Hierarchical Sequential Feature Extraction Network for Radar Target Recognition Based on HRRP

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***Abstract*—Radar high resolution range profile (HRRP) contains lots of discriminative information for radar automatic target recognition (RATR). The temporal dependence information in HRRP can provide the scatter distribution information at different times, which is particularly important for RATR and attracts intensive attention among researchers. Recently dynamic methods have been proposed to extract time sequential features for RATR and achieved promising performance. However, most of these time sequential features extraction methods only focus on temporal dependence information between HRRP range cells and pay little attention to the time sequential features of HRRP sequences. Aiming at this problem, a novel hierarchical time sequential feature extraction network is proposed in this paper. In the proposed method, we firstly transform one whole HRRP sample into several small HRRP sequences by the sequential information preprocessing (SIP) module, and then, we proposed the time sequential feature between HRRP range cells (TSFR) module and time sequential feature between HRRP sequences (TSFS) module to extract hierarchical sequential features. Compared with other time sequential feature extraction methods, the proposed TSFS module extracted time sequential features of HRRP sequences based on the information of temporal dependence between HRRP range cells, rather than from HRRP sequences directly. Besides, we also employed a feature fusion module to improve the stability of the model. In order to demonstrate the effectiveness of proposed method, experiments on an airplane electromagnetic calculation dataset were conducted and experimental results showed the superiority of it. At last, comparative experiments have been conducted to explore the contribution of each module in the hierarchical time sequential feature extraction network.**

Keywords—high resolution range profiles (HRRP), radar automatic target recognition (RATR), feature extraction, time sequential feature, long short term memory networks (LSTM)

I. INTRODUCTION

A high resolution range profile(HRRP) is the amplitude of the coherent summations of the complex returned echoes from target scatterers in each range cell [1], [2]. It can provide discriminative target structure information such as scattering fluctuation, scatterer distribution, geometry size and target shape, which is extremely important for radar automatic target recognition(RATR). Furthermore, HRRP data have the advantage of low data complexity and can be efficiently processed. Therefore, RATR based on HRRP has received considerable attention in radar communities [3]-[6].

Generally, radar target recognition method can be divided into three parts: data preprocessing, feature extraction and classifier design. As an important feature of HRRPs, several time sequential feature extraction methods [7]-[10] have been proposed in recent years. The authors of literature [7] successfully employed hidden Markov model(HMM) to make use of the time sequential information between HRRP samples. However, building an appropriate HMM for such high dimensional HRRPs is challenging. To solve this problem, Pan *et al*. [8] proposed a HRRP recognition method with spectrogram feature named multi-task truncated stick-breaking hidden Markov model, which successfully fused related aspect-frame data and utilized them for recognition. In literature [9], the authors developed a truncated stick-breaking hidden Markov model with time-evolving transition probabilities, which can extract both spatial structure feature among HRRP range cells and time sequential feature for recognition. Literature [10] utilized the two dimensional spectrogram feature of HRRP data to improve the recognition performance, of which the spectrogram contains the variational information of frequency domain feature versus time domain feature. Although these aforementioned methods have contributed to the development of HRRP recognition, it is still challenging to efficiently capture complex temporal dependence between range cells for manual feature extraction.

Last few years have witnessed the booming and success of deep learning, which provides an end-to-end method for target recognition. In [11], the authors employed one-dimensional convolutional neural network (CNN) to learn time sequential information of HRRPs and proposed a two-dimensional CNN to extract the corresponding spectrogram feature. Besides CNN, recurrent neural networks (RNN) [12]-[15] have also been employed to extract time sequential features between HRRP range cells for its natural superiority in handling time sequential data. Chu *et al*. [12] proposed a novel attention enhanced convolutional gated recurrent unit network to effectively improve the representation of spatial and temporal features for RATR based on HRRP. The authors of literature [13] developed a recurrent gamma belief network for HRRP recognition, which successfully made use of the time sequential information between HRRP range cells. In [14], Chen *et al*. proposed tensor recurrent neural network with Gaussian mixture model to make full use of temporal

