Research Article

Detection of Road Foreign Body Intrusion with Synthetic Aperture Radar

Lili Hou1,2 and Qian Zhang2

1Shijiazhuang Tiedao University, School of Information Science and Technology, Shijiazhuang 050043, China
2Shijiazhuang Tiedao University, Key Laboratory of Large Structure Health Monitoring and Control, Shijiazhuang 050043, China

Correspondence should be addressed to Qian Zhang; zhangqian@stdu.edu.cn

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1. Introduction

Foreign body intrusion influences the safety of the surrounding infrastructure and the normal operation of transportation lines. The application of synthetic aperture radar (SAR) technology is a new detection method of road foreign body intrusion [1–3]. As an active remote sensing technique, SAR can monitor wide areas of the earth and thus provides a viable way to detect road foreign body intrusion in a wide range. Due to the influence of clutter and noise, foreign body intrusion is not easy to detect.

The core issue of detecting foreign body intrusion is suppression clutter and noise, which can be performed by displaced phase center antenna (DPCA), along-track interferometry (ATI), or space-time adaptive processing (STAP) [1]. DPCA and ATI are limited to two-channel systems. In multichannel systems, the obtained data cannot be used sufficiently, resulting poor clutter suppression ability. The STAP method can significantly improve the clutter suppression ability of multichannel systems in case of strong clutter and noise. However, in nonhomogeneous environment, the performance of the STAP method will be influenced because of the inaccurate interference covariance matrix.

Kalman filtering has already been used in numerous applications; this paper adopts Kalman filtering to suppress clutter and noise, and the SAR data of each channel is regarded as a measurement of the scene. By reasonably setting the state update equation and measurement equation, foreign body intrusion can be gradually separated from clutter and noise in the process of recursive. Because of no requirement of the interference covariance matrix, the proposed detection method compared with STAP has a better performance in nonhomogeneous environments.

Since the antenna steers from one azimuth angle to another and transmits amount of pulses in each angle, a large quantity of SAR data need to be processed and will be a burden for the storage system. In recent years, there has been a growing interest in compressed sensing (CS) theory, which can be used to recover sparse signals [4, 5]. Some valuable
literature on CS theory applications in the radar system has been published [6–14]. In [6], an inversed synthetic aperture radar (ISAR) imaging method based on CS was proposed, in which a high image quality can be realized even though a very limited amount of pulses are available. In [9], CS theory is utilized to implement SAR imaging for a coast area, wherein only 50% of the raw data itself is used to achieve the unambiguous SAR image. In [15], the combination of CS theory and space-time adaptive processing (STAP) are adopted to perform ground moving target indication (GMTI). In [16], a method to estimate motion parameter with CS theory is introduced. In this paper, the SAR data in the azimuth is sparsely sampled to reduce data sampling. Then, before detection of foreign body intrusion, CS theory is utilized to reconstruct the sparsely sampled data.

The paper is organized as follows. Section 2 presents the mathematical model of detecting road foreign body intrusion. In Section 3, CS theory is introduced to reconstruct the sparsely sampled SAR data. A detailed description of the detection method based on Kalman filtering is presented in Section 4. Simulated results and real data processing results are presented in Section 5 to validate the effectiveness of the proposed method. Finally, some conclusions are drawn in Section 6.

2. Mathematical Model

In this section, the mathematical model of detecting road foreign body intrusion is given. In order to monitor the road foreign body intrusion, the antenna of SAR steers from one angle to another in a periodic manner. In each scan and each angle, the antenna transmits amount of pulses and steps to next angle. In data processing, each angle is considered as a coherent processing interval. The antenna scanning is shown in Figure 1. The SAR data is consisted of stationary scene echo (called clutter), foreign body echo, and noise. After range compression, range migration correction, and azimuth compression, the SAR data is transformed to range-Doppler domain for detection of road foreign body intrusion by separating foreign body signal from the SAR data.

