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An improved Sparse Representation classify algorithm for Radar HRRP Targets Recognition

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Abstract: *In this paper, based on the target-aspect sensitivity of target HRRP and the sparse representation method (SR), we propose an improved radar high resolution range profile (HRRP) recognition algorithm, called asymmetrical segment weighted sparse representation (ASWSR). The main innovation of ASWSR lies in using the constant false alarm rate (CFAR) trick to segment the HRRP into three parts, and then calculate the weight of each part based on the length and the power in each districts. Performing the SR method on each sub-HRRPs, getting the sparse coefficients of each parts, extracting the main target information part in HRRP respectively. Finally, use the weights to weight the reconstruction error of corresponding part and by searching the least reconstruction error to give out the target recognition result. Experiment results demonstrate the effectiveness of our proposed method.*

Keywords: *Sparse representation, High resolution range profile, Target recognition*

1. INTRODUCTION

Radar HRRP recognition in the military applications is of important significance. So far, an enormous volume of literature has been devoted to investigate various radar target recognition methods, these methods can be roughly divide into three categories: the range profile based, especially the HRRP based; the synthetic aperture radar (SAR) image based and the signal feature based. When using the HRRP to recognize target, there are three challenges: the target-aspect sensitivity, the time-shift sensitivity and the amplitude-scale sensitivity. The scattering center model [1], coherent averaging [2], Bayesian Gmma model [3] and HMM model [4] have been well studied to surmount the target-aspect sensitivity. For the time-shift sensitivity, the HRRP-based statistical model, the higher order spectra and the invariant feature are given in [5]-[7]. Du et al. use l_2 normalization of HRRP to overcome the amplitude-scale sensitivity [5].

Recently, some new methods integrating with the theory of SR has been proposed, Wright et al. first introduced the SR method into face recognition and it shown state-of-art performance [8]. SR seeks a linear representation, with smallest number of no-zero elements, of the test sample in terms of the over complete dictionary and then be recovered efficiently via l_1-minimization. The SR method assigns the class label of test sample to the class, which has the least representation error, directly. So the SR can be view as a learning machine in which the classification process is accomplish by using reconstruction methods. For radar target recognition, Dong et al. proposed the joint sparse representation for target recognition [9] and Wang et al. introduced the modified SR and manifold learning methods to the HRRP target recognition [10], both achieved a certain success.

In this paper, we propose a modified SR method to recognize the radar target HRRPs, called ASWSR. Based on the length and power in the different parts of HRRP, we assign different weights in the dictionary and then a modified SR method is used to accomplish the target classification. Experiments are executed to test the performance of proposed method and results show that our method obtains the best performance on the HRRP dataset.

2. THE REVIEW OF TARGET-ASPECT SENSITIVITY AND SPARSE REPRESENTATION

In this section, the target-aspect sensitivity and the basic theory of sparse representation are provided.

2.1 Target-aspect Sensitivity

According to the geometry and structure characteristics of three real military targets: infantry fighting vehicle (IFV) BMP2, armored fighting vehicle (AFV) T72 and tank BTR70, we use the method proposed in [1] to build their scattering centre models and get the simulated HRRPs. The phenomenon of the target-aspect sensitivity is shown in fig 1. It shows that the slight variation of target-aspect (the azimuth angle between the target and radar) will cause HRRP conspicuous change.

2.2 Sparse Representation

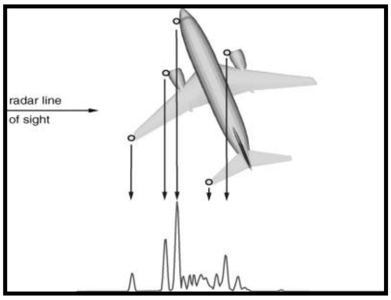

Fig 1: *HRRP of an aircraft, which containing the target structure signatures, such as the target size, the scatter distribution, changing along with the radar line of sight (RLOS)*

SR is a task of reconstructing a signal by selecting a fewest bases from the over complete dictionary and keeping the reconstruction error as little as possible [11]. Given a training dictionary of n samples $X = [x_1, x_2, \ldots, x_n]$, $X \in R^{m\times n}$, for a sample $y \in R^m$, the objective function of SR is use the smallest number of nonzero coefficients in α to accomplish the optimal approximation $y = X\alpha$. The recent development of compressed sensing [12] shows that if the representation is sparse enough, the minimal solution problem is equivalent to solution of the following l_1-norm minimization problem.

