ISSN: 2278-0181
IC3S - 2016 Conference Proceedings

Speckle Noise Removal in SAR Images based on Sparse Coding by Dictionary Learning and Collaborative Filtering

[1]Sidheswar Routray, [2]Arun Kumar Ray
[1,2]School of Electronics Engineering,
KIIT University, Bhubaneswar,
Odisha,India

[3]Chandrabhanu Mishra
[3]Department of Instrumentation & Electronics,
CET, Bhubaneswar,
Odisha,India

***Abstract*— Recently, dictionaries combined with sparse learning techniques became extremely popular in computer vision and image processing. Three basic approaches to image denoising are spatial domain method, transform domain method and dictionary learning method. Generally, dictionary learning is based on learning a large group of image patches in such a way that each patch in the output image is expressed as a linear combination of few atoms of the dictionary. This paper presents a method based on dictionary learning and collaborative filtering to despeckle Synthetic Aperture Radar (SAR) image. In this paper, we present a comparative result among different dictionary learning algorithms based on DCT, K-SVD and BM3D applied on the Synthetic Aperture Radar (SAR) despeckling task. The experimental results show that the proposed K-SVD algorithm is provide an adequate results in removing speckle noise from the SAR images.**

Keywords*— SAR, Sparse Representation, Dictionary Learning, K-SVD, BM3D

I. INTRODUCTION

Synthetic aperture radar (SAR) is a kind of imaging system, which allows acquisition of high resolution images of different places on the earth. Normally, noise is introduced in SAR images during image acquisition process and always a good denoising algorithm is necessary to remove the noise [1]. Due to the nature of image acquisition process, the noise introduced in SAR images are called speckle. Speckling is multiplicative noise which degrades the quality of image and makes the analysis of SAR images very difficult [2]. The goal of despeckling SAR images is to reconstruct a clean image and to preserve all important features of the SAR image such as edges, textures etc.

Speckle is frequently modeled as multiplicative noise and mathematically expressed as follows

$$y_k = x_k * z_k \qquad \text{---------------------------------} \qquad (1)$$

where y_k represents the corrupted image, x_k is the original image and z_k denotes the noise level.

Speckle noise removal in SAR image has been a popular research area since last two decades and many scholars have developed a no of algorithms to remove speckle noise. Many classical despeckling methods such as Lee filter [4], Frost filter [4], Kuan filter [6] and wavelet [7] have been developed to remove speckle noise in SAR images. These filters use a priori statistical information of speckle noise and fail to provide edge and texture details of the original SAR image. Due to the multi-resolution characteristics of wavelet transformation, it is frequently used for despeckling of SAR images [1], [7]. In Wavelet shrinkage techniques, it use a set of wavelet bases on the image and wavelet transform coefficients are thresholded to remove the high frequency variation. Due to the multi-resolution techniques of wavelet transform, the texture preservation is better in comparison to the statistical methods such as Lee [4], Frost [5], but performance of wavelet transformation method is quite responsive to threshold limit. Non-local means (NLM) which is based on self-similarity patches has also been used for removal of speckle in SAR images [8]. This method identifies the self-similar patches in an image and filtering is carried out on those patches.

To prevent from over-smoothing and removal of important texture details, sparsity-driven methods have been widely used for SAR despeckling over last decade. In this paper we propose an idea of dictionary learning to the SAR image formation problem. The idea behind dictionary learning is to learn a large group of image patches in such a way that each patch in the output image is expressed as a linear combination of few atoms of the dictionary. [9].

This paper presents a method for speckle noise removal in SAR images based on sparse coding by dictionary learning and collaborative filtering. Compared with traditional methods, this method can produce better despeckling effect and image fidelity.

II. SPARSE DECOMPOSITION

Decomposition of the signal with Fourier Transform, Shot-Time Fourier and wavelet transform is based on a complete orthogonal basis, which has some defects on a detailed description of the signal. So researchers were interested in decomposition the signal on an over-complete dictionary. The element in the dictionary is equivalent to the basis, which is referred to as atom. The over-complete dictionary has redundancy, which ensures that the representation of signal is sparse[10-11].

