Towards Better Understanding of SAR Image: Feature Enhancement via Non-Local and Low-Rank Approach

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Abstract. Feature enhancement for synthetic aperture radar (SAR) images is of great significance for their understanding and interpretation. In this work, we aim to address the issues by introducing the low-rank constraint into non-local means framework, dubbed NL_LR. The non-local means framework takes advantages of the non-local self-similarity of SAR images, which makes this approach efficient in noise suppression and preservation of structures and resolution. When estimating the value of the target pixel, a low-rank matrix can be constructed with vectorization of similar image patches. By exploiting this low-rank prior of patch matrix and decomposition of sparse and low-rank matrices, the denoised low-rank patch matrix is more accurate which will also increase the accuracy of feature enhancement. Afterwards, the numerical algorithm is designed. Numerical experiments on the real-data of SAR images show that our novel method can reduce the noise in homogeneous areas especially speckle noise efficiently, preserve the structural feature, especially edges and textures and improve the resolution at the same time. Visually, the result of the proposed method is obviously improved.

Keywords. SAR image; feature enhancement; non-local; low-rank.

1. Introduction

Synthetic aperture radar (SAR) is a high-resolution remote sensing technique, and is widely applied in numerous fields such as environmental monitoring, earth-resource mapping, and military systems [1]. However, due to the errors caused by the imaging system and the signal propagation, the quality of SAR images decreases and the features degrades. Feature enhancement can highlight these features, which makes SAR images easier and more accurate to interpret and recognize. Therefore, feature enhancement for SAR images is of great significance for SAR image applications.

The existing methods for feature enhancement can be divided into several categories, such as the multi-look approaches which sacrificing the resolution [2, 3], filtering methods based on local statistic characteristics which cannot protect strong scatters or structural features well [4-12], and the multi-resolution methods [13]. In addition, the regularization methods [14] and partial differential equation (PDE) methods [15] are also common. However, the regularization methods are not effective in speckle suppression and may lead to the loss of weak targets while PDE methods are insufficient in resolution improvement and target enhancement. Buades proposed the non-local means (NL-means) and the estimated value of target pixel is a non-local averaging of all similar pixels in the image, which is more favorable for the textured or periodic case due to the nature of the algorithm [16]. The problem of sparse and low-rank matrix decomposition was highlighted and intensively studied by [17] and alternating direction methods to solve the problem were proposed in [18]. Since then, methods based on non-local
and low-rank prior are widely used in compressive sensing and image processing. Dong proposed a non-local low-rank regularization approach and explored its application into compressive sensing of both photographic and MRI images [19]. Based on edge detection and neural network, Chen proposed a non-local low-rank matrix completion method and applied the non-local inter-pixel correlation to image interpolation effectively [20]. Liu proposed a super resolution reconstruction method for single image based on non-local sparse and low-rank regularization [21]. Wen proposed a joint adaptive patch sparse and group low-rank model and develop an image restoration framework based on the model [22].

In this paper, we directly implement feature enhancement for SAR images in space domain. The novel model is established by introducing the low-rank constraint into NL-means framework, dubbed NL_LR. Figure 1 shows the schematic diagram of the approach. Due to the non-local self-similarity, there are many neighborhoods similar to neighborhood of the target pixel. With vectorization of these similar image patches, the row of the patch matrix is the vector of similar image patch and the patch matrix is low-rank. Assuming the patch matrix is noisy and the noise is sparse, decomposition of sparse and low-rank matrices is carried out to obtain the low-rank component, namely the denoised patch matrix. Based on the denoised patch matrix, more accurate weights and values of pixels with similar neighborhoods will be used to estimate the value of target pixel.

![Schematic diagram of the approach.](image)

The paper is structured as follows: In Section 2, we give an overview of weighted NL-means method and propose the novel SAR image feature enhancement approach based on non-local and low-rank constraints. Numerical experiments are provided in Section 3 to illustrate the effectiveness of our proposed method.

2. Feature Enhancement via Non-Local and Low-Rank Approach

In this section, the novel feature enhancement approach for SAR images is proposed based on non-local and low-rank constraints. Sparse and low-rank matrix decomposition is applied on the patch matrix constructed by the non-local similar image patches. Finally, we show the algorithm for numerical solution.