$$\hat{\alpha} = \arg\min_{\alpha} \|\alpha\|_1 \quad s.t.\ y = X\alpha \tag{1}$$

When noise is included in sample y, a perfect reconstruction is typically not feasible. Therefore, we give the sparse reconstruction an error tolerance ε>0.

$$\hat{\alpha} = \arg\min_{\alpha} \|\alpha\|_1 \quad s.t.\ \|y - X\alpha\| \le \varepsilon \tag{2}$$

Normally, the Eq. (2) is approximated by loosening the error constraints and including a regularization term as follows

$$\hat{\alpha} = \arg\min_{\alpha} \{\|\hat{y} - X\alpha\|_2^2 + \gamma \|\alpha\|_1\} \tag{3}$$

where γ is a weighting constant, it gives a tradeoff between the reconstruction error and the sparsity of α. The objective function of recognition is to find the smallest error among all classes, given by

$$identity(y) = \arg\min_{i=1,2,\ldots,c} \|y - X^i \hat{\alpha}^i\|_2 \tag{4}$$

where X^i and $\hat{\alpha}^i$ is the training samples and coding vector associated with the i-th class. c is the total class number.

3. THE PROPOSED METHOD

In this section, we first give the asymmetrical segment of HRRP and then we present the proposed method and its steps in detail.

3.1 The Asymmetrical Segment of HRRP

Taking the BMP2 for example as demonstrated in the fig 2. We find that the useful target information, P2 district in the figure, is just occupy a fraction among the whole HRRP and the other districts are useless or less useful. It's obviously unreasonable, if we given the same weight to each feature in the dictionary of SR method.

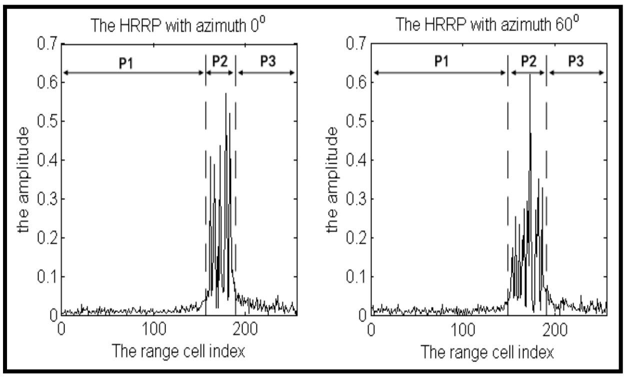

Fig 2: *HRRP of BMP2 with the azimuth 0°and 60°*

We preprocess the original HRRP with l_2-normalization and use the constant false-alarm rate (CFAR) detector to pick out the target district P2, in which the really useful target information is mainly contained, so the HRRP is divided into three districts: P1, P2 and P3. Considering the target-aspect sensitivity, the length of P2 district is changing along with the azimuth, the average length of each part is used, the weights calculated for each part is defined in Eq. (5).

$$\hat{\omega}_{P_i} = \sum_i P_i \Big/ P_i \qquad i = 1, 2, 3. \tag{5}$$

Perform the normalization to Eq. (5).

$$\omega_{P_i} = \hat{\omega}_{P_i} \Big/ \sqrt{\sum_i \hat{\omega}_{P_i}^2} \tag{6}$$

If the lengths of the three districts are equal, the weights of three parts are the same. In order to reflect the completeness of the proposed method and improve recognition accuracy of the three kinds of targets, we continue to add the following weight constraints.

$$\omega_{S_i} = \sum_j x_j^2 \Big/ \sum_i \sum_j x_j^2 \qquad x_j \in S_i \tag{7}$$

where x_j is the j-th feature value of HRRP, S_i is the feature value set in district P_i. The final weight is defined in Eq. (8).

$$\omega_i = \omega_{S_i} \cdot \omega_{P_i} \Big/ \sqrt{\sum_i (\omega_{S_i} \cdot \omega_{P_i})^2} \qquad i = 1, 2, 3. \tag{8}$$

3.2 The Asymmetrical Segment Weighted SR

As discussed in Section 3.1, the useful target information is just occupies a fraction of HRRP, it is improper to utilize the holistic HRRPs to compose the overcomplete dictionary. We introduce the weight into the sparse representation to reconstruct a modified overcomplete dictionary. Each district of training samples and test sample are weighted by corresponding weights value to generate a weighted dictionary and a weighted sample.

$$X^S_{P_i} = \omega_i X_{P_i} \tag{9}$$

$$y^S_{P_i} = \omega_i y_{P_i} \tag{10}$$

Then join the sub-dictionary together in turn to compose the weighted dictionary and weighted test sample.