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dependence across the range cells of HRRP. The literature [15] developed a target-aware recurrent attention network to effectively explore the temporal dependence. The authors of [15] employed RNN to extract time sequential features between range cells within a HRRP sample and utilized the attention mechanism to weight each timestep in hidden state. Although these end-to-end deep learning methods reduce the complexity of manual feature extraction process, they only focus on the time sequential information between range cells within a HRRP sample and pay little attention to time sequential features between HRRP sequences, which contains deeper time sequential features.

To solve the problem mentioned above, a novel hierarchical time sequential feature extraction network for HRRP recognition is proposed in this paper. The novel hierarchical time sequential feature extraction network is roughly divided into four parts: sequential information preprocessing(SIP) module, time sequential feature between HRRP range cells(TSFR) extraction module, time sequential feature between HRRP sequences(TSFS) extraction module and feature fusion module. Inspired by [14], we employed the SIP module to transform one whole HRRP sample into several small HRRP sequences. Furthermore, we proposed a TSFR module and a TSFS module to extract the hierarchical time sequential features, which is important for HRRP recognition. Besides, we developed a feature fusion module to improve the stability of the whole model. The major contributions of this paper are summarized as follows:

1) A novel HRRP recognition method named hierarchical time sequential feature extraction network is proposed in this paper, which can extract not only time sequential features between HRRP range cells, but also time sequential features between HRRP sequences.

2) A novel TSFR module is proposed to extract time sequential features between HRRP range cells. Further more, based on the temporal dependence across HRRP range cells, a novel TSFS module is developed to extract time sequential features between HRRP sequences.

3) The SIP module is employed to transform one whole HRRP sample into several small HRRP sequences and the feature fusion module is proposed to improve the stability of the whole HRRP recognition model.

II. Proposed Method

A. Hierarchical Time Sequential Feature Extraction Network

The hierarchical time sequential feature extraction network is roughly divided into 4 parts: the sequential information preprocessing(SIP) module, the time sequential feature between range cells(TSFR) extraction module, the time sequential feature between sequences(TSFS) extraction module and the feature fusion module. The framework of the proposed hierarchical time sequential feature extraction network is shown in Fig. 1. As seen from Fig. 1, the HRRP sample is firstly processed by SIP module, which divides a complete HRRP sample into several HRRP sequences.

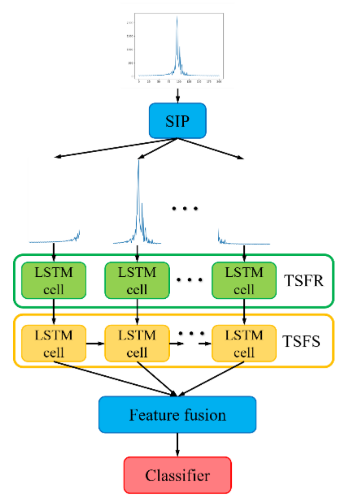


Fig. 1. The framework and data stream of the hierarchical time sequential feature extraction network.

We use $\mathbf{h}=\{h_1,h_2,...,h_n\}$ denotes one HRRP sample, where $h_i(i=1...n)$ represents the range cells of HRRP and n is the length of HRRP. We use $\mathbf{h_{SIP}}=\{h_{1,l},h_{2,l},...,h_{L,l}\}$ represents the HRRP sample processed by SIP module and $h_{j,l}(j=1...L)$ is one HRRP sequence, l is the length of the HRRP sequence. The mentioned above SIP process can be represented by (1).

$$\mathbf{h_{SIP}}=\mathbf{h}\left[S(i-1)+1:S(i-1)+W\right] \tag{1}$$

where W is the length of the window function and S is the step length of the window function.

