

# Dictionary Learning for SAR Images Despeckling

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## ABSTRACT

In recent years, dictionaries combined with sparse learning techniques became extremely popular in computer vision. The image denoising approaches can be categorized as spatial domain, transform domain, and dictionary learning based according to the image representation. Using machine learning, sparse representations have become a trend and are used image and vision applications. The general idea of dictionary learning for image denoising by learning a large group of patches from an image dataset such that each patch in the estimated image can be expressed as a linear combination of only few patches from this redundant dictionary. The aim of the present paper is to demonstrate that both SVD and PCA has same task in image denoising provided that they are learned directly from the noisy image. In this paper, we present a result of comparison among four dictionary learning algorithms K-SVD, and local PCA, hierarchical PCA and global PCA 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:** *Spare representation, dictionary learning, SAR images, Deseckling, K-SVD, PCA.*

## 1. INTRODUCTION

Synthetic Aperture Radar (SAR) images are usually corrupted by noise that arises from an imaging device, there is always a need for a good filtering algorithm to remove all disturbances, thus enabling more information extraction. Synthetic aperture radar (SAR) system is all-time and all-weather imaging system used for earth surveying. SAR systems transmit electromagnetic waves, and produce images by coherent integration of received pulses. In coherent systems, backscatter signals add to each other coherently, and random interference of electromagnetic signals causes the speckle noise. Speckling is multiplicative noise which deteriorates the image quality and makes the interpretation of SAR images very difficult. The goal of removing speckles from the SAR image is to represent a noise-free image and preserve all important features of the SAR image, as for example edges, textures, region borders, etc.

Despeckling of SAR image has been a hot research area during last two decades. One may classify these systems in two categories: those directly applied to the signal and those uses wavelet transform before processing [1]. In wavelet shrinkage techniques, wavelet transform coefficients are thresholded. The research on wavelet thresholding and threshold selection for signal denoising, because wavelet provides an appropriate basis for separating noisy signal from the image signal. The motivation is that as the wavelet transform is good at energy compaction, the small coefficients are more likely due to noise and large coefficient due to important signal features. These small coefficients can be thresholded without affecting the significant features of the image. Currently, many approaches are based on the observation that most images are comprised of self-similar patches. Patch-based methods are founded on the assumption that the latent image has a locally sparse representation in some transform domain. Where each patch of size  $k \times k$  (with  $k$  usually between 8 and 12) is

denoised separately and inserted into the denoised image. Usually, averaging is performed in areas of overlapping patches.

Taking advantage of the redundancy of small sub-images inside the image of interest, new robust methods have emerged that can properly handle both constant, geometric and textured areas. Those methods range from the original Non Local Means (NL-Means) [2], optimal spatial adaptation [3] to the state-of-the-art algorithms BM3D [4], NLSM [5] and BM3D [6]. The NL-Means and its derivatives exploit the redundancy inside an image in order to yield efficient yet simple algorithms. However, this simplicity is obtained by considering only simple combinations of the input data, such as weighted averaging and iterative diffusion processes. Hence, these algorithms do not exploit another powerful property that empowers many image processing algorithms, which is, the sparsity. Where, the sparsity concept arises recently in compressive sensing (CS) theory [7, 8, 14, 15] which proved that any sparse signal or image can be reconstructed from samples fewer than number of elements in a signal or image. BM3D, K-SVD [13, 16] and patched PCA [9] are built around patches sparsity. However, K-SVD gave one step forward by introducing of algorithms based on patch dictionaries learned from examples of images, which updates the image representation with a more adaptive model. For a single patch, several similar dictionary atoms could be used for its reconstruction and they will be updated with the information from the noisy image during the approximation process. The main motivation behind this family of methods is that the dictionaries will capture only the meaningful variations of the appearance of the patches. Hence, even if trained on noisy data, they will more likely retain the lower frequencies and non-random parts of the patches and reject the noise. Requiring that the patches have a sparse decomposition on the dictionary then prevents from introducing further blur in the output,

