Multi-channel Synthetic Aperture Radar Imaging of Ground Moving Targets Using Compressive Sensing

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ABSTRACT Integrated with the array technique, multi-channel processing can be applied to synthetic aperture radar of ground moving target imaging (SAR GMTIm), which is very powerful in remote sensing of smart city. To reduce the data sampling amounts, compressive sensing (CS) can be used by exploiting a sparse prior of moving targets. In this paper, the SAR GMTIm from data of compressive sampling is addressed by proposing a novel reweighted sparse algorithm. Here, we mainly focus on sparse imaging and clutter suppression for heterogeneous scene of urban areas. In the scheme, the phase of interferogram and the magnitude after displaced phase center antenna (DPCA) are incorporated to derive the weights on sparsity-constraint. Due to the joint usage of magnitude and phase, the proposed reweighted sparse algorithm can improve the performance of clutter suppression. Finally, experiments using the simulated and measured data are performed to confirm the effectiveness of the proposed algorithm.

INDEX TERMS Multi-channel synthetic aperture radar (SAR), ground moving target imaging (GMTIm), smart city, reweighted sparse, clutter suppression.

I. INTRODUCTION

As a modern remote sensor, synthetic aperture radar (SAR) can work all-time and all-weather, which has found a wide application in both civilian and military areas [1-5]. The characteristic of high resolution in two-dimensions (2D) are very powerful in the remote sensing of smart city by providing urban map, vehicle detection and so on [3-6]. Combined with the technique of array signal processing [7-12], the multi-channel SAR can be adopted for ground moving targets imaging (GMTIm), known as SAR GMTIm [11]. For multi-channel SAR, the huge amounts of echo data place a high burden on current radar system. From the compressive sensing (CS) theory [13], it is possible to recover a sparse signal from fewer samples than those Nyquist requires by exploiting a sparse prior. In fact, SAR image of moving targets is sparse after clutter suppression using multi-channel technique, such as space-time adaptive processing (STAP) [12], displaced phase center antenna (DPCA) [14, 15] and etc. As a result, it provides a rational to apply CS to SAR GMTIm using the data of compressive sampling, which can effectively relax the burden of current radar system.

For SAR GMTIm, the clutter suppression is an important issue to determine the imaging and detection performances of moving targets [11, 12]. In the case of compressive sampling, the DPCA technique can work well and may be an ideal
choose among the existing methods of clutter suppression. After the processing of DPCA, the sparse approach of SAR GMTIm can be applied to improve the imaging performance. In fact, the sparse approach essentially assumes that the response of moving targets is stronger than the noise and residual clutters. In the application of urban areas, this assumption may not hold in some cases [5]. The building usually exhibits the property of spatial variance and time variance, which is treated as heterogeneous clutter. The DPCA technique is sensitive to channel mismatch and can leave significant residual clutters over the strong buildings [5, 12]. In this case, it is hard to distinguish between moving targets and strong residual clutters, degrading the sparse imaging performance. To our knowledge, there is no straightforward way to solve this problem for sparse SAR GMTIm, which motivates our study in this paper.

In this paper, we focus on sparse SAR GMTIm with improved performance of clutter suppression. Accordingly, a reweighted sparse algorithm is proposed to deal with the strong residual clutters, especially for the heterogeneous clutters of urban buildings. In the scheme, both the magnitude and interferometric phase from multi-channel data are used to reconstruct the weights of sparsity-constraint, promoting the robustness of clutter suppression. Compared with the traditional sparse methods, the proposed reweighted sparse algorithm is more powerful in dealing with the heterogeneous clutters. Finally, the experimental analysis using the simulated and measured data is introduced to confirm the effectiveness of the proposed algorithm.

