Aircraft Identification Based on CS and SVM Techniques

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Abstract

For increasing radio frequency (RF) signal stealth effect, this paper presents a novel method to generate high-resolution range picture (HRRP) with compressed sensing (CS) technique, and using support vector machine (SVM) technique to separate different aircraft. Firstly, this paper constructs a suitable DFT frame depending on sparse representation of HRRP, and designs the sensing matrix with randomly sampled time points. Secondly, we transmit signal determined by sensing matrix and get target echoes. Then, we utilize those target echoes, sensing matrix and DFT frame to get sparse expression. Finally, we make use of those sparse data to construct HRRP and employ it to identify target. Simulations show that our method could afford normal target identification rate if there are small types of aircraft, with almost half of signal emission energy, which is benefit to improve RF signal stealth effect.

Keywords: HRRP, Compressed Sensing, RF Stealth, SVM

1. Introduction

High-resolution range picture (HRRP) depicts the target structure along radar sight when radar signal frequency is in optical section, and is widely studied in radar target identification [1-3]. HRRP comes from the inverse discrete Fourier transform (IDFT) of the target echoes of linear frequency modulation (LFM) signal or stepped-up frequency signal, and signal band-wide decides range picture resolution. For stepped-up frequency signal, if the interval between two adjacent radar transmission frequencies is smaller and the band-wide of stepped-up frequency signal is larger, the HRRP affords more fine detail of target.

Airborne phased-array radar is a kind of multi-function radar; it can detect target range, velocity and generate HRRP with active transmitting signal. However, it is danger for radar transmitting signal frequently because of the fast development of passive radar detection system. RF signal stealth is aimed at decreasing detected probability of radar signal by passive detection system, and reduce transmission time is one of the important keys to improve radar RF stealth effect when radar is detecting target information [4].

Compressed sensing (CS) is a novel sampling and data recover technique [5-7]. It relies on sparsity and incoherence of data in some transformed domain. Its main idea is to sample at a low rate and use computational power to reconstruct original data. Thus, this paper wants to generate HRRP with CS technique since that HRRP shows sparsity in frequency domain. The maximum benefit from CS is that we can get main HRRP character with less radar transmission time.

2. Data model of radar target echoes

HRRP is the absolute values of IDFT of backscattering echoes from target. Fig. 1 shows two HRRP of a plane, where radar faces plane in two different directions.
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Figure 1. Two HRRP of a plane in two different directions

CS theory is fit for high signal to noise ratio (SNR), therefore this paper intends to research HRRP of targets on air with CS. For a target on air, there is higher SNR and no interference. Define data model of radar target echoes as:

\[ y(m) = \sum_{l=1}^{L} a_l \exp\left(-j4\pi f(m)r_l / c\right) + \nu(m) \]
\[ = \sum_{l=1}^{L} a_l \exp\left(-j4\pi r_l / c\right) \exp\left(-j2\pi.m/\Delta f . 2r_l / c\right) + \nu(m) \]  \hspace{1cm} (1)
\[ = \sum_{l=1}^{L} b_l \exp\left(-j2\pi.m/\Delta f . 2r_l / c\right) + \nu(m) \]

where, \( y(m) \) is the \( m \)th radar target echo, \( L \) is the number of strong backscattering centres, \( a_l \) represents backscattering amplitude of the \( l \)th scattering center, \( r_l \) is relative radial distances of the \( l \)th scattering center, \( f(m) = f_0 + m.\Delta f \), \( f_0 \) is the original emission frequency, \( \Delta f \) is a fixed interval between two closed emission frequencies, \( m \) stands for the \( m \)th stepped frequency, \( c \) is light speed, \( \nu(m) \) denotes additive white Gaussian noise (AWGN).

The resolution definition of HRRP is \( R = c/(2B) \) and \( B = M.\Delta f \), where \( R \) represents resolution and \( B \) is bandwidth. The non-ambiguity distance of HRRP is defined as \( R_n = c/(2.\Delta f) \). If the aircraft length is 25 meter, \( \Delta f \) should less than 6MHz. If the resolution needs to be less than 10 centimeter, \( B \) should be larger than 1.5GHz. That is, we have to sample target echoes over 250.

In fact, HRRP is IDFT of \( y(0),\cdots,y(M-1) \) and is sparse in frequency domain. With the fast development of passive radar detection system, less signal transmission is the key to improve RF signal stealth performance when fighter equipped with phased-array radar is detecting target. CS technique affords a possibility for reconstructing original data with overwhelming probability although the sampling rate is far less than Shannon sampling theory, if original data has sparse property in a determinate domain.

