Azimuth Ambiguity Suppression in SAR Images Based on VS-KSVD Dictionary Learning and Compressive Sensing

Xinchang Hu, Pengbo Wang*, Yanan Guo, Qian Han and Xinkai Zhou
School of Beihang University, Beijing, China

*Corresponding author e-mail: 201821100102@std.uestc.edu.cn

Abstract. The azimuth ambiguities appear widely in Synthetic Aperture Radar (SAR) images, which causes a large number of false targets and seriously affect the quality of image interpretation. Due to under-sampling in Doppler domain, ambiguous energy is mixed with energy from the main zone in the time and frequency domains. In order to effectively suppress the ambiguous energy in SAR images without loss of resolution, this paper presents a novel method of KSVD dictionary learning based on variance statistics (VS-KSVD) and compressed sensing (CS) reconstruction. According to the statistical characteristics of distributed targets, the dictionary that represents the ambiguities is selected and suppressed by coefficient weighting, in which local window filtering is carried out to remove the block effect and optimize the edge information. Finally, the high resolution images with low-ambiguity can be reconstructed by CS. With the proposed approach, the feasibility and effectiveness of the proposed approach is validated by using satellite data and simulation in suppressing azimuth ambiguity.

1. Introduction
In the process of spaceborne SAR moving relative to the target, the radar will receive the echoes in both the main zone and the ambiguity zone. Since the beam pattern has sidelobes extending beyond the main lobe, the sidelobes of other periods mix with each other in main zone. In order to solve the problem of azimuth ambiguity, the pulse repetition frequency (PRF) can be increased. However, SAR systems often need to find a balance between the azimuth ambiguity energy and the range observation width so that PRF is limited to certain restrictions. The solutions to this problem are generally divided into two kinds: one is to suppress the sidelobes by spectral weighting [1], and the other is from the perspective of signal processing, which has shown better performance.

The ambiguity suppression method based on signal processing usually calculates the region of azimuth ambiguity by analyzing the Azimuth Ambiguity-to-Signal Ratio (AASR), and then subtracts the recovered ambiguity signal from the original signal to obtain the suppressed image [2]. However, for complex scenes, it needs accurate radar parameters to calculate. The Compressed Sensing (CS) algorithm proposed in recent years provides a new way to solve the above problems. The optimization method replaces the traditional matching filtering and makes full use of the prior information of the scene to get better results. Xiao Peng et al. separated the real target energy and azimuth ambiguity energy by truncating the doppler frequency of complex images and used CS to invert the high-resolution imaging [3].
A novel strategy for azimuth ambiguity suppression in SAR images based on VS-KSVD dictionary learning and CS reconstruction is proposed in this paper, which is organized as follows. The VS-KSVD dictionary learning algorithm is introduced in Section II. With a brief description of compressed sensing, the united azimuth ambiguity suppression method based on VS-KSVD dictionary learning and CS is presented in Section III. Finally, the simulation results and real data verification are given in Section IV.

2. VS-KSVD dictionary learning
When the SAR image is divided into blocks, the structure and details of complex features such as edges are different for each block, so are the corresponding dictionary structure. In this Section, especially for SAR images of coastal areas, variance is chosen as the main measurement of image statistical characteristics to reflect the difference between regional strong target and background. It can be proved that the dictionary training for image blocks with different characteristics is more adaptable to the original image and the reconstruction effect is better.

2.1. KSVD
KSVD is mainly implemented by two steps: sparse coding and dictionary updating [4]. The specific algorithm steps are given as follows.
1) Input Parameters: the dimension of dictionary is $M \times N$, sparsity is $K$, initial dictionary $A$ is DCT basis, and each column is normalized.
2) Adopting OMP algorithm for sparse coding, it can be expressed as
\[
\tilde{x}_i = \arg \min_x \| y_i - A_{(i-1)} X_k \|_2 \quad s.t. \| x \|_0 \leq k_0
\]
where $\tilde{x}_i (1 \leq i \leq M)$ is the sparse representation, and their set forms matrix $X_{(i)}$.
3) In the updating stage of KSVD dictionary, each random number $j$ can be processed as follows by updating the column of the dictionary and obtaining the sparse basis:
   a) Defines the training set $\Omega_{ji} = \{ i \geq 1 \leq i \leq M, X_{(i)}[j_0, j] \neq 0 \}$ that uses column vectors $a_j \in A_i$.
   b) The error matrix $E_{ji} = Y - \sum_{j \neq j_0} a_j x_j^T$ is calculated, where $x_j$ is row $j$ of $X_{(i)}$.
   c) Constrain $\Omega_{ji}$ by selecting only the columns corresponding to $E_{ji}$, resulting in $E_{Rji}$.
   d) Apply SVD to decompose $E_{ji} = U A V^T$ and update $a_{ji} = u_i$ and $x_{ji} = \Lambda[1,1] \cdot v_i$.
   e) When $\| Y - AX \|_2^2$ is small enough, iteration is stopped; otherwise, iteration continues.
4) Outcome: $A_{(i)}$. $Y = X \cdot A$ denotes the representation of the image under dictionary.