The platform moves with velocity $V$, channel 1 transmits linear frequency modulation (LFM) signal, both channel receive echoes, and $d_k$ ($k = 1, 2, \ldots, K$) is the distance between the $k$th channel and the first channel. In SAR systems, the relationship between Doppler frequency of the $i$th Doppler cell and the corresponding azimuth angle is shown as (1). Suppose that the foreign body from azimuth angle of $\theta$, and clutter scatter from azimuth angle of $\theta_c$ fall into same Doppler cell and same range cell in the range-Doppler domain. The signal model of the $k$th channel in the $i$th Doppler cell and the $j$th range cell can be expressed as (2):

\[
f_i = \frac{2V}{\lambda} \cos \theta_c,
\]

\[
Z_k(i,j) = C_k(i,j) + T_k(i,j) + N_k(i,j),
\]

where $C_k(i,j)$, $T_k(i,j)$, and $N_k(i,j)$ denote clutter, foreign body, and noise, respectively. In addition, $C_k(i,j)$ and $T_k(i,j)$ can be written as

\[
C_k(i,j) = C_1(i,j) \times \exp\left(-\frac{2\pi}{\lambda}d_k \cos \theta_c\right), \quad (3)
\]

\[
T_k(i,j) = T_1(i,j) \times \exp\left(-\frac{2\pi}{\lambda}d_k \cos \theta_t\right), \quad (4)
\]

where $C_1(i,j)$ and $T_1(i,j)$ are clutter and foreign body of the first channel, $\exp\left(-\frac{2\pi}{\lambda}d_k \cos \theta_c\right)$ and $\exp\left(-\frac{2\pi}{\lambda}d_k \cos \theta_t\right)$ are error phases among channels of clutter and foreign body, and $\lambda$ is the wavelength.

Substituting (1), (3), and (4) into (2), (2) can be rewritten as

\[
Z_k(i,j) = C_1(i,j) \times \exp\left(-\frac{2\pi}{\lambda}d_k \cos \theta_c\right) + T_1(i,j)
\]

\[
\times \exp\left(-\frac{2\pi}{\lambda}d_k \cos \theta_t\right) + N_k(i,j).
\]

After compensation the error phases of clutter, SAR signal can be approximately expressed as

\[
Z_k(i,j) = Z_k(i,j) \times \exp\left(j\frac{\pi d_k f_i}{V}\right) = C_1(i,j) + T_1(i,j)
\]

\[
\times \exp\left(-\frac{2\pi}{\lambda}d_k \cos \theta_t\right) \times \exp\left(j\frac{\pi d_k f_i}{V}\right) + N_k(i,j),
\]

where $Z_{C_1}(i,j) = C_1(i,j)$ and $Z_{T_1}(i,j) = T_1(i,j) \times \exp\left(-j\frac{2\pi}{\lambda}d_k \cos \theta_t\right) \times \exp\left(j\frac{\pi d_k f_i}{V}\right)$ are clutter and foreign body after compensation, respectively.

3. Sparse Signal Reconstruction

Before detection of foreign body intrusion, the SAR data in the azimuth is sparsely sampled to reduce data sampling. Then, CS theory is utilized to reconstruct the sparsely sampled SAR data.
3.1. CS Theory. Assume that signal \( y \in \mathbb{C}^P \) can be linearly represented in a redundancy basis. Signal \( y \) is sparse if only \( L \)'s of its coefficients are nonzero, with \( L \ll P \), and thus, the sparsity of the signal is \( L \). CS theory, as an effective tool for reconstructing sparse signals, can be demonstrated as follows.

Let \( y \in \mathbb{C}^P \) denote a finite signal of interest, and suppose that there exists a basis matrix \( \psi = [\psi_1, \psi_2, \ldots, \psi_P] \) such that \( y = \psi \theta \), where \( \theta \) is the corresponding coefficient vector. By making \( M \)-reduced dimensional measurements in the form of \( x = \phi y \), where \( \phi \in \mathbb{C}^{M \times P} \), \( \phi \) is the measurement matrix to be carefully set to satisfy that \( \psi \theta \) has a restricted isometry property. In the case that the submatrix of any \( M \) column of \( \psi \phi \) is approximately orthogonal, \( \psi \theta \) has a restricted isometry property. If the \( M \geq O \left( \log (P/L) \right) \) condition is satisfied, the \( L \) largest coefficients can be recovered from \( L \).

\[
\hat{\theta} = \arg \min \| \theta \|_1, \quad \text{subject to } x = \psi \theta. \tag{7}
\]

3.2. SAR Data Reconstruction Based on CS. Suppose that the SAR data of a certain range cell after sparse sampling is denoted as \( s \) (8), where \( M \) and \( N_a \) are the number of the sparse and nonsparse sampling:

\[
s = [s_1, s_2, \ldots, s_M]^T, \quad M < N_a. \tag{8}
\]

In the SAR system of wide area surveillance (WAS) mode, the main beam is quite narrow, and the PRF is so high that the foreign body is out of the main clutter and the velocity is ambiguous. For high PRF results in the sparsity of the signals in the range-Doppler domain, we can use few samples to reconstruct the range-Doppler data using the CS theory.