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because it forces the reconstruction algorithm to select a linear combination of only a few significant atoms from the dictionary, instead of equally spreading the error over many of them. Another patch based denoising algorithms are the local PCA, hierarchical PCA and global PCA, which perform hard and soft thresholding using shrinkage function on the coefficients of the patches in image-specific orthogonal dictionaries and obtain the denoised patch by zeroing all the small coefficients in the representation of the noisy patch in the learned basis [9]. Recently, sparse representation has been used in SAR images despeckling [1]. In this paper, we exploit CS theory using the patch-based dictionary algorithms for despeckling of SAR image, by illustrate the benefit of adaptively dictionary learning using K-SVD and PCA algorithms. Moreover, in order to correctly validate our analysis, we compare the results of SVD and PCA decomposition schemes.

The rest of this paper is organized as follows: in section 2, we briefly outline the SVD and PCA algorithms. Section 3, the SAR image despeckling problem is described. The experimental results and analysis are given in section 4. The conclusions is drawn in section 5.

## 2. SVD Vs. PCA

Today SVD (Singular Value Decomposition) and PCA (Principal Component Analysis) are amongst the most frequently used tools to solve statistical, signal processing and modeling tasks. SVD is the optimal matrix decomposition in a least square sense that it packs the maximum signal energy into a few coefficients as possible [17,18]. Using SVD, a  $X$  can be written as:

$$X = USV^T \quad (1)$$

where orthogonal matrices  $U$  and  $V$  contain the left and right singular vectors of  $X$ , respectively, and the diagonal of  $S$  contains the singular values of  $X$ . A key property of SVD is its relation to the rank of a matrix and its ability to approximate matrices of a given rank. Digital images are often represented by low rank matrices and, therefore, able to be described by a sum of a relatively small set of eigenimages.

$$X = \sum_{i=1}^k s_i u_i v_i^T \quad (2)$$

Where PCA is a linear transformation technique for dimensionality reduction. It projects the data from original space to its eigen space to increase the variance by keeping the lower order principal components and ignoring higher order ones. Such lower order components often contain the most important aspects of data. In PCA, the eigenvalue decomposition of the data covariance matrix is computed as  $E\{XX^T\} = \Phi \Delta \Phi^T$  where the columns of matrix  $\Phi$  are the eigenvectors of the data covariance matrix  $E\{XX^T\}$  and  $\Delta$  is a diagonal matrix containing the respective

eigenvalues. The goal of PCA is to find an orthonormal transformation matrix  $P$  to de-correlate  $X$ , i.e.  $Y = PX$  so that the co-variance matrix of  $Y$  is diagonal. By setting:

$$P = \Phi^T \quad (3)$$

$X$  can be de-correlated. Generally speaking, the energy of a signal will concentrate on a small subset of the PCA transformed dataset, while the energy of noise will evenly spread over the whole dataset. Therefore, the signal and noise can be better distinguished in the PCA domain. The computational basis of PCA is the calculation of the SVD of the data matrix, or equivalently the eigenvalues decomposition of the data covariance matrix SVD is closely related to the standard eigenvalues-eigenvector or spectral decomposition of a square matrix  $X$

## 3. SAR Image Despeckling

Synthetic Aperture Radar (SAR) images are usually corrupted by noise that arises from an imaging device, there is always a need for a good filtering algorithm to remove all disturbances, thus enabling more information extraction. The SAR images are corrupted by a noise called speckle, which makes the interpretation of SAR images very difficult. The goal of removing speckles from the SAR image is to represent a noise-free image and preserve all important features of the SAR image, as for example edges, textures, region borders, etc. The Speckle noise in SAR images is usually modelled as a purely multiplicative noise process of the form

$$y = z \cdot s \quad (4)$$

If  $\hat{s} = s - 1$  and  $e = z \cdot \hat{s}$ , one begins with a multiplicative speckle  $s$  and finish with an additive speckle  $e$ . So, the degradation model for the denoising problem can be described as [19]:

