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Robust Target Recognition for High-resolution Range Profile by Feature Fusion

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***Abstract*—High resolution range profile (HRRP) plays a key role in wideband radar target recognition. This paper exploited the multi-feature based recognition for HRRP by random forest (RF) classifier. Firstly, an improved convolutional neutral network is employed to extract the deep features in the HRRP, which has excellent recognition performance in high signal to noise ratio(SNR) but sensitive to the SNR deviation between training and test data. Then we combine the structure features with the deep features for performance improvement in various noise environment. RF is utilized as the multi-feature based classifier, which has prominent recognition performance and efficient computational complexity. To improve the robustness of the RF classifier, noises with various power are randomly added to the training data. Experimental results verify that the recognition performance is improved by increasing the SNR variation in training data as the RF classifier can effectively learn the most reliable features in different SNR environment and gain robustness in lower SNR.**

Keywords—High resolution range profile; multi-features; recognition; convolutional neutral network(CNN); rondom forest.

I. INTRODUCTION

High resolution range profile(HRRP) reflects the energy distribution of the wideband target along the slant range direction, which provides important information for radar automatic target recognition(RATR)[1]. Compared to synthetic aperture radar(SAR) imaging[2], HRRP-based RATR requires lower system complexity and less computing resources. Therefore, HRRP-based RATR is widely exploited in theoretical researches and practical applications. Although HRRP can be directly utilized for recognition by template matching[3], it is sensitive to time-shift and aspect angle change[4]. Moreover, template matching will be easily interfered by noise and clutter. Therefore, it is necessary to explore HRRP feature-based recognition for better performance.

In the range domain, features are proposed to describe the HRRP structure, such as length, energy distribution, symmetry, et al. Scatter centers are also important features which reflect the scattering characteristics of the target[5]. In the frequency domain, power spectrum and magnitude of the frequency spectrum are widely used as they are translation invariant[6]. Besides, transforms such as Wavelet, Mellin, high-order spectrums are utilized for better feature extraction[7]. Recently, neutral networks are introduced for deep feature exploitation. Convolutional neutral network(CNN), the well-known deep learning architecture [8], are translation invariant as they extract the local structures of HRRP. In [9], CNN is employed for automatically feature extraction and recognition in multistatic radar systems. In[10], the residual attention pyramid pooling net(RAPPNet) is proposed using HRRP for drone recognition. In[11], a target recognition method based on continuous multi-frequency modulation period fusion of one-dimensional range profile is proposed

However, HRRP-based recognition by CNN are sensitive to noise. Specifically, when the signal-to-noise ratio(SNR) difference is large between training data and test data, the recognition performance will decrease severely. Therefore, we introduce the multiple-feature based recognition which combines CNN features with the structure features for robustness improvement in different noise environment.

In the paper, a multiple-feature based robust recognition scheme is proposed. CNN features are extracted adaptively by well-training. Then they are combined with structure features as the input of the Random Forest(RF) classifier. To improve the robustness in different scene, noises with different power are added to the training data. By learning the features of HRRP in different SNR, the recognition performance of RF can be improved when the SNRs for training and test data are not matched.

This paper is organized as follows. The signal model is introduced in Section II. The target recognition system is demonstrated in Section III. Real data experiments are carried out in Section IV, verifying the superiority of the recognition system. Conclusion are given in Section V.

II. HRRP FEATURE EXTRACTION

A. Signal model

The echoes from vehicles at high frequencies can be modeled as a sum of independent sactterers, where geometric theory of diffractions(GTD) is widely used to describe the scattterer model. The frequency and time response of the target can be written as

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$$H(f)=\sum_{k=1}^{K} A_k \exp\left[-j2\pi \frac{2R_k}{c} f\right], \tag{1}$$

$$h(t)=\sum_{k=1}^{K} A_k \delta\left(t-\frac{2R_k}{c}\right), \tag{2}$$

where A_k and R_k represent the complex amplitude and the radial range of the kth scatterers to the radar, respectively.

