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DWT Based PCA and K-Means Clustering Block Level Approach for SAR Image De-Noising

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Abstract— Visual data are transmitted as the high quality digital images in the major fields of communication in all of the modern applications. These images on receiving after transmission are most of the times corrupted with noise. This thesis focused on the work which works on the received image processing before it is used for particular applications. We applied image denoising which involves the manipulation of the DWT coefficients of noisy image data to produce a visually high standard denoised image. This works consist of extensive reviews of the various parametric and non parametric existing denoising algorithms based on statistical estimation approach related to wavelet transforms connected processing approach and contains analytical results of denoising under the effect of various noises at different intensities .These different noise models includes additive and multiplicative type's distortions in images used. It includes Gaussian noise and speckle noise. The denoising algorithm is application independent and giving a very high speed performance with desired noise less image even in the presence of high level distortion. Hence, it is not required to have prior knowledge about the type of noise present in the image because of the adaptive nature of the proposed denoising algorithm.

Keywords— *Image - denoising, DWT, Gaussian noise , PCA ,K mean clustering.*

I. INTRODUCTION

The performance of image-denoising algorithms using wavelet transforms can be improved significantly by taking into account the statistical dependencies among wavelet coefficients as demonstrated by several algorithms presented in the literature. The performance can also be improved using simple models by estimating model parameters in a local neighborhood. Some recent research has addressed the development of statistical models of wavelet coefficients of natural images and application of these models to image denoising [5]. Recently, highly effective yet simple schemes mostly based on soft thresholding have been developed [1]. In [10], the wavelet coefficients are modeled with a Gaussian a priori density, and locally adaptive estimation is done for coefficient variances. Also, prior knowledge is taken into account to estimate coefficient variances more accurately. In [1], the interscale dependencies are used to improve the performance. In [2], the simple soft-thresholding idea is used for each of the wavelet subbands, and the threshold value is estimated to minimize the mean-square error. The models that exploit the dependency between coefficients give better results compared to the ones using an independence assumption [5]. However, some of these models are complicated and result in high computational cost. In [12], a bivariate probability density function (pdf) is proposed to model the statistical dependence between a coefficient and its parent, and the corresponding bivariate shrinkage function is obtained. This new rule maintains the simplicity, efficiency, and intuition of soft thresholding. An explicit multivariate shrinkage function for wavelet denoising is also presented in [4]. In this letter, the local adaptive estimation of necessary parameters for the bivariate shrinkage function will be described. Also, the performance of this system will be demonstrated on both the orthogonal wavelet transform.

II. LITERATURE REVIEW

Not too long ago, the twin-tree difficult wavelet transform has been proposed by **Alin Achim et. Al. (2005) [8]**, as a novel evaluation instrument offering near shift-invariance and extended directional selectivity in comparison with the usual wavelet transform. Within this framework, we describe a novel method for eliminating noise from digital portraits. We design a bivariate maximum a posteriori estimator, which relies on the family of isotropic -steady distributions. Making use of this quite new statistical model we are able to higher seize the heavy-tailed nature of the data as well as the interscale dependencies of wavelet

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coefficients. We experiment our algorithm for the Cauchy case, in comparison with a couple of recently released methods. The simulation results exhibit that our proposed manner achieves cutting-edge performance in phrases of root mean squared error.

Aleksandra Pizurica and Wilfried Philips (2006) [9], They strengthen three novel wavelet domain denoising approaches for subband-adaptive, spatially-adaptive and multivalued photograph denoising. The core of our technique is the estimation of the chance that a given coefficient comprises a significant noise-free element, which we call "signal of interest." on this appreciate, we analyze instances the place the likelihood of sign presence is 1) fixed per subband, 2) conditioned on a neighborhood spatial context, and three) conditioned on understanding from multiple image bands. All the chances are estimated assuming a generalized Laplacian prior for noise-free subband data and additive white Gaussian noise. The outcome reveal that the new subband-adaptive shrinkage perform outperforms Bayesian thresholding strategies in phrases of mean-squared error. The spatially adaptive version of the proposed method yields higher results than the existing spatially adaptive ones of an identical and larger complexity. The efficiency on color and on multispectral portraits is sophisticated with admire to recent multiband wavelet thresholding.