These HRRP sequences generated by the SIP module are then input to the TSFR module, which is formulated as (2).

$$\mathbf{h_{TSFR}}=TSFR(\mathbf{h_{SIP}}) \tag{2}$$

The time sequential features $\mathbf{h_{TSFR}}$ between range cells extracted by the TSFR module are further input to the TSFS module to extract the time sequential feature $\mathbf{h_{TSFS}}$ between HRRP sequences, which is then processed by the feature fusion module. The TSFS process can be defined as (3), and the feature fusion process can be calculated as (4)-(5).

$$\mathbf{h_{TSFS}}=\{\mathbf{h_{F1}},\mathbf{h_{F2}},...,\mathbf{h_{FL}}\}=TSFS(\mathbf{h_{TSFR}}) \tag{3}$$

$$\mathbf{h_f}=\{h_{f1},h_{f2},...,h_{fm}\}=\sum_{j=1}^{L}\alpha_j\mathbf{h_{Fj}} \tag{4}$$

$$\mathbf{h_o}=\{h_1,h_2,...,h_k\}=\mathbf{W_o}\times\mathbf{h_f}+b_o \tag{5}$$

where L is the number of HRRP sequences and m represents the dimension of $\mathbf{h_{Fj}}(j=1...L)$.

At the end of the data stream, the softmax classifier outputs the recognition result of HRRP samples according to the fused features $\mathbf{h_f}$, which is formulated as (6). In (6), p_c is the probability that the input HRRP sample belongs to class c and k is the total number of target classes.

$$p_c = \frac{\exp(h_c)}{\sum_{i=1}^{k} \exp(h_i)} \tag{6}$$

B. Time Sequential Feature between Range Cells(TSFR) Extraction Module

As seen from Fig. 1, the TSFR extraction module is realized by several long short term memory networks(LSTM) cells, the number of LSTM cells is equal to the number of HRRP sequences L. It is worth mentioning that we creatively cut off the connection between different LSTM cells, which is not only beneficial to learn the temporal dependence across HRRP range cells better but also alleviates the gradient disappearance problem. Based on the above designed structure, one LSTM cell is supposed to only extract time sequential feature between range cells of the corresponding HRRP sequence. The calculation process (7)-(14) of one LSTM cell can be represented by (15), where $LSTM$ denotes the LSTM cell, $\mathbf{X^t}$ is the input HRRP sequence, $\mathbf{H^{t-1}}, \mathbf{H^t}$ represents hidden state at timestep $t-1$ and t, $(\mathbf{C^t}, \mathbf{H^t})$ is the output of LSTM cell, $\mathbf{C^t}$ denotes the cell state at timestep t. The TSFR extraction module process can be formulated as (16).

$$\mathbf{f^t} = S(\mathbf{W_f X^t} + a_f + \mathbf{V_f H^{t-1}} + b_f) \tag{7}$$

$$\mathbf{i^t} = S(\mathbf{W_i X^t} + a_i + \mathbf{V_i H^{t-1}} + b_i) \tag{8}$$

$$\mathbf{o^t} = S(\mathbf{W_o X^t} + a_o + \mathbf{V_o H^{t-1}} + b_o) \tag{9}$$

$$\mathbf{g_c} = \tanh(\mathbf{W_c X^t} + a_c + \mathbf{V_c H^{t-1}} + b_c) \tag{10}$$

$$S(x) = \frac{1}{1+\exp(-x)} \tag{11}$$

$$\tanh(x) = \frac{\exp(x)-\exp(-x)}{\exp(x)+\exp(-x)} \tag{12}$$

$$\mathbf{C^t} = \mathbf{i^t} \odot \mathbf{g_c} + \mathbf{f^t} \odot \mathbf{C^{t-1}} \tag{13}$$

$$\mathbf{H^t} = \mathbf{o^t} \odot \mathbf{tanh(C^t)} \tag{14}$$

$$(\mathbf{C^t}, \mathbf{H^t}) = LSTM(\mathbf{X^t}, \mathbf{H^{t-1}}) \tag{15}$$

TABLE I. THE DETAIL SIMULATION PARAMETERS OF THREE DIFFERENT KINDS OF AIRCRAFT

Aircraft Type	Height (m)	Fuselage Length (m)	Wingspan (m)	Wing Area (m^2)
P-51	4.17	15.67	10.70	21.83
F-35	4.33	20.08	13.20	42.70
F-117	3.78	9.82	11.30	84.80

