HRRP Target Recognition Based on Sparse Representation

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Abstract. When high resolution range profiles (HRRP) are used to recognize radar target, a few traditional recognition methods analyze the sparseness of HRRP samples. In order to overcome the large sample size problem and simplify the recognition procedure, sparse representation is an effective way to compress HRRP samples and extract the features. Thus, a structure redundant dictionary and a fast sparse representation algorithm are introduced to implement radar target recognition here. The simulation results show that this algorithm has higher recognition rate and better denoising performance. It is easy and practical for radar target recognition.

1. Introduction

With the continuous progress of science and technology, modern warfare has undergone tremendous changes in form. In order to cope with these changes, modern weaponry is developed to be long-distance range, intelligent, digital and stealthy. The high resolution range profiles (HRRP) of radar have attracted wide attention because they contain accurate target information. In practice, in order to obtain the high resolution range profiles (HRRP), wideband radars are often used to detect them. Although such methods can improve resolution ratio, but they also face the problems of dealing with large-scale targets echo samples. In order to make the high resolution radar target recognition algorithms feasible, it is necessary to compress the data effectively. In fact, the physical processes observed by radar at some point are very limited, so these data can be compressed. Based on this opinion, this paper uses the sparse representation method of digital image processing technology to realize radar target recognition.

2. Sparse Representation

Signal decomposition method is very important in signal processing, Orthogonal decomposition is often used in traditional using. This kind of decomposition method is relatively simple, but it can not achieve good sparse representation. Especially for signals with wide time-frequency field, the processing effect of orthogonal decomposition is worse. A good decomposition method should select the corresponding basis function according to the characteristics of the signal itself in order to achieve signal decomposition. In this paper, a redundant dictionary with some non-orthonormal basis is applied in spare representation of radar high resolution range profile. The sparse representation model is as follows:
The redundant dictionary \( \mathbf{G} = \{ \mathbf{g}_\gamma \}_{\gamma \in \Gamma} \) (\( |\Gamma| > N \)), Hilbert space \( \mathbf{R}^N = \text{span}(\mathbf{D}) \), vector \( \mathbf{g}_\gamma \) is an atom. For any signal \( \mathbf{f} \in \mathbf{R}^N \), select \( K \) atoms (\( K << N \)) from the redundant dictionary \( \mathbf{G} \). The sparse representation of signal \( \mathbf{f} \) is equivalent to solving the following problem:

\[
\min \| \mathbf{f} - \mathbf{g}_i \|_0 \quad \text{s.t.} \quad \mathbf{f} = \sum_{i=0}^{K-1} \langle \mathbf{f}, \mathbf{g}_i \rangle \mathbf{g}_i \tag{1}
\]

Two important elements will be involved: construct redundant dictionary; select appropriate sparse decomposition algorithm.

### 2.1. Construction of Structural Partition Redundant Dictionary

There are many methods to construct redundant dictionaries, but some of them do not consider the structural characteristics of dictionary atoms. Using a redundant dictionary with good structure characteristics can not only simplify the decomposition operation, but also make the signals expression are approximated sufficiently. In this paper, we will construct a structural partition redundant dictionary based on Gabor dictionary. In Gabor dictionary, the atom \( \mathbf{g}_\gamma \):

\[
\mathbf{g}_\gamma(t) = \frac{1}{\sqrt{s}} \mathbf{g}\left(\frac{t-u}{s}\right) \cos(\nu t + w) \tag{2}
\]

\[
\mathbf{g}(t) = e^{-\pi t^2} \tag{3}
\]