$$y = z + e \quad (5)$$

where column vectors  $z$  and  $y$  denote the (vectorized) underlying latent image and its noisy observation, respectively. The vector  $e$  represents zero-mean white noise with variance  $\sigma^2$ . There have been numerous denoising algorithms to estimate  $z$  from  $y$ , and in general most of these methods can be categorized as patch-based filters. Patch-based filtering is founded on the assumption that the latent image has a locally sparse representation in some transform domain. Where each patch of size  $k \times k$  (with  $k$  usually between 8 and 12) is denoised separately and inserted into the denoised image. Usually, averaging is performed in areas of overlapping patches. Denoising relies on an over-complete dictionary  $D$  of size  $k^2 \times m$ , where  $m > k^2$ . The dictionary contains a set of atoms, which can be thought of as basis functions. The idea

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underlying dictionary-based denoising methods is to denoise by approximating the noisy patch using a sparse linear combination of atoms. The problem to be solved is usually the following [19]:

$$\min \|\alpha\|_0 \text{ s. t. } \|x - D\alpha\|_2 \leq \varepsilon, \quad (6)$$

where the  $\ell_0$ -pseudo norm enforces sparsity of the solution. It is possible to replace the  $\ell_0$ -norm with the  $\ell_1$ -norm, in which case the problem is convex, though better solutions are usually obtained using the  $\ell_0$ -norm. The quality of the denoising result is highly dependent on the choice of the dictionary  $D$ . Three possibilities exist: (a) The dictionary can be designed, (b) the dictionary can be learned globally on a dataset of noise-free images, or (c) the dictionary can be learned adaptively from the noisy image itself. The K-SVD is an iterative algorithm that learns a dictionary on the noisy image at hand using patches. Dictionaries learned in such a way often contain features also present in the image on which the dictionary was learned. This algorithm employs an alternate optimization process in two steps: keeping fixed the dictionary  $D$ , create the sparse representation matrix  $x$  using the orthogonal matching pursuit (OMP) algorithm [13, 16] and then in the second step, update both the dictionary and the representations using a rank-one approximation obtained by the singular values decomposition (SVD). This implies that the corresponding patch residual after denoising is necessarily orthogonal to the chosen atoms. Finally the denoised image is obtained by averaging the cleaned patches.



FIG. 1. SAR IMAGE THAT COVER THE PYRAMIDS OF GIZA, EGYPT.

#### 4. EXPERIMENTS ON SOME REAL SAR IMAGE

To illustrate the behavior of the K-SVD dictionary learning algorithm and other patch-based denoising algorithms, they are tested on some real SAR images which contains reach texture regions. We have used the default parameters and the implementations provided by

the algorithms' authors. As shown in Fig. 1, the SAR image used in this study cover the area of pyramids of Giza, Egypt [10].

The learning step of updating the dictionary relies on an SVD-decomposition, hence the name of the algorithm. Dictionaries learned in such a way often contain features also present in the image on which the dictionary was learned, see Fig. 2. The Fig. 3 shows a result obtained with K-SVD. A quantitative evaluation of the K-SVD algorithm on two benchmark images damaged by synthetic Additive White Gaussian Noise (AWGN) equal 20, and patch size equal 8 pixels, in comparison with three patch based denoising algorithms, local PCA, hierarchical PCA and global PCA, which perform hard thresholding on the coefficients of the patches in image-specific orthogonal dictionaries [9] is shown in Table1. Another used SAR image, is an image of the North Sea, England with an oil slick in it as shown in Figure 4.

