Self-Organizing Maps Based Feature Extraction Methods for HRRP Recognition

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ABSTRACT

In radar High Resolution Range Profile (HRRP) recognition field, an effective feature extraction process is the main point to improve whole recognition performance. As the targets' HRRP is the amplitude of coherent summations of complex return from scatters in each range cell, some data-driven compression methods, like PCA, LDA, etc. are widely used and achieve good results under experimental conditions, but still doesn't contribute much to solving the inherent problem of HRRP, such as small-sample problem. For these reasons, a series of SOM based feature extraction methods are introduced to explore the possibility in HRRP recognition. From machine learning perspective, these SOM based methods might more comprehensively describe the inherent structure relations within the original HRRP data distribution with its competitive learning process. In this paper, three category simulation experiments are presented to analysis the feature extraction, data storage, cluster result and classifier design. Of these experiments, SOM combined with multi-layer neural network can reduce the over fitting problem of directly apply the multi-layer neural network for HRRP recognition, which further prove the feasibility of SOM application in HRRP recognition.

Keywords: radar target recognition; HRRP; feature extraction; SOM

1. INTRODUCTION

In this part, two related aspects will be introduced to find more comprehensive and forward-looking information about the current situation in HRRP recognition field and the potential developing trend.

A target's HRRP, which is a one dimensional projection result along the target's line of sight, reflects the targets backscattering sum from scatters in each range cell. HRRP can provide relative rich information about target's geometrical shape and characteristics. Using HRRP or extracting features from original HRRP is an important research direction in radar target recognition[1]. Although, compared to the other radar image like ISAR and SAR, HRRP is much easier to obtain, HRRP based technologies still have some troubles. The main problems can be summarized as sensitivity elimination problem and dimension reduction problem[2].

On this premise, the conventional research path is under the process as data preprocessing, feature extraction/selection and classifier design. During early developing stage of HRRP feature extraction methods, it is found that HRRP can reflect some special shape structure or periodic rotation of the propeller which may supply much more potential discriminant information[3]. Along with the development of wideband radar technology, the resolution which represents the range cell become much more higher, the azimuth sensitivity of HRRP has become a main factor affecting feature extraction and classification[4].

To eliminate the azimuth sensitivity as well as other two sensitivity problems, features that have definite physical meanings are widely used, such as power spectrum, central moment, HRRP's time-frequency information[5], target's length extracted from HRRP[6], or features obtained from modern spectral estimation[7]. But confined to fundamental electromagnetic scattering theory, finding features of these type is hard to make a further breakthrough in recognition performance. So some data compression based dimension reduction methods like PCA or LDA get more attention[8]. In recent research, statistical modeling combined with data compression methods gradually become the main direction[9], for example the PPCA based methods[10], whose effect of statistical feature extraction is mainly affected by the design of calculation process. Although, some deep learning methods are utilized in HRRP recognition, the over-fitting problem still a main challenge.

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The second aspect focus on SOM algorithm which happens to be a kind of learning methods that can describe the inherent pattern within a dataset with minimal computing. The idea of SOM is motivated by simulating the signal processing in human brain, its' computable versions were invented by Teuvo Kohonen[11] and have been the subject in many machine learning area. Because SOM can applied as a feature classifier to optimize maps to a stable representation of features and regions of interest, SOM based technologies are widely used in detection of critical variations in image time series[12]. In order to obtain more precision in time series prediction, complex network topologies like hierarchical SOMs are proposed under different evaluating metrics[13]. With its clustering performance, SOM combined with generative model method is put forward to interpret discrete representation learning on time series[14]. In intrusion detection, some clustering algorithm based SOMs have good performance in distinguishing different categories[15]. In speech recognition field, SOM with other neural network scheme also accomplish the goal of enhancing classification accuracy with lower SNR ratio[16].

Analyzing high dimensional data like HRRP can be very difficult. SOM based algorithms has advantages in exploring data analysis, dimension reduction and clustering problems with relatively fewer computation, which will provide a promise solution for HRRP recognition.