II. SIGNAL MODEL

\[ s_i(t, t_s) = s_i(t, t_s) \cdot \exp \left[ -j2\pi \frac{d}{\lambda} (i-1) \right], i = 1, \ldots, I \]  

where \( s_i(t, t_s) \) is the echo of channel one (treated as reference channel) in the range time \( t \) and azimuth time \( t_s \) domain, \( d \) is the baseline between two adjacent channels for a uniform array, \( \lambda \) is the wavelength of transmitted signal, and \( V \) is the velocity of radar platform. In (1), the phase term is introduced by the range velocity \( v_r \) of the moving target, which is the major difference between the multi-channel data. For clarity, the 2D spectrum of \( s_i(t, t_s) \) needs to be analyzed, which can be written in an approximate form as [1, 2]

\[ s_i(f_x, f_y) = W_i(f_x) \cdot \exp \left[ -j4\pi\sigma_0 \sqrt{\left( \frac{f_x + f_o}{c} \right)^2 - \frac{f_x^2}{4f_o^2}} \right] \]

\[ W_i(f_x - f_o) \cdot \exp \left[ -j2\pi f_o \left( \frac{(V - v_r) - v_x - v_r}{v_r} \right) \right] \]

where \( c \) denotes the transmitting velocity of the electromagnetic wave, \( v_x \) is the azimuth velocity of the moving target, \( W_i(\cdot) \) and \( W_o(\cdot) \) are the window functions in the range frequency \( f_x \) and Doppler \( f_o \) domain, respectively, \( f_o (c = \lambda \cdot f_x) \) is the carrier frequency of transmitted signal, \( f_o \) is the Doppler center introduced by the range velocity \( v_r \) of
the moving target, and \( v_r \) is the total velocity of the radar platform and moving target. Then, the discrete signal model of the \( i \)th channel can be expressed as

\[
s_i = H(v_i)(e + x_i) + n_i
\]

where \( s_i \) is the pre-processed echo data while \( x_i \) and \( e \) are the SAR images of moving targets and stationary clutters, respectively. It is ideally assumed that \( e \) is the same for all the channels. In (3), \( n_i \) is the system noise and \( H(v_i) \) is a discrete SAR observation matrix of the moving targets \([16-18]\). Here, \( H(v_i) \) is a dynamic matrix to indicate the motion of moving targets. For stationary clutters \( (v_r = 0) \), \( H(v_r = 0) \) reduces to be deterministic. Exploiting the difference of signal characteristic, the multi-channel technique can be used to detect the moving targets. Here, the DPCA technique \([14, 15]\) is used due to its simplicity and effectiveness on the data of compressive sampling. In the procedure of DPCA, the \( i \)th channel data are subtracted by the one of reference channel, and the data after DPCA can be written as

\[
s_i - \text{DPCA} = H(v_i)x_i - \text{DPCA} + cn_i - \text{DPCA} = 2, \ldots, I
\]

where \( s_i - \text{DPCA}, x_i - \text{DPCA} \) and \( cn_i - \text{DPCA} \) are the echo data, SAR image and a total of residual clutter and noise after DPCA, respectively. Due to the presence of \( v_r \), the motion compensation of moving targets is necessary for the well-focused image. In fact, the time-frequency approach is an effective tool of estimating the parameters of moving targets \([20-26]\). It is assumed that \( v_r \) can be estimated by using some of the existing methods \([24-26]\). Then, the parametric dictionary \( H(v_i) \) in (3) or (4) is determined and can be constructed. Considering that the accurate formulation of \( H(v_i) \) is complicated, an approximate form is suggested to be used by effectively reducing the computational complexity \([27, 28]\).

In the case of compressive sampling, the strategy of under sampling needs to be designed. In this paper, sparse aperture is used by under-sampling the data in the azimuth dimension. The pulses of full aperture are randomly selected with compressive random sampling \([26]\). In this case, the Doppler spectrum of \( s_i \) or \( s_i - \text{DPCA} \) is ambiguous. So \( s_i \) or \( s_i - \text{DPCA} \) needs to be in the azimuth time domain to avoid the Doppler ambiguity. Then, the signal model of sparse aperture can be expressed as

\[
s_i = \Phi H(v_i)(e + x_i) + n_i
\]

\[
s_i - \text{DPCA} = \Phi H(v_i)x_i - \text{DPCA} + cn_i - \text{DPCA}
\]

where \( \Phi \) is an under-sampling matrix of sparse aperture. To avoid the use of more variable symbols, we still use \( s_i \), \( s_i - \text{DPCA} \) and \( cn_i - \text{DPCA} \) in (5) in the case of compressive sampling.