The specific Gabor dictionary can be obtained by fine sampling of \( \gamma = (s, u, v, w) \) and substituting them into formula (3). Sampling method: \( \gamma = (\alpha', p\alpha', \Delta u, k\alpha', \Delta v, \Delta w) \), \( \alpha = 2 \), \( \Delta u = 1/2 \), \( \Delta v = \pi \), \( \Delta w = \pi/6 \), \( 0 < j \leq \log_2 N \), \( 0 \leq p \leq (2^{-j+1}) N \), \( 0 \leq k \leq 2^{+1} \), \( 0 \leq i \leq 12 \). The atoms in the dictionary are different, but the displacement factors of some atoms varies. Therefore, the dictionary can be divided into several sub-atomic libraries. If only one representative atom is selected from each sub-library for storing, the dictionary storage will be reduced. In the sparse decomposition of signals, if other atoms in the same sub-library are used, only the representative atoms need to be translated. This process only involves translation operation, which is computationally small and easy to obtain. Therefore, this dictionary based on atomic structure partition will be adopted in this paper.

### 2.2. IGAMP

Assuming that the unidimensional high resolution range profile signal is \( \mathbf{x} \); the structural redundant dictionary is \( \mathbf{D} = \{ \mathbf{g}_\gamma \}_{\gamma \in \Gamma} \); \( \mathbf{g}_\gamma \) is a normalized atom. IGAMP is realized by two steps based on MP (Matching Pursuit, MP) algorithm. Conventional MP algorithm will select the most matching atoms from redundant dictionary and use their linear combination to realize sparse representation of HRRP samples. The specific process is as follows:

Firstly, the atoms that match the signal best are selected:

\[
\langle \mathbf{x}, \mathbf{g}_{\gamma_0} \rangle = \sup_{\gamma \in \Gamma} \langle \mathbf{x}, \mathbf{g}_\gamma \rangle \tag{4}
\]

\[
\mathbf{x} = \langle \mathbf{x}, \mathbf{g}_{\gamma_0} \rangle \mathbf{g}_{\gamma_0} + \mathbf{R}_1 \mathbf{x} \tag{5}
\]

\( \mathbf{R}_1 \mathbf{x} \) is the signal residual from the first decomposition.

Next, the signal residual after each optimal match is decomposed:

\[
\mathbf{R}_i \mathbf{x} = \langle \mathbf{R}_i \mathbf{x}, \mathbf{g}_{\gamma_i} \rangle \mathbf{g}_{\gamma_i} + \mathbf{R}_{i+1} \mathbf{x} \tag{6}
\]

\[
\langle \mathbf{R}_i \mathbf{x}, \mathbf{g}_{\gamma_i} \rangle = \sup_{\gamma \in \Gamma} \langle \mathbf{R}_i \mathbf{x}, \mathbf{g}_\gamma \rangle \tag{7}
\]

After the nth step decomposition, the sparse decomposition result of HRRP samples is as follows:
It is found that MP algorithm is complex and cumbersome during sparse decomposition of HRRP samples. To solve the problem, conventional MP algorithm will be improved in two aspects. Firstly, GA (Genetic Algorithm) is used to improve MP algorithm. For Gabor dictionary, optimizing atoms is actually to optimize structural parameters according to the corresponding relationship between atoms and structural parameters. In order to realize sparse decomposition of HRRP, select individuals from many structural parameters of Gabor redundant dictionary to form the initial population. Subsequently, atomic optimization and signal decomposition are performed. In the process, the absolute value of the product of signal residuals and sub-library atoms is used as the fitness function. After several evolutions of crossover and mutation, the optimum atom is finally searched out. Through experiments, it’s found that when the evolutionary generation is 36, GAMP algorithm has higher evolutionary accuracy and does not extend the decomposition.

Secondly, it is proved in document [9] that the inner product operation can actually be converted into the cross-correlation operation between the residuals and the atoms. For this reason, the fast cross-correlation operation is used instead of the inner product operation, and the number of step points is adjusted to reduce the amount of calculation. At last, the operation speed of the decomposition algorithm will be further improved and the accuracy will be guaranteed.

