SNR of the signal of MMW radiometer is low, the recognition rate will become bad. So we have to have

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some additional conditions, such as the scope of height, in application. Thus, the recognition rate must be improved[4].

In this paper, an extracting method of the signal feature vector is presented to comress the data and reduce the noise, according to the capability of space decomposition of wavelet transform. Then the classifier of Bp neural network is constructed. Because of good fault-tolerance and robust of neural network, the classifier developed by the authors not only is robust to signal distribution and noise, but also has high speed of recognition and the small size memory of system. The result of simulation to the signal of SNR=3dB shows that the method is effective.

1 Wavelet Transform Based Feature Extraction

The definition of discrete wavelet transform (DWT) for the signal $f(n)$ is

$$DWT_f[j,k] = 2^{-j/2}\sum_n f(n)\Psi\left(\frac{n-k\cdot 2^j}{2^j}\right) \quad j,k \in Z \tag{1}$$

where $\Psi(n)$ is the wavelet function.

When $\Psi(n)$ is a compact-support orthogonal wavelet which was proved and constructed by Deubechies, Eq. (1) decomposes $f(n)$ into a series of projections in orthogonal subspace.

The key to the target recognition is feature extraction. There are many methods of extracting features. In this paper, target signal is decomposed into projection in a series of orthorgnal subspace, then the features of each subspace are extracted and combined into a target feature vector. This method makes it easy to extract features and the features are relatively concise and accurate because there is no redundancy of each component.

Let wavelet function be the compact function constructed by Daubechies. One of the MMW simulation signal wave without noise is transformed to four classes. So the signal is decomposed to five orthogonal subspaces. In order to find the distribution of the signal feature in each subspace, the following method is adopted. Setting the decomposition signal at certain level to be zero, while keeping others unchanged, then a signal wave is reconstructed, which is shown in Fig. 1. According to the loss of reconstruction signal, we can think that the less the loss, the less information the component has, and vice versa. So we can think that according to Fig. 1. there is little information of target in D_1 subspace, a little more information in D_2、D_3 subspaces, and the main information is in D_4、A_4.

In this paper, $D_4 f$、$A_4 f$ and the energies of $D_2 f$、$D_3 f$ are combined into the feature vector $\vec{T}$:

$$\vec{T} = \{D_{4,1}, D_{4,2}, \ldots, D_{4,M}, A_{4,1}, A_{4,2}, \ldots, A_{4,M}, \overline{D}_3, \overline{D}_2\}$$

where M=N/16, N is the number of samples of original signal.

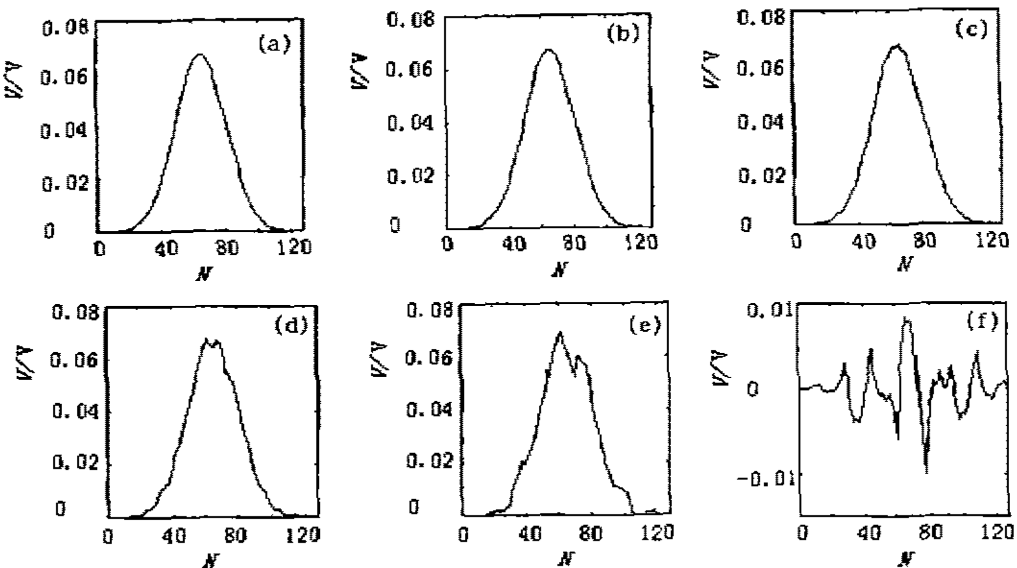

Fig. 1 The reconstruction of the MMW radiometer signal
(a) original signal, (b) reconstruction when $D_1 f=0$, (c) reconstruction when $D_2 f=0$,
(d) reconstruction when $D_3 f=0$, (e) reconstruction when $D_4 f=0$,
(f) reconstruction when $A_4 f=0$

图 1　毫米波辐射计信号重建情况
(a) 原始信号，(b) $D_1 f=0$ 时的重建情况，(c) $D_2 f=0$ 时的重建情况，
(d) $D_3 f=0$ 时的重建情况，(e) $D_4 f=0$ 时的重建情况，(f) $A_4 f=0$ 时的重建情况

In fact, the information of $D_4 f+A_4 f$ is the same as that of $A_3 f$. It is beneficial to later recognition that $A_3 f$ is divided into approximate sector $A_4 f$ and detailed sector $D_4 f$. On the other hand, because $D_1 f$ has little information, the feature vector $\vec{T}$ hasn't the information of D_1 subspace. So $\vec{T}$ hasn't noise in D_1. In the same way, the noise of D_2、D_4 can be well depressed.

