Radar Emitter Signal Recognition Based on EMD and Neural Network

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***Abstract*—Radar emitter signal (RES) recognition is the important content in radar reconnaissance and signal processing. In order to study the problem of RES recognition, and to improve the RES recognition rate of the electronic warfare equipment, the empirical mode decomposition (EMD) theory and wavelet packet (WP) are introduced into RES feature extraction. A new RES recognition method is proposed based on WP, EMD and neural network (NN). It uses wavelet packet to finish decomposition, de-noising and reconstruction of the RES. Then obtain the intrinsic mode function (IMF) through EMD, which can embody the characteristics of the RES. The energy of each IMF are calculated and normalized, which would be regarded as the feature vector. By constructing back propagation neural network (BPNN) classifier and redial basis function neural network (RBFNN) classifier, it realizes the RES recognition finally. Experiment results show that the RES recognition method based on WP, EMD and NN is an effective recognition method, which can achieve satisfying correct recognition rate in a larger signal to noise ratio, and has certain reference value in follow-up in-depth study.**

***Index Terms*—radar emitter, signal recognition, empirical mode decomposition, neural network, wavelet packet**

I. INTRODUCTION

In electronic intelligence system (ELINT), electronic support measure system (ESM) and radar warning receiver system (RWR), the identification of RES is an important part. It is a more important factor to determine the level of radar countermeasures equipment and technology [1]. With the intensification of electronic countermeasures, new complex radar systems with strong anti-interference and stealth ability are emerging, which would gradually play more and more important role. The traditional method for RES identification is difficult to obtain satisfactory result, therefore it is necessary to conduct in-depth study of RES feature extraction and RES recognition.

Now, the application environment of RES is increasingly became complex. Many scholars have conducted in-depth study in RES recognition. Included RES recognition based on wavelet [2] [3], RES recognition based on time frequency atom approach [4], they are all based on Fourier transformation and have many deficiencies, such as the limitation of time and frequency resolution, low-precision, and so on. Moreover, most of these studies are qualitative research and less consideration of noise [5], this is not conducive to practical application. SO how to improve signal to noise ratio with using monitoring and signal processing technology, and how to highlight the inherent characteristics of the signal by suppressing the background noise are the key of RES identification. For the above reasons, this paper presents a new method for RES recognition, which is based on empirical mode decomposition, wavelet packet and neural network. First, it uses the WP to implement the decomposition, de-noising and RES reconstruction, and then decompose the reconstruction signal with EMD algorithm, prominent the local features that RES itself have, and complete feature extraction. Finally, it realized the signal classification and recognition of different RES through the designing of BPNN and RBFNN classifier.

II. EMPIRICAL MODE DECOMPOSITION ALGORITHM

A. EMD Principel

In 1998, EMD, the core of Hilbert-Huang transform (HHT), was proposed by N.E. Huang [6]. It has been proved effective for many actual signals and widely used, such as earthquake [7], vibration [8], flow [9], etc. The HHT data processing system (HHT-DPS) has been used and commercialized successfully [10].

Empirical mode decomposition is an analysis method for non-linear signal. This method is based on the local time scale characteristic of the signal. It can decompose the original signal into a series of intrinsic mode functions [11], [12]. With the analysis of these intrinsic

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mode functions, characteristics of the original signal can be more accurate grasped in effectively. The frequency that contained in each IMF is not only associate with the sampling frequency, and more importantly is that it also changes with the change of the signal itself, so EMD is an adaptive signal analysis method, which frees from the limitations of Fourier transform fundamentally and has a good ability of signal de-noising [13]. It is ideal for non-stationary and non-linear signal processing.

EMD is essentially a stationary method of signal processing through the decomposition of non-stationary signal. It can obtain a series of intrinsic mode functions by the decomposition of non-stationary signals. Time scale features of the signal are shown in these intrinsic mode functions. The theory of EMD assumes that the signal is composed of different intrinsic mode functions. Each IMF can be either linear or non-linear. But these IMF components must satisfy two conditions: First, the number of extreme points should be the same with the number of zero-crossing points, or the number difference between extreme points and zero-crossing points is only one. Second, the mean of the upper and lower envelope must be zero. Upper and lower envelope is constituted by its local maximum and minimum values. Thus, any signal can be expressed as the sum of a finite number of IMF components through empirical mode decomposition.