The transmitted wideband stepped frequency signal is denoted by

$$s(t)=\sum_{n=0}^{N-1} \mathrm{rect}\left(\frac{t-nT_r}{T_p}\right)\exp\left(j2\pi f_n t\right), \tag{3}$$

where T_r and T_p represents the pulse repeat time(PRT) and pulse width respectively. $f_n = f_0 + N\Delta f$, in which f_0 is the carrier frequency and Δf is the frequency step. The received signal $s_r(t)$ is the convolution of the transmitted signal $s(t)$ and the target response $h(t)$, i.e,

$$\begin{aligned} s_r(t) &= s(t) * h(t) \\ &= \sum_{n=0}^{N-1}\sum_{k=1}^{K} A_k \mathrm{rect}\left(\frac{t-nT_r-2R_k/c}{T_p}\right)\exp\left(j2\pi f_n (t-2R_k/c)\right) \end{aligned}. \tag{4}$$

After down-conversion and IFFT for each range cell, the HRRP of the target can be obtain as

$$\begin{aligned} &S_r(m) \\ &= \sum_{k=1}^{K} A_k \exp\left(-j2\pi f_0 \frac{2R_k}{c} + j\frac{N-1}{N}\pi\left(\frac{-2R_k N\Delta f}{c}+m\right)\right)\frac{\sin\left[\pi\left(\frac{-2R_k N\Delta f}{c}+m\right)\right]}{\sin\left[\frac{\pi}{N}\left(\frac{-2R_k N\Delta f}{c}+m\right)\right]} \end{aligned}, \tag{5}$$

where m=0,1,…,N-1. (5) indicates that the target's HRRP equals to the sum of sinc shape waveforms whose intensities and locations correspond to each scatterer. It needs to be mentioned that the high speed relative motion between target and radar will corrupt the HRRP, which should be estimated and compensated roughly[12].

Before feature extraction, the HRPP needs to be normalized and segmented. Usually the maximum of the HRRP is utilized for normalization as

$$x(m)=\frac{S_r(m)}{\max\left(\left|S_r(m)\right|\right)}. \tag{6}$$

The segmentation process determines the target area and cuts the corresponding HRRP apart from the whole range HRRP. Slide-window is an effective approach to detect the target area in the range profile[13].

B. CNN feature extraction

Assume the target HRRPs are normalized and segmented appropriately according to the above discussion. In this section, CNN features and structure features are explored to extract the distinctive information for recognition.

RAPPNet proposed in [11] is introduced to exploit the deep features in the HRRPs. The architecture of RAPPNet is shown in Fig.1.

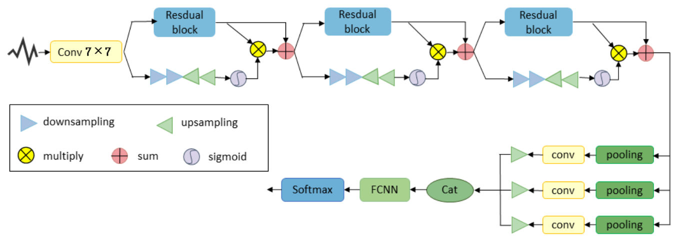

Fig.1 The RAPPNet architecture

The RAPPNet is composed of three parts. The first is the Residual Attention Network, which is built by stacking Attention Modules which generate attention-aware features. The feature extraction part consists of three residual attention modules, each of which includes two parts: the trunk branch and the mask branch. The main branch is composed of residual convolution blocks for feature processing, while the output of the mask branch serves as the weight of the main output.

The second part is the Pyramid Pooling Module. By adaptively adjusting the pooling kernel and step size at different scales, the original feature map is subjected to multi-scale pooling to output three feature maps of different sizes. Then, linear interpolation is performed to restore these feature maps to their original size. Subsequently, all feature maps are concatenated according to the channel dimension. Finally, a composite feature map is obtained to achieve a balance between global information and local detail information.

The third part is the classification module, including a 16-unit fully-connected hidden layer and a fully-connected softmax output layer, after which the output represents the CNN feature.

C. Multiple feature fusion

Although CNN can extract distinct features for recognition, it still has limitations. In the experimental results of Section IV, CNN features will be shown to be sensitive to noise. Therefore, more features needs to be applied in our recognition system.

As shown in (5), HRRP structure is mainly determined by the dominant scatterers on the target. Sparse recovery methods are exploited to improve the accuracy for scatterer center extraction[5][13]. Based on the scatterers, structure feature s including length feature, scatterer features, fluctuation feature, contrast feature, symmetry feature, energy distribution feature are utilized for recognition [14].