III. PROPOSED METHOD

Considering that (5) is an ill-posed problem due to the compressive sampling, the SAR image formation of moving targets is treated as a problem of sparse signal recovery. After DPCA, \( x_i - \text{DPCA} \) is usually sparse in SAR image domain because the number of moving targets is usually limited. By exploiting a sparse prior, the sparse imaging approach can be employed as

\[
\begin{align*}
\{ s_i - \text{DPCA} \} &= \underset{s_i - \text{DPCA}}{\arg \min} \| \mathbf{X}_i - \text{DPCA} \|_2 \quad \text{s.t.} \quad \| \text{DPCA} - \Phi H(v_i)x_i - \text{DPCA} \| \leq \epsilon \\
&= \text{arg min} \| \mathbf{X}_i - \text{DPCA} \|_2 \\
&= \text{arg min} \| \mathbf{X}_i - \text{DPCA} \|_1 \\
&= \text{arg min} \| \mathbf{X}_i - \text{DPCA} \|_2 ^2 \\
\end{align*}
\]

The pulses of full aperture are randomly selected with compressive random sampling \([26]\). In this case, the Doppler spectrum of \( s_i \) or \( s_i - \text{DPCA} \) is ambiguous. So \( s_i \) or \( s_i - \text{DPCA} \) needs to be in the azimuth time domain to avoid the Doppler ambiguity. Then, the signal model of sparse aperture can be expressed as

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Actually, the weighted matrix in (7) refers to using the magnitude of SAR image after DPCA processing. In other words, the derivation of weighted matrix comes from the idea of DPCA. However, the interferometric phase is not used in (7). Empirically, using both the magnitude and phase during the reconstruction of weights benefits to the sparse imaging. Unfortunately, the correct interferometric phase is unavailable in the case of compressive sampling because the phase is polluted by some artifacts of high-level side and grating lobes. To retrieve the interferometric phase, high-quality SAR images need to be reconstructed. For non-sparse scene, sparse SAR image formation is still an open question due to the random phase nature of complex SAR image [16, 17, 27]. In fact, the interferometric phase is only necessary for the areas of strong residual clutters and moving targets. From this aspect, only partial areas of SAR image need to be reconstructed from the sparse aperture data, which exhibits a sparse prior. From the analysis above, the proposed reweighted sparse algorithm is expressed as

\[ \tilde{x}_{DPCA} = \arg \min_{x_{DPCA}} \| \mathbf{W}(\mathbf{x}_c, X) \mathbf{x} \|_2^2, \]

subject to

\[ \| \mathbf{I} - \mathbf{DPCA} \mathbf{x}_c - \mathbf{DPCA} \mathbf{x} \|_2^2 \leq \varepsilon \]

\[ \mathbf{x}_c = \mathbf{e} + \mathbf{x}_i \]

where \( \mathbf{x}_i = \mathbf{e} + \mathbf{x}_c \) is a total SAR image of moving targets and strong residual clutters. In (8), the reweighted sparse approach is also used by placing the same weights as (7), enforcing sparsity constraint on the areas of moving targets and strong residual clutters in SAR image. As a result, the sparse imaging of \( \mathbf{x}_c \) can be ensured with promising performance. Note that the solutions of \( x_{DPCA} \) and \( \mathbf{x}_c \) in (8) are dependent on each other. There is no closed-form solution of (8) and the numerical method is necessary. In this case, the Quasi-Newton method is suggested to be utilized due to its acceptable accuracy and efficiency [27]. In each iteration, \( x_{DPCA} \) and \( \mathbf{x}_c \) are estimated sequentially to update the weights in (8). More specifically, the estimation of \( x_{DPCA} \) is used to update \( \mathbf{W}(X) \), which is used to newly estimate \( \mathbf{x}_c \). The estimation of \( \mathbf{x}_c \) is used to obtain the interferometric phase, which is incorporated during the reconstruction of \( \mathbf{W}(\mathbf{x}_c, X) \).

