

# Polarimetric HRRP recognition based on feature-guided Transformer model

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Polarimetric high-resolution range profile (HRRP) holds great potential for radar automatic target recognition (RATR) owing to its capability of providing both polarimetric and spatial scattering information. In recent years, deep learning (DL) has obtained state-of-the-art results in many classification tasks and has drawn great attention in the RATR field. However, as one of the most challenging tasks in RATR, small training sample case will restrict the application of DL because its superior performance generally depends on a large number of training samples. A feature-guided deep model based on Transformer framework is proposed for polarimetric HRRP recognition with limited training samples. In the proposed model, artificial features are introduced to the attention module to guide the model focus on the range cells of HRRP with more target scattering information so as to reduce the dependence of the model on the number of training samples. Several different approaches are also studied to measure the similarity between artificial features and HRRP data to further improve the learning capacity of the model. Experimental results demonstrate that the proposed feature-guided Transformer model modifying by Cosine similarity measure is able to achieve a better performance for polarimetric HRRP recognition with limited training samples.

**Introduction:** Polarimetric high-resolution range profile (HRRP) represents the distribution of target scattering centres along the radar line-of-sight. Because it can provide rich target information in both polarimetric and spatial dimension and has a low requirement on the acquisition, storage and processing, it plays an important role in radar automatic target recognition (RATR) community [1].

Numerous polarimetric HRRP recognition methods have been proposed in the past few decades [2]. In recent years, as a fast-developing technique, deep learning has achieved a series of remarkable results in various classification tasks and has drawn great attention in RATR field. As a kind of end-to-end approach, deep learning has the advantage to automatically extract deep features and produce final classification results. Many classic deep learning frameworks, such as convolutional neural network (CNN) [3] and recurrent neural network (RNN) [4], have been studied for polarimetric HRRP recognition. In general, deep learning requires a huge number of samples to acquire a well-trained model [5]. However, it is a big challenge to obtain substantial HRRP samples of radar target especially non-cooperative target [6]. Consequently, improving the performance of deep models with small training samples is a valuable research topic in HRRP-based RATR field.

In this paper, we propose a feature-guided Transformer model for radar polarimetric HRRP recognition with limited training samples. In the model, artificial features are introduced to the attention module, with which the model can concentrate on the range cells of HRRP with more target scattering information, and the negative impact of the limited size of training samples can be reduced. In addition, to better measure the similarity between artificial features and HRRP data, four similarity measures are also studied to enhance the learning capacity of the model. Experimental results based on measured polarimetric HRRP data prove the effectiveness of the feature-guided model in small training sample cases and indicate that the model can achieve a better performance after

modifying by Cosine similarity measure, showcasing good potentials in practical applications.

**Feature-guided Transformer model:** Transformer is a novel deep model proposed for sequence tasks [7] and has achieved influential results in natural language processing [8] and image processing [9] fields. One of the core components of the model is the self-attention mechanism. Specifically, the input is transformed into a query matrix  $\mathbf{Q}$ , a key matrix  $\mathbf{K}$  and a value matrix  $\mathbf{V}$ , and the output is a weighted value matrix  $\mathbf{V}$ , where the weight assigned to  $\mathbf{V}$  is the similarity between  $\mathbf{Q}$  and  $\mathbf{K}$ . The self-attention mechanism can be described as

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d}}\right)\mathbf{V} \quad (1)$$

where 'softmax' is SoftMax function which is performed to normalize the attention matrix to probability distribution,  $\sqrt{d}$  is the scaling factor and  $d$  equals the length of the input data, controlling the dot product of  $\mathbf{Q}$  and  $\mathbf{K}$  which is not too large.

The essence of attention mechanism comes from human visual attention mechanism. When people perceive things, this mechanism helps them pay more attention to specific parts according to their needs and learn core information with limited data. Inspired by this, we establish a feature-guided model based on Transformer model for polarimetric HRRP recognition with limited training samples. The core idea is utilizing the polarimetric features of HRRP, which contain an abundance of prior knowledge of samples to guide the model focus on the range cells of HRRP with more target scattering information and thus improve the learning ability under small samples and achieve better performance.

