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Group Sparse Representation Based Dictionary Learning for SAR Image Despeckling

SU LIU[1,2], GONG ZHANG[1,2], (Member, IEEE), AND WENBO LIU[3]
[1]Key Laboratory of Radar Imaging and Microwave Photonics, Ministry of Education, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China
[2]College of Electronic and Information Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China
[3]College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

Corresponding author: Gong Zhang (gzhang@nuaa.edu.cn)

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ABSTRACT Since the sparse representation coefficients of synthetic aperture radar (SAR) images often appear in clusters with intrinsic structure, traditional sparse representation theory cannot capture this property. In this paper, the concept of group sparse representation (GSR) is utilized to exploit the intrinsic structure of SAR images. Different from traditional patch-based sparse representation theory, GSR is able to sparsely represent images in the domain of group which contains the image patches with similar structure. Based on the multiplicative speckle noise model, a novel dictionary learning algorithm based on GSR (GSR-DL) for SAR image despeckling is proposed. The proposed algorithm mainly consists of three steps. First, in order to realize the recovery of despeckled SAR image by the GSR model, a mean filter is included in the modeling process. Second, the proposed GSR-DL algorithm is used to calculate the optimal dictionary and group sparse representation coefficients. Third, the despeckled SAR image is reconstructed by the learned dictionary and coefficients. The experimental results on SAR images manifest that the proposed GSR-DL algorithm achieves a better performance than other state-of-the-art despeckling algorithms.

INDEX TERMS Image denoising, synthetic aperture radar, image representation, dictionaries, group sparse representation.

I. INTRODUCTION

SAR plays an important role in military field for situation awareness under all weather conditions, day or night. As a source of ground information, SAR images play an important role in providing powerful support to commands and decisions [1]. Because of the coherent imaging mechanism of SAR system, SAR images are seriously corrupted by speckle noise which makes it difficult to detect and recognize targets from SAR images. Speckle noise suppression is therefore essential for the understanding of SAR images [2].

In the past few years, numbers of algorithms have emerged for SAR image despeckling. Overall, there are mainly three kinds of despeckling techniques [3]: 1) statistical; 2) transformed domain based; 3) partial differential equation based. Such as Lee filter [4], MAP filter [5] and their enhanced versions, these statistical approaches calculate the value of the despeckled SAR image by using the pixels in local sliding windows based on minimum mean square error (MMSE) or maximum a posteriori (MAP) estimation criterion. Based on partial differential equation, total variation (TV) [6] algorithm and its enhanced versions achieve outstanding performance in capturing stair casing artifacts and sharper edges. Yuan and Ghanem [7] proposed TV-PADMM which solves the l_0 TV-based image restoration problem with l_0–norm data fidelity. Besides, transformed domain based despeckling methods have aroused wide concern for the past few years. Feng and Lei [8] applied date-driven tight frame and wavelet transform to SAR image despeckling. Besides, there are several interesting methods are proposed for impulse noise suppression, which are worth learning. Chen *et al.* [9] proposed a weighted couple sparse representation model in

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which the dictionary is directly trained on the noisy raw data by addressing a weighted rank-one minimization problem for better feature extraction performance. Yin *et al.* [10] proposed a novel model that uses a devised cost function involving semi-supervised learning based on a large amount of corrupted image data with a few labeled training samples. These methods reconstruct the noisy image from a large volume of imaging data by learning methods or sparse representation methods, which are quite enlightening.

Sparse representation (SR) method belongs to the second category [11], which aims to find the optimal sparse representation vectors of SAR images in transformed domain. As a powerful tool, sparse representation theory has attracted much attention and been successfully applied to image denoising [12], image classification [13] and image restoration [14]. For SAR image despeckling, Xu *et al.* [11] utilizes the nonlocal sparse model and the iterative regularization technique to denoise the log-intensity SAR image. These works mainly based on the traditional SR theory which is under the hypothesis that the nonzero coefficients appear randomly and independently. However, compared with one-dimension signals, SAR images contain lots of spatial structure information. The sparse coefficients of SAR image often appear in form of clusters with intrinsic structure which is difficult to be captured using traditional SR theory. In order to solve this problem, GSR is proposed recently [14]. Different from SR theory, GSR exploits the concept of group as the basic unit of sparse representation instead of using patches. Up to now, GSR theory has already been successfully applied to image imprinting, deblurring and image CS recovery [14]. For medical image denoising and fusion, Li *et al.* [12] proposed Dictionary learning algorithm with group sparsity and graph regularization (DL-GSGR). Sun *et al.* [13] proposed a new group sparse discriminative dictionary learning model for classification. While GSR shows better performance in various image processing applications, there are no relevant SAR image despeckling works based on GSR theory.

Motivated by this, we proposed a GSR-DL algorithm for SAR image despeckling. The proposed algorithm is initially formulated with three parts. Firstly, a filter is utilized to reduce the speckle noise and to provide the approximation of despeckled SAR image. According to related probability theory and the properties of speckle noise [1], [3], the filtered SAR image is the unbiased estimation of filtered despeckled SAR image. Hence, filtering step can guarantee the precise grouping of patches. Secondly, the proposed GSR-DL algorithm is used to calculate the optimal dictionary and coefficients. Thirdly, the despeckled SAR image is reconstructed by the obtained dictionary and coefficients. Finally, the main contributions of this paper are listed as the following:

(1) we establish the GSR model of SAR images;
(2) a mean filter is included in the modeling process to deal with speckle noise suppression and the GSR-DL algorithm is proposed to solve this optimization problem;
(3) we demonstrate experimental results by comparing the proposed GSR-DL to other five state-of-art algorithms.

The rest of this article is organized as follows. In Section 2, the theory of GSR is briefly reviewed. Then, the GSR-DL algorithm for SAR image despeckling is proposed in detail. In Section 3, experimental results on SAR Images are presented, which validate the effectiveness of GSR-DL algorithm. At last, conclusions are drawn in Section 4.

II. GSR-BASED DICTIONARY LEARNING FOR SAR IMAGE DESPECKLING

In this subsection, the group sparse representation model of SAR image is established at first.