B. EMD Algorithm

EMD method can divide the non-stationary signal into the sum of several IMF components. The aim of EMD algorithm is to get a series of IMFs with better performance through the decomposition of the poor performance signal. The process of calculating is shown as follows.

Step1：All local extreme points of the original signal $s(t)$ are calculated.

Step2：By cubic spline function, the upper envelope u_x(t) is fitted with all local maximum points on the envelope, and the lower envelope v_x(t) is fitted with all local minimum points.

Step3：The mean of upper and lower envelope is calculated.

$$m_1(t) = (u_x(t) + v_x(t))/2 \tag{1}$$

Using the following formula to calculate, then get $h_1(t)$.

$$h_1(t) = s(t) - m_1(t) \tag{2}$$

Step4：If $h_1(t)$ meet the IMF conditions, $h_1(t)$ would be recorded as an IMF. If it does not meet IMF conditions, and then $s(t)= h_1(t)$, repeat the process K times, until get $h_{1k}(t)$ to meet the IMF conditions.

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t) \tag{3}$$

$h_{1k}(t)$ will be seen as the first IMF, denote

$$C_1(t) = h_{1k}(t) \tag{4}$$

Step5：The original signal $s(t)$ minus the residual $C_1(t)$, get the residual signal $r_1(t)$, take the residual signal $r_1(t)$ as a new original signal, repeat the decomposition process, then get $C_2(t)$.

Step6：Repeat the process until received residual signal $r_n(t)$ is a monotone signal or $r_n(t)$ is less than the threshold given in advance, then stop. EMD process is shown in Fig.1.

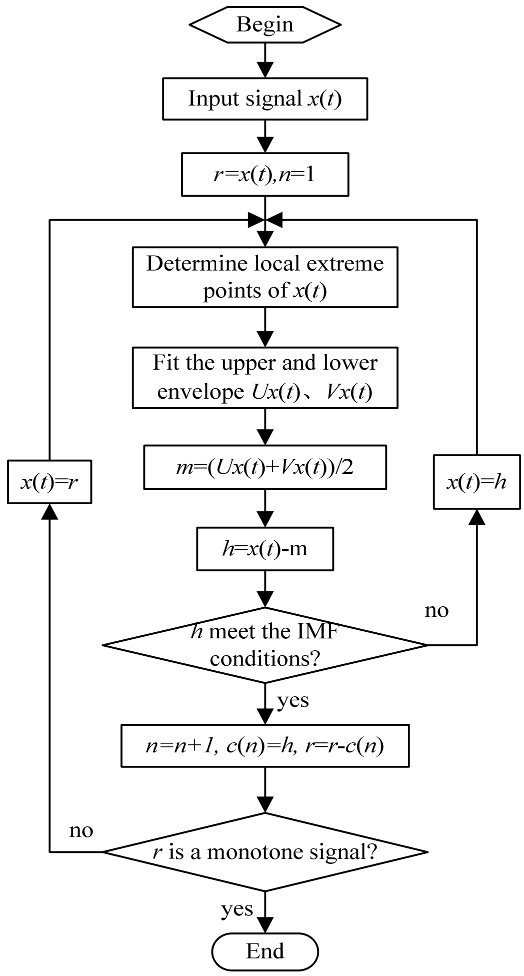


Figure 1. EMD arithmetic flow chart

C. EMD Energy Entropy

If the RES is decomposed by EMD, get n IMF components $C_1(t)$, $C_2(t)$, …, $C_n(t)$ and a residual component $r_n(t)$. The energy of each IMF components is denoted with E_1, E_2, …, E_n. Each IMF components $C_1(t)$, $C_2(t)$, …, $C_n(t)$ contain the different frequency of the original signal, so the vector $E=\{E_1, E_2, \ldots, E_n\}$ constitute the energy division of the RES in frequency domain. The EMD energy entropy is defined as follows.

$$EMD_{EN} = -\sum_{i=1}^{n} p_i \lg p_i \tag{5}$$

Where, P_i is the percentage that the energy of the ith IMF accounts for the total signal energy.

