OPTIMIZATION OF WEIGHTED HIGH-RESOLUTION RANGE PROFILE FOR RADAR TARGET RECOGNITION

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Abstract: For the recognition of high-resolution range profile (HRRP) in radar, the weighted HRRP can reduce the instability of range cells caused by the attitude change of targets. A novel approach is proposed to optimize the weighted HRRP. In the approach, the separability of weighted HRRPs in different targets is measured by designing an objective function, and the weighted coefficients are computed by using the gradient descent method, thus enhancing the influence of stable range cells. Simulation results based on five aircraft models show that the approach can effectively optimize the weighted HRRP and improve the recognition accuracy.

Key words: radar target recognition; high-resolution range profile; scattering center model; gradient descent method

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INTRODUCTION

The radar automatic target recognition (RATR) is known as a highly promising technique to identify the unknown target from its radar echoes. As one of the wideband radar echo forms, the high-resolution range profile (HRRP) represents the projection of complex returned echoes from target scatters to the radar line-of-sight (LOS). HRRP contains more target structure signatures than narrowband radar echoes and has been shown as a highly discriminative target feature[1-11].

Template matching method based on the maximum correlation coefficient criterion (MCC-TMM)[2] is a commonly used method in radar HRRP recognition. By segmenting the target-aspect[3-4], the average HRRP is used as the template in each target-aspect sector, and the class of test HRRP is determined by the matching scores between it and each template when applying MCC-TMM. The average HRRP can suppress the interaction among scatters in the same range cell, which is caused by the target-aspect changes. Therefore, the average HRRP is capable of reducing the HRRP target-aspect sensitivity[1-2]. However, the average HRRP model is based on the hypothesis that there are a large number of small scatters and no more than one predominant scatter in each range cell. Unfortunately, this is not true for most real targets[5-7]. If there are several predominant scatters in a range cell, the amplitude of the corresponding range cell greatly fluctuates as target-aspect changes, hence the average HRRP cannot describe the electromagnetism characteristics of scatters.

In view of this, Du[11] proposed a weighted HRRP recognition method, where the weighted coefficients are determined by the inverse standard deviation of amplitude in each range cell. Considering that the amplitude of stable range cells have a relatively larger value of inverse standard deviation than that of unstable range cells, the role of stable range cells can be enhanced by multiplying the weighted coefficients, while the

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impact of unstable range cells can be reduced. However, owing to the insufficient data and the low SNR in the practical application, the accuracy of the estimated standard deviation is poor, which limits the improvement of recognition accuracy.

To resolve the problems mentioned above, a novel approach is proposed to optimize the weighted HRPP in this paper. Based on Ref. [12], an objective function is defined to measure the separability of weighted HRRPs in different targets firstly, and then optimal weighted coefficients are chosen through optimizing the objective function for recognition. Simulation results demonstrate the effectiveness of the proposed approach compared with Du's method.

1 PROPERTIES OF HRRP

Radar works in the optical region, and the electromagnetism characteristics of targets can be described by the scattering center model. According to this model, a high-resolution range profile is the coherent summation amplitude of complex time returns from target scatters in each range cell. The mth complex returned echo in the nth range cell without motion through range cells (MTRC) of scatters can be written as

$$\boldsymbol{x}_n(m) = \sum_{i=1}^{l_n} A_{n,i} \exp\left[-\mathrm{j}\left(\frac{4\pi}{\lambda}\Delta r_{n,i}(m) + \psi_{0,n,i}\right)\right] \tag{1}$$

where l_n denotes the number of target scatters in the nth range cell, $\Delta r_{n,i}(m)$ the distance between radar and the ith scatter in the mth sampled echo, $A_{n,i}$ and $\psi_{0,n,i}$ denote the amplitude and initial phase of the ith scatter echo, respectively. In radar HRRP recognition, a subset of HRRPs from a target-aspect sector without MTRC of scatter is defined as a HRRP frame. Because the position and intensity of scatter approximately remain unchanged within a HRRP frame, the amplitude of each range cell has a certain statistical characteristic.