$$X^C = [X^S_{P_1}, X^S_{P_2}, X^S_{P_3}] \tag{11}$$

$$y^C = [y^S_{P_1}, y^S_{P_1}, y^S_{P_1}] \tag{12}$$

It is obvious to see that measure matrix X^C is affected by ω_i, we also assume that test sample y^C can be written as a linear combination of the X^C and define it as

$$y^C = X^C \alpha^C + \xi \tag{13}$$

where $\|\xi\|_2 = \varepsilon$, similar to Eq. (3), the sparse coefficient vector α^C is obtained by solving the following minimization problem

$$\alpha^C = \arg\min_{\alpha} \{\|y^C - X^C \alpha\|_2^2 + \gamma \|\alpha\|_1\} \tag{14}$$

Generally, we know that if the important part in the HRRP is not well represented, the reconstruction error will be larger and the classification rate will be lower. From the definition of ω_i, we can find that the weight assigned to the district which contains the target useful information is the largest. That is to say, the target useful information district in HRRP is heavily weighted and the other districts are lightly weighted, this is helpful to well represent the test samples and reconstruct them, more accurately, with smaller errors. After the sparse coefficient vector α^C is obtained through the dictionary learning, the classification result is given by finding the smallest reconstruction error of all classes as defined in Eq. (4). Following the above procedure, the modified SR algorithm is summarized in Table 1 in brevity, we named it ASWSR.

The proposed ASWSR is specific applied in the field of radar HRRP targets recognition, as the problems of target-aspect, time-shift and amplitude sensitivities may mislead the result of classification or recognition. On the basis of SR, the useful information in the dictionary is heavily weighted, the less useful information is lightly weighted, which leads to smaller reconstruction error and better performance.

Table 1: *ASWSR algorithm*

Input: Training set X and testing sample y with column l_1-normalized.
1: segment the HRRP of each class into three sub-HRRPs ($X_{P_1}, X_{P_2}, X_{P_3}$) using the CFAR detector. 2: Calculate the weight ω_i using Eq. (1) - (4). 3: Reconstruct the weighted over complete dictionary X^C and the test sample y^C by Eq. (9)- (12). 4: Solve l_1-norm optimization problem in Eq. (14), obtain the sparse coefficient vector α^C.
Output: $identity(y) = \arg\min_i \|y - X^C_i \alpha^C_i\|_2 \quad i = 1, 2, ..., C$.

4. EXPERIMENT

4.1 Experiment Setup

In this section, we carry out the classification experiments on the simulated millimeter wave radar HRRPs, the experiment environment is setting as follows. The corner reflectors with different positions and radar cross sections (RCS) are used to simulate the three targets. The stepped frequency wave (SFW) is used to detect the target with the range resolution 0.293m and 256 range cells in each HRRP sample. For each target, we obtain 360 HRRPs with azimuth from 0 ° to 179.5° at interval 0.5° , each range cell corresponding to one feature. It means that each HRRP has 256 features or dimension and the total number of HRRP samples of three targets are 1080. In the experiments, we compare the proposed method with the related methods MCC-TMM [6], K-NN and the SR [11] to demonstrate the effectiveness of the proposed method. TMM is a fundamental method in HRRP recognition, the label of the test sample is determined by the matching scores between test sample and the templates. Here we use TMM under the maximum correlation coefficient (MCC-TMM), in which the matching score is decided by the correlation coefficient between test sample and templates. In traditional SR, the training samples are used in the dictionary to sparsely represent the test sample and the sparse coefficient is used to reconstruct the label of the test sample.

4.2 Experiment Result and Analysis

Firstly, we give out the segment by the CFAR detector and corresponding weights for the three kinds of

HRRPs in fig 3. We can see the useful district in HRRP is heavily weighted while the less useful districts are lightly weighted. The length of target districts are different, it corresponds to the projection length of the target on the RLOS.