A. GROUP SPARSE REPRESENTAITON MODEL OF SAR IMAGE

Mathematically, the vector representation of clean SAR image is denoted by $\boldsymbol{y} \in \mathbb{R}^N$, where N is the size of the whole image vector. Using sliding window with size $\sqrt{P} \times \sqrt{P}$, we extract a large number of image patches from SAR image which are the raw materials for the dictionary. The extracted image patch at location $k, k = 1, 2, \cdots, n$ is denoted by $\boldsymbol{y}_k \in \mathbb{R}^P$, where n is the total number of image patches. It is well established that the speckle noise in SAR image is characterized by the multiplicative noise model [1]. Based on this model, the speckled SAR image $\boldsymbol{x}$ is assumed to be the product of the underlying image intensity $\boldsymbol{y}$ and speckle noise $\boldsymbol{w} : \boldsymbol{x} = \boldsymbol{w}.*\boldsymbol{y}$, where $.*$ denotes the element-wise multiplication of two vectors and $\boldsymbol{w}$ is usually modeled as a white random process which has exponential distribution, with unitary mean and variance, independent of $\boldsymbol{y}$.

Aiming to explore the intrinsic structure of SAR image in a unified framework, we intend to establish the GSR model of SAR image. We assume that the SAR image can be approximated by a union of limited patch groups. As shown in Figure 1, for each reference patch $\boldsymbol{x}_i$, denoted by small green square, search the most similar patches in the training window (big red square). Then, these patches are gathered together as a group $\boldsymbol{x}_{G_i}$. Noted that, the most similar blocks are selected according to a minim Euclidian distance criterion. Under the assumption, we intend to sparse represent SAR images with these groups. Matrix $\boldsymbol{x}_{G_i}, i = 1, 2, \cdots, c$ is constructed by the patches in one group, which has the a similar structure and $\boldsymbol{x}_{G_i} \in \mathbb{R}^{L \times q_i}$, where c is the number of groups and $n = \sum_{i=1}^{c} q_i$, respectively, q_i denotes the total number of patches in group G_i. This process can be expressed in a clear and concise equation, as following

$$\boldsymbol{x}_{G_i} = \boldsymbol{R}_{G_i}(\boldsymbol{x}), \tag{1}$$

where $\boldsymbol{R}_{G_i}(\cdot)$ is an function that collects the group $\boldsymbol{x}_{G_i}$ from the speckled SAR image $\boldsymbol{x}$, respectively, the transposition of function $\boldsymbol{R}_{G_i}(\cdot)$, defined by $\boldsymbol{R}_{G_i}^T(\cdot)$ is able to put the patches back at the corresponding position in the recovered SAR image, padded with zero elsewhere. Then, the reconstruction of despeckled SAR image $\boldsymbol{x}$ from groups is expressed as

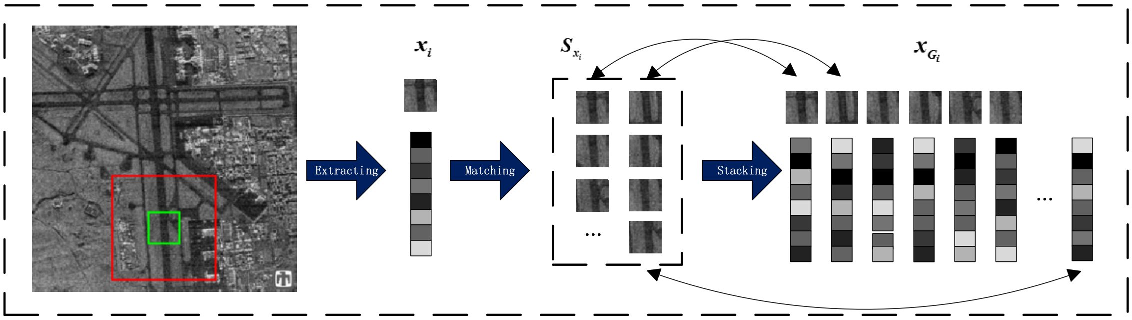


FIGURE 1. Illustrations for the group construction. Extract each patch vector x_i from image x. For each x_i, denote S_{x_i} the set composed of its c best matched patches. Stack all the patches S_{x_i} in the form of vector to construct the group, denoted by x_{G_i}.

following

$$\boldsymbol{x} = \sum\nolimits_{i=1}^{c} \boldsymbol{R}_{G_i}^T \left(\boldsymbol{x}_{G_i}\right) . \Big/ \sum\nolimits_{i=1}^{c} \boldsymbol{R}_{G_i}^T \left(1_{P\times c}\right), \tag{2}$$

where the operator character ./ denotes the element-wise division of two matrixes, and $1_{P\times c}$ is a matrix which all the elements of it are equal to 1 and the size of it is $P \times c$.

The dictionary used is denoted as $\mathbf{D}$. The sub-dictionary of $\mathbf{D}$ which has the same column as $\mathbf{D}$ in group G_i is denoted as $\mathbf{D}_{G_i}$. As above, the basic assumption of GSR model is that each group $\boldsymbol{x}_{G_i}$ can be sparsely represented by atoms of a sub-dictionary $\mathbf{D}_{G_i}$, as following

$$\boldsymbol{x}_{G_i} = \boldsymbol{D}_{G_i}\boldsymbol{\alpha}_{G_i}, \tag{3}$$

where $\boldsymbol{\alpha}_{G_i}$ is the sparse representation vector of group G_i. Based on GSR model, the recovery of despeckled image $\boldsymbol{x}$ can be formulated as following

$$\begin{aligned} \boldsymbol{x} &= \boldsymbol{D}_G \circ \boldsymbol{\alpha}_G \\ &\stackrel{def}{=} \sum\nolimits_{i=1}^{c} \boldsymbol{R}_{G_i}^T \left(\boldsymbol{D}_{G_i}\boldsymbol{\alpha}_{G_i}\right) . \Big/ \sum\nolimits_{i=1}^{c} \boldsymbol{R}_{G_i}^T \left(1_{L\times c}\right). \end{aligned} \tag{4}$$