2. PROBLEMS IN HRRP FEATRURE EXTRACTION

2.1 Fundamental Information about HRRP

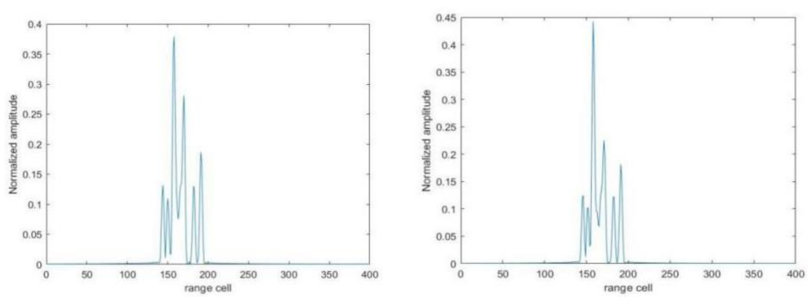
According to electromagnetic scattering theory, when radar bandwidth increases, the object can be simplified to scatter point model that consist of multiple scattering elements. As this assumption, the echo of the $k$thscattering point in the$m$thrange cell can be expressed as,

$$x_m(k) = \sigma_k \, exp[-j(\frac{4\pi}{\lambda} r_k - \psi_k)] \qquad (1)$$

In Eq. (1),$\sigma_k$represents the magnitude of reflexes in$k$thscattering point;$r_k$is the radial distance of$k$thscattering point.$\psi_k$is the initial phase. The echo of$m$thrange cell can be obtained through coherent summation as,

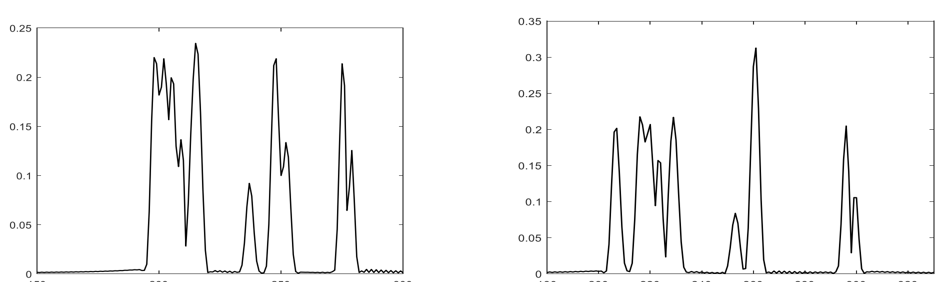
$$x_m = \sum_{k=1}^{K_m} \sigma_k \, exp[-j(\frac{4\pi}{\lambda} r_k - \psi_k)] = \sum_{k=1}^{K_m} \sigma_k \, e^{j\phi_k} = |x_m| \, exp(j\phi_m) \qquad (2)$$

In Eq. (2), $K_m$represents the number of scattering points in$m$thrange cell;$|x_m|$is the real range profile;$\phi_m$represents the phase of complex range profile. In practical application, the real range profile is widely used, so a certain HRRP is defined as$[|x_1|, |x_2|, \dots, |x_m|]$.



(a) HRRP under in an initial azimuth (b) HRRP after 4° azimuth change

Figure 1 HRRP smooth changes along small range azimuth



(a) HRRP under 0^o azimuth (b) HRRP changes after target posture change

Figure 2 HRRP's drastic changes caused by posture change under same azimuth

The factors affecting HRRP can be observed in Fig. 1 and Fig. 2. The reasons are summarized as follows: (1) the number, intensity, and location of scattering points; (2) the distribution of scattering points in the radar range window; (3) the distribution of scattering points in the range cell.

Considering the combined effect of azimuth and posture change, in practical application an azimuth range will be preset to minimize the sensitivity problem. The azimuth range are defined as $\Delta\varphi < \Delta R/W$, W represents the target's transverse length, ΔR represents the HRRP's resolution. It is very hard to build a dataset that covers all postures of a target, so the compromise solution is to split the dataset into more sub-datasets under the condition $\Delta\varphi < \Delta R/W$.

2.2 Problems in Applying Data Compression Algorithm

Because the azimuth sensitivity, data compression algorithms like PCA, LDA are very necessary as a feature extraction solution for both data storage and recognition performance. These methods are based on liner transformation $Y = W^T X$, the main goal is to solve $\boldsymbol{W}$ to meet the requirements of reducing dimensionality and improving separability. In brief, a criterion of separability $J(\boldsymbol{W})$ and a constraint condition $g(\boldsymbol{W})$ should be defined first, then construct a cost function $L(\boldsymbol{W}, \lambda) = J(\boldsymbol{W}) - \lambda g(\boldsymbol{W})$, and calculate the derivative $\frac{\partial L(\boldsymbol{W},\lambda)}{\partial \boldsymbol{W}} = 0$ to obtain the projection matrix $\boldsymbol{W}$. However there are four deficiencies must be overcome.