This work offered by means of **Florian Luisier et. Al. (2007) [3]**, a new method to orthonormal wavelet image denoising. Rather of postulating a statistical mannequin for the wavelet coefficients, we instantly parametrize the denoising method as a sum of fundamental nonlinear processes with unknown weights. We then minimize an estimate of the imply square error between the easy photograph and the denoised one. The important thing point is that we have at our disposal a very correct, statistically independent, MSE estimate—Stein's unbiased threat estimate—that depends upon the noisy picture by myself, not on the easy one. Just like the MSE, this estimate is quadratic within the unknown weights, and its minimization quantities to solving a linear procedure of equations. The existence of this a priori estimate makes it pointless to plan a exact statistical mannequin for the wavelet coefficients. Rather, and contrary to the customized in the literature, these coefficients aren't regarded random anymore. We describe an interscale orthonormal wavelet thresholding algorithm centered on this new approach and show its near-most efficient performance—each regarding pleasant and CPU requirement—via comparing it with the results of three modern-day nonredundant denoising algorithms on a large set of scan photos. An exciting fallout of this gain knowledge of is the progress of a new, workforce-delay-headquartered, parent–baby prediction in a wavelet dyadic tree.

This work provided by way of **Hossein Rabbani (2009) [7]** a new image denoising algorithm headquartered on the modeling of coefficients in each subband of steerable pyramid using a Laplacian chance density operate (pdf) with regional variance. This pdf is able to model the heavy-tailed nature of steerable pyramid coefficients and the empirically discovered correlation between the coefficient amplitudes. Within this framework, we describe a novel method for snapshot denoising situated on designing both highest a posteriori (MAP) and minimal mean squared error (MMSE) estimators, which depends on the zero-imply Laplacian random variables with excessive neighborhood correlation. Despite the simplicity of our spatially adaptive denoising process, both in its problem and implementation, our denoising outcome achieves better performance than a number of released methods akin to Bayes least squared Gaussian scale combination (BLS-GSM) method that is a brand new denoising manner.

A new procedure established on the curvelet transform is proposed by using **Qiang Guo et. Al. (2010), [11]** for photo denoising. This system exploits a multivariate generalized spherically contoured exponential (GSCE) probability density perform to model neighboring curvelet coefficients. Established on the multivariate chance model, which takes account of the dependency between the estimated curvelet coefficients and their neighbors, a multivariate shrinkage operate for picture denoising is derived via maximum a posteriori (MAP) estimator. Experimental results show that the proposed approach obtains higher performance than the present curvelet-established photograph denoising system.

III. METHODOLOGY

In the convention approach of work first of all we have performed wavelet decomposition on the noisy image, then the estimation the noise-free dwt coefficients is performed by using the Bayesian model based estimation. The Bayesian estimation process is performed by calculating a probability density function (pdf) for modeling of the DWT coefficients of the denoised image. The denoised image is reconstructed by using the inverse wavelet transform (IDWT).

In this work we have not used above mentioned previous approaches called as parametric model-based based approach in which the formulation of the marginal distribution of wavelet coefficients is performed. Our proposed work is non-parametric wavelet coefficients model which can automatically adapts to the image data, in this way it can proved to be better in performance in respect of the conventional parametric model approaches which uses a models that has fixed formulation calculated in advance. Furthermore, in our approach a maximum a posteriori (MAP) estimation-based denoising method is used by incorporating the proposed model of the Bayesian estimation framework.

A non-parametric statistical model to formulate the distribution of wavelet coefficients followed by the derivation of the proposed MAP estimation-based image denoising approach. Experimental results are provided to show that the proposed MAP estimation-based image denoising algorithm outperforms the conventional algorithms.

Proposed Image Denoising Approach:

A PCA in hybrid with clustering approach is applied in this work for performing image denoising. If the noisy wavelet coefficient are found for a noisy image (yi, where 'i' is the index), the objective is to recover the noise-less wavelet coefficient (si) via PCA analysis formulae.

The proposed approach uses 2-D discrete wavelet decomposition using a Daubechies's wavelet of noisy image for calculating noisy wavelet coefficients. Then, the proposed approach applies mathematical approach developed on MATLAB for the calculation of each noise-free components excluding those of the LL subband. Finally, the inverse wavelet transform is applied to obtain the denoised image.

