The Research on Denoising of SAR Image Based on Improved K-SVD Algorithm

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Abstract. SAR images often receive noise interference in the process of acquisition and transmission, which can greatly reduce the quality of images and cause great difficulties for image processing. The existing complete DCT dictionary algorithm is fast in processing speed, but its denoising effect is poor. In this paper, the problem of poor denoising, proposed K-SVD (K-means and singular value decomposition) algorithm is applied to the image noise suppression. Firstly, the sparse dictionary structure is introduced in detail. The dictionary has a compact representation and can effectively train the image signal. Then, the sparse dictionary is trained by K-SVD algorithm according to the sparse representation of the dictionary. The algorithm has more advantages in high dimensional data processing. Experimental results show that the proposed algorithm can remove the speckle noise more effectively than the complete DCT dictionary and retain the edge details better.

1. Introduction

SAR is a coherent system capable of producing over-resolution remote sensing images. The SAR images are processed by processing the amplitude and phase of the received continuous signals. The SAR has all-weather, all-weather, multi-band and multi-polarization modes of operation, Variable side-view, strong penetration and high-resolution features make SAR images widely used in industry, civil and military applications. SAR images are often polluted by some noises and seriously affect the quality of the images, which makes the SAR image processing very difficult. Therefore, in the image processing, the suppression of noise is particularly important. At present, the commonly used filtering technology mainly includes spatial domain filtering, transform domain filtering and K-SVD noise suppression based on signal redundancy sparse representation [1,2,3]. The processing effect of spatial domain filtering technology depends largely on the selection of the filtering window, and it is difficult for the image to retain the image details after the restoration, which has the problem of edge blurring. Frequency-domain filtering technology first transform the image, Then transform coefficients are filtered in the frequency domain, The last inverse transform to the time domain, The technique is superior to the spatial domain processing technique at the edge of the image, but the Gibbs effect often appears in the uniform area and the edge in the processed image [4,5]. The research of literature [6,7] shows that the K-SVD algorithm based on dictionary learning algorithm can effectively preserve the speckle noise while preserving the edge and detail of the image, and the algorithm has a good adaptive

In this paper, we use this algorithm to denoise noisy SAR images.

2. K-SDV algorithm
The K-SDV algorithm is a process of approximately sparse representation of a signal $X$ under a set of bases, the algorithm is implemented by alternating the two steps of the sparse representation of the current dictionary and the updating of the dictionary using the sparse system. The improved K-SDV algorithm also uses the dictionary $D$ as the sparse signal $X$ by the training signal $Y$. Fixed $X$ unchanged, and then look for a better training dictionary $D$ [8,9].

Algorithm process is as follows:

Let the training sample set $Y = [y_1, y_2, y_3, ..., y_N]$, the original signal $X$, the sparsity $K$, the initialization dictionary $D = D_0$, the number of iterations $k = 1$;

Step 1: Update the dictionary. Solve equation (1) by greedy algorithm and look for support set $w_k$.

$$w_k = \{i | 1 \leq i \leq K, x^k_f(i) \neq 0\}$$

s.t. $\forall i, \|x_i\| \leq K$  \hspace{1cm} (1)

Step 2: Calculate the error $E_k$.

$$E_k = Y - \sum_{j \neq k} d_j X_j^T$$  \hspace{1cm} (2)

Step 3: Remove $E_k$ zero input to get $E^k_R$.

$$E^k_R = E^k_k \Omega_k$$ \hspace{1cm} (3)

Step 4: Perform SVD decomposition on $E^k_R$ to obtain:

$$E^k_R = UD\nu^T$$ \hspace{1cm} (4)

The dictionary is updated, where $d_k$ in the first row of $U$ is $\Omega_k$ optimized, while the sparse vector $X^k_R$ is updated and the product of the first column of $V$ and $\Delta(1,1)$ is selected.

Step 5: After obtaining the dictionary $D$, $k = k + 1$. At this time, the update of one column in $D$ is completed, and the columns in $D$ are updated one after another according to the method from Step 1 to Step 4 to obtain the updated dictionary $D$.

K-SVD algorithm flow shown in Figure 1.

