SAR Image Target Detection Method Based on Sparse Representation

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ABSTRACT

An image target detection algorithm based on sparse representation theory is proposed in this paper for the problem of SAR target detection platform, such as noise, geometric distortion and cover effect. This algorithm is constructing an over-complete dictionary by using SVD Dictionary Learning Method based on the idea of vector clustering. With the completeness of the dictionary, important information in the image can be captured by extracting a small amount of image features, which makes the complex background noise of SAR images generated in the high-speed motion state more robust. On the other hand, the algorithm has the ability of reconstruction, and can reconstruct the test sample by using the sparse coefficient selected by the characteristic function, and select the class with the least reconstruction error as the category of the test sample. The algorithm occlusion has good robustness in target occlusion, rotation and complex background. The detection accuracy and computing speed have improved compared to similar classic algorithms.

KEYWORDS
SAR; Radar; Detection; Sparse Representation.

INTRODUCTION

In recent years, many experts at home and abroad hammer to find a method to present the result of signal processing and image processing results as simple as possible. A new research field is opened up when Mallet proposed the idea of sparse representation in 1993. In recent years, the research of sparse representation is becoming more and more prevalent. Now many of the traditional signal representation theory based on non-redundant orthogonal linear transformation, such as discrete cosine transform, wavelet transform. While DCT cannot effectively extract the features of the signal with time-frequency local characteristics. The wavelet transform is not good for linear singularity and does not have directional sensitivity. The basic idea of the new signal sparse representation theory is to make the over-complete
dictionary as close as possible to the structure of the sparse approximation signal. The
dictionary can be constructed arbitrarily to find the optimal combination of several
columns to express the signal as a sparse approximation or highly nonlinear
approximation [1-4].

**SIGNAL SPARSE REPRESENTATION ANALYSIS**

Firstly, the target over-complete dictionary is constructed, the input test image is
divided into blocks, and then the coefficients of each image sub-block are calculated,
and the difference of the representation coefficients of each sub-block is quantitatively
compared to determine whether the image sub-block contains small target to complete
the target detection task. The task can be divided into three: the structure of over-
complete dictionary, the solution of sparse representation coefficient and the
reconstruction of test sample to calculate the reconstruction error.

**Construction Of Over-Complete Dictionary**

The research methods of dictionary construction problems can be divided into two
types: one is the theory of harmonic analysis which is represented by wavelet
transform and the other is adaptive algorithm, a typical method of which is SVD
dictionary learning. SVD dictionary learning algorithm is based on vector clustering
quantification idea which apply the optimization method to the construction of over-
complete dictionary, with the original image data remain to be decomposed to train the
dictionary atoms, to obtain the ultra-complete dictionary which can effective reflect
the image characteristics. Compared with the theory of harmonic analysis represented
by wavelet transform, SVD dictionary learning algorithm has low computational
complexity and short computation time.

In this project, the training samples are divided into two classes, one is the target,
and the other is the combination of background and the noise which will be referred to
as the background. Because of the few training samples of military targets in SAR
images, the background sample images is generated by a normal random distribution
matrix [4]. And a small target image is generated by the two-dimensional Gaussian
model [5-8] which is superimposed with the background image to generate small
target sample image. And then use the small target samples and background samples
to construct the over-complete dictionary. The two-dimensional Gaussian model for
small target modeling is as follows:

\[
I_x(i, j) = I_{max} \exp\left\{-\frac{1}{2} \left( \frac{(i-x_0)^2}{\sigma_x^2} + \frac{(j-y_0)^2}{\sigma_y^2} \right) \right\}
\]  

(1)

Among them, \(I_{max}\) is the gray value of the center pixel of the target, and \((x_0, y_0)\) is
the center point coordinate of the target area, \(\sigma_x\) and \(\sigma_y\) are the horizontal and vertical
spread parameters, respectively, which control the dispersion characteristics of the
target pixel. By adjusting the above parameters, a small target image with different
brightness, different position and different shape can be generated [4].

The classification method of sparse representation calculates the coefficient of
sparse representation of the test sample from the over-complete dictionary constructed
by a large number of training samples, and the classification of the test sample is determined. The element that constructs the over-complete dictionary can be either the direct image pixel or the transformed characteristic data. If the image pixels are directly used, they are usually sampled by Gaussian random projection because of the large number of image pixels. However, there are some differences between SAR image classification and other optical image classification due to the coherent speckle noise and other factors. On the one hand, non-target regions in SAR images contain a large amount of noise, on the other hand, the target which is affected by speckle noise has a large fluctuation on the radar incident waves. If the SAR image is directly classified, it will affect the recognition performance.

In this paper, the target region is segmented by image segmentation, the non-target region is set to zero value and the segmented target slice is cut out to chips. Then PCA feature is extracted from the chips. PCA is a linear transformation, the transformation of the principal components is mutually orthogonal. The target information in the original image can be represented by the former principal components. By selecting certain feature dimensions, the influence of noise in the image can be reduced to reduce the influence of the speckle noise on the performance of the algorithm. These eigenvectors obtained by PCA can be used as column vector combination to generate super complete dictionary.