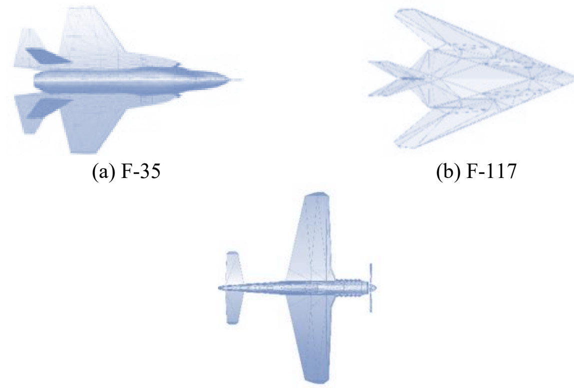

(a) F-35
(b) F-117
(c) P-51

Fig. 2. The 3D model of three different simulated aircrafts.

$$\begin{aligned}(\mathbf{C^t}, \mathbf{h_{TSFR}}) &= LSTM(\mathbf{h_{SIP}}, None) \\ \mathbf{h_{TSFR}} &= TSFR(\mathbf{h_{SIP}})\end{aligned} \tag{16}$$

C. Time Sequential Feature between Sequences(TSFS) Extraction Module

We can seen from Fig. 1, the TSFS extraction module is also composed of LSTM cells. The difference between TSFR LSTM cells and TSFS LSTM cells is that we cut off the connection of TSFR LSTM cells while keep TSFS LSTM cells connected. The TSFS extraction module is supposed to extract time sequential feature between HRRP sequences from the input time dependence between HRRP range cells, which is processed by the TSFR extraction module. The TSFS extraction module process can be defined as (17).

$$\begin{aligned}(\mathbf{C^t}, \mathbf{h_{TSFS}}) &= LSTM(\mathbf{h_{TSFR}}, \mathbf{H^{t-1}}) \\ \mathbf{h_{TSFS}} &= TSFR(\mathbf{h_{TSFR}})\end{aligned} \tag{17}$$

III. EXPERIMENTS IMPLEMENTATION AND RESULTS

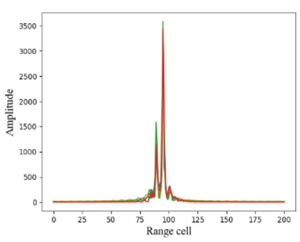
In order to demonstrate the superiority of the proposed method, we conducted comparative experiments in this paper. We introduced the airplane electromagnetic calculation dataset firstly, and then, we compared the proposed method and traditional deep learning methods. Furthermore, we also performed ablation experiment of the proposed method, which shown the performance of each module in hierarchical time sequential feature extraction network. We carried out all the experiments on a laptop with NVIDIA GeForce GTX 1650 based on Pytorch.

A. Dataset

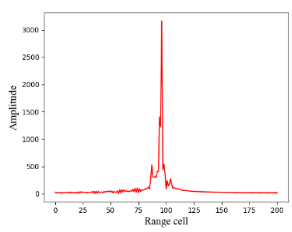
In this paper, the experiments are conducted on the airplane electromagnetic calculation dataset simulated on the electromagnetic 3D aircraft model simulation software. The electromagnetic calculation dataset contains three types of aircraft: F-35, F-117 and P-51. Table I gives the detail simulation parameters of above three different aircrafts. Fig. 2 shows the 3D model of these three different aircrafts.