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3. SAR image speckle model

The K-SVD algorithm is suitable for zero-mean additive speckle noise and has no significant effect on the multiplicative speckle noise existing in SAR images, and smoothes phenomenon. In order to overcome this problem, the SAR image can be logarithmically transformed, the multiplicative noise transformed into additive, then the K-SVD algorithm is used to denoise the changed image, However, the mean of image noise after logarithmic change is non-zero, the result is that the denoised SAR image can not maintain the original radiation characteristics well. this paper, the speckle model of SAR image is used to make up for the shortcomings of the logarithmic transform in converting the multiplicative model into the additive model [10,11,12].
SAR image multiplicative speckle can be expressed as:

\[ y = x^n n \]  \hspace{1cm} (5)

Where \( n \) is a coherent noise with mean 1 and variance \( \sigma_n^2 \), \( y \) denotes the observed signal, \( x \) is the original signal.

From (5) a signal-dependent additive noise model of (6) can be obtained.

\[ y = x \cdot n = x + x(n - 1) = x + \tilde{n} \]  \hspace{1cm} (6)

Where \( \tilde{n} \) is the phase-add noise of signal \( x \).

Due to the signal and noise are two mutually independent stochastic processes, all of the signal obtained for the mean and variance of \( x \):

\[ \mu_x = E(x) = \frac{E(y)}{E(n)} = E(y) = \mu_y \]  \hspace{1cm} (7)

\[ \sigma_x^2 = \frac{(\sigma_y^2 - \sigma_n^2)}{\sigma_n^2 + 1} \]  \hspace{1cm} (8)

The average of the signal-dependent noise \( \tilde{n} \) is:

\[ E(\tilde{n}) = E(x)E(n - 1) = 0 \]  \hspace{1cm} (9)

At this moment, \( \tilde{n} \) can be regarded as the additive noise of the signal \( x \), the purpose of restraining the speckle is to remove \( \tilde{n} \) from the observed signal.

4. Improved algorithm for image denoising method

If the original image is contaminated by noise, it can be expressed as \( Y = X + n \), \( Y \) is the observed signal, \( X \) is the no-noise signal and \( n \) is the noise. The goal is to image denoising noise-free signal recovery signal \( Y \) from the observation \( X \). The processing of the algorithm is as follows: Firstly, \( X \) is initialized, \( X = Y \) and \( D \) are DCT dictionaries, and the approximate solution of each small image is obtained by OMP algorithm. Secondly, the dictionary is upgraded, the optimal \( D \) is found by K-SVD algorithm, and the sparse representation of approximate image is obtained. Finally, Orthogonal Matching Pursuit algorithm is used to reconstruct the original image and remove noise [13].

Algorithm steps are as follows:

1. Input noisy image;
2. Loop: initialize the number of iterations \( K \), \( k = 1 \);
3. noise image block;
4. training dictionary;
5. judge whether the number of iterations is satisfied; Not satisfied: \( k = k + 1 \);
6. Iteration over;
7. OMP algorithm reconstructs the image; outputs the denoising image.

After partitioning the noisy image, each subgraph is sparsely represented in the dictionary \( D \) with a given dictionary \( a \), \( a = \{a_1, a_2, ..., a_k\} \). The K-SVD denoising algorithm firstly performs training on the dictionary containing the noisy subgraph \( y \) and then reconstructs the non-noisy image \( X \) according to the obtained dictionary. This process can be expressed as the optimization process of equation (10).

\[ \bar{X} = \arg \min_{X,DA} \{ \lambda \| Y - X \|_2^2 + \sum_p \| a_p \|_0 + \sum_p \| Da_p - R_pX \|_2^2 \} \]  \hspace{1cm} (10)

In the formula, \( \bar{X} \) is a denoised image, \( \lambda \) is a Lagrange factor, and \( R_p \) is a matrix of subgraph \( p \).

Iteratively perform sparse coding and dictionary update of K-SVD algorithm. Sparse coding using matching pursuit algorithm to solve equation (11).

\[ \forall p: \min \| a_p \|_0 \text{ s.t. } \sum_p \| Da_p - R_pX \|_2^2 \leq (c\sigma^2) \]  \hspace{1cm} (11)

Among them, \( a_p \) is a sparse representation of subgraphs.

The dictionary update phase is to define a set of representation of any row in the matrix, using equation (2) to calculate the error \( E_k \) and applying singular value decomposition equation (3) to update the sparse coefficient.
After obtaining the training dictionary by K-SVD algorithm, each subgraph is sparsely represented. The denoised image $\hat{X}$ can be obtained by equation (12).

$$\hat{X} = \arg \min_{X} \{ \lambda \| Y - X \|_2^2 + \sum_p \| D_{ap} - R_{ap} X \|_2^2 \}$$  (12)

Calculated:

$$\hat{X} = (\lambda I + \sum R_p^T R_p)^{-1}(\lambda I + \sum R_p^T D_{ap})$$  (13)

Where, $I$ is the identity matrix.