According to M. Elad et al. [10], the sparse decomposition problem is formulated as

$$\min_{D, x_i} \| y - Dx_i \|_2 \text{ subject to } \| y_i - Dx_i \|_2 < \varepsilon \text{ -----(2)}$$

Where, x_i represents a vector containing the linear combination of atoms from the redundant dictionary, D is called dictionary, ε represents the tolerable limit of the error, $\|.\|_0$ denotes the l_0 norm representing the number of non-zero elements of the vector.

The above problem involves the choice of the dictionary and to find sparses solutions x. The choice of this dictionary and computation of x is not straight forward. Hence, it is a NP-hard (Non-deterministic Polynomial-time) problem [9-10]. Many researchers have proposed several pursuit algorithms such as Orthogonal Matching Pursuit algorithm, Basis Pursuit, FOCUSS etc to provide the approximate solutions of the above problem. The Orthogonal Matching Pursuit (OMP) algorithm attempts to find a sparse representation of a signal given a specific dictionary. One can use a fixed dictionary of overcomplete basis like DCT, wavelets, curvelets, short-time Fourier transform [10-11]. However, such basis may not be the best overcomplete dictionary for all kinds of signals and hence, depending on the various applications, a data dependent dictionary may be the best option. Among different dictionary updation methods, K-SVD algorithm is quite simplistic and has low computational cost. It is based on SVD approach and is more appropriate for processing of image signal [10].

A. K-SVD BASED DESPECKLING

The problem of sparse representation can be defined by Eq. 2. We assume problem formulation presented in the former equation and extend it to include the complete set of observed signals denoted by the set $Y = \left\{ y_i \in [1, K], y_i \in R^n \right\}$ as

$$\min_{D, x_i} \| y - Dx_i \|_F \text{ subject to } \| x_i \|_2 < \varepsilon \text{ -----------------(3)}$$

where x is formed by the combination of all vectors x_i and $\| y - Dx_i \|_F$ denotes the Frobenius norm square which represents the square of every elements in the matrix.

The K-SVD algorithm attempts to minimize the cost function iteratively, by first finding x using the OMP algorithm (using an initial estimate of D). This coding is highly effective because it minimizes the error in representation and at the same time maintains a sparsity constraint as defined in Eq. 3. After completion of sparse coding stage, the algorithm proceeds to update the atoms of the dictionary, one atom at a time, such that the error term is further reduced [11]. The K-SVD algorithm is highly efficient for training dictionaries to achieve sparse signal representations. Due to the flexibility of K-SVD algorithm, it can work with any pursuit algorithm such as basis pursuit, matching pursuit or FOCUSS.

Here, we discuss the application of the K-SVD algorithm to despeckling of SAR images. The noisy image is divided into a set of patches and the vectorised version of each patch is treated as signals, thereby restricting the dimensionality of each atom in the dictionary [9]. However, the size of the patch has to be chosen such that it encodes enough details of the underlying signal. Dealing with patches as signals, the K-SVD algorithm can be effectively scaled to de-noise large images [10], [11].

For a given image Y, the denoising method can be used to find a set of patches Z which are related by

$$Y = Z + \eta \text{ --------------------(4)}$$

where η is the noise which corrupts the patches. The noise over the entire image is assumed to be zero mean gaussian noise. In order to find the denoised image patches Z, we define an optimization problem akin to that defined in Eq. 3 which involves minimization of the cost function.

III. SAR DETAILED PRESERVING ABILITY USING BM3D

Inspired by the image self-similarity and the interscale and intrascale correlations between wavelet coefficients, Dabov *et al.* [12] projected a powerful method for image denoising based on block matching and 3-D Transform Domain collaborative filtering (BM3D).Block Matching is the process of grouping similar 2-D fragments of the image into 3-D data arrays called as groups. Here 3-D represents the 3-D transform, which is the combination of 2-D transform within a group and the 1-D transform across the group. BM3D can achieve a high level of sparse representation of the noise –free image. BM3D is realized by two steps. Each step includes 3-D transformation of groups, the shrinkage of transform spectrum, and inverse 3-D transformation. These two steps are varied by the ways of shrinking the transform spectrum. Hard thresholding is done in the first step and wiener filtering is performed in the second step. The weighted average of several estimates of each patch is calculated in each step. Due to the self-similarity of image patches and the correlation of wavelet coefficients, BM3D performs as one of leading image denoising techniques.