Under the hypothesis of group sparsity constraint, the sparse representation vectors can be obtained by solving the following optimization problem

$$\hat{\boldsymbol{\alpha}}_G = \arg\min_{\alpha_G} \frac{1}{2} \left\|\boldsymbol{D}_G \circ \boldsymbol{\alpha}_G - \boldsymbol{x}\right\|_2^2 + \lambda \left\|\boldsymbol{\alpha}_G\right\|_0, \tag{5}$$

where $\hat{\boldsymbol{\alpha}}_G$ is the estimated group sparse representation vector. Substituting the multiplication noise model into this formula. The optimization function shown in Eq. (5) can be rewritten as following

$$\hat{\boldsymbol{\alpha}}_G = \arg\min_{\alpha_G} \frac{1}{2} \left\|\boldsymbol{D}_G \circ \boldsymbol{\alpha}_G - \boldsymbol{wy}\right\|_2^2 + \lambda \left\|\boldsymbol{\alpha}_G\right\|_0, \tag{6}$$

For simplicity, we utilize the expression $\boldsymbol{wy}$ to represent $\boldsymbol{w}. * \boldsymbol{y}$ without confusion. Noted that $\boldsymbol{wy}$ is not a strict matrix-vector multiplication. Since the existence of speckle noise term, this formula reconstruct the speckled SAR image $\boldsymbol{x}$ instead of despeckled SAR image $\boldsymbol{y}$. There is no chance to realize the recovery of despeckled SAR image directly by solving this equation.

B. GSR-DL FOR SAR IMAGE DESPECKLING

In order to remove speckle noise, the formation of speckle noise is discussed at first. Noted that the noise-like feature in SAR image is the true electromagnetic measurement although it is called speckle noise. SAR produces a radiation and captures the signals backscattered from a resolution cell which contains several scatterers and that no one yields a reflected signal much stronger than the others (distributed target), then the received signal can be viewed as the incoherent sum of several backscattered waves [3], $Ae^{j\phi} = \sum_k A_k e^{j\phi_k}$. Since the scatterers are much smaller than the resolution cell, the basic information about the observed scene is given by each propagation path interferes. Due to the different phases of each path, these waves may sum in a constructive or destructive way. Hence, even if the underlying reflectivity field is uniform, it appears as affected by speckle noise after the SAR imaging system.

Under the assumption that the speckle noise is termed as fully developed [15], [16], the probability density function (pdf) of received signal $\boldsymbol{x}$ can be given by the following multiplicative model, as shown in Eq. (7)

$$\boldsymbol{x} = \boldsymbol{wy} \tag{7}$$

where $\boldsymbol{w}$ is usually modeled as a white random process which has exponential distribution $p_{\boldsymbol{w}}(\boldsymbol{w}) = e^{-\boldsymbol{w}}$, with unitary mean and variance. Hence, the scattering information from interested region is carried by the average intensity or Radar Cross Section (RCS) at each speckled pixel. In order to realize the recovery of depseckled SAR image through GSR model, we enforce the mean filter to obtain the average intensity, or the scattering information contained in the speckled image. The flow diagram of GSR-DL algorithm is shown in Figure 2.

At first, the mean filter is performed on the whole image. We further discuss the influence of filtering from the view of group. We assume that there is an image patch selected from the homogeneous region of SAR image, centering at the location k. Then the average value of this image patch can be calculated as following

$$\begin{aligned} \frac{1}{2P} \sum\nolimits_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} x_i &= \frac{1}{2P} \sum\nolimits_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} w_i y_i \\ &= y_i \cdot \frac{1}{2P} \sum\nolimits_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} w_i. \end{aligned} \tag{8}$$

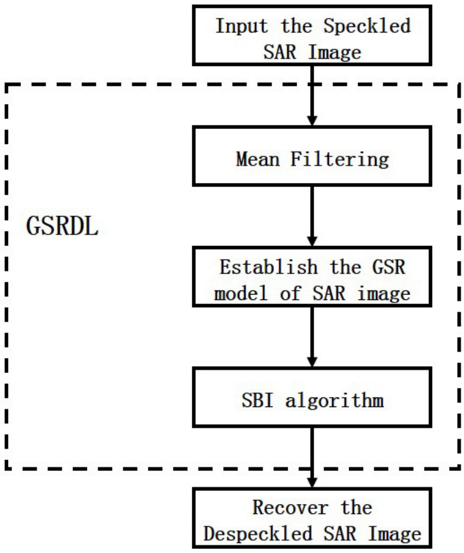


FIGURE 2. The flow diagram of GSR-DL algorithm.

As we known, $\frac{1}{2P}\sum_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} w_i$ is the unbiased estimation of the expectation of $\boldsymbol{w}$ which is 1. Hence, y_i is the pixel's value in the center of the filtered $\boldsymbol{x}_k$. In the same way, when the image patch comes from the heterogeneous region of filtered SAR image, the average value of this image patch can be calculated as following,

$$\begin{aligned}\frac{1}{2P}\sum_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} x_i &= \frac{1}{2P}\sum_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} w_i y_i \\ &= \overline{y_i}\frac{1}{2P}\sum_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} w_i, \end{aligned} \tag{9}$$

where $\overline{y_i} = \sum_{i=k-\sqrt{P}+1}^{k+\sqrt{P}} y_i$. Respectively, $\overline{y_i}$ is the pixel's value in the center of the filtered $\boldsymbol{x}_k$. Similarly, this deduced formula can be applied to all pixels. Instead of calculating the average of one image patch, we calculate the average of image patches in one group, which contains patches with similar structures. We can easily reach this conclusion, the average of group is the unbiased estimation of the despeckled image patches of the group. Generally speaking, Eq (9) shows the mechanism of mean filter. By the use of a mean filter $\mathbf{H} \in \mathbf{R}^{\sqrt{P}\times\sqrt{P}}$, the filtered SAR image $\boldsymbol{r} = \mathbf{H}\boldsymbol{w}\boldsymbol{y}$ which we obtained can be considered as the unbiased estimation of $\mathbf{H}\boldsymbol{y}$. Hence, the key role of mean filter $\mathbf{H}$ is realizing the recovery of despeckled SAR image with multiple noise model. At the same time, this mean filter $\mathbf{H}$ provides the approximation of despeckled SAR image and lead to accurate construction of training patch group.