2.1. Weighted Non-local Means

NL-means method takes the non-local averaging of all similar pixels in the image as the value of target pixel [16]. Namely, the value of target pixel is estimated as the weighted mean of values of pixels whose neighborhood is similar to neighborhood of the target pixel.
For a given image $g$, the estimated value of target pixel $x_i$ is computed as a weighted average of all the pixels in the image

$$NL_g(x_i) = \sum_j w(x_i, x_j) g(x_j),$$

(1)

where $g(x_j)$ is the value of pixel $x_j$ in the given image $g$, $w(x_i, x_j)$ is the weight between pixels $x_i$ and $x_j$ to measure the similarity between them, and satisfies the usual conditions $0 \leq w(x_i, x_j) \leq 1$ and $\sum_j w(x_i, x_j) = 1$. It shows that the feature-enhanced value at $x_i$ is a weighted mean of the values of all pixels whose neighborhood is similar to neighborhood of $x_i$. For the convenience of discussion, $N_i$ is defined as a square neighborhood with its central pixel $x_i$ and fixed size, and $v(\cdot)$ refers to the vectorization of matrices. So that $v(N_i)$ represents the intensity gray level vector of neighborhood of $x_i$. Choose the weighted Gaussian Euclidean distance, namely

$$d(x_i, x_j) = \|v(N_i) - v(N_j)\|_{L^a}^2$$

(2)

where $a > 0$ is the standard deviation of the Gaussian kernel. Its properties are briefly discussed in [16]. Then, the weight can be represented as

$$w(x_i, x_j) = \frac{1}{Z(i)} e^{-\frac{\|v(N_i) - v(N_j)\|_{L^a}^2}{\sigma^2}}$$

(3)

where

$$Z(i) = \sum_j e^{-\frac{\|v(N_i) - v(N_j)\|_{L^a}^2}{\sigma^2}}$$

is a normalizing constant to ensure $\sum_j w(x_i, x_j) = 1$, and $h$ acts as a filtering parameter which controls the decay of the exponential function. Considering the relationship between the exponential function and the weight, $h$ controls the decay of the weights as a function of the Euclidean distances. It shows that the NL-means not only compare the values of the single central pixels but also the values of pixels in the neighborhood. This means that the geometrical configuration in the whole neighborhood is also compared to make the method more robust.

2.2. Feature Enhancement via Non-Local and Low-Rank Approach

Since the neighborhoods are similar to neighborhood of $x_i$, the matrix formed by their vectorizations is low-rank. $P(i)$ is the patch matrix, which is a low-rank matrix consisting of the neighborhood of $x_i$ and its similar neighborhoods

$$P(i) = \begin{bmatrix} v(N_i) \\ v(N_j) \\ \vdots \\ v(N_{nk}) \end{bmatrix}$$

(4)
Assuming the noise in $\mathbf{P}(i)$ is sparse, $\mathbf{P}(i)$ is consisted of a low-rank matrix and a sparse matrix. The problem of sparse and low-rank matrix decomposition is discussed in [18]. As a result, $\mathbf{P}(i)$ is recoverable for its sparse and low-rank components and they can be recovered by solving the following convex optimization problem:

$$\begin{align*}
\min_{\mathbf{P}'(i), \mathbf{e}(i)} & \left\| \mathbf{P}'(i) \right\|_F + \gamma \left\| \mathbf{e}(i) \right\|_1 \\
\text{s.t.} & \mathbf{P}'(i) + \mathbf{e}(i) = \mathbf{P}(i)
\end{align*}$$

(5)

where $\mathbf{P}'(i)$ is the denoised low-rank component of $\mathbf{P}(i)$, $\mathbf{e}(i)$ is the noise of $\mathbf{P}(i)$ which is sparse, and $\gamma > 0$ is the regularization parameter which makes a balance between the sparse and low-rank components. $\| \cdot \|_F$ refers to the nuclear norm which is the sum of all singular values, and $\| \cdot \|_1$ represents the $l_1$ norm which is the component-wise sum of absolute values of all entries. The nuclear norm constrains the low-rank property of $\mathbf{P}'(i)$ while the $l_1$ norm constrains the sparsity of $\mathbf{e}(i)$. With less effect of noise, the value of the target pixel estimated from $\mathbf{P}'(i)$ will be more accurate.