The EMD energy entropy of several different RES at different SNR is showed in table I. It is easy to see that EMD energy entropy is decreased with the increase of

SNR. However, within 10db range, the little change of EMD energy entropy indicates that the feature of energy entropy has certain noise immunity. At the same time we can see that the different RES has different EMD energy entropy, therefore the energy entropy of EMD can be used to form the identification feature vector of RES.

TABLE I.

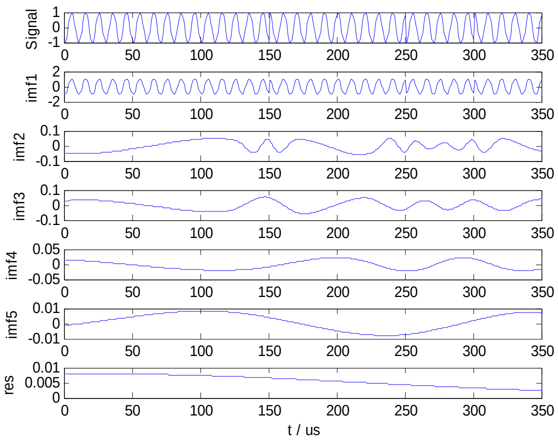
EMD ENERGY ENTROPY OF RES

RES Signal	BPSK	QPSK	CSF	LFM	FSK	NLFM
5db	0.0174	0.0048	0.1561	0.0058	0.0222	0.0116
10db	0.0106	0.0032	0.1502	0.0014	0.0177	0.0062
15db	0.0080	0.0038	0.1360	0.0012	0.0053	0.0015
20db	0.0050	0.0012	0.0629	0.0008	0.0038	0.0009

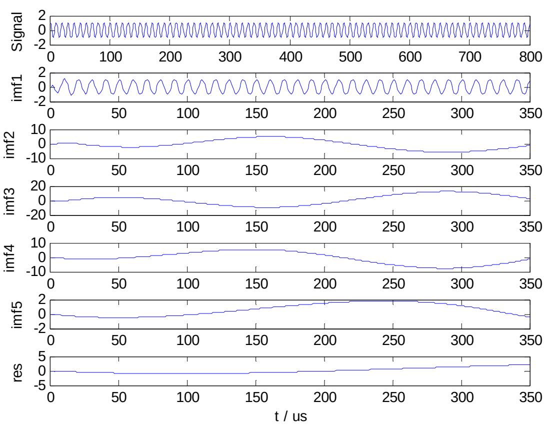
D. *EMD of RES*

EMD diagrams of BPSK, QPSK, LFM, FSK and NLFM radar signal is shown in Fig.2 (a)-(e). It's easy to see that the IMF components reflect the characteristics of radar signals almost entirely. But if the original signal was added in noise disturbance, as shown in Fig.2 (f)-(g), IMF components of EMD would increase since the noise involved in the decomposition. This means that the dimension of the feature vector will be increased correspondingly when added in noise. It will reduce the effectiveness of radar signal decomposition.

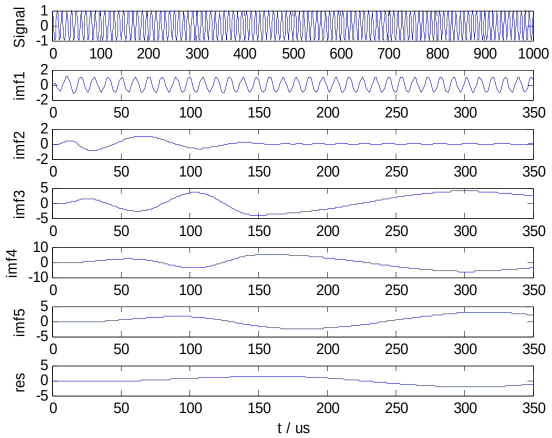
On the other hand, noise will confuse the original signal waveform characteristics, this will lead to errors in the decomposition process has been accumulated, and eventually lead to inaccurate IMF component.