3. Unidimensional HRRP Target Recognition Based Sparse Decomposition

For HRRP, in order to avoid the reduction of recognition performance caused by amplitude sensitivity, amplitude l2 norm normalization is used to eliminate the adverse effects. Target recognition which is based on redundant dictionary and IGAMP includes two following processes:

3.1. Training process

In the training phase, the sample signals are sparsely decomposed to construct the category dictionary of different targets. Assume that HRRP training samples contain L-class targets \( Y_l \in \mathbb{R}^{N \times 1} (l = 1, 2, \ldots, L) \), the process of extracting category dictionary is as follows:

1) Construct Gabor dictionary based on atom structure

Firstly, according to dictionary atomic expression (2)(3), a conventional Gabor dictionary is constructed by discretizing the time-frequency parameters. Then, the Gabor redundant dictionary \( D \) is generated by partitioning the set \( D_G \) according to the atomic structure characteristics.

2) Obtain sample category dictionary

HRRP training samples are sparsely decomposed by using IGAMP algorithm. A set of optimum atoms for representing \( Y_l \) is obtained and a category dictionary \( D_l (l = 1, 2, \ldots, L) \) is constructed.

3.2. Testing process

Testing simples are \( y \); Category dictionaries obtained in training stage are \( D_l (l = 1, 2, \ldots, L) \); Sparse representation coefficients of test samples are \( \varphi_l (l = 1, 2, \ldots, L) \); Sparse coefficient is \( T^* \). Test steps are as follow:

1) Sparse decomposition

Sparse coefficient based on SNR, the sparse decomposition coefficients \( \varphi_l (l = 1, 2, \ldots, L) \) are obtained by IGAMP algorithm based on different dictionaries \( D_l (l = 1, 2, \ldots, L) \).

2) Target recognition

If the test samples don’t match the selected category dictionary, the reconstructed signal must be quite different from the original signal. Therefore, we can try to use the reconstruction error as the basis of category determination.
The parameter $y$ represents real test samples and $\hat{x}$ represents the samples without noise. Noise is expressed as $n$, the reconstructed samples error is $e_i$.

$$
\begin{align*}
\begin{cases}
 y = \hat{x} + n \\
 \hat{x} = D_l \phi_l + e_i
\end{cases} \quad (l = 1, 2, \cdots, L) 
\end{align*}
$$

(9)

It can be transformed into a quadratic programming problem to solve $\hat{x}$.

$$
\hat{x} = \arg \min_x \lambda \|x - y\|^2 + \|D_l \phi_l - x\|^2
$$

(10)

In formula (10), $\lambda$ is a regularization parameter. Then, the reconstruction error will be expressed as:

$$
\|e_i\| = \|\hat{y} - D \phi_i\|
$$

(11)

Sample category determination method can be formulated as:

$$
I^* = \arg \min_{l=1, 2, \cdots, L} \|e_i\|  \quad l = 1, 2, \cdots, L
$$

(12)

With the same SNR and $\lambda$, the classification method based on formula (11) and (12) is equivalent to the classification method based on minimum reconstruction error.

4. Simulation Analysis

4.1. Explanation of simulation data

The simulation system OS: Windows 7, CPU frequency: 1.5GHz, RAM: 4GB, Software tool: MATLAB 2011b. The radar center frequency is 10 GHz. The radar bandwidth is 1.4GHz. There are three types of aircraft targets (B-1b, F-15, MIG-21). The azimuths of them are 0° – 30° and the direction intervals are 0.1°. The target pitching angles are 0° and 3°, the attitude angle and rolling angle of them are both 0°.

| Tab.1 Simulation target parameters |
|-----------------------------------|
| Model    | Captain/m | Wingspan/m |
| B-1b     | 46.17      | 21.84       |
| F-15     | 19.45      | 13          |
| MIG-21   | 15.76      | 7.15        |

In the experiments, training samples are extracted from the first half of simulation data, 300 samples are extracted for each target. Testing samples are extracted from the rest of simulation data. In order to analyze the noise robustness of this algorithm, white noise will be added to the test samples.