(1) The HRRP data distribution does not conform to normal distribution. According to scatter points distribution in each range cell, the HRRP distribution represents as Rice distribution, Rayleigh distribution or multimodal distribution, so LDA can't directly applied.

(2) Issues with less categories. For LDA, the optimization problem is transformed into eigenvalue decomposition problem of scatter matrix $\boldsymbol{S}_w^{-1}\boldsymbol{S}_b$, if the number of sample classes is L, thus the rank of projection matrix $\boldsymbol{W}$ obtained from linear transformation $\boldsymbol{Y} = \boldsymbol{W}^T\boldsymbol{X}$ is $L-1$. For HRRP recognition, most of the targets are non-cooperative and have limited types, so the $L-1$ dimension feature is insufficient to provide needed classification information.

(3) Small sample problem is caused by whether the inter class scatter matrix is invertible. Because inter class scatter matrix is defined as

$$\boldsymbol{S}_w = \sum_{i=1}^{L} P_i E[(\boldsymbol{x} - \boldsymbol{\mu}_i)(\boldsymbol{x} - \boldsymbol{\mu}_i)^T] \quad (3)$$

In Eq. (3) $P_i \approx N_i/N$ represent prior probability, $\boldsymbol{\mu}_i$ is mean vector of $\boldsymbol{i}$-th class. Because the number of samples is N, the rank $R(\boldsymbol{S}_w) \le N$. If original HRRP data dimension is n and satisfies $N < n$, then $\boldsymbol{S}_w$ is invertible. This problem is getting worse as the dimension of HRRP increase.

(4) Data mix problem in projection boundary. Taking the projection of two-dimensional data as an example, the final projection vector $\boldsymbol{W} = \boldsymbol{S}_w^{-1}(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_2)$. According to $\boldsymbol{Y} = \boldsymbol{W}^T\boldsymbol{X}$, LDA projection is affected by mean vector, failure to highlight the role of boundary data.

Although many modified strategies inspired from above 4 outcomes can be utilized in LDA to improve recognition performance, how to design these strategies and eliminate the corresponding increased computational complexity is still a challenging task.

3. SOM BASED METHODS FOR HRRP FEATURE EXTRACTION

From the perspective of machine learning, the more efficient the reproduction of raw data, the more intelligent it can be reflected. The SOM algorithm is precisely possible to reproduce the topological structure of the original data through a competitive learning approach, which achieves dimensionality reduction as well as retaining data distribution information. Compared to LDA based algorithms, it avoids matrix inverse problem and is very suitable for HRRP recognition tasks.

3.1 SOM Algorithm

SOM is an unsupervised artificial neural network that can be used for visualization and exploratory data analysis of high dimensional datasets. The fundamental structure (one dimensional output) of SOM is illustrated in Fig.3.

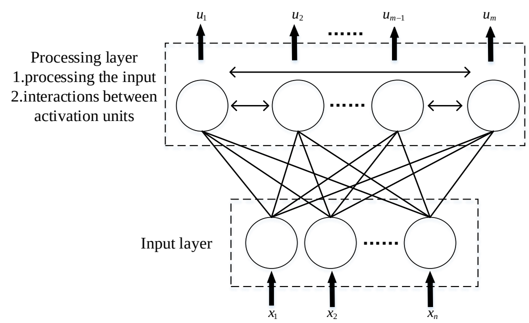


Figure 3 fundamental structure of SOM

If the inputs of SOM are $X = \{x_1, x_2, ..., x_n\}$, the outputs of SOM are $u_1, u_2, ..., u_m$. The purpose of optimization is to solve the output weight coefficient w_{in} of the most matching input vector x, w_{in} represents the weight of i-th neuron in the processing layer. So u_i is expressed as

$$u_i = \sigma[w_{ij}x_j], x_j \in \boldsymbol{X} \tag{4}$$

$\sigma[]$ is activation function. According to competitive learning mechanism in the processing layer, the best matched neuron is defined as $u_m = max\{u_i\}$, considering the role of adjacent neurons in processing layer, u_m is calculated as

$$u_m = max\{\sigma[w_{ij}x_j + \sum_{k\in S_i}\gamma_k u_k]\} \tag{5}$$

In Eq. (5), γ_k is distance function between i-th neuron and k-th neuron, expresses the impact of distance changes on competitive value. S_i represents the set of neurons adjacent to i-th neuron. If ensure the distance function γ_k satisfies,

$$\gamma_k = \begin{cases} \gamma_m = 1, & k = m \\ \gamma_k = \gamma_k, & k = k \end{cases} \tag{6}$$