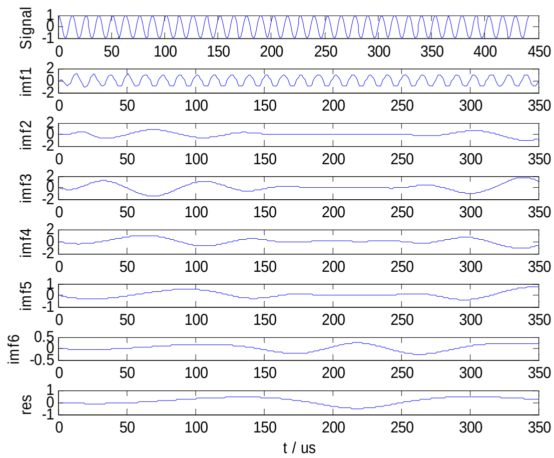
(a) EMD map of BPSK radar signal



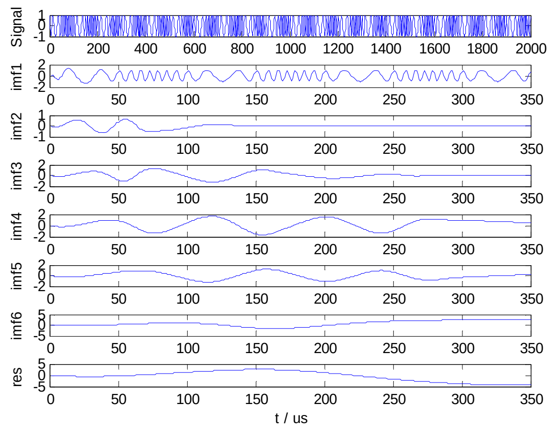
(b) EMD map of QPSK radar signal



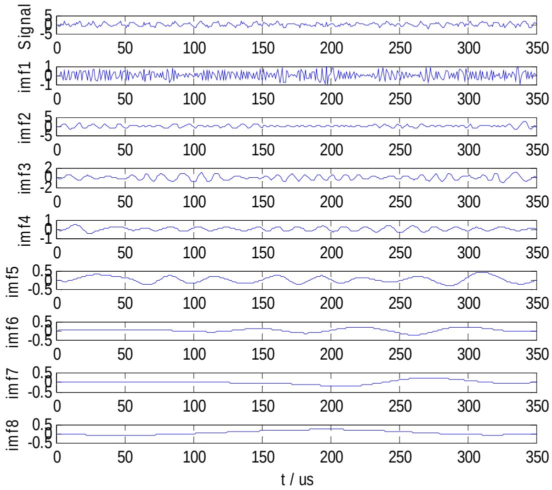
(c) EMD map of LFM radar signal



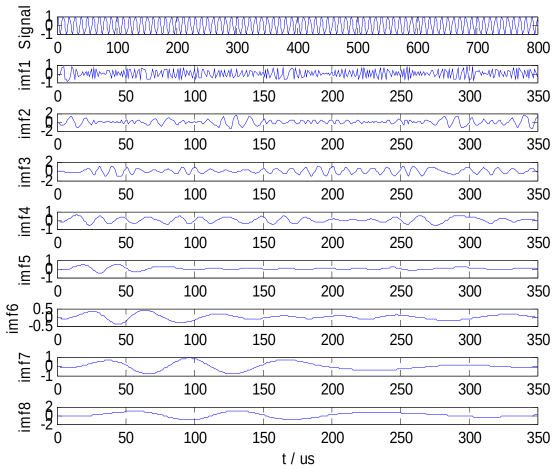
(d) EMD map of FSK radar signal



(e) EMD map of NLFM radar signal



(f) EMD map of BPSK when adding 5db noise



(g) EMD map of QPSK when adding -10db noise

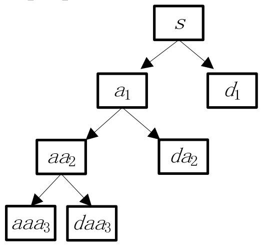
Figure 2. RES empirical mode decomposition map

With further increase of noise intensity, EMD of the original signal would lose the meaning of decomposition. Therefore, measures must be taken to reduce noise interference. For efficient and accurate feature extraction of RES, it is essential to RES to finish noise reduction processing by using wavelet packet.