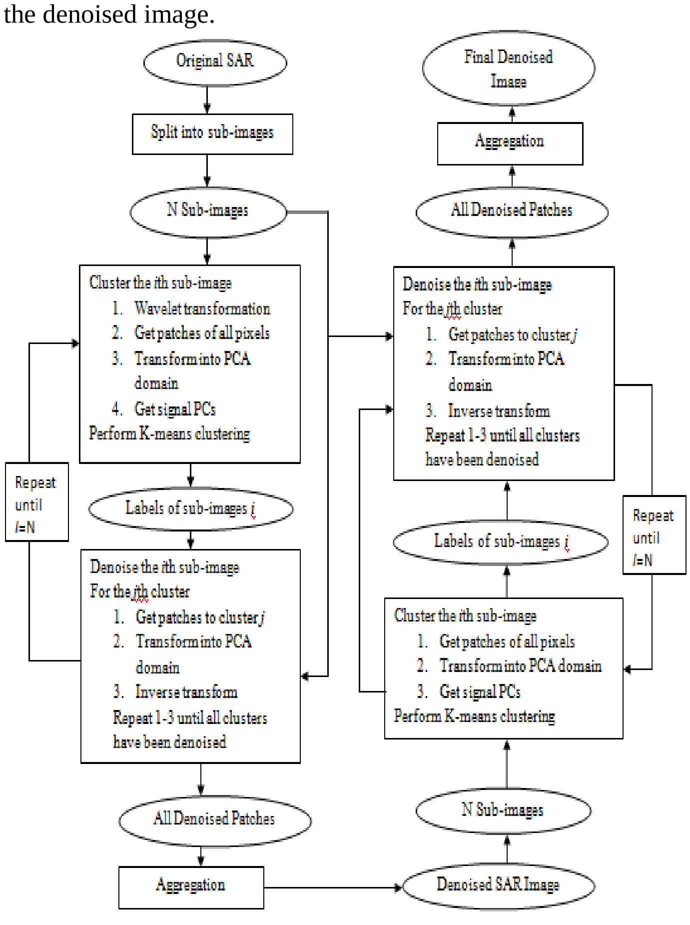

Fig 1: Flow Chart

IV. RESULT AND DISCUSSION

In this work we are working on different SAR images obtained from various website links. We added two types of noises on these two images and after that denoising procedure applied on them with different Mean variance and density. There are two types of noise which we add in our images:

1. Gaussian, 2. Speckle

We calculate the PSNR value by changing the value of mean, variance ((0, 0.001) to (0, 0.1)) and density (0.001 to 0.1).

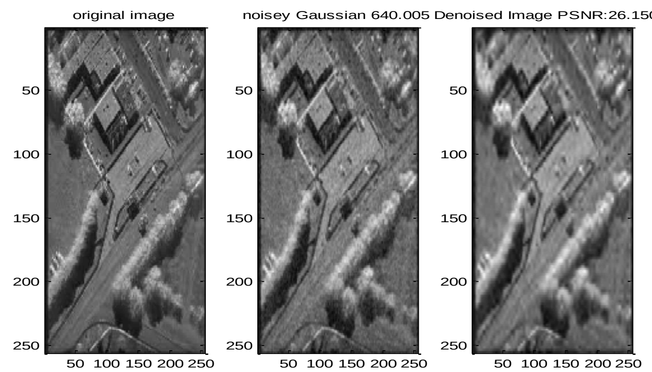

Fig 2(a): Original, noisy and denoised SAR image 1 for Gaussian noise at mean 0.001 and variance 0.005

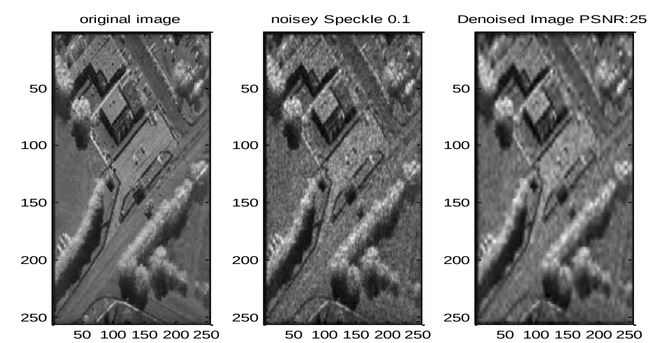

Fig 2(b): Original, noisy and denoised SAR image 1 for speckle noise at noise density 0.1

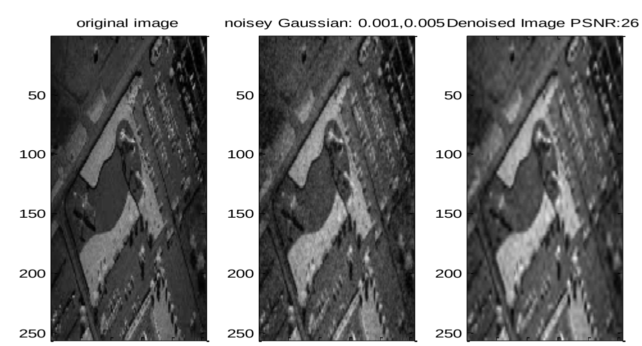

Fig 3(a): Original, noisy and denoised SAR image 2 for Gaussian noise at mean 0.001 and variance 0.005