The power of $\boldsymbol{x}_n(m)$ in Eq. (1) can be written as

$$|\boldsymbol{x}_n(m)|^2 = \boldsymbol{x}_n(m)\boldsymbol{x}_n^*(m) = \sum_{i=1}^{l_n} A_{n,i}^2 + 2\sum_{i=1}^{l_n}\sum_{k=1}^{i-1} A_{n,i}A_{n,k}\xi_{nik}(m) \tag{2}$$

where

$$\xi_{nik}(m) = \cos[\theta_{nik}(m)]$$

$$\theta_{nik}(m) = -\frac{4\pi}{\lambda}[\Delta r_{n,i}(m) - \Delta r_{n,k}(m)] + (\psi_{0,n,i} - \psi_{0,n,k})$$

The first term at the right side of Eq. (2) is referred as the scatter auto-term (SAT), which is the energy summation of scatters within a range cell. Without MTRC, SAT remains invariant, so it is considered as a stable feature of a HRRP frame. The second term at the right side of Eq. (2) is referred as the scatter cross-term (SCT), which is the conjugate multiplication summation of echoes from different scatters within a range cell. With the target-aspect changing, the corresponding positions of scatters within a range cell immediately change, which leads to the amplitude fluctuation according to SCT and makes the recognition difficult.

Ref. [1] pointed out that for a large number of small scatters and no more than one predominant scatter, SCT in Eq. (2) tended to be a random process with zero mean. Therefore, the average HRRP is

$$\hat{\boldsymbol{x}} = \left(\frac{1}{M}\sum_{m=1}^{M} |x_n(m)|^2\right)^{1/2} \tag{3}$$

Eq. (3) can be used to represent a stable template of a HRRP frame whose SCT is suppressed effectively by being averaged, where M denotes the number of samples in a HRRP frame. However, the average HRRP model is based on the hypothesis that there are a large number of small scatters and no more than one predominant scatter in each range cell of the target, which is not true for most real targets. If there are several predominant scatters, especially 2—3 scatters, in a range cell, the HRRP amplitude has great fluctuation with the target-aspect changing due to the difference in range-shifts among predominant scatters[11]. In this case, the average HRRP cannot describe the electromagnetism characteristics of scatters, hence, in radar HRRP recognition, the role of stable range cells should be enhanced, while the impact of unstable range cells should be reduced.

2 OPTIMIZATION OF WEIGHTED HRRP

Supposing that there are c kinds of targets and each target has L HRRP frames, HRRPs and the average HRRP of the lth frame in target k are respectively written as

$$\boldsymbol{x}_{kl}(m) = [x_{kl1}(m), x_{kl2}(m), \cdots, x_{kld}(m)]^{\mathrm{T}} \quad m = 1, 2, \cdots, M \tag{4}$$

$$\hat{\boldsymbol{x}}_{kl} = \left[\sqrt{\frac{1}{M}\sum_{m=1}^{M}|x_{kl1}(m)|^2}, \sqrt{\frac{1}{M}\sum_{m=1}^{M}|x_{kl2}(m)|^2}, \cdots, \sqrt{\frac{1}{M}\sum_{m=1}^{M}|x_{kld}(m)|^2}\right]^{\mathrm{T}} \tag{5}$$

where d denotes the range cell index. The weighted coefficients of the lth frame in target k are defined as

$$\omega_{kl} = [\omega_{kl1}, \omega_{kl2}, \cdots, \omega_{kld}]^{\mathrm{T}} \tag{6}$$