To sum up, the feature enhancement method based on non-local and low-rank constraints can be expressed as

$$\begin{align*}
\text{NL}_{-LR} \hat{g}(x_i) &= \sum_j w'(x_i, x_j) \mathbf{g}(x_j) \\
\min_{\mathbf{P}'(i), \mathbf{e}(i)} & \left\| \mathbf{P}'(i) \right\|_F + \gamma \left\| \mathbf{e}(i) \right\|_1 \\
\text{s.t.} & \mathbf{P}'(i) + \mathbf{e}(i) = \mathbf{P}(i)
\end{align*}$$

(6)

where $\mathbf{g}(x_j)$ is the denoised value of pixel $x_j$, and $w'(x_i, x_j)$ is weight between $x_i$ and $x_j$ computed based on the denoised patch matrix $\mathbf{P}'(i)$.

The algorithm can be briefly summarized as follows:

| Algorithm for feature enhancement |
|-----------------------------------|
| **Input** $\hat{g} \in \mathbb{R}^{mn}$ |
| For $i = 1:m \times n$ |
| Find the neighborhoods of $x_i$ and the similar neighborhoods |
| Construct $\mathbf{P}(i)$ |
| Use LRSD for the low-rank component of $\mathbf{P}(i)$, namely $\mathbf{P}'(i)$ |
| Compute the weights and estimate the value of $x_i$ based on $\mathbf{P}'(i)$ |
| **End** |
| **Output** $\hat{g}$ |

3. Numerical Experiments

In this section, our novel feature enhancement approach is applied to the RADARSAT-2 data of Vancouver in April 2008 and data of the Pentagon provided by Sandia National Laboratories, and then compare the results with the existing methods, such as the sparse regularization method, PDE method, and the enhanced Wiener filter method (EWF) [23] to evaluate its performance.

3.1. Evaluation of Image Features

In this subsection, four indexes are used to evaluate the performance of different approaches for SAR image feature enhancement.
Spatial resolution is the number of pixels which is corresponding to the relative 3-dB mainlobe width. When the value is smaller, the resolution is higher. Equivalent number of looks (ENL) is an index to describe the degree of speckle suppression. When ENL is larger, the speckle is reduced more efficiently. Edge preservation index (EPI) is an index to describe the effect of structure preservation. When EPI is larger, the structures are preserved better. Target-to-clutter ratio (TCR) is an index to measure the contrast of targets and clutters. When TCR is larger, the clutter is suppressed more efficiently. Formulas can be seen in Chapter III of [24] and its references of further details and extensions, which will not be repeated here.

3.2. Experimental Results and Analysis

The original SAR image dataset 1 is shown in figure 2, from which it can be seen that the speckle noise and defocus is very heavy. Besides, the feature-enhanced results of the image dataset 1 by different approaches are also presented in figure 2 with a zoomed-in region shown in figure 3. It shows that all the methods enhance the features to some extent. The novel method reduces the noise sufficiently, especially in the homogeneous areas and dark areas, but the targets in the homogeneous areas are well-preserved and even enhanced. At the same time, the structural feature such as edges and textures are also well-preserved. In addition, the sidelobe is suppressed and the image resolution is improved to a certain extent. However, the sparse regularization method sharpens the target at the cost of loss of weak targets and denoising, and the PDE method cannot preserves the resolution while suppressing the speckle noise. The EWF method reduces the noise especially in the homogeneous areas, but causes serious blurring. Table 1 shows the experiment indexes of the original SAR images and the feature-enhanced ones by different approaches. From the point of view of indexes, all the indexes of our proposed approach are much better than that of the original. Compared with the original image, the novel approach increases the spatial resolutions by 10.16% in azimuth and 30.44% in range, ENL by 3.32, EPI by 12.00% and TCR by 0.59dB. It is remarkable that, although our approach does not achieve the first place according to ENL and EKI, it greatly increases the resolution, EKI and TCR at a small cost of ENL when compared with the PDE method and the EWF method, and it greatly increases the resolution, ENL and TCR at the cost of EKI when compared with the regularization method. This is what we except. That is to say, our proposed approach can efficiently take a compromise among speckle noise suppression, resolution improvement and structure preservation such as edges and textures.

Figure 2. Comparison of feature-enhancement images of dataset 1 by different methods. (a) original image, (b) NL_LR, (c) regularization, (d) PDE, (e) EWF.