In this case, γ_k is very important for it creates the connection between the input space and the output lattice space and should meet the requirements: (1) γ_k needs to reach its maximum when the node is the winning node; (2) γ_k should be symmetric about the winning node; (3) when the distance between the adjacent node and winning node increases, γ_k should decrease.

Eq. (5) has a maximum, when the winning neuron and its neighboring neurons meet the maximum inner product (w, x). That means the weight vector rotate towards the input vector, thus the offset Δw might be obtained as

$$\Delta w = \gamma_k(s)\alpha(s)[x - w_i(s)] \tag{7}$$

So the iteration step for SOM is represented as

$$w_v(s+1) = w_v(s) + \gamma_k(s)\alpha(s)[x(t) - w_v(s)] \tag{8}$$

In Eq. (7) and Eq. (8), s indicates the number of iterations; subscript v represents a collection of winning neurons and their neighboring neurons; t represents the index of the training sample.

3.2 Further Modifications in SOM

If original data have a complex structure, the conventional SOM can't reflect the whole distribution comprehensively with static network structure. A possible operation is directly add a SOM competitive layer, taken two dimensional output SOM to illustrate which is shown in Fig. 4.

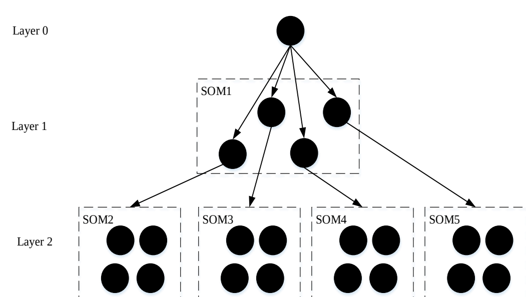


Figure 4 hierarchical SOM structure

The first competitive layer can be regarded as a SOM, the second competitive layer is another SOM, that means the output of first SOM is the input of the second SOM, the calculation rule about this structure is same as conventional SOM, (1)the best matched neurons$[u_1, u_2, \ldots, u_n]$ should be calculated first from first SOM layer;(2)obtain the corresponding input data$x_1, x_2, \ldots, x_k$which are mapping to$u_k$of first layer;(3)remapping the input$x_1, x_2, \ldots, x_k$to second layer's output under the competitive learning rule. The whole process illustrates original data hierarchical structure and can be used for data analyzing and preprocessing.

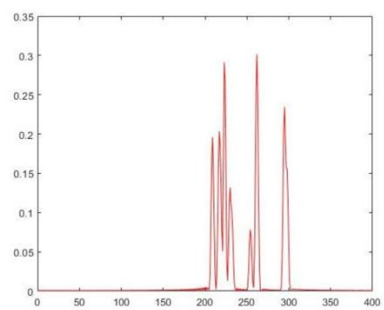
This above basic strategy is also static, the mapping performance depends on manual settings. The increasing layer process and increasing neurons process can be regarded as two parts that generating the whole SOM structure, if some evaluation criteria of SOM are utilized to measure the quantization error, topographic error or distribution error between the weight vector and input data, some dynamic generating SOM structure will be got.

4. EXPERIMENTS AND RESULTS

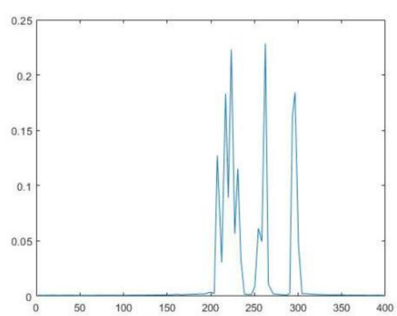
In the simulation experiments, considering the radar reference frame and target reference frame, four different targets' HRRP are obtained under step frequency radar system according to scattering center model theory.