So the corresponding weighted HRRPs and the weighted average HRRP are

$$\boldsymbol{y}_{kl}(m) = [\omega_{kl1}x_{kl1}(m), \cdots, \omega_{kld}x_{kld}(m)]^{\mathrm{T}} = \omega_{kl} \circ \boldsymbol{x}_{kl}(m) \quad m = 1, \cdots, M \tag{7}$$

$$\hat{\boldsymbol{y}}_{kl} = \left[\omega_{kl1}\sqrt{\frac{1}{M}\sum_{m=1}^{M}|x_{kl1}(m)|^2}, \cdots, \omega_{kld}\sqrt{\frac{1}{M}\sum_{m=1}^{M}|x_{kld}(m)|^2}\right]^{\mathrm{T}} = \omega_{kl} \circ \hat{\boldsymbol{x}}_{kl} \tag{8}$$

Where " $\circ$ " denotes the entrywise product.

Du[11] defined the weighted coefficients as the reverse standard deviation of amplitude in each range cell within HRRP support region, and proposed the support region for reducing the impact of noise. According to the above definition, weighted coefficients of the lth frame in target k can be written as

$$\omega_{kl} = [\omega_{kl1}, \omega_{kl2}, \cdots, \omega_{kld}]^{\mathrm{T}} = \left[0, 0, \cdots, \frac{1}{\sigma_{kl(i-1)}}, \frac{1}{\sigma_{kl(i)}}, \frac{1}{\sigma_{kl(i-1)}}, \cdots, 0, 0\right]^{\mathrm{T}} \tag{9}$$

where $\sigma_{kl(i)}$ denotes the standard deviation of amplitude in the ith range cell. However, Du's method has some disadvantages when applied in the practical application: (1) Owing to the target-aspect sensitivity of HRRP, the training samples are usually insufficient, so the statistic results of standard deviation are inaccurate; (2) When SNR is low, the decision of HRRP support region is inaccurate; (3) The weighted coefficients are heuristically determined without further optimization for classification, thereby, the improvement of recognition accuracy is restricted.

To overcome the shortcomings mentioned above, an optimization approach is proposed to optimize the weighted HRRP for recognition. Based on Ref. [12], the following objective function is defined to measure the separability of weighted HRRPs with a variety of weighted coefficients for different targets

$$J(\omega) = \sum_{\substack{1\leqslant k\leqslant c\\1\leqslant l\leqslant L}}\sum_{\boldsymbol{x}\in S_{kl}}\exp\left(\frac{d^2(\boldsymbol{y}, \hat{\boldsymbol{y}}_{kl})}{\min\limits_{\substack{1\leqslant i\leqslant c\ i\neq k\\1\leqslant j\leqslant L}} d^2(\boldsymbol{y}, \hat{\boldsymbol{y}}_{ij})}\right) \tag{10}$$

where $d^2(\boldsymbol{y}, \hat{\boldsymbol{y}}_{kl}) = \|\boldsymbol{y} - \hat{\boldsymbol{y}}_{kl}\|^2 = \|\omega_{kl} \circ \boldsymbol{x} - \omega_{kl} \circ \hat{\boldsymbol{x}}_{kl}\|^2$, S_{kl} denotes a set of HRRPs of the lth frame in target k. In fact, the defined objective function $J(\omega)$ is composed of two major parts. The numerator part defines the distance between the weighted HRRP sample and the weighted average HRRP template of its corresponding frame, which represents the within-class distance of the training data. The denominator part defines the distance between the weighted HRRP sample and the weighted average HRRP template of each frame in another targets, which represents the between-class distance of training data. It is known that if the within-class distance is small while the between-class distance is large, the separability of the training data is strong. Therefore, to optimize the objective function $J(\omega)$ the weighted coefficients ω is found, which shorten the distance of numerator part as small as possible and lengthen the distance of denominator part as large as possible. It is seen that the smaller the value of $J(\omega)$, the higher the separability of weighted HRRPs with different targets, and the exponential function is used for speeding up the convergence of optimization. Therefore, optimized weighted coefficient ω^* can be computed by minimizing the objective function $J(\omega)$.