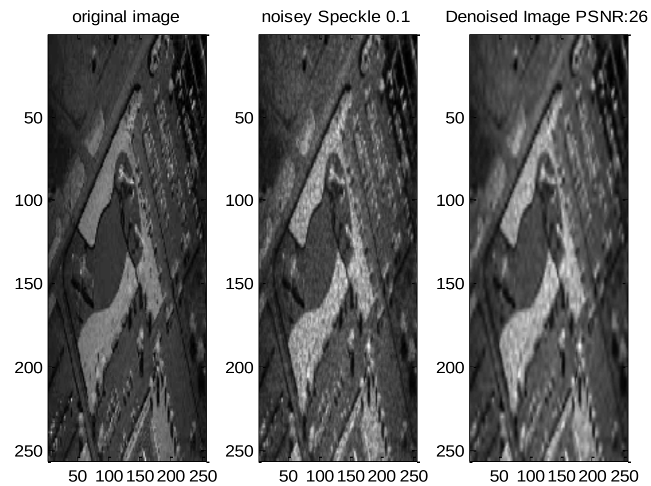

Fig 3(b): Original, noisy and denoised SAR image 2 for speckle noise at noise density 0.1

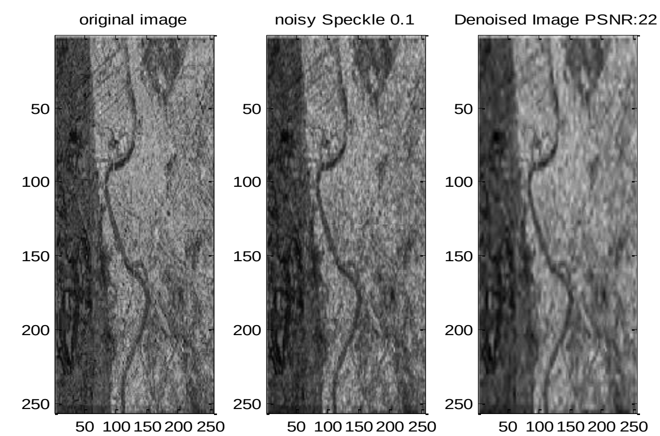

Fig 4(a): Original, noisy and denoised SAR image 3for Gaussian noise at mean 0.001 and variance 0.005

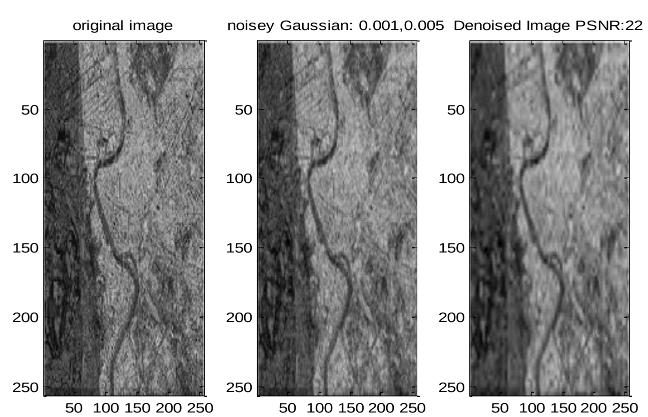

Fig 4(b): Original, noisy and denoised SAR image 3 for speckle noise at noise density 0.1

Table 1: PSNR value for different SAR images

Noise Type:	**Image ➔ Name**	1.jpg	2.jpg	3.jpg
gaussian	**Mean,var**	0.001, 0.005	0.001, 0.005	0.001, 0.005
	PSNR	26.15dB	26dB	22dB
speckle	**Density**	0.1	0.1	0.1
	PSNR	25dB	26dB	22dB

V. CONCLUSION

We have performed analytical investigation of the results of our proposed algorithm for SAR image denoising techniques and compared to various literature for results on standard images. In our implementation the bivariate PCA analysis function is applied along with k-mean clustering to the magnitude of the DWT coefficients, which is more shift invariant than the real or imaginary parts. To measure the denoising performance of the improved algorithm we applied the peak signal-to-noise ratio (PSNR).It has been observed that for lossy image processing the PSNR should be in between 25 to 30. In this work estimation of noise free coefficients is applied to the values of the DWT coefficients of different SAR image. We have currently explored the algorithm performance on several images at the effects of Gaussian and speckle types of noise effect at different noise intensity. The Gaussian noise mean and variance are taken at 0.001 and 0.005 respectively and speckle noise intensity is 0.1.For different images the PSNR is observed normal 26 to 29.Hence it justifies that our proposed implemented denoising algorithm is useful in SAR image denoising. In future we can proceed in a direction for the further improvement of the denoising statistical image model by consideration of the other non parametric bivariate-stable distributions. We can also consider intrascale dependencies of wavelet coefficients by means random fields to significantly improve the overall performance of a denoising algorithm in future.

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