Based on the GSR model, we substitute the filtered image $\boldsymbol{r}$ into Eq. (6). The optimization problem can be rewritten as following

$$\hat{\alpha}_G = \arg\min_{\alpha_G} \frac{1}{2}\left\|\mathbf{H}\boldsymbol{D}_G \circ \boldsymbol{\alpha}_G - \boldsymbol{r}\right\|_2^2 + \lambda\left\|\boldsymbol{\alpha}_G\right\|_1. \tag{10}$$

The framework of split Bergman iteration (SBI) [17] method was proposed for solving a broad class of l_1 regularization problem. SBI method is shown to be powerful in solving various variation models and converges very quickly when applied to some sorts of objective functions, especially for problems comprised by l_1 regularization term [18]. In this paper, we adopt SBI to solve the previous optimization problem. The constrained optimization problem discussed in SBI is formulated as following

$$\min_{\boldsymbol{u}\in \boldsymbol{R}^N, \boldsymbol{v}\in \boldsymbol{R}^M} f(\boldsymbol{u}) + g(\boldsymbol{v}), \quad s.t.\ \boldsymbol{u} = \boldsymbol{G}\boldsymbol{v}, \tag{11}$$

where $\boldsymbol{G} \in \boldsymbol{R}^{M\times N}$ and $f: \boldsymbol{R}^N \to \boldsymbol{R}$, $g: \boldsymbol{R}^M \to \boldsymbol{R}$ are convex functions. Base on SBI algorithm, we rewrite the optimization problem Eq. (10) as following

$$\arg\min_{\alpha_G, u} \frac{1}{2}\left\|\mathbf{H}\boldsymbol{u} - \boldsymbol{r}\right\|_2^2 + \lambda\left\|\alpha_G\right\|_0, \quad s.t.\ \boldsymbol{u} = \boldsymbol{D}_G \circ \boldsymbol{\alpha}_G. \tag{12}$$

We define $f(\boldsymbol{u}) = \frac{1}{2}\left\|\mathbf{H}\boldsymbol{u} - \boldsymbol{r}\right\|_2^2$ and $g(\boldsymbol{\alpha}_G) = \lambda\left\|\boldsymbol{\alpha}_G\right\|_0$. Correspondingly, the original minimization problem is split into two subproblems. Updating the value of $\boldsymbol{D}_G$ and $\boldsymbol{\alpha}_G$ iteratively until the stopping criterion is satisfied. Then, the algorithm outputs the learning dictionary $\boldsymbol{D}_G$ and the group sparse representation vector $\hat{\boldsymbol{\alpha}}_G$. Substituting results into Eq (4), the recovery of despeckled SAR image is realized through

$$\boldsymbol{x} = \boldsymbol{D}_G \circ \hat{\boldsymbol{\alpha}}_G \tag{13}$$

We further summarized the complete version of GSR-DL algorithm in Table 1. Noted that, the maximum iteration number which mentioned in Table 1 is adjustable and determined by the convergence rate.

TABLE 1. A complete version of GSR-DL algorithm.

Input: The speckled SAR image $\boldsymbol{x}$ and mean filter $\mathbf{H}$.
Step1: Filter the speckled SAR image $\boldsymbol{x}$ and obtain the filtered speckled SAR image $\boldsymbol{r}$.
Step2: Define function $f(\boldsymbol{u}) = \frac{1}{2}\left\|\mathbf{H}\boldsymbol{u} - \boldsymbol{r}\right\|_2^2$ and function $g(\boldsymbol{\alpha}_G) = \lambda\left\|\boldsymbol{\alpha}_G\right\|_0$, where $\boldsymbol{u} = \boldsymbol{D}_G \circ \boldsymbol{\alpha}_G$.
Step3: By the use of SBI algorithm, update $\boldsymbol{u}$ and $\boldsymbol{\alpha}_G$ until maximum iteration number is reached.
Output: The recovery of despeckled SAR image $\boldsymbol{y} = \boldsymbol{u} = \boldsymbol{D}_G \circ \hat{\boldsymbol{\alpha}}_G$.

III. EXPERIMENTS

In this section, several experiments are performed on reducing speckle noise, verifying the proposed GSR-DL algorithm. Three different 1-look Terra SAR-X images with size 256 × 256 are used: Horse Track with 1 meter resolution [see Figure 3(a)], Buildings with 1 meter resolution [see Figure 3(b)] and Airport with 3 meters resolution [see Figure 3(c)]. We selected a number of classical and state-of-art approaches such as Enhanced Lee filter [19], SARBM3D [20], KSVD [21], KLLD [22] and nonlocal mean (NLM) [23] filter for comparison. The Enhanced Lee filter

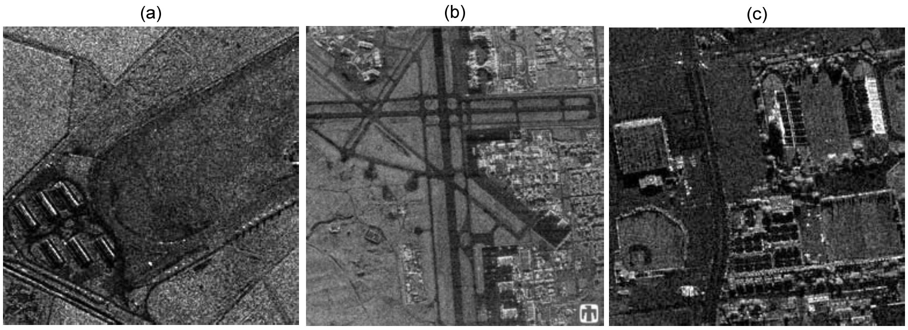


FIGURE 3. SAR images used in the experiment. (a) Horse Track (1 meter); (b) Airport (3 meters); (c) Buildings (1 meter).

is an adaptation of the Lee filter and also uses local statistics. NLM filter is a generalization of the concept of data-driven weighted averaging, in which each pixel is weighted according to a function of the Euclidean distance between a local patch centered at the reference pixel and a similar patch centered at a given neighboring pixel [24]. The SARBM3D combines the advantages of the nonlocal principle and the wavelet representation. KSVD, KLLD and GSR-DL belong to the category of transformed domain based methods, which utilize the data-driven learning dictionary for SAR image despeckling. Three sets of experiment are designed to evaluate the proposed method in different ways. The first two experiments display the intermediate results of our algorithms which clearly present the processing procedure. The last set of experiment compares the proposed method with comparing algorithms on two different SAR images.