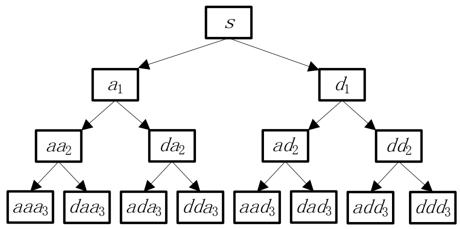
III. Wavelet Packet De-noising

In practice, RES signal will undoubtedly be subject to varying degrees noise interference. When the SNR is lower or the signal itself is complex, subsequent signal processing is difficult to obtain satisfactory results. In the time-frequency analysis method, the wavelet transforms is similar to windowed Fourier transformation, and has been widely used. Time-frequency domain localization and time-frequency window variable are distinctive features of wavelet analysis. This makes it superior to the traditional Fourier analysis in the analysis of non-stationary signals.

Wavelet packet analysis is developed based on the wavelet analysis. The signal de-noising idea of WP is consistent with wavelet analysis, but its analysis tools are more complex and flexible. Due to the constraints of *Heisenberg uncertainty principle*, frequency resolution of wavelet analysis is not ideal in the high frequency. Application of wavelet analysis is limited for this reason [14]. Decomposition structure of wavelet and wavelet packet are shown in Fig.3, it is easily to see that the wavelet packet analysis can achieve multi-level signal frequency division, complete decomposition of the signal frequency at higher frequency band, improve the signal resolution in time-frequency domain, and reduce the noise interference, so it is a more precise signal frequency analysis method [15].



(a) Structure of wavelet decomposition



(b) Structure of wavelet packet decomposition

Figure 3. Structure map of wavelet and wavelet packet decomposition

This is an impotent function of wavelet packet analysis to achieve noise reduction processing. In order to compare the noise reduction effect of wavelet and wavelet packet, an original signal was added in noise, as shown in Fig.4, the noise reduction results of wavelet and wavelet packet is given respectively. It can be seen from this figure that the de-noise effect of wavelet packet is better than the de-noise effect of wavelet.

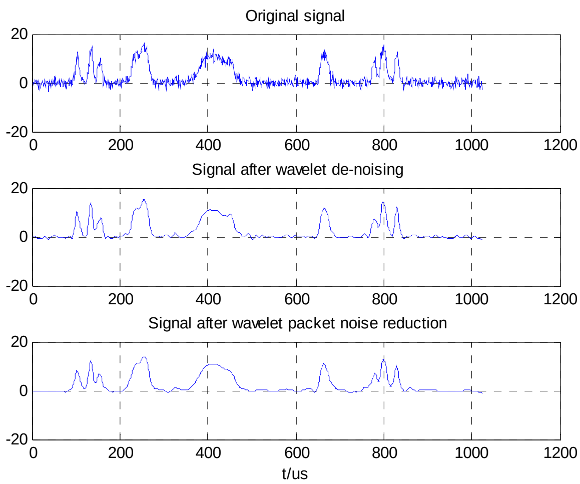


Figure 4. De-noising effect map of wavelet and wavelet packet

IV. RES Feature Extraction

Assuming that the original signal is de-noised with wavelet packet, the de-noising signal is decomposed through EMD method, then get n IMF components $C_1(t)$, $C_2(t)$, …, $C_n(t)$ and a residual component $r_n(t)$. The energy of each IMF components is represented with E_1, E_2, …, E_n. Since the n IMF components C_1(t), C_2(t), …, C_n(t) contain the different frequency of the original signal, the vector $E=\{E_1, E_2, \ldots, E_n\}$ forms the characteristics vector of RES [16]. The steps of EMD energy feature extraction of the RES are shown as follows.

