IDENTIFICATION ON TARGET PROFILES OF MMW RADAR BASED ON WAVELET NEURAL NETWORK *

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Abstract An artificial neural network with the hidden layer consisting of wavelets was presented for the identification on target profiles of step frequency MMW radar. The good localization characteristics of wavelet functions in both time and frequency space allowed hierarchical multi-resolution learning of input-output data mapping. The mathematic frame of the neural network and error back propagation algorithm were introduced. The procedure of the identification which uses wavelet neural network was described in detail. Then the presented approach was applied to the target profile identification of step frequency MMW radar. The results indicate that the method is valuable for target profile identification.
Key works wavelet, neural network, multi-resolution analysis, target identification, radar signal, image processing.

基于小波神经网络的毫米波雷达目标距离像识别 *

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摘要 给出一种隐层由小波基组成的神经网络用于实现频率步进毫米波雷达目标一维距离像的识别.利用小波变换所具有的良好的时频分析特性,实现了输入输出之间映射关系的多分辨学习.介绍了小波神经网络的数学框架及其误差反向学习算法.详细描述了用小波神经网络进行识别的步骤.将所提出的小波神经网络用于频率步进毫米波雷达目标一维距离像的识别.实验结果表明该方法对目标距离像的识别是有效的.
关键词 小波,神经网络,多分辨分析,目标识别,雷达信号,图像处理.

Introduction

Let $h(x) \in L^2(R)$ be the mother wavelet that satisfies the admissibility condition, i.e.

$$\int_R \frac{|\hat{h}(\omega)|^2}{|\omega|} d\omega < \infty, \tag{1}$$

where $\hat{h}(\omega)$ is the Fourier transform of $h(x)$. The corresponding families of dilated and translated wavelets are defined by

$$\{h_{m,n}(x) = a^{-\frac{2}{m}} h(a^{-m}x - nb), \quad (m,n) \in Z^2\}, \tag{2}$$

where a and b are, respectively, the dilation and translation parameters. By proper selection of a and b, $\{h_{m,n}(x)\}$ are called discrete daughter wavelets which may constitute the frame of $L^2(R)$, i.e.

$$A\|f\|^2 \leqslant \sum_{(m,n)\in Z^2} |<h_{m,n}, f>|^2 \leqslant B\|f\|^2, \tag{3}$$

where $f \in L^2(R)$, $<h_{m,n}, f> = \int_R h_{m,n}(t) f(t)dt$ is the inner product, $A > 0$ and $B > 0$ are the frame bounds. If $A = B = 1$, $\{h_{m,n}(x), (m,n) \in$

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$Z^2\}$ is an orthonormal basis. In this case, it leads to

$$f(x)=\sum_{(m,n)\in Z^2}<h_{m,n},f>\cdot h_{m,n}(x). \quad (4)$$

The outstanding characteristic of the wavelet transform is that wavelet transform has good localization in both time and frequency space[1]. The lattice points of the mother wavelets $\{h_{m,n}(x)\}$ are located on $(nba^m, \pm a^{-m}\omega_0)$. The width of the time-window of $h_{m,n}(x)$ can be changed with the variation of the frequency. This property is very useful for the analysis of non-stationary signals and the learning of the nonlinear function. In order to get a multi-resolution analysis, the transform projects $f(x)$ to different scales. It is possible to select a set of wavelets to get the best presentation of $f(x)$ or the input data for the network.

Based on the previous discussion, the wavelet neural networks(WNN)can be defined as follows:

$$f(x)=\sum_{i=1}^{N}w_i h_i(x)=\sum_{i=1}^{N}w_i h\left(\frac{x-b_i}{a_i}\right), \quad (5)$$

where $w_i\in R$, $a_i\in R^d$, and $b_i\in R^d$, d is the dimension of the input, and N is the number of the wavelet bases. a_i and b_i are chosen according to the wavelet transform. The values of a_i and b_i construct a regular lattice. The WNN can be used to implement $R^d\Rightarrow R$ mapping.