A. PERFORMANCE INDEXES

The performance of algorithms are assessed by using several indexes. We compute the mean structural similarity (MSSIM) index to evaluate the structural similarity between two images, which is defined as following

$$\mathbf{MSSIM} = \mathbf{E}_r\left[\frac{(2\mu_\theta(\mathbf{r})\mu_{\hat{\theta}}(\mathbf{r})+C_1)(2\sigma_{\theta\hat{\theta}}(\mathbf{r})+aC_2)}{(\mu_\theta^2(\mathbf{r})+\mu_{\hat{\theta}}^2(\mathbf{r})+C_1)(\sigma_\theta^2(\mathbf{r})+\sigma_{\hat{\theta}}^2(\mathbf{r})+C_2)}\right], \tag{14}$$

where $\mu_\theta(\mathbf{r})$, $\sigma_\theta^2(\mathbf{r})$, $\mu_{\hat{\theta}}(\mathbf{r})$, $\sigma_{\hat{\theta}}^2(\mathbf{r})$ and $\sigma_{\theta\hat{\theta}}(\mathbf{r})$ are the local mean, variance and covariance of two compared images, where C_1 and C_2 are two suitable constants. The range of the MSSIM value lies in [0, 1] with the largest 1 standing for perfect quality.

The edge save index (ESI) [25] and contrast improvement index (CII) are used to evaluate the despeckling performance. CII is defined as following:

$$\mathbf{CII} = \frac{\hat{\sigma}_r^2}{\sqrt[4]{\hat{\boldsymbol{M}}_r}}\frac{\sqrt[4]{\boldsymbol{M}_r}}{\sigma_r^2}, \tag{15}$$

where $\hat{\boldsymbol{M}}_r$ and $\boldsymbol{M}_r$ are fourth-order moments of the 1-D signals for despeckled and speckled image.

B. ANALYSIS OF INTERMEDIATE RESULTS

As analyzed above, the conclusion is reached that the filtered image $\boldsymbol{r} = \mathbf{H}\boldsymbol{w}\boldsymbol{y}$ is the unbiased estimation of $\mathbf{H}\boldsymbol{y}$ and provides the approximation of despeckled SAR image which leads to accurate construction of training patch group. The first experiment is designed to verify this inference. However, the real despeckled SAR image is unknown. We use the despeckled SAR image of Buildings obtained by our proposed algorithm instead as an approximation. The mean filter used in this experiment is a 7×7 uniform kernel. The gray-scale and histogram images of speckled SAR image, despeckled SAR image, blurred speckled SAR image and blurred despeckled SAR image in Figure 4 and Figure 5.

TABLE 2. CE and MSSIM between the images in Figure 4.

	(a)& (b)	(c)& (d)
Cross Entropy	0.0828	0.0027
MSSIM	0.4955	0.9799

It is visually self-evident that the histogram images of blurred despeckled image and blurred speckled image are very similar Figure 5(c) and Figure 5(d). The CE and MSSIM is used to evaluate the difference between two images. The smaller CE means less difference between two images. As Table 2 shows that the CE between images are lowered from 0.0828 to 0.0027. The value of MSSIM indicates that the structure similarity increased from 0.4955 to 0.9799 during the filtering process. The experimental results verify the above conclusions.

The following set of experiment demonstrates the reconstruction ability of GSR-DL and displays the intermediate results. By enforcing the mean filter and GSR-DL algorithm, the despeckling process are divided into two steps. The mean filter removes lots of speckle noise with the loss of image details as shown in Figure 6(b). Due to the structurelessness of speckle noise, GSR-DL reconstructs the structural information of SAR image Figure 6(c) from the filtered speckled SAR image Figure 6(b). For better presentation, Figure 7 shows the difference images between speckled image, filtered image and reconstructed image.

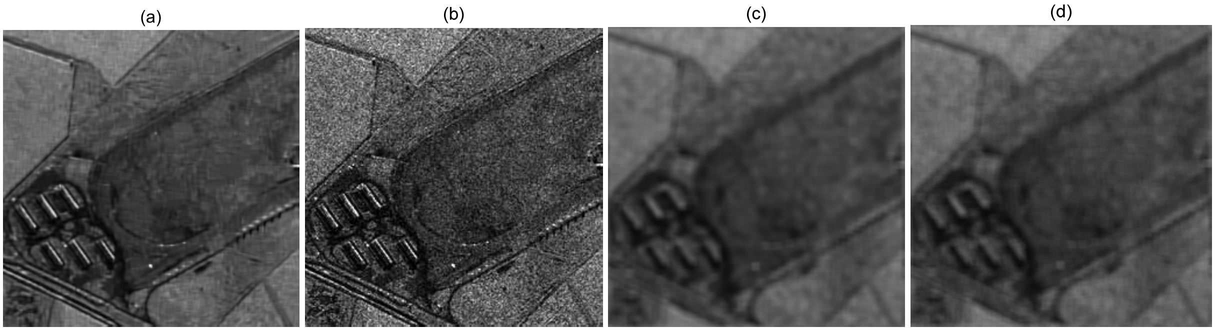


FIGURE 4. SAR images of Horse Track. (a) Despeckled image. (b) Speckled image. (c) Filtered despeckled image. (d) Filtered speckled image.