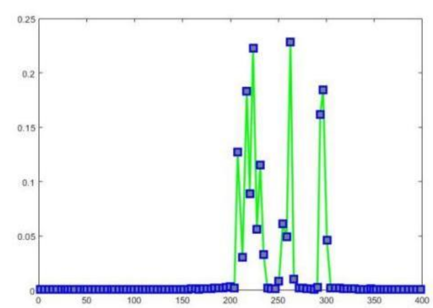
The basic parameters are as follows, the step frequency is 2MHz, the pulse repetition frequency is 4KHz, the step number is 200. Thus the corresponding range resolution is 0.375m, and the number of range cells is 400. In order to get the training data and testing data, the targets' yaw angle, pitch angle, roll angle are preset to$0°$. The azimuth angle range is set to$0 \sim 180°$, and echo data is taken every$0.1°$, so the total number of samples of four targets is 7204. K-fold method is utilized to divided 7204 samples into training sample set and testing sample set. Set$k = 5$, so the number of training data is 5764, the number of cross validation samples is 1440.

Simulation experiment 1, feature extraction. From the perspective of data fitting, HRRP is treated as a one-dimensional time series. When HRRP is taken as SOM's input, add another dimension of time sampling interval to simulate the range cell of HRRP equivalently, so the input weight is the feature extraction result of the data.



(a) original HRRP



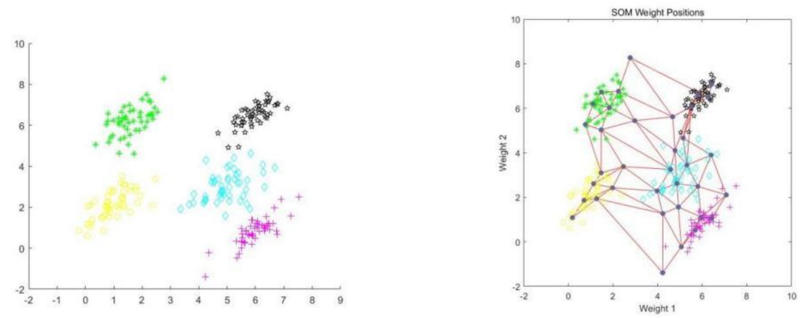


(b) reconstructive HRRP (c) position relation of 100 weights

Figure 5 the process of SOM extracting HRRP features

To ensure the effect of feature extraction as well as save as much raw data information as possible, a SOM network with 100 output units is utilized. In Fig 5(b), the reconstructive HRRP basically reflects the crest of original HRRP. In Fig 5(c), 14 of 100 weights corresponds to the peek point of HRRP, meanwhile the other are not so important. In reference[17], these mutation points which can be regarded as a physical feature of HRRP for recognition can reflect the scattering center of the target. The feature extraction result is similar to the Relax algorithm.

Simulation experiment 2, clustering and encoding. At first, the numerical methods are utilized to test the clustering effect of SOM. 5 sets of two dimensional Gaussian distributions with different mean and covariance are generated as shown in Fig 6(a).

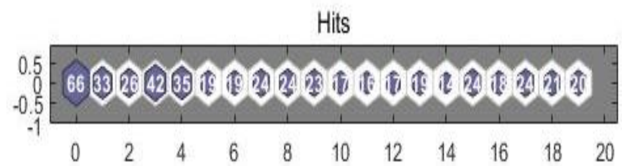


(a) 5 sets Gaussian distribution (b) SOM weight vector approximates the data

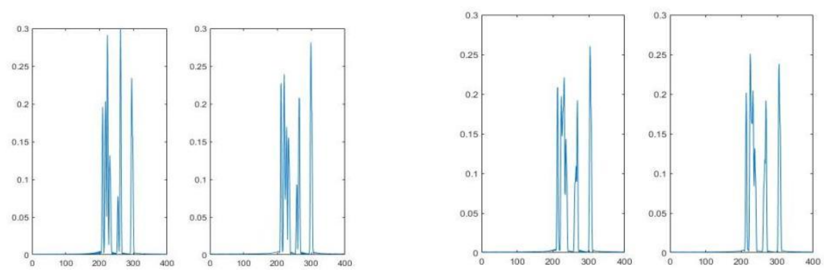
Figure 6 clustering effect of SOM neural network

The clustering effect of SOM is illustrated in Fig 6(b), due to the existence of competitive learning mechanism, the input weight of SOM network gradually approaches the input vector and learns the internal structure of the input vector.