Now, the key problem is how to effectively integrate the interferometric phase during the reconstruction of \( \mathbf{W}(\mathbf{x}_c, X) \). For multi-channel SAR GMTI, the interferometric phase of stationary scene is near zero while that of a moving target deviates from zero. This characteristic can be used to distinguish between strong clutters and moving targets, which is also the basic principle of ATI technique [5]. In (7), the basic idea of enhancing the sparsity is that the small weights are laid on the large signal coefficients while the large weights on the small signal coefficients, which can effectively suppress the noise or clutter. Inspired by this idea, the same procedure can be applied to (8) by placing larger weights on the residual clutters. Accordingly, the weighted matrix \( \mathbf{W}(\mathbf{x}_c, X) \) is created as

\[ \mathbf{W}_{\text{new}} = \left[ \frac{1}{\sum_{i=2}^{\infty} (1 - \cos(\phi_{mi}))} \right]^{1/2} \left[ \left( \sum_{n=1}^{N_n} |x_{mn}|^2 \right)^{-1} \right] \]

\[ \phi_{mi} = \angle \left( \mathbf{r}_c, \mathbf{r}_m \right), \quad i = 2, \ldots, I \]

where the first term of the weight is contributed by the interferometric phase. The deduction of \( 1 - \cos(\phi_{mi}) \) in (9) comes from

\[ 1 - \cos(\phi_{mi}) = \| \exp[j \cdot \phi_{mi}] \|^2 / 2 \]

which is used to evaluate the interferometric phase. For clutters, the interferometric phase \( \phi_{mi} \) is near zero and we have \( \sum_{i=2}^{\infty} \| \exp[j \cdot \phi_{mi}] \|^2 = 0 \). As a result, large weights from the interferometric phase are laid on the clutters in (9). On the contrary, the weights are smaller for the moving targets, benefiting to protect the moving targets. In this way, the signature of moving targets can be enhanced by incorporating the magnitude and phase, which can effectively improve the sparse imaging performance.

The computational load of the proposed algorithm is necessary to be introduced by evaluating the real-time implementation. Compared with the conventional sparse imaging approach, the proposed algorithm in this paper needs additional calculation of weights in (9), which is the main difference. The calculation of weights depends on the recovery of interferometric phase, which only consumes a little computational load. As a result, the main complexity of the proposed algorithm lies into the iterative solution of sparse imaging. For each iteration, the computational load mainly comes from the construction of \( \mathbf{H}(\mathbf{v}_i) \) or its inverse processing [27]. As has been mentioned in (4), an approximation of \( \mathbf{H}(\mathbf{v}_i) \) can be used by reducing the computational complexity [27, 28]. In this case, the computational load of \( \mathbf{H}(\mathbf{v}_i) \) is \( O(N_v \cdot N_a \log_2 N_v) \) by using the fast Fourier transform (FFT). Here, \( N_v \) and \( N_a \) are the discrete numbers in the range and azimuth dimensions, respectively. Note that, as \( N_v \) or \( N_a \) increases, the computational load grows in an approximately linear trend, which is very time-consuming. To overcome this, proper segmentation in the range dimension can be applied and then the proposed algorithm is performed in a parallel manner in each block.

IV. EXPERIMENTAL ANALYSIS

A. SIMULATED DATA EXPERIMENTS

In this subsection, experiments based on simulated data are performed to show the effectiveness of the proposed algorithm. The parameters of simulated radar system are