IV. EXPERIMENTAL RESULT & DISCUSSION

We have tested the behavior of the K-SVD dictionary learning algorithm and Collaborating filter based denoising algorithms on some SAR images which contains reach texture regions. In order to test the despeckling ability of K-SVD & BM3D algorithm for SAR image, here we have introduced despeckling based on DCT dictionary. The SAR image used in this study is LibCong. Dictionaries learned in such a way often contain features also present in the image on which the dictionary was learned, shown in Fig. 1. The Fig. 2. shows a result obtained with DCT, K-SVD and BM3D respectively. A quantitative evaluation of the K-SVD algorithm on Libcong image damaged by noise with standard deviation of 25 and patch size equal 8 pixels. Fig.3. shows the PSNR result of three dictionary learning based denoising algorithms KSVD, BM3D & DCT Dictionary. Here, PSNR is used as quality metric for the assessment of image quality to evaluate the denoising performance of various methods.

Peak Signal to Noise Ratio (PSNR) values can be calculated by comparing original image and distorted image. PSNR is given by

$$PSNR = 10\log_{10}\frac{L^2}{MSE} \qquad \text{--------------------------(5)}$$

where L represents the dynamic range of the image and MSE denotes the mean squared error between the original and the distorted image.

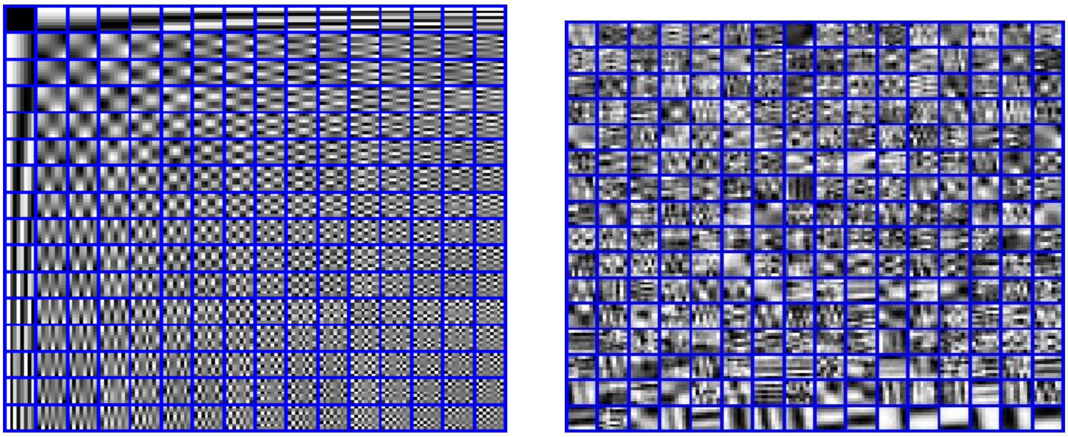

Fig.1. DCT Dictionary & Adaptive Dictionary

(a) (b) (c)

(d)

(e)

Fig. 2. Comparison results of different dictionary learning methods on Libcong SAR image with standard deviation $\sigma = 25$: (a) Original Clean Image (b) Noisy Image, PSNR: 20.178 dB (c) Denoised Image using DCT dictionary, PSNR: 24.0058dB (d) Denoised Image using KSVD, PSNR: 24.1782dB (e) Denoised Image using BM3D, PSNR: 24.127 dB