This paper want to introduce spectral compressed sensing at first in section II. Then, to research HRRP generated by CS technique and using those reconstructed HRRPs to identify target with support vector machine (SVM).

### 3. Spectral compressed sensing

Suppose that
\[ z = \Phi y \]  
(2)

\[ y = \Psi \Theta \]  
(3)

\[ z = \Psi \Theta \]  
(4)

where, \( z \) is observed data, \( y = [y(0), \cdots, y(M-1)]^T \) is original data vector, \(^T\) denotes transpose, \( \Phi \) is a \( N \times M \) measurement matrix, \( \Psi \) represents a \( M \times M \) orthogonal basis matrix. Our purpose is to obtain approximate \( y \) from \( z \). \( y \) is called \( L \) spectral peaks from IDFT of \( y \) and \( L \ll M \). For fighter, \( L \) is usually less than 20 and \( M \) is usually larger than 128. When \( N \geq L \log(M/L) \), a sparse signal \( y \) can be approximately recovered from its compressive measurement \( z \) via some algorithms.

It is obvious that \( \Psi \) is a IDFT frame and \( \Theta \) is frequency spectral values of \( y \) since HRRP is IDFT of \( y \). According to CS theory, \( \Theta \) and \( \Psi \) deeply affect approximate recovery performance of \( y \) from \( z \). Let \( \Theta = \begin{bmatrix} \theta(0) & \theta(1) & \cdots & \theta(M-1) \end{bmatrix} \). If the elements of \( \Theta \) is sorted and \( |\theta(i)| < C \cdot i^{-p} \) for some \( p \leq 1 \), where \( C \) is a constant, the smaller the decay exponent \( p \) the better the recovery performance. Let \( \Psi = \begin{bmatrix} r_0 & r_1 & \cdots & r_{M-1} \end{bmatrix} \), the better the orthogonal property between \( r_{m_1}, r_{m_2} \), where \( m_1 \neq m_2 \) and \( 0 \leq m_1, m_2 \leq M-1 \), the better the recovery performance.

With CS theory, incoherence between \( r_{m_1}, r_{m_2} \) is also the significant key to recover data besides sparsity of data. Emmanuel [5] has defined the coherence between the sensing basis \( \Phi \) and the representation basis \( \Psi \) as:

\[
\mu(\Phi, \Psi) = \sqrt{M} \max_{1 \leq i, j \leq M-1} \left| (\phi_i, \psi_j) \right|
\]  
(5)

where, \( \Phi = [\varphi_0, \varphi_1, \cdots, \varphi_{M-1}] \), \( \Psi = [\psi_0, \psi_1, \cdots, \psi_{M-1}] \), \((\cdot, \cdot)\) represents inner product and \( \mu(\Phi, \Psi) \in \left[1, \sqrt{M} \right] \). He also has pointed that if \( \Psi \) is the Fourier basis, where \( \psi_m(i) = \frac{1}{\sqrt{M}} \exp(i 2\pi m i / M), \) \( i = 0, \cdots, M-1 \), and \( \Phi \) is the spike basis, where \( \varphi_m(i) = \delta(i-m) \), the coherence \( \mu(\Phi, \Psi) = 1 \), if the sinusoid frequencies in (1) are integral. That is, spikes and sinusoids are maximally incoherent, and the smaller the \( \mu(\Phi, \Psi) \) the better the orthogonal property between \( r_{m_1}, r_{m_2} \).

Generally, the absolute values of DFT of (1) are:

\[
|Y(k)| = \left| \sum_{l=0}^{M-1} b_l \sin \left( \pi (k - \omega_l) / M \right) \right| \quad k = 0, \cdots, M-1
\]  
(6)

where, \( \omega_l = 2\pi \cdot (\Delta f / f_0) \cdot 2r_l / c \). If \( k_1 = \omega_1, k_2 = \omega_2, \cdots, k_L = \omega_L, i_1, i_2, \cdots, i_L \in [0, M-1] \), then

\[
|Y(k)| = \left| \sum_{l=0}^{L} b_l \delta(k - \omega_l) \right| \quad k = 0, \cdots, M-1
\]  
(7)