Now we construct the CS dictionary (including measurement matrix and sparse matrix). The slow time in the azimuth can be denoted as \( t_a = [0: N_a - 1] \cdot \Delta t \), where \( \Delta t \) is pulse repetition time, after sparse sampling it becomes \( t = [0: M - 1] \cdot \Delta t \), where \( M \) is the pulse number after sparse sampling, and the measurement matrix \( \phi \) can be expressed as

\[
\phi = \begin{bmatrix}
1 & 0 & 0 & \ldots & 0 \\
0 & 0 & 1 & \ldots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \ldots & 1
\end{bmatrix}_{M \times N_a}. \tag{9}
\]

The Doppler frequency can be denoted as \( f_d = [0: N_a - 1] \cdot \Delta f_D \), where \( \Delta f_D \) is the frequency interval, \( \Delta f_D = \text{PRF/N}_a \). The sparse matrix can be expressed as

\[
\psi = \begin{bmatrix}
f^{(1)}(1), & f^{(2)}(1), & \ldots, & f^{(N_a)}(1)
\end{bmatrix}, \tag{10}
\]

\[
f^{(j)}(j) = \exp(-j2\pi f_d(j)t_a), \quad 0 \leq j \leq N_a.
\]

So, the CS dictionary is

\[
\Theta = \phi \psi. \tag{11}
\]

Assume that the signal after reconstruction is \( I = [\sigma_1, \sigma_2, \ldots, \sigma_{N_a}]^T \), so we can obtain

\[
s = \Theta I. \tag{12}
\]

In fact \( \Theta \) is a partial Fourier matrix, equation (12) has infinite solutions, as shown in Ref. [4, 5]. \( \Theta \) satisfies RIP, so we can reconstruct \( I \) in high possibility by solving the following equation (13). And thus, the sparsely sampled SAR data can be reconstructed:

\[
\min \| I \|_1, \quad \text{s.t. } s = \phi \psi I. \tag{13}
\]

4. Detection of Foreign Body Intrusion

This section will mainly discuss detection of road foreign body intrusion with the reconstructed SAR data. Framework based on CS theory and Kalman filtering is shown in Figure 2.

According to equation (6), clutter and foreign body of the \( k \)th channel in the \( \theta \)th Doppler cell and the \( \theta \)th range cell can be expressed as (14) and (15), where \( d_{k-1} = d_k - d_{k-1} \) is the distance between \( k \)th and \( k-1 \)th channel, \( \xi_{k-1}(i, j) \) and \( \xi_{k-1}(i, j) \) which is called system noise is the errors between \( k \)th and \( k-1 \)th channel of clutter and foreign body, respectively. These two noises are independent, zero-mean Gaussian noise with distribution equation (16), \( P \) is probability distribution, \( Q \) given as (17) is the covariance matrix, and \( Q_C \) and \( Q_T \) are the variances of the state variables:

\[
C_k(i, j) = C_{k-1}(i, j) + \xi_{k-1}(i, j); \tag{14}
\]

\[
T_k(i, j) = \exp\left(-\frac{j2\pi f_d k-1 \cos \theta_i}{\nu}\right) \times \exp\left(j \frac{\pi d_{k-1} \nu}{\nu}ight) \times T_{k-1}(i, j) + \xi_{k-1}(i, j); \tag{15}
\]

\[
P(\xi_{k-1}(i, j), \xi_{k-1}(i, j)) \in N(0, Q). \tag{16}
\]

\[
Q = \begin{bmatrix}
Q_C & 0 \\
0 & Q_T
\end{bmatrix}. \tag{17}
\]

From the abovementioned analysis, the state update equation and the measurement equation of the SAR system can be constructed as (18) and (19), where \( A_k(i, j) = [1 \ 1] \) is the state transition matrix and \( B_k(i, j) = [1 \ 1] \) is the gain matrix between state variables and measurement. Measurement noise \( N_k(i, j) \) is also zero-mean Gaussian distribution with distribution equation \( P(N_k(i, j)) \in N(0, R_N) \) and \( R_N \) is the variance of the measurement. Note that, in simulated and real SAR data processing, the initial numerical values of \( Q_C, Q_T, R_N \) are set as \( Q_C = Q_T = R_N = \sigma^2 \), where \( \sigma^2 \) is the power of the noise.
\[ H_1(i, j) = P_1(i, j) B_1^T(i, j) B_1(i, j) + R_1 \]

\[ H_k(i, j) = P_k(i, j) B_k^T(i, j) B_k(i, j) + R_k \]