The simulated aircraft data is based on an X-band radar, and the simulation frequency range is $9.5GHz \sim 10.5GHz$

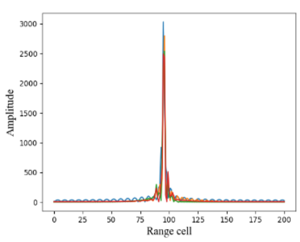
with the step length of $5MHZ$. The size of the simulated dataset we obtained is $901 \times 101 \times 201$, where 901 means taking one HRRP sample every 0.1° in radar azimuth angle $0^{\circ} \sim 90^{\circ}$, 101 means taking one HRRP sample every 0.1° in radar pitch angle $0^{\circ} \sim 10^{\circ}$, and 201 means the dimension of one HRRP sample. We choose the $46^{th} \sim 49^{th}$ pitch angle of three different types aircraft HRRPs in all of the azimuth angels as training dataset, and choose the 50^{th} pitch angle of the corresponding aircrafts in all of the azimuth angles as test dataset. Fig. 3 shows the three different types aircraft HRRPs, where Fig. 3(a), 3(c) and 3(e) show the HRRPs of F-35, F-117 and P-51 in training dataset, respectively. It is worth mentioning that we draw the HRRPs of $46^{th} \sim 49^{th}$ pitch angles in the same figure. As seen from Fig. 3, Fig. 3(b), 3(d) and 3(f) show the HRRPs of the above three different types aircraft in test dataset which contains the 50^{th} pitch angel HRRPs.



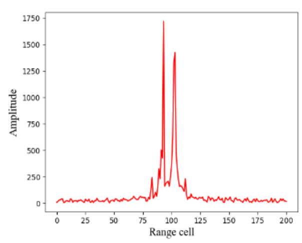
(a) The HRRPs of F-35 in training set.



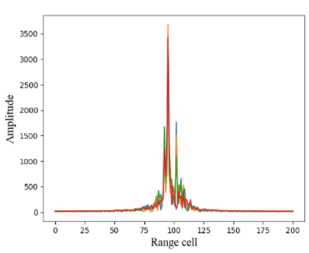
(b) The HRRPs of F-35 in test set.



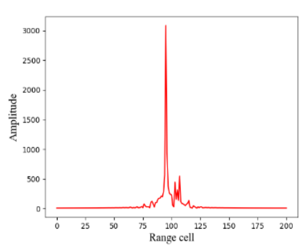
(c) The HRRPs of F-117 in training set.



(d) The HRRPs of F-117 in test set.



(e) The HRRPs of P-51 in training set.



(f) The HRRPs of P-51 in test set.

Fig. 3. The HRRPs of three different types aircraft in training and test dataset.

B. Comparative and Ablative Experiment Results

In this section, the comparative experiments with traditional LSTM methods and the ablative experiments of the proposed method are conducted based on above simulated dataset. The length of window function W is set to 100, the step length is set to 10, the number of HRRP sequences L is equal to 11, the hidden size of LSTM cells in TSFR extraction module is 100, the hidden size of LSTM cells in TSFS extraction module is 150, the learning rate of the proposed method is set to 0.00005. Table II shows the best recognition accuracy of each method. As seen from Table II, the proposed hierarchical time sequential feature extraction network achieved the highest recognition accuracy. LSTM(*) means traditional one layer LSTM method, which is represented by '*', LSTM(2 layers) means the traditional two layers LSTM method, *+SIP+TSFR(#) means adding SIP module to '*' and transformed the traditional LSTM cells to TSFR LSTM cells, which is represented by '#', #+TSFS means adding TSFS module into '#' and the proposed method is the whole hierarchical time sequential feature extraction method. It is worth mentioning that we strictly controlled the variables: the hidden size of LSTM(*) is equal that of LSTM cells in TSFR extraction module, the hidden size of LSTM(2 layers) is equal to that of LSTM cells in TSFS extraction module and the learning rate is set to 0.00005 to all of the comparative methods. The precision, recall and F1-score results are shown in Table III, which demonstrated the superiority of the proposed method.