However, it is almost impossible to have (7) because it is very difficult to know \( \omega_l \) and to have \( k_j = \omega_l \) in advance. The best way to make \( k_j \) be close to \( \omega_l \) is to pad \( y \) with zeros. That is \( y_{dzt} = [y^T \ 0 \ \cdots \ 0]^T \). \( y_{dzt} \) is a vector whose length is \( M' \), where \( M' \gg M \).
4. Reconstruct HRRP with CS technique

Assume that

\[ e(q, \omega) = \frac{1}{\sqrt{M'}} \left[ e^{j\omega} \ldots e^{j(M'-1)\omega} \right] \tag{8} \]

where, \( \omega = q \cdot 2\pi / M' \), \( q = 0, \ldots, M'-1 \). Marco [6] has showed that \( L \) sparse signal would be recovered well when \( \left| \left( e(q \cdot 2\pi / M'), e(q \cdot 2\pi / M') \right) \right| \leq \frac{1}{16} (L - 1) \). That is, \( \frac{M'}{M} \) is limited by \( L \).

For fighter, we can determine \( M' \) and construct \( \Psi' = \left[ e(q_0, \omega)^T \ e(q_1, \omega)^T \ldots e(q_{(M'-1)}, \omega)^T \right]^T \)

since we have known that \( L \) is usually less than 20. We also can determine \( N \) with \( N \geq L \log(M'/L) \).

According to non-uniform sampling technique introduced by Emmanuel [5], we construct \( \Phi \) with randomly sampled time points due to the incoherence between spikes and sinusoids. This paper recovers original data with convex optimization methods [7].

5. Simulations

This paper generates target HRRP with physical optics algorithm based on graphic pixels, and \( f_s = 10 \text{GHz} \), \( \Delta f = 5 \text{MHz} \), \( L \leq 20 \) (scattering centers number of the target is no more than 20), bandwidth \( B = 640 \text{MHz} \), resolution \( \Delta R \approx 24 \text{cm} \). According to Shannon sampling theory, we should take 128 samples at least to get HRRP. However, we only need to sample \( N \) point, where \( N \geq L \log(M'/L) \), to construct HRRP with CS technique. Here, we suppose that \( N = 64 \).

It means that we only need 64 samples.

Fig. 2 shows two HRRP, where “+” denotes HRRP constructed by Shannon sampling theory and “o” represents HRRP constructed by CS technique. From fig. 2, we can see that HRRP constructed by CS technique are overwhelming approximately to classical HRRP.

![Figure 2. HRRP constructed by Shannon sampling theory and CS technique, respectively](image)

Then, we consider a HRRP dataset of five turntable aircraft models, Su27, F16, M2000, J8II, and J6, which have similar sizes. The dataset is provided by the Target Electromagnetism Characteristics Research Center affiliated to Nanjing University of Aeronautics and Astronautics, China. Each target has 360 HRRPs, and each HRRP has 128 range cells, where half of the HRRPs are selected for training by SVM [8, 9] and the others are used for test.

Table I shows target recognition results by classical SVM and our methods. From table 1, we know that target recognition results with CS and SVM techniques are worse than classical SVM method. And if there are only three types of aircrafts, the identification rate with our method is tolerate, which is showed in table 2.
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Table 1. Recognition results by classical SVM and our methods %

<table>
<thead>
<tr>
<th>Method</th>
<th>Su27</th>
<th>F16</th>
<th>M2000</th>
<th>J82</th>
<th>J6</th>
<th>Average</th>
</tr>
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<td>SVM</td>
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<td>82</td>
<td>89</td>
<td>81</td>
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<td>86</td>
</tr>
<tr>
<td>CS and SVM</td>
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<td>65</td>
<td>74</td>
<td>77</td>
<td>80</td>
<td>77</td>
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</tbody>
</table>

Table 2. Recognition results by our method %

<table>
<thead>
<tr>
<th>Method</th>
<th>Su27</th>
<th>J82</th>
<th>J6</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>CS and SVM</td>
<td>91</td>
<td>82</td>
<td>82</td>
<td>85</td>
</tr>
</tbody>
</table>

Our experiments show that CS technique is useful to reconstruct target HRRP and improve RF stealth performance. However, for target identification, the identification results are tolerated only for small types of aircraft. Fig. 3 shows root mean square error (RMSE) of all HRRPs with CS technique, including Su27, J82 and J6, relative to all original HRRPs at different azimuths. From fig. 3, we know that the estimation error of HRRP with CS technique cannot neglect even though the reconstruction probability of CS technique is overwhelming.

Figure 3. RMSE of HRRP with CS technique relative to original HRRP

6. Acknowledgement

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7. References

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