The target signal is sampled into 128 points, as Fig. 1 shows. The Ref. [4] pointed out that the peak of signal corresponds to the antenna aiming at the center of target. In practical application, the decision must be made as soon as the antenna aims at the center of target, and the first half part of the waveform contains the whole information because of the symmetry of the waveform. So we can analyze only the 64 points in the first half part of waveform to extract the features. And the method not only is reasonable, but also can compress the data.

The 64 points in the first half part of waveform are transformed into four levels by DWT. Thus $N=64$, $J=64/16=4$, and $D_4 f$、$A_4 f$ have four points, respectively. The energy of $D_2 f$、$D_3 f$ is one-dimensional. So the feature vector is 10-dimensional, which is proved effective by the following neural network classifier.

2 Neural Network Classifier

According to the principle of radiometer, the waveforms of the radiometer are simulated [4]. The radiometer signal parameters are defined as follows:

(1) The angle (θ) between the scanning line and target,

(2) The deviation (d) between the scanning line and the target's center,

(3) The distance (D) between the radiometer antenna and the target,

(4) The target's size (s).

The radiometer signal is studied when θ is 0°, 30°, 45°, 60°, 90°, respectively, d is 0, 0.25m, 0.5m, respectively, D is 30m, 40m, 50m, 60m, 70m, 80m, 90m, 100m, 110m, 120m, respectively, and s is 3m×5m, 4m×6m, 5m×7m, respectively. All the interference signal is simulated by Gauss white noise and superimposed on the ideal signal to obtain the radiometer signal. One of the simulated radiometer signal for which SNR is 3dB is shown in Fig. 2.

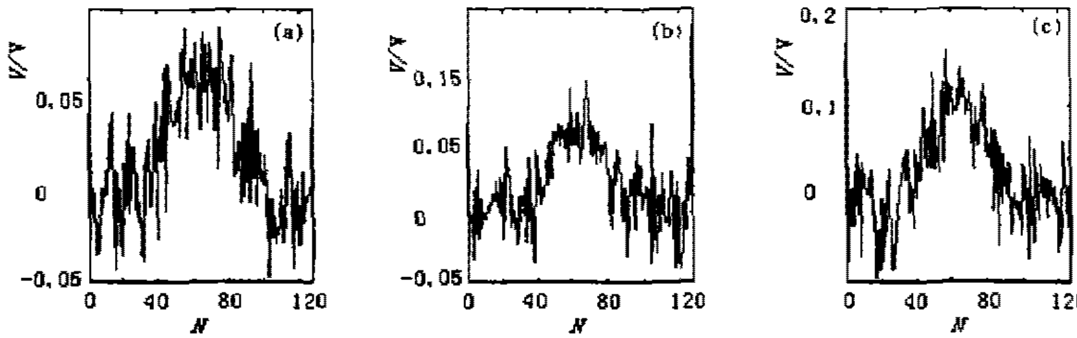

Fig. 2 Three kinds of signal of MMW radiometer (SNR=3dB)
图2 3种毫米波辐射计信号 (SNR=3dB)

The constant false alarm rate (CFAR) is used in detecting target in cluster noise. The approach used frequently is the moving-window-detection. The moving-window-detection method decides detecting threshold by the difference of neighborhood samples, which is realized simply in real time.

After extracting features of target, many classification methods can be adopted. The nearest-neighbor method is one of the simple ones. Setting the templet to be the mean vector in a certain height. Then the result of recognition is shown in Table 1, according to the nearest-neighbor method rule. The result is not good because of the dispersion of waveform. The neural network is adopted as follows.

Neural network computation is a distributed process, in which all the neurons operate in parallel, thus it has fault tolerance and robust. So it can avoid large size memory of the system caused by the small section of distance (H). In addition, neural network can adapt itself to the dispersion of waveform caused by angle, deviation, distance and noise.

Since it is simple and easy to realize, the three-layer feed-forward network is used in this paper. The neuron number of input layer is defined according to the dimension of feature vector and that of output layer is chosen according to the kinds of targets, respectively. The neuron number of hidden layer is experimentally defined. The neuron activation function is typically a smooth one, e.g. the Sigmoid function $f(x)$.

$$f(x) = \frac{1}{1 - e^{-x}}$$

Here, some waveforms are used to train the neural network and others are used to test the result of target classification as shown in Table 1.

Table 1 Classification results of three kinds of targets

表 1　对 3 种目标的分类结果

method \ target	3m ~ 5m	4m ~ 6m	5m ~ 7m	average recognition
the nearest-neighbor method	38.00%	44.67%	42.67%	41.56%
Bp neural network	93.33%	98.67%	95.33%	95.55%

According to Table 1, the neural network classifier is obviously better than the nearest-neighbor method. Comparing the method in Ref. [4], the method developed in this paper not only overcomes the limit to the distance between the radiometer and target, but also improves the recognition rate.

3 Concluding Remarks

Signal analysis and feature extraction are the key problems of MMW radiometer. Neural network and wavelet theory are introduced to the target classification of MMW radiometer in this paper. With the development of the neural network and wavelet theory, the target classification method obtained in this paper will be developed further and becomes more perfect.

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小波变换和神经网络在毫米波辐射计目标识别中的应用*

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摘要　本文采用小波变换把毫米波辐射计的目标信号分解为一系列正交子空间上的投影,利用重构矩法分析信号特征在各子空间的分布,依次提取各子空间上的特征,然后融合这些特征,组成特征矢量.采用神经网络对目标信号特征矢量进行建模.用此方法对低信噪比的毫米波辐射计的信号进行仿真试验,结果表明该方法克服了传统方法对噪声和目标信号散布的敏感,取消了对目标和辐射计天线之间距离的限制,与最近邻法相比,该方法大大提高了识别率.

关键词　小波变换,毫米波辐射计信号,特征提取,分类,神经网络

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