The flowchart of the proposed feature-guided Transformer model is shown in Figure 1. For a given polarimetric HRRP with  $n$  polarimetric channels and  $l$  range cells, the real and imaginary part of HRRP data in each polarimetric channel are coded into a data matrix whose size is  $l \times 2$  and fed into a linear projection layer. The size of the data matrix will be mapped from  $l \times 2$  to  $l \times d$  via the linear projection layer in order to facilitate the model to extract target information. Simultaneously,  $m$  artificial features are extracted from each range cell, so that a feature matrix with the size of  $l \times m$  can be obtained from the original HRRP data. The size of the feature matrix is also mapped into  $l \times d$  by the linear projection layer to be consistent with the data matrix. Then, positional encodings are added to the  $n$  data matrices and the feature matrix to retain positional information of HRRP range cells. Next, these  $n$  data matrices and the feature matrix are fed into an  $n$ -head self-attention module. In each self-attention, the data matrix of a certain polarimetric channel is mapped into a key matrix  $\mathbf{K}$  and a value matrix  $\mathbf{V}$ , and the feature matrix is mapped into a query matrix  $\mathbf{Q}$ . Subsequently, the

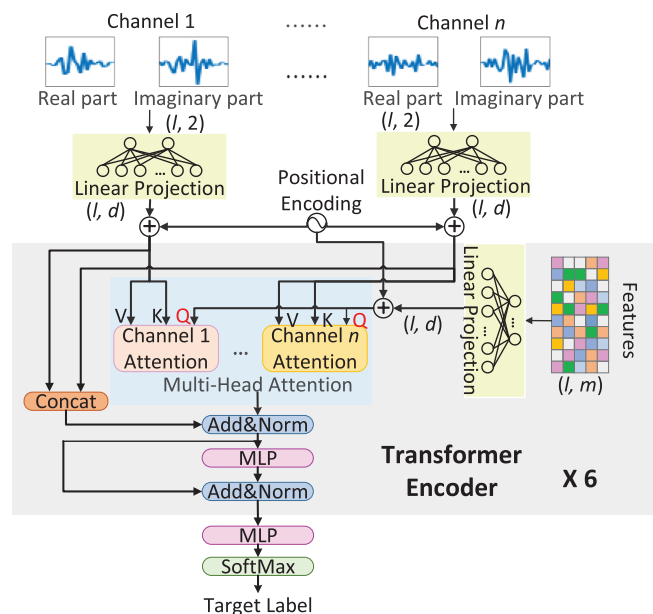


Fig. 1 Flowchart of the feature-guided Transformer model

Table 1. Recognition results of different models

			PA (%)			
Methods		OA (%)	Target1	Target2	Target3	Target4
T-Dot (no-fea)		67.05	22.59	92.85	74.38	78.36
Feature-guided model	T-Dot	92.52	95.71	98.76	81.62	93.99
	T-Cos	<b>96.62</b>	<b>98.76</b>	<b>99.43</b>	92.29	<b>96.00</b>
	T-Jac	95.07	98.28	99.24	87.05	95.71
	T-Dice	95.88	96.57	<b>99.43</b>	<b>92.67</b>	94.85
	T-Corr	91.28	91.33	97.33	85.14	91.33

outputs of the  $n$ -head self-attention module are integrated by a residual connection layer and fed into a normalization layer and an MLP layer, which are consistent with the original Transformer encoder [7]. Finally, six identical Transformer encoder blocks are stacked, thus constituting the proposed deep model, and an MLP and a SoftMax layer are adopted at last to predict the target label.

*Attention module with different similarity measures:* In the original self-attention module,  $\mathbf{Q}$  and  $\mathbf{K}$  both come from the same input, and scaled-dot operation measures the similarity between  $\mathbf{Q}$  and  $\mathbf{K}$ . However, in the proposed model,  $\mathbf{Q}$  and  $\mathbf{K}$  come from artificial feature and HRRP data, respectively. In order to better measure the similarity between features and HRRP data, we further explore four additional similarity measures: Correlation coefficient (Corr), Cosine (Cos), Dice coefficient (Dice) and Jaccard coefficient (Jac) [10]. Taking two vectors  $x$  and  $y$  with  $k$  dimensions as examples, the formulas of the four methods are respectively described as

$$\text{Corr}(x, y) = \frac{k \sum_{i=1}^k x_i y_i - \sum_{i=1}^k x_i \sum_{i=1}^k y_i}{\sqrt{k \sum_{i=1}^k x_i^2 - \left(\sum_{i=1}^k x_i\right)^2} \sqrt{k \sum_{i=1}^k y_i^2 - \left(\sum_{i=1}^k y_i\right)^2}} \quad (2)$$