According to the theory of multi-resolution analysis[2], an orthogonal wavelet basis can be constructed. The orthogonal wavelet basis function of $L^2(R)$ is of the form

$$h_{m,n}(x)=\{a^{-\frac{m}{2}}h(2^{-m}x-n),\ (m,n)\in Z^2\}, \quad (6)$$

where m and n are the dilation and translation indices. So, the orthonormal wavelet basis function neural network can be defined by using the orthonormal bases. The advantage of this network is that the computational expense is greatly reduced. This paper is organized as follows. In section 1, the properties of wavelet network and learning algorithm are introduced. In section 2, the application of the wavelet neural network to the target identification of step frequency MMW radar is illustrated. And the method of determining the structure of wavelet neural network is presented. Then, the training procedure of wavelet network is described. The results of identification on the target of step frequency MMW radar are also given in this section. The experimental results show that the neural networks obtain much better performance. In section 3, conclusions are finally drawn.

1 Wavelet neural network and learning algorithm

In terms of the results above, wavelets appear to be a promising method in a feature space for identification. The extraction of features in this case is the inner products of a set of wavelets with the input signal. These features can be inputted to a classifier. The major problem is which wavelets should be selected and how to select. We consider the combined classifier and wavelet feature detector given by [3]

$$y_i(t)=f\left[\sum_{j=1}^{K}w_{ij}\cdot\left(\sum_{k=1}^{M}x_k(t)\cdot h\left(\frac{k-b_j}{a_j}\right)\right)\right], \quad (7)$$

where $x_k(k=1,2,\cdots,M)$ is the input for the kth training vector $X(t)$, $y_i(i=1,2,\cdots,N)$ is the output for the ith training vector $Y(t)$. M is the node number of input layer, N is the node number of output layer, K is the node number of hidden layer, and $f(z)=\frac{1}{1+e^{-z}}$ is a sigmoid function. This classifier can be depicted as the neural network in Fig. 1. And $X=[x_1,x_2,\cdots,x_M]^T$ is the input vector, $h(x)$ is the mother wavelet function,

$$h(i,b_j,a_j)=h\left(\frac{i-b_j}{a_j}\right),$$

$$W=\begin{bmatrix} w_{11} & \cdots & w_{1N} \\ & \vdots & \\ w_{K1} & \cdots & w_{KN}\end{bmatrix}$$ is the weight matrix,

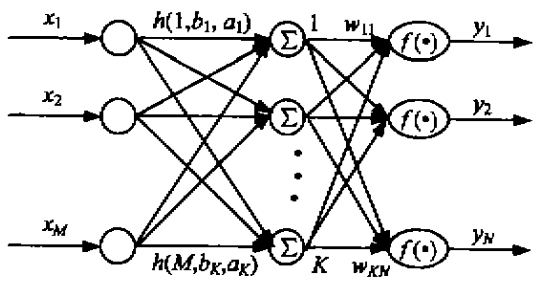

Fig. 1 Wavelet neural network diagram for target identification

图1 用于目标识别的小波神经网络结构框图

$$U=\begin{bmatrix}u_1\\ \vdots \\ u_K\end{bmatrix}=\begin{bmatrix}\sum_{i=1}^{M}x_ih(i,b_1,a_1)\\ \vdots \\ \sum_{i=1}^{M}x_ih(i,b_K,a_K)\end{bmatrix},$$

and $Y=[y_1,y_2,\cdots y_N]^T=f[WU]$ is the output vector of the network.