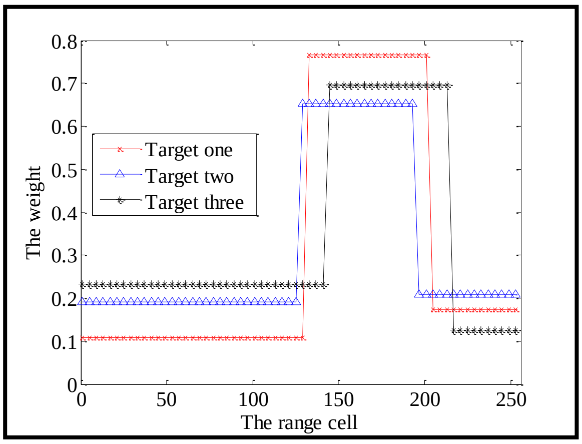

Fig 3: *The segmental weight coefficient of the three class targets (with the SNR=10dB in the HRRP)*

Secondly, we perform the experiments use the HRRP samples without noise. Choose k (k=15,18,21,…,120) samples from all the 1080 samples as the training set and k=120 samples from the rest samples as the testing set randomly. For MCC-TMM, the 5 nearest azimuth are averaged as the template. Each test performs 20 times, taking the average result as the final result. The average recognition rate against the number of training set is shown in fig 4. Table 2 gives the average recognition and standard deviation when training set k=120.

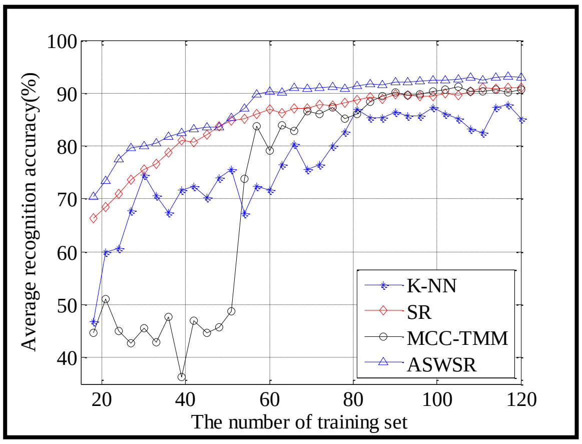

Fig 4: *Average recognition rate of four methods*

It easy to see that the performance of ASWSR is the best, the K-NN is the worst. The average recognition rate of ASWSR is nearly 2.5 percentage points higher than the MCC-TMM and 1.5 percentage points higher than SR. Simultaneously, stand deviations of ASWSR is the smallest. The performance tend to stable when the training set reach a certain number except the K-NN. As MCC-TMM is template based, when the training set small, the result is pretty bad. When training samples increase to a certain number, the recognition performance rapidly improving and then stabilizing. After analyzing ASWSR algorithm, we can get the conclusions that the using of asymmetrical segment weight, which gives a high weight to the useful district of HRRP in the dictionary of SR, leads to the higher recognition rate than SR.

Tabel 2: *Average recognition rate and stand deviations*

	MCC-TMM	***K-NN***	***SR***	***ASWSR***
mean	***90.69***	***85.19***	***91.73***	***93.25***
std	***1.07***	***1.65***	***0.99***	***0.78***

Finally, according to the analysis in Section 1, there always exists noise in HRRPs. We add noise into HRRPs, so as to be close to the true target environment. Setting the training set k=120 and the recognition rate curve versus the SNR is shown in fig 5.

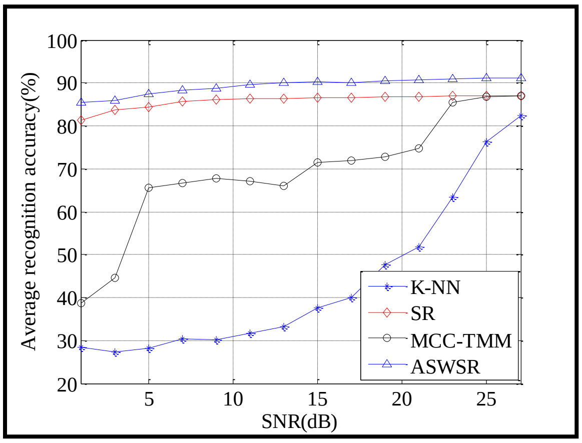

Fig 5: *Average recognition rate with different SNR*

Fig 5 shows the performance of all the methods improves along with the increasing of the SNR. The SR and ASWSR are more robust than the other two, as introducing the error tolerance ε during the optimization in Eq. (6). The average accuracy of ASWSR is the highest under all the test SNR conditions.

5. CONCLUSION

In this paper, we proposed a modified sparse representation methods, named ASWSR, to accomplish the recognition of three different targets using their HRRPs. In the dictionary of ASWSR, we give a large weight to the useful district and a light weight to the less useful district. Then, through solving the l_1-norm optimization problem get the best sparse coefficients to accomplish the classification task. Experiments show that our method yields a better performance than the other algorithms.

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