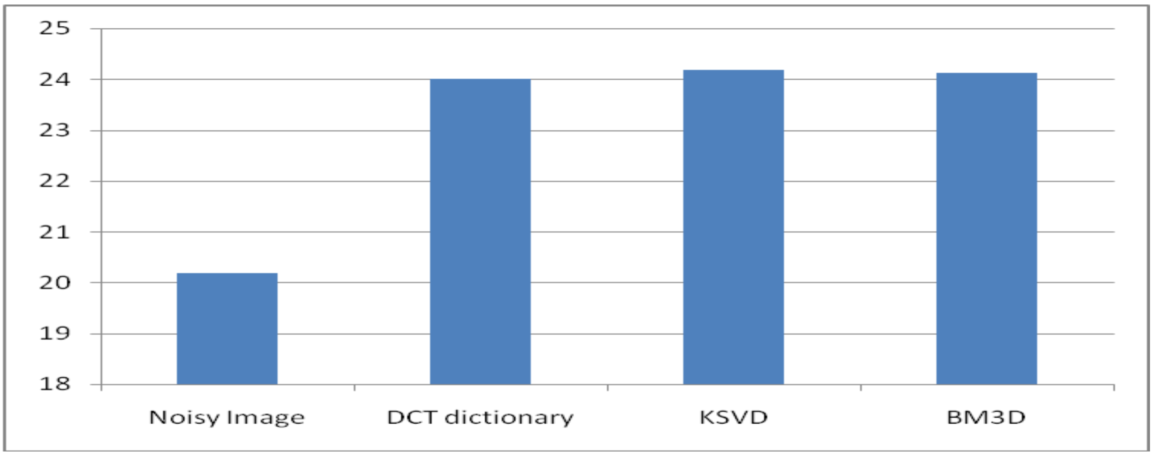

Fig. 3. Comparision of PSNR values of different denoising methods

V. CONCLUSION

In this paper, we have presented a comparative study for despeckling task of the SAR images using dictionary based learning algorithms. All the algorithms learned the dictionary from the SAR image itself. Through the experiment, we have demonstrated that K-SVD algorithm shows great advantages. Because sparse representation can best distinguish between the useful information and noise information in image, and K-SVD algorithm is better than the algorithm of fixed over-complete dictionary.

REFERENCES

[1] Guo H, Odegard J E, Lang M, et al. Speckle Reduction via Wavelet Shrinkage with Application to SAR Based ATD/R[R]. Technical Report CML TR94-02, CML, Rice University, Houston, 1994.

[2] F. Argenti and L. Alparone, "Speckle Removal from SAR Images in the Undecimated Wavelet Domain", IEEE Trans. on Geosci. And Remote Sens., 40(11), pp. 2363 –2212, Nov. 2002.

[3] S. Foucher, SAR image filtering via learned dictionaries and sparse representations, IEEE International Remote Sensing and Geoscience Symposium,2008.

[4] Lee J S. Digital image enhancement and noise filtering by use of local statistics, IEEE Transactions on Pattern Analysis and MachineIntelligence,2(2) :165-168,1980.

[5] Frost S V. A model for radar images and its application to adaptive digital filtering of multiplicative noise[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 4(2):157-166, 1982.

[6] Kuan D T, Sawchuk A A, Strand T C, et al. Adaptive noise smoothing filter for images with signal dependent noise[J]. IEEE Tran. On Pattern Analysis Machine Intelligence,7(2):165-177, 1985.

[7] A. Achim, P. Tsakalides, A. Bezarianos, SAR image denoising via Bayesian wavelet Shrinkage based on heavy tiled modeling, IEEE Transactions on Geoscience and Remote Sensing, 41(8), 2003.

[8] J. Jiang, L. Jiang, and N. Sang, "Non-local sparse models for SAR image despeckling," in *Proc. IEEE Int. Conf. Comput. Vis. Remote Sens.*, pp. 230–236, 2012.

[9] V. Abolghasemi and L. Gan, "Dictionary learning for incomplete SAR data," in International Workshop on Compressed Sensing Applied to Radar, 2012.

[10] M. Elad, M. Aharon, Image denoising via sparse and redundant representations over learned dictionaries, IEEE Transactions on Image Processing, 15(12), 2006.

[11] Aharon M, Elad M, Bruckstrein A M. The K-SVD: an algorithm for designing of over-complete dictionaries for sparse representation[J]. IEEE Transaction on Image Processing, 54 (11) :4311-4322, 2006.

[12] K. Dabov, A. Foi, V. Katvonik, K. Egiazarian, Image denoising by sparse 3D domain collaborative filtering, IEEE Transactions on Image Processing, 16(8), 2007.

[13] C. Delledale, L. Denis, F. Tupin, Iterative Weighted Maximum Likelihood Denoising with Probabilistic Patch-Based Weights, IEEE Transactions on Image Processing, 18(12), 2009.