The clustering of HRRP is achieved through a one dimensional SOM network with 20 output units. The output unit reflect the main characteristics of HRRP clustering center. This process can be seen as a new perspective of HRRP framing compared to HRRP framing at equal intervals based on azimuth range as$\Delta\varphi < \frac{\Delta R}{W}$. The Correspondence between training HRRP and output neurons is shown In Fig 7(a), different unit is matched to different numbers of HRRP.



(a) Correspondence between training data and output units

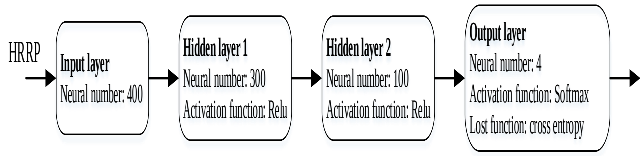


(b) 2 HRRP matched to the 15th unit (c) 2 HRRP matched to the 18th unit

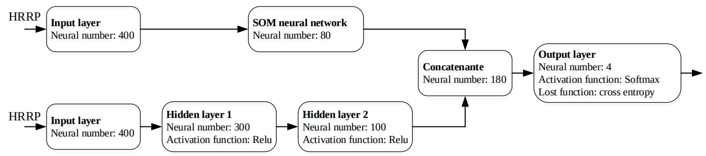
Figure 7 clustering effect of HRRP based on SOM neural network

In Fig 7(b) and (c), HRPP in the same cluster is used for comparative analysis. Although the clustering effect does not exhibit a certain degree of orderliness, the HRRP in same clustering has a relatively stable peek position and the changes are mainly reflected in peek amplitude. The outputs are re-encoding of the original data according to the structural characteristics, which still reflects the internal relationship of inputs. The corresponding code is [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0] for Fig 7(b); the corresponding code is [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0] for Fig 7(c). The encoding result can be regarded as a feature vector for recognition.

Simulation experiment 3, SOM combined with multi-layer neural network for recognition.



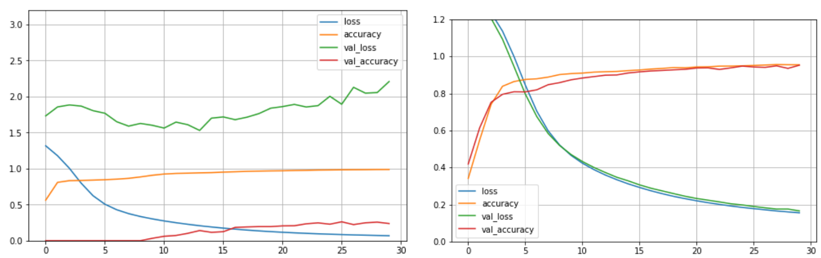
(a)HRRP as an input to the multi-layer neural network



(b)HRRP as an input for both SOM and multi-layer neural network

Figure 8 two different neural networks for HRRP recognition

HRRP with 400 dimension can be directly applied to multi-layer neural network as illustrated in Fig. 8(a). Because HRRP itself contain a lot of redundant information and HRRP recognition is a typical small sample problem, this method might face over-fitting problem. An SOM combined with multi-layer neural network method that is described in Fig 8(b) is proposed to improve the recognition performance.



(a)cross-validation results for multi-layer networks (b)cross-validation results for combined networks

Figure 9 cross-validation results

Fig. 9(a) shows that after 30 epochs of training, the recognition rate of this multi-layer neural network for the training samples has been improving close to 1, and the training loss decrease with the improvement of the recognition rate. By contrast, the recognition effect on the validation sample is poor. The final recognition rate does not exceed 0.3 and the validation loss is very high. This indicate that there is an over-fitting problem. Fig. 9(b) shows that this neural network structure has better generalization performance than directly applying multi-layer neural network since the fusion of the output of SOM neural network. The changes of recognition rate and loss for the training set and validation test set are consistent, and the recognition rate both reach 95%.

5. SUMMARY

In the application of SOM neural network in HRRP recognition, the feasibility of extracting HRRP features were analyzed based on the characteristics of SOM. Because its feature extraction process is based on the competitive learning mechanism, its network weights are constantly close to the input data reflecting the internal topological relationship. Meanwhile its output has an exclusive feature, which not only recodes the original data, but also preserves the clustering relation. Therefore, the fusion of the original feature vector and SOM encoded feature vector through the decision layer of neural network can greatly weaken the over-fitting to the training data and enhance the model's generalization ability.

6. ACKNOWLEDGEMENT

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