Figure 3. Zoomed-in of feature-enhancement regions in the red block of dataset 1 by different methods. (a) original image, (b) NL_LR, (c) regularization, (d) PDE, (e) EWF.
Table 1. Experiment indexes of image 1.

|          | Resolution Azimuth | ENL  | EKI  | TCR (dB) |
|----------|--------------------|------|------|----------|
| original | 2.09               | 3.84 | 1    | 26.40    |
| NL_LR    | 1.89               | 7.16 | 1.12 | 26.99    |
| Reg      | 2.06               | 0.72 | 1.38 | 22.48    |
| PDE      | 2.05               | 8.48 | 0.77 | 26.71    |
| EWF      | 2.45               | 9.02 | 0.58 | 26.90    |

Figure 4 shows the original SAR image dataset 2, whose quality and features are severely degraded, and the feature-enhanced results by different methods. Figure 5 illustrates the zoomed-in. Similarly, all the methods can accomplish the feature enhancement. The regularization method can enhance the strong scattering targets, while it acts like truncation, which leads to loss of information with low gray values. The PDE method reduces the noise but it causes image blurring and resolution decrease. The EWF method can suppress the noise efficiently at a large cost of resolution and the single point targets are almost lost. Our proposed method sufficiently suppresses the noise and improves the resolution, which highlights the edges of large homogeneous areas with different gray value level and visually make the edges and textures more obvious. Table 2 shows the experiment indexes of the original SAR images and the feature-enhanced ones by different approaches. From the point of view of indexes, all the indexes of our proposed approach are much better than that of the original at an acceptable loss of EKI. Compared with the original image, our proposed approach increases the spatial resolutions by 21.50% in azimuth and 4.34% in range, ENL by 2.70 and TCR by 0.57dB while EPI decreases 3.58% which is acceptable. When compared with the results of the other two methods, it can make a balance among speckle suppression in the homogeneous areas, edge preservation and even enhancement of strong scatter points.

Figure 4. Comparison of feature-enhancement images of dataset 2 by different methods. (a) original image, (b) NL_LR, (c) regularization, (d) PDE, (e) EWF.

Figure 5. Zoomed-in of feature-enhancement regions in the red block of dataset 2 by different methods. (a) original image, (b) NL_LR, (c) regularization, (d) PDE, (e) EWF.
Table 2. Experiment indexes of image 2.

|            | Resolution | ENL  | EKI  | TCR (dB) |
|------------|------------|------|------|----------|
| original   | 1.98       | 1.27 | 7.63 | 24.24    |
| NL_LR      | 1.62       | 1.21 | 10.33| 24.81    |
| Reg        | 1.77       | 1.15 | 0.26 | 21.52    |
| PDE        | 1.63       | 1.23 | 10.03| 24.39    |
| EWF        | 2.61       | 1.79 | 10.21| 23.00    |

4. Conclusion

In this paper, we investigate a novel feature enhancement approach for SAR images based on non-local and low-rank constraints. In our work, the low-rank constraint is introduced into NL-means framework. The NL-means framework takes advantage of the non-local self-similarity of SAR images, which will make this feature enhancement approach better in noise suppression and preservation of structures and resolution. Besides, when estimating the value of the target pixel, a low-rank patch matrix can be constructed with vectorization of neighborhood of the target pixel and the similar neighborhoods. By exploiting this low-rank prior and decomposition of sparse and low-rank matrices, the denoised low-rank patch matrix is more accurate than the original one, so that this will also increase the accuracy of the novel approach.

The experiment results show that the performance of the novel approach is much better when compared with the sparse regularization approach and PDE approach. The proposed feature enhancement approach for SAR images based on non-local and low-rank constraints can suppress the noise sufficiently in homogeneous areas and preserve the structural feature, especially edges and textures. What’s more, it can preserve and even improve the resolution at the same time. And visually, the result of the proposed method is obviously better than results of the other two.

Despite the results above, we will further improve our research in several aspects. Considering the computational complexity, fast algorithms need to be designed. Based on the NL-means framework, the parallel implementation of the algorithm can greatly reduce the computational cost. Besides, we will take advantage of different types of low-rank prior, such as the low-rank tensor consisting of similar image patches to improve the performance of feature enhancement. What’s more, taking multiple SAR images of the same area as the original images to be feature-enhanced, and fusing information in multiple SAR images may further improve the performance.

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