Step1：EMD decomposition of the RES signal, select the first 5 IMF components which contains the main information.

Step2：The energy of each IMF component is calculated by using the following formula.

$$E_i = \int_{-\infty}^{+\infty} \left|c_i\right|^2 dt, \qquad i = 1,2,\cdots,5 \tag{6}$$

Step3：Construct a feature vector by using the energy element of first 5 IMF components, which contains the main information of the original signal.

$$T = [E_1, E_2, \ldots, E_5] \tag{7}$$

Step4：Feature vector will be normalized with the following method.

$$E = \left[\sum_{i=1}^{5}\left|E_i\right|^2\right]^{1/2} \tag{8}$$

$$T' = \left[E_1/E, E_2/E, \cdots, E_5/E\right] \tag{9}$$

Vector T' is the normalized vector, and been taken as the input feature vectors of follow-up handle.

V. Classifier Designing

A. BPNN Classifier

Due to its inherent properties of self learning, adaptability, robustness and parallelism, artificial neural networks in general outperform other artificial intelligence techniques for pattern classification problem [17]. Back propagation neural network (BPNN) adopt a supervised learning for training the input pattern. The architecture of the BPNN model used in this study is three-layered. Its neurons number of the output layer is taken as 3, the output tolerance is taken as 0.05, and the training error is set to 0.001. The structure of BPNN classifier is shown in Fig.5.

B. RBFNN Classifier

Radial basis function neural network (RBFNN) belongs to the feed-back NN. As BP neural network, RBF neural network is consist of three layers. The first layer is import layer and is consist of signal source point. The second layer is connotative layer and the connotative unit number is decided by the descriptive question. The transform function of connotative unit is radial symmetrical for center point and it isn't minus and linear function. The hidden radial basis layer applies a nonlinear transformation form the input space to the hidden space, and the hidden space is of high dimensionality. The third layer is output layer, it responds to input style.

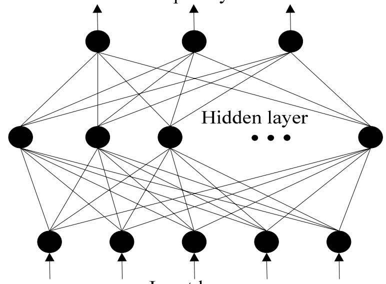


Figure 5. The structure of BPNN classifier

RBFNN is a kind of feed forward network constructed on the theory of function approximation. The basic idea of RBFNN is to found connotative layers by RBF function. The connotative layers transform input variable to high dimension space from low dimension space, then the question of linear inseparability in low space can be solved. The transfer function of hidden layer neural forms basis function of the approximation ellipsoid surface [18]. The advantages of RBFNN are the quick learning speed, good function approximation ability and high classification performance [19]. According the number of connotative unit, there are normalized network and generalized network in RBFNN. Generalized network is used more in practice for convenience. The structure of RBFNN classifier is shown in Fig.6.

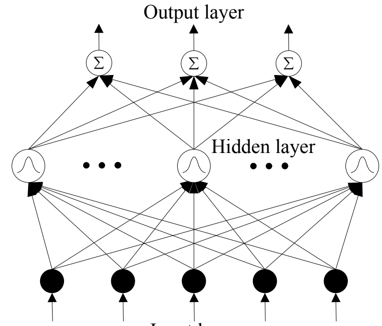


Figure 6. The structure of RBFNN classifier

Each node of hidden layer is called the center of RBFN. The neuron transfer function is Gaussian RBF. The weight values from input layer to hidden layer are all set to be 1. The transfer function of the output layer is linear and the weight values from hidden layer to output layer are adjustable, so the output is a weighting sum of the hidden layer.