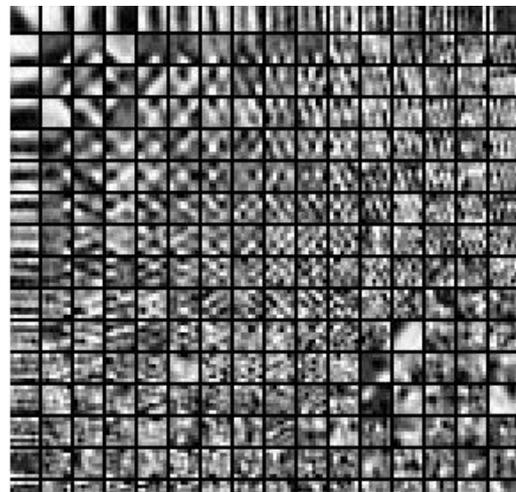


FIG. 2. THE TRAINED DICTIONARY FOR PYRAMIDS OF GIZA SAR IMAGE.



FIG. 3. THE RESULT OF APPLYING KSVD ALGORITHM ON SAR IMAGE COVER THE PYRAMIDS OF GIZA, EGYPT.

The most commonly used metric for image quality assessment is the peak signal-to-noise ratio (PSNR), which is a full-reference metric and calculated between two images. For an image  $x$ , the peak signal to noise ratio (PSNR) of its estimate  $\hat{x}$  is defined as

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$$\text{PSNR}(x, \hat{x}) = 10 \log_{10} \frac{255^2}{\frac{1}{LM} \sum_{i=1}^L \sum_{j=1}^M (\hat{x}(i, j) - x(i, j))^2} \quad (7)$$

where  $L$  and  $M$  are the dimensions of the image  $x$ , and  $x(i, j)$ ;  $\hat{x}(i, j)$  are the pixel value of the input and the estimate image at the pixel location  $(i, j)$ .



FIG.4. SAR IMAGE THAT COVER NORTH SEA, ENGLAND.

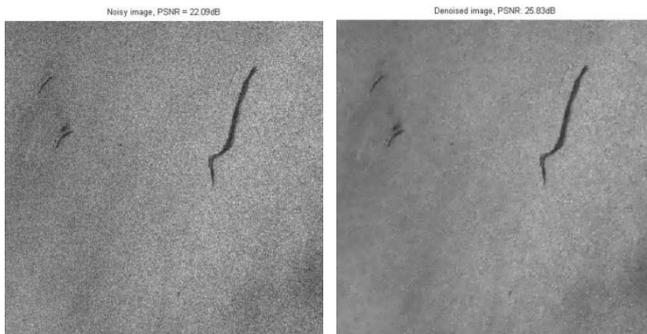


FIG.5. THE RESULT OF APPLYING KSVD ALGORITHM ON SAR IMAGE COVERS NORTH SEA, ENGLAND.

TABLE 1: EVALUATION THE OTHER DESPECKLING ALGORITHMS ON SAR IMAGES

	K-SVD		local PCA		Hierarch.PCA		global PCA	
	Giza	Sea	Giza	Sea	Giza	Sea	Giza	Sea
PSNR	25.72	25.83	25.5	24.48	25.7	25.65	25.59	25.54

As shown in Table 1, the K-SVD has good results in comparison with other techniques, due its ability to detect weak signals in the image by obtaining matrix approximations with the strong signal which is the true dimensionality of our image. On the other side, the PCA-based denoising algorithms empirically zeroing out all the small coefficients in the representation of the noisy patch in the learned basis, which is same strategy used in wavelet denoising [11]. From this results of both types of SVD and PCA have more in common than might be

supposed. Actually, PCA can be given via a singular value decomposition [12].

## 5. CONCLUSION AND FUTURE WORK

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. The used algorithms are based on singular value decomposition (SVD) and principle components analysis (PCA). However, there is a direct relation between PCA and SVD in the case where principal components are calculated from the covariance matrix. Overall, we observed the SVD based algorithm perform significantly better than the PCA based algorithms. Despite the success of these patch denoising algorithms they have many hyper-parameters that need to be tuned for desired adaptation. In the future work, this problem can be tackled.

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