**Solution of Sparse Coefficient**

When sparsity is used as the regularization condition, Equation 2 can be transformed to the solving of the following problem:

$$
\min_x \| x \|_0, s.t. \quad y = \Phi x
$$

(2)

Among them, $\| x \|_0$ means the $\ell_0$ norm of x and the value is the number of nonzero entries in the vector. To solve the problem of indefinite equation under the condition of minimizing the norm is a NP problem, the researcher develops a series of greedy algorithms to solve it.

Although the greedy algorithm can solve the above problem, but its numerical solution is not stable. The results of sparse representation and compression sensing theory show that when x is sufficiently sparse, the solution of sparse solution can be equivalent to the problem of minimizing the $\ell_1$ norm:

$$
\min_x \| x \|_1, s.t. \quad y = \Phi x
$$

(3)

The $\ell_1$ norm denotes the sum of the absolute values of the vector x non-zero coefficients. The equation in Equation 3 can be relaxed by introducing a smaller amount of noise $\varepsilon$, so that an approximate solution of the sparse coefficient vector can be obtained by minimizing the norm by solving the convex optimization method:

$$
\min_x \| x \|_1, s.t. \quad \| y - \Phi x \| \leq \varepsilon
$$

(4)

At present, there are linear programming (LP) and second-order Cone programs (SOCP) for solving equations 4. Compared with the linear programming method, the
SOC algorithm has less complexity. In this paper, the SOC algorithm is used to solve the sparse vector.

**Detector Design**

Given the observation samples belonging to the target, \( y_i \in Y^i \), \( i = 1, 2, \ldots, n \), we can get the sparse representation vector \( x_i \in X^i \). In theory, only when corresponding to the target, the coefficient of \( x_i \) is non-zero, so that \( y_i \) can be easily identified. In reality, however, the non-zero terms of \( x_i \) do not only correspond to a single category because of the noise and the error in solution process. In this case, the class information of \( y_i \) determined based on the distribution of non-zero terms in the sparse representation vector \( x_i \). A classification strategy based on minimum reconstruction error is designed in this paper, which makes full use of linear structure information of sparse representation vectors.

For each target \( y_i \), define its characteristic function: \( \delta_i: R^+ \to R^+ \). Given a sparse representation vector \( x_i \in R^+ \), the nonzero entry in \( \delta_i(x) \in R^+ \) corresponds only to the target \( i \), and the coefficients for the other classes are all zero. Reconstruction of the observed sample \( y_i \) using the target training sample, that is, \( \hat{y}_i = \Phi \delta_i(x) \). The classification of \( y_i \) can be obtained by finding the minimum reconstruction error.

\[
\min_{\delta_i} \| y - \Phi \delta_i(x) \|_2
\]  

Among them \( r_i(y) \) is the reconstruction error of the target training sample for the observed sample \( y_i \).

**SIMULATION RESULT**

The size of detection window for sparse representation is 30 * 30, and the moving step of the detection window is set to 5 pixels.

**Simulation Experiment of Sea Target**

The data of Burke and cnv73 under different posture are fitted to the measured sea clutter data as test samples. The radar parameters of the sea clutter data are as follows: 64 PRTs per CPI, 2K data points in PRT, 80MHz signal bandwidth, (640/6) MHz sampling frequency, 10us signal pulse width and positive frequency modulation. The target detection method of SAR image based on sparse representation is used in the simulation. The detection window size set for sparse representation is 30 * 30, the moving step detection window is set to 5 pixels. The simulation results are shown in Fig.1.
In Fig.1(a), Target 1 is the Washington aircraft carrier (180° attitude, HH polarization), Target 2 is the Burke Cruiser (45° attitude, HH polarization), Target 3 is the Burke Cruiser (90° attitude, HH polarization), and Target 4 for the Burke cruiser (145° attitude, HH polarization).

In Fig.1(b), Target 1 is the Burke cruiser at (25° pitching, 45° attitude, VV polarization), Target 2 is the Burke Cruiser (20° pitching, 0° attitude, HH polarization), Target 3 is the Washington aircraft carrier (20° pitching, 90° attitude, HH polarization), and Target 4 is a Burke cruiser (25° pitching, 145° attitude, VV polarization).

CONCLUSION

It can be seen from Fig.1 (a), (b) that the target detection results based on the sparse representation have some false alarm. However, in the SAR image, the amplitude and intensity information of the pixel are more important in the target detection process, which is the main reason for the leak detection and the false-alarm. In the SAR image, the sparse representation method is used to detect the target. Police the main reason. On the other hand, the number of positive and negative samples is small, so that the training of the classifier is not complete, resulting in the low target detection accuracy. Meanwhile, the accuracy of the target detection is affected by the detection window size that is fixed and the step size that is too large.

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