4.2. Analysis of simulation

4.2.1. Training process simulation

In the training stage, the structure partition dictionary and IGAMP sparse decomposition algorithm will be used to extract the category dictionary of various targets. Before that, we verify the decomposition efficiency of different algorithms and compare the processing speed of algorithms.

| Tab.2 Comparisons of Decomposition Speed of Different Algorithms |
|---------------------------------------------------------------|
| Algorithm                                         | Decomposition Speed |
| MP algorithm based on Gabor dictionary            | 1                  |
| MP algorithm based on structure partitioning redundant dictionary | 4.2               |
| GAMP algorithm based on structure partitioning redundant dictionary | 7.1               |
| IGAMP algorithm based on structure partitioning redundant dictionary | 11.2              |

Table 2 compares the decomposition speed differences of the same HRRP samples based on different redundant dictionaries and different sparse decomposition algorithms. The decomposition
The speed of MP algorithm based on Gabor dictionary is taken as the baseline, the second method (MP algorithm based on structure partitioning dictionary) accelerates dictionary generation by using atomic structure characteristics and improves the decomposition speed of sample signals, but the improvement is limited. For the third method, GA is used to search for the best atom, which reduces the compute and improves the search efficiency. The fourth method further improves the MP algorithm. The fast inter-correlation analysis is used instead of inner product operation, which further shortens the operation time of the whole algorithm and improves the efficiency of category dictionary.

4.2.2. Testing process simulation

The category dictionary generated during the training phase will be used in the testing phase. In order to verify the effectiveness of the new recognition algorithm, the redundant dictionary and decomposition algorithm will be verified respectively. In Fig. 1, the effect of redundant dictionary and different sparse decomposition algorithms on the same target recognition is analyzed.

![Fig.1 Comparison of Target Recognition Effect Based on Different Sparse Decomposition Algorithms](image1)

In terms of recognition performance, there are some differences among the three algorithms. The recognition effect of MP algorithm is relatively poor, the other two methods have higher recognition rate than MP algorithm because of GA optimization, but the recognition performances of the two get little differences. With the increase of SNR, the three algorithms all present stable recognition performance. The IGAMP algorithm adopts cross-correlation operation and this cross-correlation operation is realized by multi-point jump operation, which reduces the number of operation points. Therefore, as shown in Table 1, the IGAMP is the fastest algorithm, in the case of recognition rate.

Compared with similar RATR algorithms, the realization principles of them are different. So the recognition effects are different too. Table 2 shows the recognition effect of the structure partition dictionary and IGAMP sparse decomposition algorithm, Principal Component Analysis(PCA) and Support Vector Machines(SVM).

![Fig.2 Comparison of Recognition Effectiveness among Different RATR Algorithms](image2)
In principle, both the recognition algorithm adopted in this paper and PCA algorithm are based on reconstructed model. The difference between them is that the structured redundant dictionary is used to analyze HRRP samples in this paper. Because the dictionary contains a large number of features and does not require orthogonal atoms among them, the accuracy of sparse signal representation is higher. PCA algorithm is limited in the above aspects. Some simulations also show that with the increase of SNR, the average recognition rate of the proposed algorithm is gradually higher than that of PCA.

As shown in Figure 2, with the increase of SNR, the recognition rate of various algorithms increases. When the SNR is low, the recognition rate of all algorithms is low, but the algorithm in this paper can still have a higher recognition rate than other algorithms. So the RATR algorithm based on redundant dictionary and IGAMP present a more robust recognition effect for noise and had the best performance.

5. Conclusion
In this paper, a HRRP target recognition algorithm is discussed, which is based on sparse representation. Compared with the traditional RATR algorithm based on data dimension reduction, this algorithm makes more use of the sparse characteristics of HRRP. When HRRP samples are sparsely decomposed, a structure partition redundant dictionary and an IGMP algorithm are used to improve the speed and the accuracy of samples sparse decomposition. The simulation results show that even under the circumstance of low SNR, the proposed algorithm is more simple, effective and stable.

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