The most typical radial basis function is the Gaussian function, the expression is

$$u_i = \exp\left\{-\frac{(X-c_i)^T(X-c_i)}{2\sigma_i^2}\right\}, \quad i = 1,2,\cdots,P. \tag{10}$$

Where u_i is the output of the ith hidden node, X are input samples, c_i is the center value of Gaussian function, and σ_i determines the width of RBF and P is the number of hidden nodes.

In (10), the output range of hidden nodes is between 0 and 1, and the closer the input is to the center of RBF, the closer the output is to the maximum value, which means the local approximation capacity of RBFNN. The outputs of RBFNN are the linear weight sum of the output of hidden nodes.

$$y_k = \sum_{i=1}^{p} \omega_{ik} u_i , \quad 1 \le k \le m \tag{11}$$

Learning process of RBFNN is divided into two stages: the first is to determine the center value c_i and the width σ_i of Gaussian function according to all the input samples and the second is to calculate the weight value ωik of the output layer using the least squares [20], after that the parameters of hidden and output layers can be corrected to further enhance network accuracy.

VI. Simulation Analysis

To verify the effectiveness of RES signal feature extraction method, simulation is done as follows through the selecting of typical radar emitter signal and the designing of BP neural network (BPNN) classifier. The typical radar signals are the continuous wave (CW), the linear frequency modulation (LFM), the non-linear frequency modulation (NLFM), the frequency shift-key (FSK), the binary phase shift-key (BPSK), the quaternary phase shift-key (QPSK) and the chirp step-frequency (CSF) radar emitter signals.

Each radar signal generated every 5db 100 samples in the 5~20db SNR range, namely each kind of radar signal has 400 samples, and total quantity of sample is 2800. Each radar signal taken 50 samples in every 5db of the 5~20db SNR range, a total of 200 samples used for feature extraction and classifier training, the remaining 200 samples used for test samples of the signal recognition.

TABLE II.

RES Recognition Results Using BPNN Classifier Based on EMD

RES signal	Classification Accuracy (%)						
	BPSK	CSF	FSK	LFM	NLFM	QPSK	CW
5db	64.00	94.00	74.00	68.00	70.00	60.00	70.00
10db	78.00	100.00	84.00	74.00	96.00	64.00	90.00
15db	84.00	100.00	88.00	84.00	100.00	80.00	94.00
20db	94.00	100.00	98.00	100.00	100.00	90.00	100.00
Average	80.00	98.50	86.00	81.50	91.50	73.50	88.50

TABLE III.

RES Recognition Results Using BPNN Classifier Based on EMD and WP

RES signal	Classification Accuracy (%)						
	BPSK	CSF	FSK	LFM	NLFM	QPSK	CW
5db	60.00	98.00	88.00	72.00	70.00	58.00	72.00
10db	72.00	100.00	90.00	76.00	86.00	66.00	92.00
15db	78.00	100.00	94.00	86.00	100.00	72.00	96.00
20db	88.00	100.00	100.00	94.00	100.00	84.00	100.00
Average	74.50	99.50	93.00	82.00	89.00	70.00	90.00

TABLE IV.

RES Recognition Results Using RBFNN Classifier Based on EMD

RES signal	Classification Accuracy (%)						
	BPSK	CSF	FSK	LFM	NLFM	QPSK	CW
5db	66.00	98.00	76.00	70.00	72.00	62.00	72.00
10db	80.00	100.00	88.00	76.00	100.00	66.00	92.00
15db	86.00	100.00	92.00	88.00	100.00	82.00	98.00
20db	98.00	100.00	100.00	100.00	100.00	94.00	100.00
Average	82.50	99.50	89.00	83.50	93.00	76.00	90.50

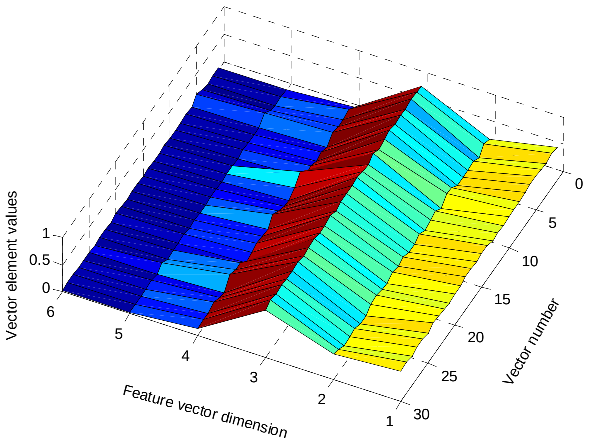
TABLE V.