2.2. Construction of Ambiguity Dictionary
Variance statistical characteristics can reflect regional characteristics of SAR images: islands, cross-sea bridges, ships and other strong targets in flat sea level have large variance, reflecting the details of the image area. However, the variance of urban buildings such as houses in the plain area is small, which is the smooth area of the image. The general azimuth ambiguity is particularly obvious at sea level. In the following, details of the basic operations for VS-KSVD dictionary learning and construction are provided in the diagram.

![Figure 1. Block diagram of VS-KSVD dictionary learning](image-url)
3. Azimuth ambiguity suppression

Compressed sensing algorithm is an optimal estimation method based on matrix model, which makes full use of the prior information of the target to recover the high-dimensional signal information from the low-dimensional observation results. Based on the dictionary that stores ambiguity energy screened by VS-KSVD in Section II, image reconstruction can be completed through CS after suppression.

3.1. Compressed Sensing Theory

Given measurement matrix \( \Phi \in \mathbb{R}^{M \times N} \) (\( M \ll N \)), the sampling value of signal \( f \) is obtained by \( y = \Phi f \).

Considering the reconstruction of \( f \) from \( y \), which is an NP-Hard problem [5]. However, if \( f \) can be sparsely represented, and \( \Phi \) meets certain properties, so that it can be proved that \( f \) can be reconstructed by solving the objective function as follows

\[
\text{arg min}_f \|f\|_0 \quad \text{s.t.} \quad \Phi f = y
\]  

where \( \|f\|_0 \) denotes L0-norm of vectors.

Compressed Sensing theory can be expressed as

\[
y = \Phi f = \Phi \Psi s = As
\]  

where \( A = \Phi \Psi \) denotes the sensing matrix [6].

3.2. United ambiguity suppression

Based on the concept and extraction method of azimuth ambiguity dictionary in Section II, a united strategy for azimuth ambiguity suppression and optimal filtering based on VS-KSVD dictionary is developed here. The main steps of algorithm are illustrated and shown in Figure 2.

![Figure 2. Block diagram of VS-KSVD dictionary learning](image)

1) Dividing the input SAR images into blocks as training samples \( M \) by size of \( N \times N \). According to the statistical histogram of variance, calculated by image blocks, empirical thresholds were selected to divide \( M \) into four clusters \( C_i \).
2) Conduct KSVD dictionary training and learning for each \( C_i \) to obtain the corresponding dictionary \( D_i \) and sparse coding matrix \( X_i \);
3) To extract the dictionary \( D_{abg} \) which stores azimuth ambiguity energy from the dictionary set based on the method elaborated in 2.2.
4) Through \( Y_i = D_i \cdot X_i \), obtain the result \( Y_i \) of each cluster class \( C_i \) under \( D_i \).
5) The pixel mean ratio \( \eta \) of the background region \( Y_{bgd} \) and the azimuth ambiguity region \( Y_{abg} \) is used as the weighted suppression coefficient of \( D_{abg} \), that is \( \eta = \text{mean}(Y_{bgd} / Y_{abg}) \).
6) Rearrange the dictionary position index by variance to get new image block \( M_{new} \).
7) To divide \( M_{new} \) into background region, transition region and strong target by the threshold of boundary, and local window filtering is performed to suppress the transition region to obtain the final optimized filtering result.
4. Experimental Results

4.1. Simulation results

The radar parameters used for SAR echo simulation and suppression are given in Table 1. We place an ideal target in the imaging center area, and set another ambiguous target far away from the main zone to make the ghost energy appear near the center zone.

| Parameter             | Value | Parameter             | Value |
|-----------------------|-------|-----------------------|-------|
| Wavelength(m)         | 0.3   | Antenna length(m)     | 4     |
| Equivalent velocity(m/s) | 100   | PRF(Hz)               | 57.62 |
| Radar altitude(km)   | 5     | Image area(km×km)     | 10    |

Figure 3 illustrates the azimuth profile of the signal after azimuth ambiguity suppression. It can be seen that there is no obvious resolution loss between the amplitude of the real target and the peak value, while the energy at the peak value of the azimuth ambiguity is suppressed by about 17dB and the sidelobes are greatly weakened and reduced.