In this paper, the gradient descent method is used to iteratively compute the optimal weighted coefficients ω^* for simplicity. According to the gradient descent method, and the updating equation is

$$\omega_{pq}^{(t+1)} = \omega_{pq}^{(t)} - \eta\left(\frac{\partial J(\omega)}{\partial \omega_{pq}}\right) \tag{11}$$

$$\frac{\partial J(\omega)}{\partial \omega_{pq}} = \sum_{x\in S_{pq}} \exp\left[\frac{d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{pq})}{\min\limits_{\substack{1\leqslant j\leqslant c\ i\neq p\\ 1\leqslant j\leqslant L}} d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{ij})}\right]\cdot\frac{2\,\omega_{pq}\circ(\boldsymbol{x}-\hat{\boldsymbol{x}}_{pq})\circ(\boldsymbol{x}-\hat{\boldsymbol{x}}_{pq})}{\min\limits_{\substack{1\leqslant j\leqslant c\ i\neq p\\ 1\leqslant j\leqslant L}} d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{ij})} + \Delta$$

$$\Delta = \begin{cases} \sum\limits_{\substack{1\leqslant k\leqslant c\\ 1\leqslant l\leqslant L}} \sum\limits_{x\in S_{kl}} -\exp\left[\frac{d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{kl})}{d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{pq})}\right]\cdot\frac{d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{kl})\cdot 2\,\omega_{pq}\circ(\boldsymbol{x}-\hat{\boldsymbol{x}}_{pq})\circ(\boldsymbol{x}-\hat{\boldsymbol{x}}_{pq})}{(d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{pq}))^2} & \underset{\substack{(i,j)\\ 1\leqslant j\leqslant c\ i\neq k\\ 1\leqslant j\leqslant L}}{\operatorname{argmin}} d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{ij}) = (p,q) \\ 0 & \text{otherwise} \end{cases}$$

where t is the iteration step, and η the learning rate.

In the test stage, for an unclassified HRRP $\boldsymbol{x}$, all the distances are calculated firstly as follows

$$d^2(\boldsymbol{y},\hat{\boldsymbol{y}}_{kl}) = \|\boldsymbol{y}-\hat{\boldsymbol{y}}_{kl}\|^2 = \|\omega_{kl}\circ\boldsymbol{x}-\omega_{kl}\circ\hat{\boldsymbol{x}}_{kl}\|^2$$
$$k=1,2,\cdots,c;\quad l=1,2,\cdots,L$$

Then, the class of HRRP $\boldsymbol{x}$ is determined by the smallest distance between its weighted form and each weighted average HRRP templates. It is observed that the proposed HRRP recognition approach is still based on the template matching method (Note: The time-shift sensitivity of HRRP is not considered in this paper, all HRRPs referred here have been time-shift compensated, and the method can be found in Ref. [11]).

3 EXPERIMENTAL RESULTS

A HRRP dataset of five turntable aircraft models with similar sizes, Su27, F16, M2000, J8II, and J6, are used in the experiment. The dataset is provided by Target Electromagnetism Characteristics Research Center affiliated to Nanjing University of Aeronautics and Astronautics. The bandwidth of the transmitted radar signal is about 500 MHz, and the azimuth range of each aircraft is 180°. Each target has 3 600 HRRPs and each HRRP has 128 range cells. For all the collected data, the Gaussian white noise is added to the inphase and the quadrature radar echoes, respectively, and SNR is about 20 dB. As a result of turntable model, there is no time-shift sensitivity in HRRP data. Meanwhile, all HRRPs are accomplished by L_2 normalization. In the experiment, one half of HRRPs are randomly selected for training, and the other are selected for testing.