Figure 1 shows the wavelet neural network (WNN). Originally, the wavelet network contains two layers. But, once the network is synthesized, the two layers are changed into one because nonlinearity does not exist between the layers. So, the WNN contains the nonlinearity of wavelet function in the artificial neurons rather than the nonlinearity of the sigmoidal function. The wavelet network classification parameters w_k, a_k and b_k can be optimized by minimizing an energy function. We use the least-mean-squares (LMS) energy function for signal representation[4,5].

$$E=\frac{1}{2}\sum_{p=1}^{L}\sum_{i=1}^{N}(d_i^p-y_i^p)^2, \tag{8}$$

where L is the number of the training samples, d_i^p is the desired value of y_i^p. Then the conjugate gradient method for adjusting the parameters of wavelet network is

$$\frac{\partial E}{\partial w_{ij}}=-\sum_{p=1}^{L}\sum_{i=1}^{N}(d_i^p-y_i^p)y_i(1-y_i)\,w_{ij}\Big(\sum_{i=1}^{M}x_ih(i,b_j,a_j)\Big), \tag{9}$$

$$\frac{\partial E}{\partial a_j}=-\sum_{p=1}^{L}\sum_{i=1}^{N}(d_i^p-y_i^p)y_i(1-y_i)\,w_{ij}\Big(\sum_{i=1}^{M}x_i\frac{\partial h(i,b_j,a_j)}{\partial a_j}\Big), \tag{10}$$

$$\frac{\partial E}{\partial b_j}=-\sum_{p=1}^{L}\sum_{i=1}^{N}(d_i^p-y_i^p)y_i(1-y_i)\,w_{ij}\Big(\sum_{i=1}^{M}x_i\frac{\partial h(i,b_j,a_j)}{\partial b_j}\Big), \tag{11}$$

$$w_{ij}^{k+1}=w_{ij}^k-\eta\frac{\partial E}{\partial w_{ij}}+\alpha\Delta w_{ij} \tag{12}$$

$$a_j^{k+1}=a_j^k-\eta\frac{\partial E}{\partial a_j}+\alpha\Delta w_{ij} \tag{13}$$

$$b_j^{k+1}=b_j^k-\eta\frac{\partial E}{\partial b_j}+\alpha\Delta w_{ij} \tag{14}$$

where k is the iterative number, η is a positive coefficient (step-size), and α is the variable factor.

The training procedure is implemented as follows: Step 1. a search direction is obtained by computer. Step 2. using a variable step-size to compute the new weight vector. At each iteration, step 1 and step 2 are carried out by computer for the representation parameter vectors W, a and b. It is better to perform a line search to find the best step-size, since this can greatly reduce the number of iteration needed for convergence.

2 Using WNN for target identification of step frequency MMW radar

2.1 Preprocessing

The step frequency radar was developed from radar technology, and it is a simple method of transmitting and receiving wide-band signals. This type of radar transmits a series of individual frequencies in a wide bandwidth B, and measures the amplitude and phase of the echo signal at each frequency. The range profiles are generated by applying an inverse DFT to the echo signal. The method has produced high quality information of subsurface structures[6]. The majority of the data used in this paper is taken from the experiment. The particular dataset of step frequency waveform is the signal consisting of a series of 128 pulses. Such data often obscures some fundamental practical issues. So, data preprocessing and feature extraction are very important. Feature extraction prior to the identification must deal with different target size and target positions in the window of the range profiles and normalization of target signals.

First, a signal-to-noise ratio (SNR) of a single range profile can be improved by taking a simple non-coherent average over a sequence of profiles. Then, in order to make the target more obvious in the window of the range profiles, the gain offset must be adjusted. Third, in order to locate target position in the window of the range profiles, we use the magnitude of the Fourier transform of the range profile for position invariant function. Here the magnitude of the Fourier transform of the preprocessed range profile forms a real feature vector. This feature vector is then used in dimensionality reduction stage. The transformed vector has appealing quality. For example, it does not depend on where the target is in the window of the range profiles, and it is always the same length regardless of the target size. This enables targets of different lengths to be easily compared.