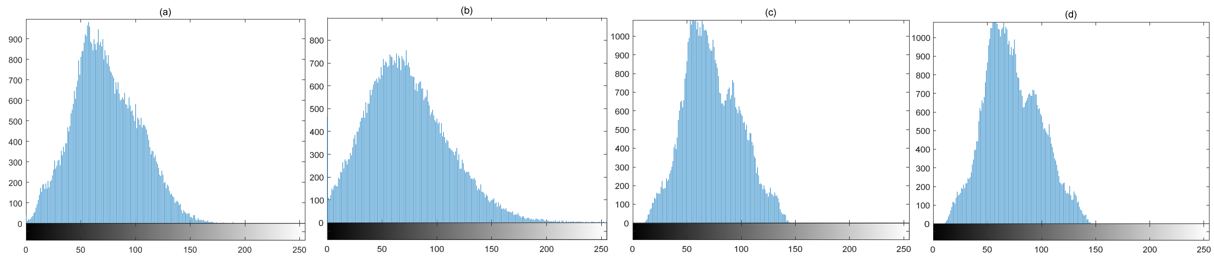


FIGURE 5. Histogram images of Horse Track. (a) Despeckled image. (b) Speckled image. (c) Filtered despeckled image. (d) Filtered speckled image.

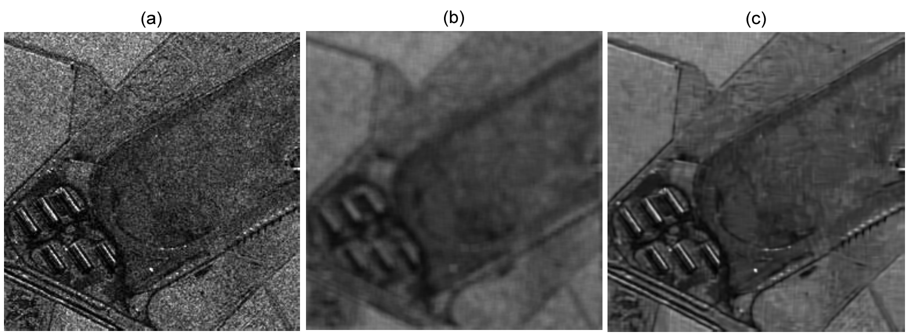


FIGURE 6. Intermediate experimental results. (a) Speckled SAR image. (b) Filtered SAR image. (c) Despeckled SAR image.

Comparing with Figure 7(a), we can see the difference image shown in Figure 7(c) recovers the structure information of SAR image and suppress the most speckle noise at the same time, as shown in Figure 7(b). By analyzing the intermediate results of our proposed algorithm, it is obvious to see the outstanding structural reconstruction ability of GSR-DL. During this process, the structure information of SAR image are recovered and the speckle noise are suppressed.

C. EXPERIMENTAL RESULTS

In this subsection, SAR images of Airport and Buildings are shown in Figure 3 are used to evaluate the despeckling effectiveness of different algorithms. For comparison, the Enhanced Lee filter, NLM filter, KSVD, KLLD and SARBM3D are utilized.

The visual comparisons of different despeckling methods are shown in Figure 8 and Figure 9. A conclusion can be reached that NLM filter [Figure 8(e)] and GSR-DL [Figure 8(f)] shows cleaner and sharper image edges than other comparing methods. While KSVD and KLLD shows better performance than the proposed algorithm in homogeneous region, they can't provide better reconstruction of the structure information of SAR image as well as GSR-DL. However, the structure information is crucial for the understanding of SAR images. The ESI and CII obtained from different methods are listed in Table 3. In particular, GSR-DL achieves the highest value of ESI and CII comparing with other despeckling methods, as labeled in bold. We also calculate the MSSIM between the despeckled SAR image obtained by different methods and speckled SAR image.

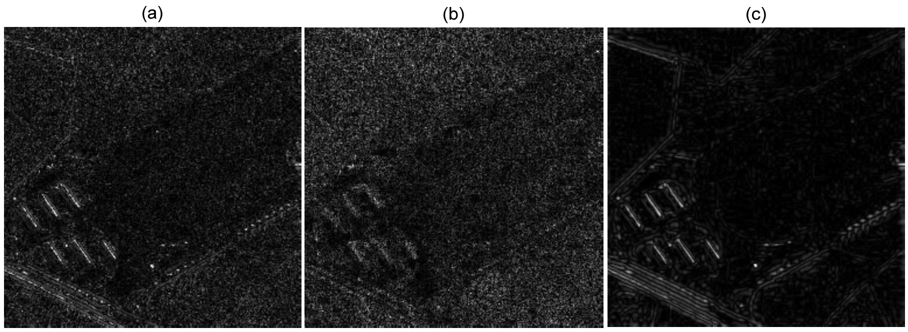


FIGURE 7. Difference image. (a) Between speckled SAR image and filtered SAR image. (b) Between speckled SAR image and despeckled SAR image. (c) Between despeckled SAR image and filtered SAR image.

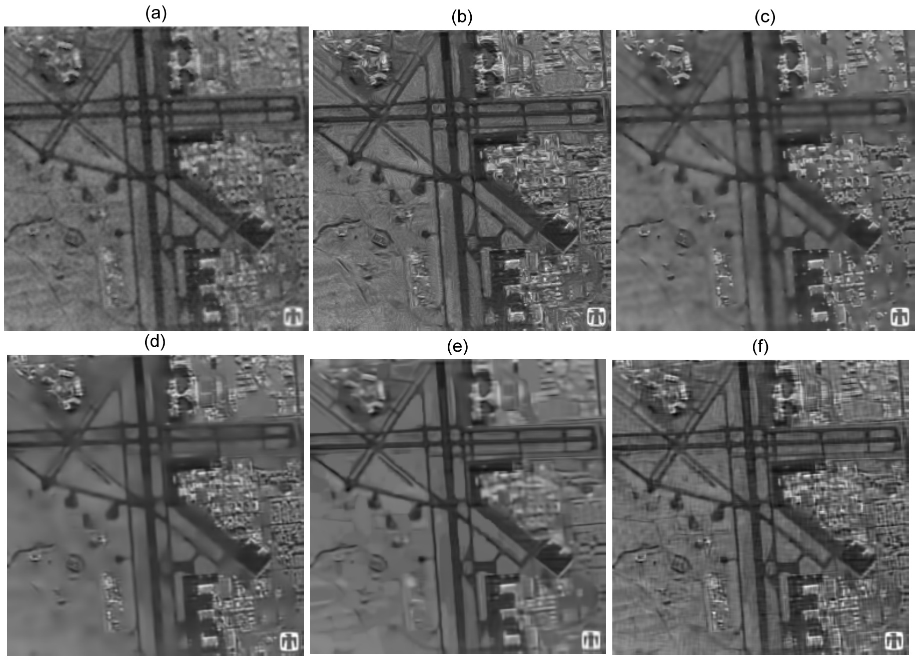


FIGURE 8. Despeckling experimental results (Airport). (a) Enhanced Lee. (b) NLM filter. (c) KSVD. (d) KLLD. (e) SARBM3D. (f) GSR-DL.