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listed in Table 1. In the simulation, there are six moving targets and their velocities are set as \((3, 3), (-3, 3),\)  
\((-5, -5), (5, -5), (4, -4),\) and \((4, 4)\) in the range and azimuth dimensions, respectively. Besides, there are nine prominent stationary targets with three of them being particularly strong. One channel of the radar system transmits LFM signals and eight channels are used to receive the echo data simultaneously. After channel balancing and channel alignment, the SAR focusing processor [1, 2] is applied to realize 2D imaging and MTRC correction. Then, the time-frequency method [24-26] is used to estimate the parameters of the moving targets. After motion compensation, the SAR image of channel one is shown in Fig. 2(a), where the stationary points are marked using a red rectangle. In Fig. 2(a), it can be seen that the three prominent targets are stronger than the moving targets, which exhibit strong clutter property. Then, DPCA is used to suppress the clutter and the DPCA-after image is shown in Fig. 2(b). In the idea case, the strong clutters can be suppressed clearly. However, as it has been analyzed in this paper, there is inevitable channel mismatch between the multi-channel data. It is assumed the phase error between two channels is 0.1 rad. In this case, the DPCA-after image of channels one and two is shown in Fig. 2(c). Compared Fig. 2(c) with (b), there are strong residuals for the three prominent stationary targets, also marked using a red rectangle in Fig. 2(c). For the strong clutters, even a little phase mismatch can introduce large residuals, where the DPCA performance is degraded dramatically. As a result, it is necessary to remove these residual clutters in sparse imaging, which is one major motivation of this paper.

Now, the experiments are performed using our proposed algorithm in this paper. To test the robustness of the proposed algorithm, random clutter with Gaussian distribution is added to each channel identically and the signal-to-clutter ratio (SCR) is set as -15 dB. Here, the sparse aperture data are used with the data amounts as a half of the full aperture, shown in Fig. 3(a). Using the conventional SAR processing, the SAR image of channel one is shown in Fig. 3(b) that there are strong artifacts, i.e. high-level grating and side lobes, in the azimuth dimension due to the compressive sampling. Due to the presence of clutters, the response of moving targets is a little weak. Then, DPCA [5] is used to remove most of the clutters and the processed image is shown in Fig. 3(c). It can be found that the SCR of moving targets is improved by applying DPCA. However, the residual clutters from the three prominent stationary targets are still obvious when the phase mismatch is set as 0.1 rad. To remove the residual clutters, the sparse imaging approach is employed. To evaluate our proposed reweighted algorithm in (8), the unweighted sparse approach in [27] is used as a comparison. Fig. 4(a) and (b) show the reconstructed SAR images before and after DPCA using the unweighted sparse approach. In Fig. 4(a), there are many residual clutters clarity, the interferometric phase between channels one and two is shown in Fig. 4(c), implying that the phase of the because the unweighted approach can not deal with the non-sparse scene well. In this case, the interferometric phase between two channels is not available. In particular, the unweighted approach can not deal with the strong residual clutters, which can be found in Fig. 4(b). Then, our proposed algorithm is employed to deal with these artifacts. Fig. 4(c) and (d) show the sparsely reconstructed images of channels one and two by using our proposed algorithm. Compared with Fig. 4(a), almost of the clutters are effectively removed in Fig. 4(c) by using our proposed algorithm. For clarity, the interferometric phase between Fig. 4(c) and (d) are shown in Fig. 4(e). In Fig. 4(e), the interferometric phase of stationary targets is near zero, implying the feasibility on detecting stationary clutters. Fig. 4(f) shows the sparsely reconstructed image of moving targets after DPCA that the strong residual clutters have been removed successfully. It can be found that our proposed algorithm has perfect performance of clutter suppression, which benefits from the use of interferometric phase. As follows, less data amounts of compressive sampling are used with a quarter of the full aperture and the sparse aperture data is shown in Fig. 5(a). The sparse imaging experiments are also performed and the results are shown in Fig. 5(b) and (c) by using the unweighted sparse approach and our proposed reweighted algorithm, respectively. Compared Fig. 5(b) with (c), our proposed algorithm can still work well to remove the strong residual clutters even when using much less sampling data.