4.2. Real data processing results

In this paper, stripe mode data with azimuth-fuzzy of TerraSAR-X Level1 SSC Product were selected for experiment, with a width of 30km, resolution of 3m, and polarization mode of single polarization. As can be seen from Figure 4, serious azimuth ambiguity occurs in the sea area. Since the scattering coefficient of buildings on land is higher than that of the sea surface, ambiguity energy radiated by strips of radiation appears on the sea surface, which interferes with the recognition of strong targets such as ships at sea level.

Figure 4. The original SAR image data
Firstly, the SAR image of size $480 \times 640$ is divided into 48 blocks as shown in Figure 4. The variance of each image block is calculated and rearranged in ascending order to obtain a new image matrix. The image blocks can be classified by selecting the threshold value from the variance statistical histogram. And after classification, VS-KSVD dictionary training is performed on them respectively, so that the cluster dictionary corresponding to different feature regions can be obtained. Figure 5 shows the four dictionaries after classified KSVD training.

![Figure 5. Classification training dictionary results](image)

Figure 5(d) corresponds to the strong target area in SAR images, containing complex edge and detail information such as ships, while Dictionary II and Dictionary I all contain the largest proportion of azimuth ambiguity energy. Therefore, different weighted suppression coefficients are assigned to different dictionaries to weaken ambiguity energy. Here, we set $\eta_i = 0.5$.

After the weighted suppression of ambiguity dictionary and optimal filtering, the SAR image can be reconstructed by CS accurately finally. The sampling rate of measurement matrix used in the experiment is 0.8, and the size of $\Phi$ is $51 \times 64$. The iteration stop conditions of the convex optimization Newton-SL0 [7] reconstruction algorithm are set as: when the maximum number of internal cycles $L_{\text{max}} = 2$ and iteration error is less than $\delta = 7.5 \times 10^{-13}$, the internal cycle is jumped out.

The effects of the proposed algorithm before and after azimuth ambiguity suppression are compared in Figure 6. There is partial aliasing caused by target interference near strong objects such as ships. By using the proposed suppression method in this paper, a clean and clear image can be obtained as Figure 6 shown, and most of the interference energy is removed and the signal-to-noise ratio is improved.

![Figure 6. TerraSAR data ambiguity suppression results](image)

5. Conclusion
An efficient azimuth ambiguity suppression algorithm was proposed for SAR imaging. It consists of two parts: VS-KSVD dictionary learning and compressed sensing. Based on the statistical of characteristics of variance, the image blocks classification can be carried out in KSVD dictionary learning and CS reconstruction, which achieves the removal of most ambiguity energy. As demonstrated by point target simulation and real data results, the proposed algorithm performed well in terms of both
imaging quality and efficiency. As a result, the better image quality can be obtained by this method. Furthermore, it provides a brand new kind solution to suppress azimuth ambiguity in the sparse dictionary field with well performance.

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References
[1] Baebaroossa S, Levrini G. An antenna pattern synthesis technique for spaceborne SAR performance optimization[J]. IEEE Tran. GEO sci. Remote Sensing, 1991, 29(2): 254-259.
[2] Zhang Z, Wang Z S. On Suppressing Azimuth Ambiguities of Synthetic Aperture Radar by Three Filters[A]. Proceedings of CIE International Conference on Radar[C]. IEEE, 2001: 624-626.
[3] Xiao P Wu Y, Yu Ze, et al. Azimuth ambiguity suppression in SAR images based on compressive sensing recovery algorithm[J]. Journal of Radars, 2016, 5(1): 35-41.
[4] Aharon M, Elad M, Bruckstein A M, K-SVD: An algorithm for designing of vercomplete dictionaries for sparse representation[J]. IEEE Trans. on Signal Processing, 2006, 54(11): 4311-4322.
[5] Donoho D L. Compressed sensing[J]. IEEE Transactions on Information Theory, 2006, 52(4): 1289-1306.
[6] Ender J H G. On compressive sensing applied to radar[J]. Signal Processing, 2010, 90(5): 1402-1414.
[7] Nhat .V.D.M., Challa .S., et al. Efficient Projection for Compressed Sensing[A]. 2008 7th IEEE/ACIS International Conference on Computer and Information Science, 2008, 322-327.