While the value of MSSIM obtained by GSR-DL is slightly lower than NLM filter, the value of ESI and CII obtained by GSR-DL are all 0.04 higher than NLM filter. The next experiment is performed on the SAR image of Horse Track, as shown in Figure 9. As listed in Table 4, similar conclusion can be reached that GSR-DL algorithm achieves the best ESI and CII. The value of MSSIM obtained by GSR-DL is 0.01 lower than NLM filter. However, compared with other learning dictionary based KSVD and KLLD algorithms, GSR-DL achieves better structural similarity, which verifies the effectiveness of our method.

The computational complexity of different algorithms are provided as follows. Assume that the number of input image pixel is N and the size of select image patch or the filtering window is B. For Enhanced Lee filter, NLM filter and SARBM3D, the compute complexity is $\mathcal{O}(NB)$. Assume the iteration number is K. For KSVD, KLLD and GSR-DL algorithm, the compute complexity is $\mathcal{O}(NBK)$. The learning dictionary based algorithms are more complicated than other

TABLE 3. Indexes of different methods (Airport).

	Enhance Lee	NLM	KSVD	KLLD	SARBM3D	GSR-DL
ESI	0.4126	0.5326	0.4026	0.3537	0.3240	**0.5726**
CII	0.8455	0.8514	0.7893	0.7620	0.8204	**0.8903**
MSSIM	0.7037	**0.8070**	0.6744	0.6104	0.6310	0.7983

TABLE 4. Indexes of different methods (Horse Track).

	Enhance Lee	NLM	KSVD	KLLD	SARBM3D	GSR-DL
ESI	0.4147	0.4819	0.4557	0.4273	0.3944	**0.5099**
CII	0.7826	0.8162	0.8188	0.7928	0.8161	**0.8394**
MSSIM	0.6632	**0.6923**	0.6660	0.6149	0.6384	0.6838

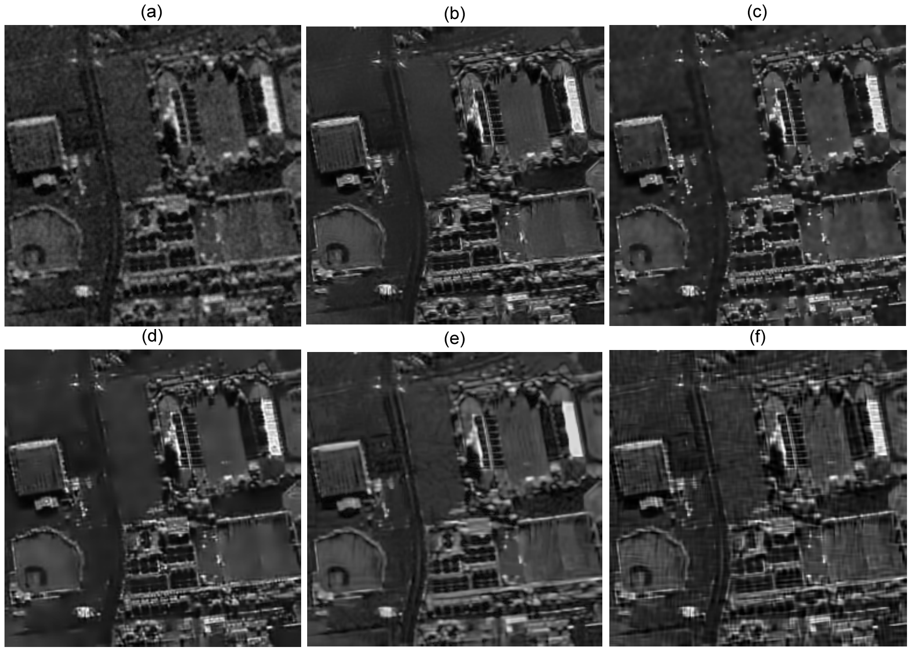


FIGURE 9. Despeckling experimental results (Buildings). (a) Enhanced Lee. (b) NLM. (c) KSVD. (d) KLLD. (e) SARBM3D. (f) GSR-DL.

three despeckled methods. Compare with KSVD and KLLD, the proposed GSR-DL algorithm obtained better despeckling presentation. The proposed GSR-DL algorithm requires about 1 minutes for SAR image despeckling on an Intel Core i5 3.30G PC under Matlab R2016a environment.

IV. CONCLUSIONS

This paper has exploited the concept of group sparse representation and the group sparsity of SAR image. Based on the analysis of multiplicative noise model and properties of speckle noise, a novel algorithm named GSR-DL algorithm is proposed for high-quality SAR image despeckling. According to the experimental results, some conclusions can be summarized as follows. Firstly, the group sparse representation theory is suitable for reconstructing the structure information of SAR image. Secondly, by the use of mean filter, we realize the SAR image despeckling with multiplicative noise model. Thirdly, experimental results certify the effectiveness of GSR-DL algorithm.