We further show the curve of recognition accuracy with epoch in Fig. 4. As seen from Fig. 4, the proposed method achieved the best performance compared other methods, and the traditional deep learning methods based on LSTM and two layers LSTM achieved mediocre performance.

TABLE II. THE BEST RECOGNITION ACCURACY OF DIFFERENT METHODS

Method	Accuracy
LSTM(*)	0.860
LSTM(2 layers)	0.877
*+SIP+TSFR(#)	0.922
#+TSFS	0.950
The proposed method	**0.956**

TABLE III. THE PRECISION, RECALL AND F1-SCORE OF THREE DIFFERENT KINDS OF AIRCRAFT

	Precision	Recall	F1-score
F-35	0.96	0.93	0.95
F-117	0.93	0.97	0.95
P-51	0.97	0.95	0.96

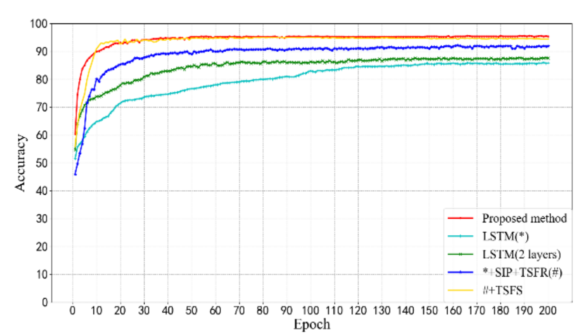


Fig. 4. The detail training process of the proposed method and comparative methods in 200 epoches.

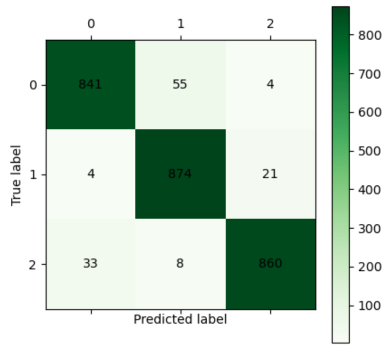


Fig. 5. The confusion matrix of the proposed method's recognition result.

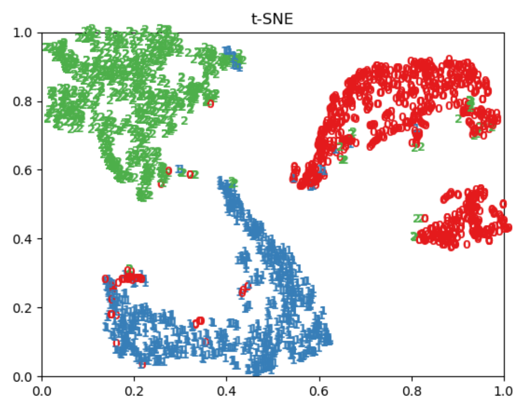


Fig. 6. The two dimension t-SNE of the test HRRP features.

Fig. 5 shows the confusion matrix of above mentioned three different types aircraft recognition results by the proposed method, where label '0' means F-35, label '1' means 'F-117', and label '2' means 'P-51'. To visualize the high dimensional test HRRP features, we employed the *t*-distributed stochastic neighbor embedding(t-SNE) to map the high dimensional test HRRP features into a two dimensional subspace in Fig. 6. In Fig. 6, red '0' represents F-35, blue '1' is F-117, and green '2' means P-51.

IV. Conclusion

In this paper, a novel hierarchical time sequential feature extraction network is proposed for RATR based on HRRP, which can not only extract time sequential features between HRRP range cells, but also learn temporal dependence across HRRP sequences. The comparative and ablative experiment results demonstrated the superiority of the proposed method and the effect of our three developed modules: SIP module, TSFR extraction module and TSFS extraction module.

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