2.2 Target profiles identification of step frequency MMW radar

Wavelet neural network was designed to recognize the patterns of small car, small metal house and reflectors. The data of experiment contain the samples of the car, the small metal house and the reflectors. We selected 150 range profiles from each pattern to construct the training samples. So, there are 450 training samples in total.

We use $h(x)=\cos(1.75x)\exp(-x^2/2)$ [7] as mother wavelet. When x goes larger or smaller, it decays very rapidly. It can be proved that this function confirms the frame condition. Let $t=(i-b_j)/a_j$, then the gradients of E are

$$\frac{\partial E}{\partial w'_{ij}}=-\sum_{p=1}^{L}\sum_{i=1}^{N}(d_i^p-y_i^p)y_i(1-y_i)w_{ij}(\sum_{i=1}^{M}x_i\cos(1.75t)\exp(-t\times t/2)), \quad (15)$$

$$\frac{\partial E}{\partial a_j}=-\sum_{p=1}^{L}\sum_{i=1}^{N}(d_i^p-y_i^p)y_i(1-y_i)w_{ij}(\sum_{i=1}^{M}x_i\{[1.75\sin(1.75t)\exp(-t\times t/2)+\cos(1.75t)\exp(-t\times t/2)]\frac{t}{a_j}\}), \quad (16)$$

$$\frac{\partial E}{\partial b_j}=-\sum_{p=1}^{L}\sum_{i=1}^{N}(d_i^p-y_i^p)y_i(1-y_i)w_{ij}(\sum_{i=1}^{M}x_i\{[1.75\sin(1.75t)\exp(-t\times t/2)+\cos(1.75t)\exp(-t\times t/2)]\frac{1}{b_j}\}). \quad (17)$$

We randomly set initial values of W between 0 and 1, dimension $a_j=6.00\ (i=1,\cdots,10)$. The number of wavelets is 10. After 1750 iterations, the system error is reduced to 0.0008. Table 1 shows the initial and final values of a and b.

Table 1 shows that the wavelet neural network has adaptively created a wide range of daughter wavelet to get the best mapping. So, it shows higher identification rate as shown in Table 2.

In Table 2, the matrix shows the classification results generated from identification on each 150 samples. The numbers represent the numbers of classified patterns. The percentages (recognition rate) are given in brackets. The average recognition accuracy is 94.22%.

Table 1 Dimensions and shifts in wavelet neural network
表 1 小波神经网络的尺度和位移

Wavelet Nubmer	Dimensions		Shifts	
	Initial a	Final a	Initial b	Final b
1	6.00	2.13	0.05	-1.32
2	6.00	4.01	0.10	-0.57
3	6.00	7.13	0.15	-0.98
4	6.00	3.78	0.20	-1.12
5	6.00	6.24	0.25	-0 89
6	6 00	5.37	0.30	0.76
7	6.00	1 49	0 35	1.98
8	6.00	4.55	0 40	2 67
9	6 00	5.56	0.45	3 74
10	6.00	6 15	0.50	3.51

Table 2 Identification results on three target profiles
表 2 3种目标一维距离像的识别结果

Actual class	Classification		
	Car	House	Reflector
Car	143 (95 33%)	4 (2 67%)	3 (2 00%)
House	2 (1.33%)	141 (94.00%)	7 (4 67%)
Reflector	6 (4.00%)	4 (3.00%)	140 (93.33%)

3 Conclusions

In this paper, a neural network with wavelet as weight coefficients is proposed. Wavelet parameters and shapes are adaptively computed to minimize an energy function. The error back propagation algorithm is derived. The wavelet basis function network is used for the classification of targets of step frequency MMW radar. It has shown that the WNN is quite promising because it is very useful for the analysis of non-stationary signals classification when the auto-regressive terms are introduced into the network. The advantage of using WNN is that the localizing characteristic of the wavelets makes the estimation of regression functions efficient. The discrete wavelet transforms provide guidelines for constructing the regression algorithm. The experimental results show that the method is valuable for target profile identification.

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