Above listed the most important structure features used in our HRRP-based RATR system, which are combined with CNN features for recognition, called multi-feature based recognition. In the next section, we illustrate the target recognition system and design a noise robust RF classifier based on the multi-features.

III. Target Recognition System

Fig.2 illustrates the overall framework of the proposed HRRP-based target recognition. In the training stage, HRRP samples of different target in various aspect angles are obtained by large amounts of outfield experiment data. Generally, the

SNRs for the training data are relatively high, which may be impractical in real RATR applications as the SNRs may vary seriously among different outfield scenes. Thus the classifier trained by the training data in certain SNR may be infeasible in other SNRs. To improve the robustness of the classifier to noise, we add additional Gaussian white noise with kinds of powers to the training HRRPs. The experiment results in Section IV will validate the effectiveness of the process in robustness improvement.

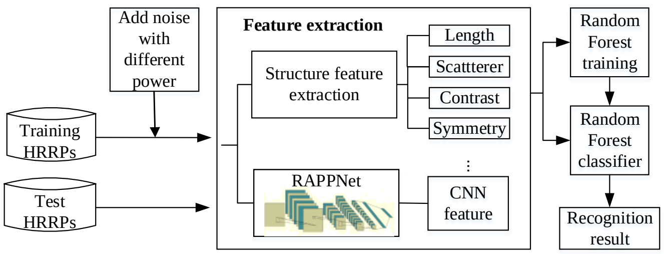

Fig. 2 The framework of the target recognition system

The features for the training data are extracted according the discussion in Section II. For the structure features, they can be obtained directly by the calculation according to their definitions, which are unsupervised learning. For CNN features, the convolutional network requires a supervised learning process, after which the features can be automatically extracted for recognition.

RF is a predominant machine learning method which can deal with the high dimensionality of data by selecting only the important features. Based on the multiple features, RF is trained as the classifier. Each individual decision tree in the random forest is constructed with a bootstrap sample from the training dataset, made up of a root node, internal node and leaves. Each node represents a feature selected by a criterion and has at least two branched corresponding to a range of values for the selected feature respectively.

In the test stage, the structure features and CNN features of the test data are extracted and input into the trained RF classifier. The output of the recognition system will be the corresponding type the test data most likely belongs to.

Above discussed the whole process of our multi-feature based target recognition system by HRRPs. The advantages of the framework lies in:

- Feature-based recognition can effectively get rid of the time-shift sensitivity and amplitude sensitivity for the original HRRPs.
- Multiple features can improve the robustness in different environments. Although CNN shows great potential in recognition, it is sensitive to noise. Combining structure features with CNN features can increase the stability of the recognition in various noise.
- RF classifier shows superiority in feature-based target classification and computational complexity, which can be well utilized in practical applications.

IV. EXPERIMENTAL RESULTS

In this section, outfield experimental results are presented to illustrate the performance of the proposed target recognition system, with Carrier frequency of 77GHz, band width of 5GHz, and Synthesized PRF of 200Hz. We focus on the recognition of five typical vehicles. The echoes are obtained in different environments with various aspect angles. Then the HRRPs of the five types are synthesized for recognition. We obtained about 5000 HRRP samples for the five types in total.

HRRPs of five type of vehicles with label 0-4 are used as the training samples by a k-fold cross validation. Parameters are tuned by the stochastic gradient descent(sgd) with adaptive moment estimation(Adam). The network is trained by the minibatch size of 100, and 100 epochs are carried out to minimize the validation error. Parameters in the CNN are then determined, after which the CNN features can be obtained for the test data.

Firstly, we evaluate the effectiveness of the CNN features in recognition. The CNN architecture in Fig.1 is trained with 40000 HRRP samples randomly selected from the 50000 samples, and the other 10000 samples are used for testing. As the original HRRPs are obtained in high SNR conditions, we add additive Gaussian white noise to them to test the robustness of CNN features. The mean recognition rates for the five types are calculated by training and test data with different Peak SNR(PSNR), as plotted in Fig.3. It can be seen that when the PSNR of test data equals to the training data, the recognition rate is highest. If SNR of the test data is far lower than the training data, the recognition decreases severely, illustrating the CNN features are sensitive to noise.