MCC-TMM, Du's method and the proposed approach are compared in the experiment. The recognition results are listed in Table 1. Due to the similar sizes of the five aircrafts, the limitation of target-aspect change is set to 3° for all of the five aircrafts to avoid MTRC of scatters, which is calculated by $(\Delta\Phi)_{\mathrm{MTRC}}=\Delta R/L$[1], where ΔR is the range resolution and L the maximum target dimension in cross range. For aircraft targets, $(\Delta\Phi)_{\mathrm{MTRC}}$ can be further increased because of the sparsity distributions of scatters. For the proposed approach, the learning rate η and the total iterative steps T are set to 2.0 and 50, respectively. Results show that the weighted HRRP significantly increases the recognition accuracy and the proposed approach effectively optimizes the weighted HRRP, thus improving the recognition accuracy compared with the Du's method.

Table 1 Recognition results of five aircrafts %

Methd	Su27	F16	M2000	J8II	J6	Average
MCC-TMM	92.3	79.4	89.3	81.3	79.5	84.4
Du's method	99.0	90.9	98.2	92.1	92.3	94.5
The proposed approach	100.0	96.0	99.3	92.5	97.7	97.1

Amplitude histograms of typical range cells in azimuth 66—69° of Su27 are given in Fig. 1. Fig. 1(a) illustrates a stable range cell (the 72nd range cell) whose corresponding optimized weighted coefficients ω is 36.78 and the inverse standard deviation $1/\sigma$ is 35.40. Fig. 1(b) illustrates an unstable range cell (the 56th range cell) whose corresponding optimized weighted coefficients ω is 9.05 and the reverse standard deviation $1/\sigma$ is 11.09. It is seen that range cells with large optimized weighted coefficients are more stable compared with small optimized weighted coefficients, and the role of stable range cells is further enhanced while the impact of unstable range cells is further reduced.

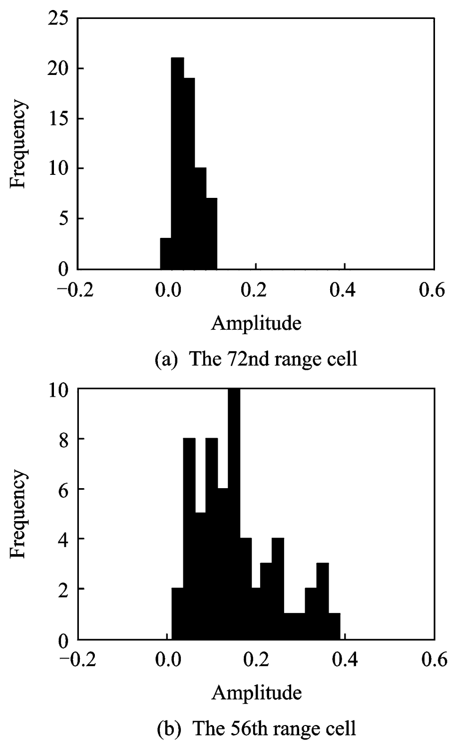

Fig. 1 Amplitude histograms of Su27 in azimuth 66—69°

4 CONCLUSION

Statistical characteristics of HRRP with different range cells are various to each other. The weighted HRRP has the ability to enhance the role of stable range cells and reduce the impact of unstable range cells. In this paper, an objective function is designed to measure the separability of weighted HRRPs in different targets using the template match method, and the weighted coefficients are then optimized by minimizing the objective function based on the gradient descent method. The effectiveness of the proposed approach is proved by the experiment on a dataset of five aircraft models.

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基于优化加权高分辨距离像的雷达目标识别

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摘要:对雷达目标高分辨距离像进行特征加权可以解决高分辨距离像各距离单元因目标姿态变化而导致的稳定性不一致问题。针对已有加权系数求解方法存在的不足,提出一种加权系数优化方法。该方法通过定义目标函数来度量不同雷达目标之间加权高分辨距离像的可分性,并采用梯度下降算法优化加权系数值,从而达到增强高分辨距离像稳定距离单元作用,减小不稳定距离单元影响的目的。基于5种飞机目标模型高分辨距离像的仿真实验表明,该方法可以有效优化加权系数,并提高雷达目标识别率。

关键词:雷达目标识别;高分辨距离像;散射中心模型;梯度下降法

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