RES Recognition Results Using RBFNN Classifier Based on EMD and WP

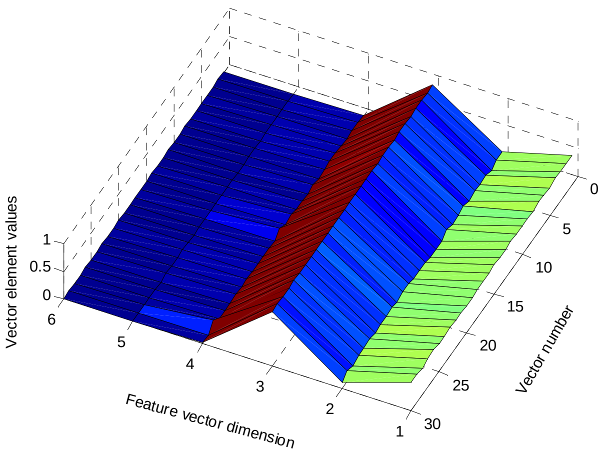
RES signal	Classification Accuracy (%)						
	BPSK	CSF	FSK	LFM	NLFM	QPSK	CW
5db	64.00	100.00	92.00	74.00	72.00	60.00	76.00
10db	76.00	100.00	94.00	78.00	90.00	68.00	96.00
15db	84.00	100.00	100.0	90.00	100.00	76.00	100.00
20db	94.00	100.00	100.00	98.00	100.00	88.00	100.00
Average	79.50	100.00	96.50	85.00	90.50	73.00	93.00

The RES recognition results using BPNN classifier based on EMD are given in table II. The RES recognition results using BPNN classifier based on EMD and WP are given in table III. The RES recognition results using RBFNN classifier based on EMD are given in table IV, The RES recognition results using RBFNN classifier based on EMD and WP are given in table V.

The experiment results show that the recognition results of RBFNN classifier is better than BPNN classifier. Moreover, the recognition accuracy of part RES is improved through the application of wavelet packet. The experiment results also show that this method has high recognition rate on the CSF, FSK, NLFM, CW radar signals. Meanwhile, results also show that the recognition result of BPSK and QPSK is not satisfactory. In order to facilitate analysis, as shown in Fig.7, feature vector surface plot is drawn with 30 feature vectors, which are extracted respectively from the BPSK and QPSK radar signals.



(a) Feature vector distribution surface map of BPSK



(b) Feature vector distribution surface map of QPSK

Figure 7. Feature vector distribution chart of BPSK and QPSK

It can be seen from the figure that feature vectors distribution of QPSK and BPSK are relatively close, separation between classes is not big enough. Mutual interference between them lead to the recognition accuracy is reduced to vary degrees. Further analysis revealed that this is due to BPSK and QPSK signals using the same sampling frequency, carrier frequency, pulse width and their basically same encoding. From another perspective, this also shows that the frequency components of IMF, which is obtained by EMD decomposed, is associated with the sampling frequency, but also changes with the signal itself. In conclusion, EMD method is not suitable for the recognition of BPSK and QPSK radar signals, but more suitable for the identification of CSF, FSK, NLFM and CW radar signals.

VII. Conclusion

So far, empirical mode decomposition method has been successfully applied in many fields, the actual effect is very significant. Because there is no a priori requirement of the conditions, it has a very good adaptive performance, and can effectively achieve non-stationary nonlinear signal decomposition and the time-frequency analysis. This provides the necessary precondition for the realization of the RES signal classification, the good performance of wavelet packet noise reduction to provide strong support for the EMD decomposition. Simulation results show that the feature extraction method is feasible based on WP and EMD. It has some practical value, but also brings up future reference for further study.

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