5. Quality evaluation index
In this paper, PSNR (Peak Signal to Noise Ratio) [14], an objective standard for evaluating image quality. PSNR is defined as the mean square error between the original image and the processed image relative to a logarithmic value of $(2^n - 1)^2$, Unit dB, expressed as:

$$\text{PSNR} = 10 \times \log_{10} \left( \frac{(2^n - 1)^2}{\text{MSE}} \right)$$  (14)

MSE is the mean square error between the original image and the processed image.

$$\text{MSE} = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [f - f']^2$$  (15)

Among them, $M \times N$ is the image size, $f$ represents the original image, $f'$ represents the degraded image.

Visible, MSE larger value indicates a serious image distortion, PSNR larger the value, the more less distortion.

6. Simulation experiments and results analysis
Two $512 \times 512$ synthetic aperture radar images were selected as the test images, and the image was smeared with standard noise $\sigma$. The K-SVD algorithm was used to verify the denoising effect of the algorithm. The original image is divided into small pieces of $8 \times 8$, and the base dictionary used by the K-SVD algorithm is a DCT dictionary with a fixed initial value. Under different standard deviations of noise, the noisy images are respectively denoised by the complete DCT dictionary and K-SVD method. The number of K-SVD training iterations is 20, Figure 2 (a), Figure 3 (a) for the training dictionary, The denoising effect is shown in Figure 2 (d), Figure 2 (e), Figure 3 (d) and Figure 3 (e). The PSNR values under two different algorithms are shown in Table 1, and the denoising time is shown in Table 2.

| $\sigma$/dB | 10    | 20    | 50    | 100   |
|-------------|-------|-------|-------|-------|
| Original image 1 |       |       |       |       |
| Noisy picture | 39.61 | 35.91 | 31.05 | 27.66 |
| DCT dictionary | 40.01 | 36.33 | 31.33 | 28.08 |
| K-SVD        | 40.22 | 36.52 | 31.61 | 28.20 |
| Original image 2 |       |       |       |       |
| Noisy picture | 31.96 | 29.17 | 26.55 | 20.18 |
| DCT dictionary | 33.42 | 30.56 | 27.28 | 22.56 |
| K-SVD        | 33.78 | 30.85 | 27.65 | 22.66 |

Table 1. PSNR values under two denoising methods with different noise standard deviations

(a) Training matrix  (b) Original image 1
(c) noisy images  (d) DCT  (e) K-SVD

Figure 2. SAR image denoising effect 1

(a) Training matrix  (b) Original image 2

(c) noisy images  (d) DCT  (e) K-SVD

Figure 3. SAR image denoising effect 2

Table 2. Time - consuming Comparison of Two Denoising Algorithms with Different Noise Standard Deviations

| | Original image 1 | Original image 2 |
|---|---|---|
| Running time/s | DCT dictionary | K-SVD |
| Original image 1 | 50.23 | 312.21 |
| K-SVD | 46.34 | 296.98 |
| Original image 2 | 40.69 | 152.32 |
| DCT dictionary | 14.36 | 49.88 |
| K-SVD | 9.21 | 26.31 |
| 100 | 109.7 | 20.51 |

Table 2. Time - consuming Comparison of Two Denoising Algorithms with Different Noise Standard Deviations

Seen in figure 2 and figure 3, superimposed on the original image after the standard deviation \( \sigma = 10 \) to obtain speckle noise noisy images, respectively dictionary DCT method and K-SVD algorithm to suppress noise. As can be seen from the figure, compared with the DCT dictionary denoising effect, the K-SVD algorithm can recover the image details well except the speckle noise, and improves the PSNR value of the denoising image. The experimental data in Table 1 also verify this conclusion. The experimental data in Table 2 shows that the denoising time of DCT dictionary is the shortest, and the denoising time of K-SVD algorithm is longer than that of DCT dictionary denoising, but in the meantime, the denoising performance is improved.

7. Conclusion
Compressed sensing theory can meet the needs of a particular transform domain sparse conditions, the signal can be expressed with a small amount of observation data, the theory can be combined with other areas to solve some new problems. In this paper, to solve the problem of the inconvenience caused by the noise in the SAR image to the subsequent processing of the image, the K-SVD algorithm is applied to the image denoising. The reconstructed image after de-manning has a higher peak signal-to-noise ratio, and the edges and details of the image are better preserved, which further improves the visual effect of the image.

Acknowledgments
This work was supported by the Scientific Research Project of Anhui Xinhua College No. 2017zr003 and the domestic outstanding young backbone talents in universities of visiting program No. gxgnfx2018070.

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