$$\text{Cos}(x, y) = \frac{\sum_{i=1}^k x_i y_i}{\sqrt{\sum_{i=1}^k x_i^2} \sqrt{\sum_{i=1}^k y_i^2}} \quad (3)$$

$$\text{Dice}(x, y) = \frac{2 \sum_{i=1}^k x_i y_i}{\sum_{i=1}^k x_i^2 + \sum_{i=1}^k y_i^2} \quad (4)$$

$$\text{Jac}(x, y) = \frac{\sum_{i=1}^k x_i y_i}{\sum_{i=1}^k x_i^2 + \sum_{i=1}^k y_i^2 - \sum_{i=1}^k x_i y_i} \quad (5)$$

The similarities obtained from these methods are all in the range of 0–1, which may make the parameter of the model too similar and reduce the learning capacity of the model. To counteract this effect, we scale the similarity by  $\sqrt{d}$ , which can be written as

$$\text{Weight}(\mathbf{Q}, \mathbf{K}) = \text{softmax}(\sqrt{d}\mathbf{Q} \otimes \mathbf{K}) \quad (6)$$

where  $\otimes$  represents the similarity measure approach. These methods will not change the complexity of the attention module, which is  $O(n^2)$ .

*Experimental settings:* We conduct the recognition experiment to verify the proposed model based on a dual polarimetric HRRP dataset. The database contains 4 classes of civilian vehicles which are common in our daily life: truck, pick-up, sedan and minibus. The data is measured by a dual polarimetric wideband radar whose bandwidth is 1250 MHz. It transmits an H linear polarization and receives H and V orthogonal polarizations simultaneously. The polarimetric HRRP samples of each vehicle are collected at 7 azimuth angles with the interval of  $45^\circ$  in the range of 0–360°, and there are 500 samples at each azimuth angle. Each class contains 3500 samples and the signal-to-noise ratio is higher than 25 dB. In the experiment, we divide the measured data into training samples and testing samples according to the ratio of 7:3. In addition, we uniformly cut out 100 range cells from each original HRRP, and align

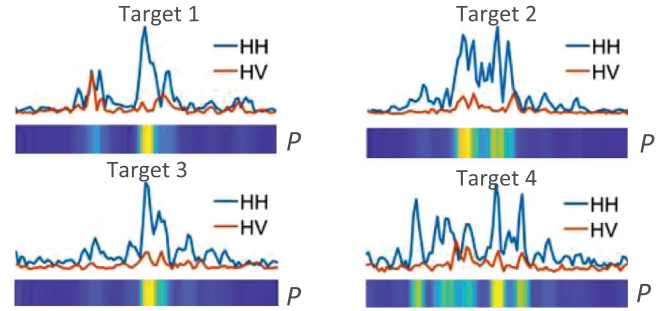


Fig. 2 HRRP samples of four vehicles and corresponding feature  $P$

the target region in the range window to tackle the time-shift sensitivity. To deal with the amplitude-scale sensitivity, each HRRP sample is normalized by dividing its L2-norm [11]. Therefore, for the input of our model, the polarimetric channel number  $n$  equals 2, the range cell number  $l$  is 100 and the input dimension of the model  $d$  is set to 32.

As for the artificial features, we extract 10 polarimetric features from each range cell of the HRRP. The features include polarization ratio, phase difference, four Mueller similarity features, three polarization correlation coefficients, and the trace of power matrix [12]. Figure 2 takes the trace of power matrix  $P$  as example and shows the dual polarimetric HRRP samples of four vehicles and their corresponding feature  $P$ .

*Recognition performance evaluation:* In this part, we evaluate the performance of six models, including the Transformer model without features (T-Dot (no-fea)), feature-guided Transformer model (T-Dot) and four models with different similarity measures (T-Cos, T-Jac, T-Dice and T-Corr). Table 1 shows the overall accuracy (OA) and the per-class accuracy (PA) of the six models. We can observe that the accuracy of the proposed feature-guided models is more than 20% higher than the T-Dot (no-fea) model. Among the feature-guided models with different similarity measures, T-Cos model performs best, and its OA reaches 96.62%, which is 4% higher than the original T-Dot model. As for the PAs, T-Cos model has the highest accuracy in three targets and outperforms other models. Experimental results verify the effectiveness of the feature-guided Transformer model and the Cosine similarity measure can further improve the performance of the model.