Then the recognition results of the multi-features using RF classifier are shown in Fig. 4, verifying that the recognition rate can be significantly improved in low SNRs by using structure features and CNN features jointly.

Next the RF classifier is tested with Linear regression (LR), support vector machine (SVM) (using RBF kernel function) and gradient boosting decision tree (GBDT) in multiple feature based recognition. LR and SVM are widely used for classification with the moderate number of training samples. Ensemble learning combining individual classifiers for a more powerful classifier can well process the classification problems with large amounts of data. RF is one of ensemble learning approaches, with decision trees that are grown using only some subsets of features and reduction for the high dimensionality of data by selecting only the important features. Compared with another well-known ensemble learning approach, gradient boosting decision tree (GBDT), RF is parallelizable which reduce the computation time significantly. Moreover, RF has relative lower generalization error and immunity against over-fitting compared to other machine learning methods. The randomness of bootstrap sampling also enhances the prediction accuracy. Fig. 5 shows the recognition results in different PSNRs(the PSNRs of training data and test data are the same), which verifies the superiority of RF to LR and SVM. Although GBDT has good recognition performance, it needs much more computional time, as listed in TABEL 1.

TABEL 1 RECOGNITION RATE AND TRAINING TIME COMPARISON(PSNR=20DB)

	LR	**SVM**	**GBDT**	**RF**
Mean recognition rate	77.30%	96.83%	98.62%	98.94%
Training time	1.86s	29.31s	11.13s	1.65s

To inrease the robustness of the RF classifier, the training HRRPs are added with different powers of noise. Then features are extracted and RF classifier is trained. Fig.6 shows the performance of the RF classifier with training data of different SNR ranges, illstrating that training data with various SNRs can effectively improve the robustness to noise.

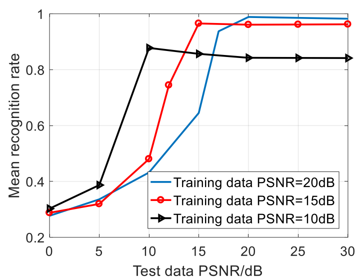

Fig. 3 Recognition results for CNN-features in different PSNR

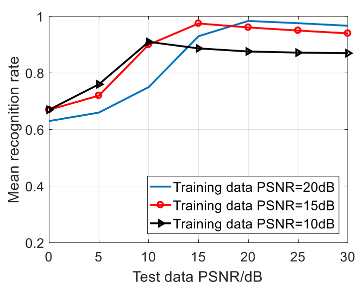

Fig. 4 Recognition results for multi-features in different PSNR

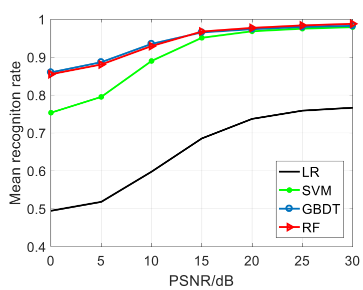

Fig. 5 Performance comparison of the four classifiers

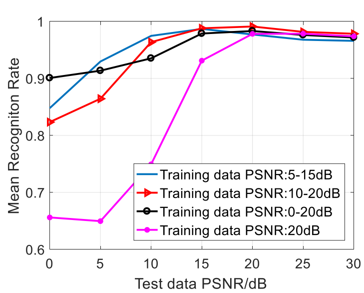

Fig. 6 Performance of RF classifier with different PSNR range of training data

V. CONCLUSIONS

The paper proposed a multi-feature based RATR architecture for HRRPs using RF classifier. In the feature extraction step, RAPPNet is well trained to extraction the CNN features. Moreover, structure features are exploited including the length, dispersion, scatterers and so on. In the classification stage, a noise robust RF classifier is designed by providing training data in various SNRs. By the large scale of outfield experimental data, the RF classifier is proved to be superior in recognition and more computationally efficient. The multi-feature recognition system is verified to significantly improve the performance of the CNN-feature based recognition in lower noise.

In the future work, fusion strategy will be optimized to fully utilize the complementarity of structural features and deep features, which enhances the robustness and accuracy of the system further.

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