\[
\begin{bmatrix}
C_k(i, j) \\
T_k(i, j)
\end{bmatrix} = A_{k-1}(i, j) \begin{bmatrix}
C_{k-1}(i, j) \\
T_{k-1}(i, j)
\end{bmatrix} + \begin{bmatrix}
\xi_{k-1}(i, j) \\
\zeta_{k-1}(i, j)
\end{bmatrix}
\]

\[
\begin{bmatrix}
C_k(i, j) \\
T_k(i, j)
\end{bmatrix} + \begin{bmatrix}
\xi_{k-1}(i, j) \\
\zeta_{k-1}(i, j)
\end{bmatrix}
\]

\[ Z_k(i, j) = B_k(i, j) \begin{bmatrix}
C_k(i, j) \\
T_k(i, j)
\end{bmatrix} + N_k(i, j)
\]

\[
A_{k-1}(i, j) = \begin{bmatrix}
1 \\
0
\end{bmatrix} \begin{bmatrix}
0 \\
0
\end{bmatrix}
\]

\[
A_{k-1}(i, j) = \begin{bmatrix}
1 \\
0
\end{bmatrix} \begin{bmatrix}
0 \\
0
\end{bmatrix}
\]
The detection algorithm of road foreign body intrusion based on Kalman filtering is designed, as shown in Figure 3, and the SAR data of every channel is regarded as a measurement of the scene; thus, the foreign body can gradually be separated in the process of recursion.

### 5. Experimental Results

#### 5.1. Simulated Results

In order to verify the effectiveness of the proposed method, simulation experiment on computer is carried out, and the system parameter is shown in Table 1. One foreign body with radial velocity of 1.8 m/s, and the signal-to-noise ratio (SNR) of 20 dB is simulated to the scene.

The normalised power of the scene before and after Kalman filtering is shown as Figure 4(a). From Figure 4(a), it can be found that the extracted power of the foreign body begins to outperform the power of the neighbourhood clutter and it is growing along with the recursion goes on. To show the trend more clearly, Figure 4(b) give the relative power of the foreign body with different recursion numbers. Therefore, the proposed method is testified by the simulation results.

To investigate the impact of the sampling ratio on the detection results, experiment under different sampling ratios is performed. The signal-to-clutter ratio (SCR) after detection of foreign body intrusion is used to measure the

### Table 1: System parameter.

| Parameters               | Value       |
|--------------------------|-------------|
| Carrier frequency        | 9.45 GHz    |
| Signal bandwidth         | 20 MHz      |
| PRF                      | 6 kHz       |
| Velocity of the platform | 100 m/s     |
| Number of channels       | 5           |
detection effect. Figure 5 shows the SCR after detection when the sampling ratios are 60%, 70%, 80%, and 90%. It can be seen that SCR will increase with the increase of sampling data. When the amount of SAR data is small, the reason why SCR is relatively low is that the reconstruction error will increase as the amount of data decreases. Thus, the residual clutter increases after detection.

Noise has some influence on the reconstruction algorithm based on compressed sensing; this paper adopts improvement factor IF = SCRout/SCRin to measure the influence of noise. Figure 6 shows the IF under different clutter-to-noise ratios (CNRs). As the reconstruction error of SAR data will increase with the increase of noise, the residual clutter after detection increases and thus IF decreases.

5.2. Real Data Processing Results. In this section, the validity of the proposed method is demonstrated by five-channel real SAR data which is obtained from a Chinese airborne SAR system. The signal of foreign body intrusion is contained in the real SAR data.

Figure 7 shows the imaging result because of the influence of clutter and noise, and foreign body intrusion cannot be detected. The detection result of foreign body intrusion is shown as Figure 8. From Figure 8, we find that most of clutter and noise is greatly suppressed and the foreign body intrusion is gradually extracted as the recursion goes on. Hence, the effectiveness of the proposed detection method in real SAR data is validated.

6. Conclusion

In this paper, SAR is introduced to detect road foreign body intrusion in a wide range. Firstly, because of large data, the SAR data in the azimuth is sparsely sampled to reduce data sampling. Then, before detection of foreign body intrusion, CS theory is utilized to reconstruct the sparsely sampled data. At last, Kalman filtering is adopted to suppress clutter and noise. By reasonably setting the state update equation and measurement equation, foreign body intrusion can be gradually separated from clutter and noise in the process of recursive. The proposed method has a big advantage when the detection range is wide.

Data Availability

The data used to support the findings of this study are included within the supplementary information file.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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