In order to visually demonstrate the impact of the attention mechanism, we take a dual polarimetric HRRP sample of target 1 as an example to visualize the attention weight. We analyze the attention weights for HRRP data of five feature-guided models, the results are shown in Figure 3. It is observed that the model will concentrate on different range cells of the targets due to different similarity measures. Compared with other methods, Cosine similarity measure makes the attention mechanism pay more attention on the range cells with strong scattering centres. Because the strong scattering centres are generally the most discriminative part in HRRP which contains more target scattering information, T-Cos model gets better recognition performance. This is in line with the experimental results that the T-Cos model achieves the highest OA.

*Performance with different numbers of training samples:* In this part, we evaluate the performance of our method with different amounts of samples. In order to effectively analyze the performance of the proposed

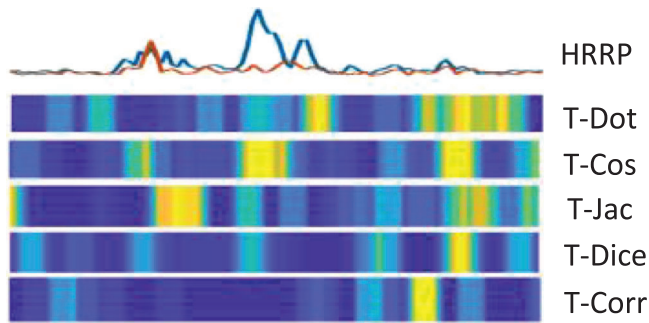


Fig. 3 Visualization of attention weights for HRRP data

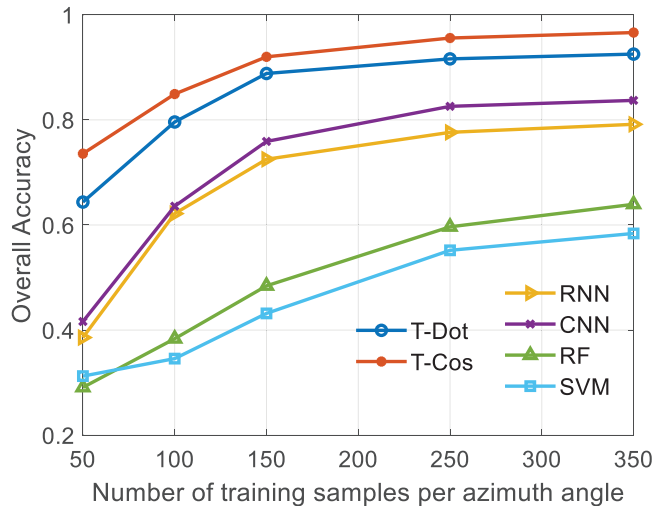


Fig. 4 Relationship between training sample number and accuracy

model, we implement two kinds of comparative methods in the experiment. The first one is the conventional method based on feature extraction and the classifier. In the method, 10 artificial features extracted are fed into a Support Vector Machine (SVM) classifier and a Random Forest (RF) classifier respectively. As for the second one, CNN [3] and RNN [4] which have been studied in polarimetric HRRP recognition are configured as comparative methods. The experimental results are shown in Figure 4. It can be observed that deep models can achieve better results than conventional methods. In addition, the proposed feature-guided model performs best among these deep models. Especially, when the number of samples per azimuth angle for each target is less than 150, the proposed model is more robust than other deep models. It indicates that the proposed feature-guided model achieves better recognition accuracy with small samples. The results also show that the Cosine similarity measure further improves the recognition performance of the proposed model.

**Conclusion:** In this paper, a feature-guided deep model based on Transformer framework is presented for polarimetric HRRP recognition with limited training samples. In the model, artificial features are employed to guide the model concentrate on the range cells of HRRP

with more target scattering information and enhance the performance of the model. Moreover, different similarity measures are established to acquire the similarity between artificial features and polarimetric HRRP data. Experiment results demonstrate the superiority of the feature-guided model for polarimetric HRRP recognition with small training samples and Cosine similarity measure which can further improve the recognition performance of the proposed model, showcasing good potentials in practical applications.

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