**TABLE I**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>Radar center frequency</td>
<td>10 GHz</td>
<td>Bandwidth</td>
<td>150 MHz</td>
</tr>
<tr>
<td>Sampling frequency</td>
<td>180 MHz</td>
<td>Range of scene</td>
<td>5 km</td>
</tr>
<tr>
<td>Pulse repetition frequency</td>
<td>3.6 kHz</td>
<td>Radar platform</td>
<td>100 m/s</td>
</tr>
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<td></td>
<td></td>
<td>velocity</td>
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**B. REAL DATA EXPERIMENTS**

In the following, the experiments are performed using measured data from an airborne platform. The radar system includes three channels, operating at X-band with signal bandwidth of 18 MHz and pulse repetition frequency (PRF) of about 830 Hz. Here, the coherent processing interval (CPI) of SAR GMTIm is about 5 s with azimuth resolution of about 1.5 m. After channel alignment and channel balancing, SAR focusing are applied and the focused SAR image of channel one is shown in Fig. 6(a). Meanwhile, the SAR image of moving targets after DPCA is shown in Fig. 6(b). Obviously, the image is sparse after DPCA. Compared Fig. 6(a) with (b), there still are some strong residual clutters even after DPCA, which are introduced by the heterogeneous clutters. In fact, DPCA is very sensitive to channel mismatch and tends to leave many strong residuals over the heterogeneous scene of strong urban buildings. For residual clutter is very small. So the interferometric phase can be used to detect these strong residual clutters.
The sparse imaging experiments are performed to confirm the effectiveness of the proposed algorithm. As a comparison, the conventional reweighted sparse approach in (7) is employed without using the interferometric phase for the weights. In the case of full aperture, Fig. 7(a) and (b) are the sparsely reconstructed images by using the conventional and our proposed reweighted sparse algorithms, respectively. Compared Fig. 7(a) with (b), it is clear that the residual strong clutters are removed using our proposed algorithm, shown in the circles of A and B. Furthermore, Fig. 7(c) shows the high-quality interferometric phase using our proposed algorithm. Then, the sparse aperture data are used with a half of the full aperture. Fig. 8(a) shows the SAR image of moving targets using the conventional SAR imaging algorithm. It can be seen that there are high-level grating and side lobes in the azimuth dimension due to the sparse sampling. Besides, the moving targets are smeared in the image domain without motion compensation. As a result, the motion compensation of moving targets needs to be implemented during the sparse imaging. Fig. 8(b) and (c) show the sparsely reconstructed images using the conventional and our proposed reweighted sparse algorithms, respectively. Compared Fig. 8(b) with (c) in the circle parts of A and B, our proposed algorithm can still effectively remove the strong residual clutters from the data of compressive sampling. All the experimental results above can be used to confirm the effectiveness of our proposed algorithm.
FIGURE 4. SAR images using sparse approaches. Unweighted sparse algorithm [28]: (a) and (b) are images before and after DPCA, our proposed reweighted sparse algorithm: (c) and (d) are images of channels one and two before DPCA, (e) is the interferometric phase between (c) and (d), and (f) is the image after DPCA.

FIGURE 5. Sparsely reconstructed SAR images (25% full aperture). (a) range profiles, (b) and (c) are images using unweighted [28] and our proposed reweighted sparse algorithms.

FIGURE 6. SAR images (full aperture). (a) channel one before DPCA, (b) image after DPCA from channels one and two, and (c) interferometric phase.

FIGURE 7. Sparsely reconstructed SAR images (full aperture). (a) conventional reweighted sparse approach, (b) and (c) are magnitude and interferometric phase images using our proposed reweighted sparse algorithm.
V. CONCLUSIONS
In this paper, we focus on sparse SAR GMTI by addressing the issues of sparse aperture and clutter suppression. Accordingly, a reweighted sparse approach is proposed to remove the strong residual clutters from the heterogeneous scene, such as urban buildings. In the scheme, the interferometric phase and the magnitude after displaced phase center antenna (DPCA) are incorporated to derive the weights on sparsity-constraint. As a result, the sparse imaging performance can be improved by effectively suppressing the clutters. All these advantages are confirmed by the experiments based on simulated and measured data. To further improve the performance of the proposed algorithm, the weighted metric on sparsity needs to be theoretically evaluated by determining some important factors, which can be treated as further study.

REFERENCES


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