REFERENCES

[1] C. Oliver and S. Quegan, *Understanding Synthetic Aperture Radar Images*. London, U.K.: SciTech, 2004.
[2] J. W. Goodman, "Some fundamental properties of speckle," *J. Opt. Soc. Amer.*, vol. 66, no. 11, pp. 1145–1150, Nov. 1976.
[3] F. Argenti, A. Lapini, T. Bianchi, and L. Alparone, "A tutorial on speckle reduction in synthetic aperture radar images," *IEEE Geosci. Remote Sens. Mag.*, vol. 1, no. 3, pp. 6–35, Sep. 2013.
[4] L. Jurkevich, P. Dewaele, P. Wambacq, and A. Oosterlinck, "Speckle filtering of synthetic aperture radar images: A review," *Remote Sens. Rev.*, vol. 8, no. 4, pp. 255–267, 1994.
[5] A. Baraldi and F. Parmiggiani, "A refined gamma MAP SAR speckle filter with improved geometrical adaptivity," *IEEE Trans. Geosci. Remote Sens.*, vol. 33, no. 5, pp. 1245–1257, Sep. 1995.
[6] J. M. Bioucas-Dias and M. A. T. Figueiredo, "Multiplicative noise removal using variable splitting and constrained optimization," *IEEE Trans. Image Process.*, vol. 19, no. 7, pp. 1720–1730, Jul. 2010.
[7] G. Yuan and B. Ghanem, "l0tv: A new method for image restoration in the presence of impulse noise," in *Proc. Comput. Vis. Pattern Recognit.*, Jun. 2015, pp. 5369–5377.
[8] W. Feng and H. Lei, "SAR image despeckling using data-driven tight frame," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 9, pp. 1455–1459, Sep. 2014.
[9] C. L. P. Chen, L. Liu, L. Chen, Y. Y. Tang, and Y. Zhou, "Weighted couple sparse representation with classified regularization for impulse noise removal," *IEEE Trans. Image Process.*, vol. 24, no. 11, pp. 4014–4026, Nov. 2015.
[10] J. L. Yin, B.-H. Chen, and Y. Li, "Highly accurate image reconstruction for multimodal noise suppression using semisupervised learning on big data," *IEEE Trans. Multimedia*, vol. 20, no. 11, pp. 3045–3056, Nov. 2018.
[11] B. Xu, Y. Cui, Z. Li, and J. Yang, "An iterative SAR image filtering method using nonlocal sparse model," *IEEE Geosci. Remote Sens. Lett.*, vol. 12, no. 8, pp. 1635–1639, Aug. 2015.
[12] S. Li, H. Yin, and L. Fang, "Group-sparse representation with dictionary learning for medical image denoising and fusion," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 12, pp. 3450–3459, Dec. 2012.
[13] Y. Sun, Q. Liu, J. Tang, and D. Tao, "Learning discriminative dictionary for group sparse representation," *IEEE Trans. Image Process.*, vol. 23, no. 9, pp. 3816–3828, Sep. 2014.
[14] J. Zhang, D. Zhao, and W. Gao, "Group-based sparse representation for image restoration," *IEEE Trans. Image Process.*, vol. 23, no. 8, pp. 3336–3351, Aug. 2014.
[15] M. Tur, K.-C. Chin, and J. W. Goodman, "When is speckle noise multiplicative?" *Appl. Opt.*, vol. 21, no. 7, pp. 1157–1159, 1982.
[16] J. C. Curlander and R. N. McDonough, *Synthetic Aperture Radar*. New York, NY, USA: Wiley, 1991.
[17] T. Goldstein and S. Osher, "The split Bregman method for L1-regularized problems," *SIAM J. Imag. Sci.*, vol. 2, no. 2, pp. 323–343, 2009.
[18] F. Xiang and Z. Wang, "Split Bregman iteration solution for sparse optimization in image restoration," *Optik-Int. J. Light Electron Opt.*, vol. 125, no. 19, pp. 5635–5640, 2014.
[19] J.-S. Lee, M. R. Grunes, and G. de Grandi, "Polarimetric SAR speckle filtering and its implication for classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 37, no. 5, pp. 2363–2373, Sep. 1999.

[20] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering," *IEEE Trans. Image Process.*, vol. 16, no. 8, pp. 2080–2095, Aug. 2007.

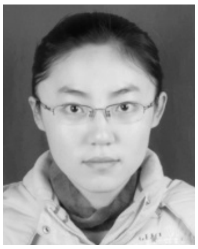
[21] M. Aharon, M. Elad, and A. M. Bruckstein, "K-SVD and its non-negative variant for dictionary design," *Proc. SPIE*, vol. 5914, p. 591411, Sep. 2005.

[22] P. Chatterjee and P. Milanfar, "Clustering-based denoising with locally learned dictionaries," *IEEE Trans. Image Process.*, vol. 18, no. 7, pp. 1438–1451, Jul. 2009.

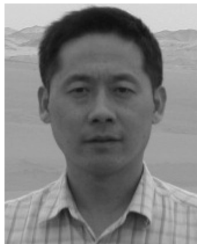
[23] S. Parrilli, M. Poderico, C. V. Angelino, and L. Verdoliva, "A nonlocal SAR image denoising algorithm based on LLMMSE wavelet shrinkage," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 2, pp. 606–616, Feb. 2012.

[24] A. Buades, B. Coll, and J.-M. Morel, "A non-local algorithm for image denoising," in *Proc. IEEE Comput. Soc. Conf. CVPR*, vol. 2, Jun. 2005, pp. 60–65.

[25] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600–612, Apr. 2004.



SU LIU was born in 1990. She received the B.E. degree from the Photoelectric Information Institute of Science and Technology, Yantai University, Yantai, China, in 2011, and the master's degree from the College of Electronics and Information Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing, where she is currently pursuing the Ph.D. degree in communication and information system. Her research interests include SAR image processing, target detection, and recognition.



GONG ZHANG was born in 1964. He received the Ph.D. degree in electronic engineering from the Nanjing University of Aeronautics and Astronautics (NUAA), Nanjing, China, in 2002. From 1990 to 1998, he was a Member of Technical Staff with the No. 724 Research Institute, China Shipbuilding Industry Corporation, Nanjing. Since 1998, he has been with the College of Electronic and Information Engineering, NUAA, where he is currently a Professor. His research interests include radar signal processing and classification recognition. He is a member of the Committee of Electromagnetic Information, Chinese Society of Astronautics, and a Senior Member of the Chinese Institute of Electronics.

WENBO LIU was born in 1968. She has been with the College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, where she is currently a Professor. Her research interests include digital signal processing, target detection and recognition, and non-linear dynamics.