International Journal of Latest Technology in Engineering, Management & Applied Science (IJLTEMAS)
2nd Special Issue on Engineering and Technology | Volume VI, Issue VIS, June 2017 | ISSN 2278-2540

Enhancement of SAR Imagery using DWT

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***Abstract*-This paper presents a new approach for the enhancement of Synthetic Radar Imagery using Discrete Wavelet Transform and its variants. Some of the approaches like nonlocal filtering (NLF) techniques, and multiscale iterative reconstruction (e.g., the BM3D method) do not solve the RE/SR imaging inverse problems in descriptive settings imposing some structured regularization constraints and exploits the sparsity of the desired image representations for resolution enhancement (RE) and superresolution (SR) of coherent remote sensing (RS). Such approaches are not properly adapted to the SR recovery of the speckle-corrupted low resolution (LR) coherent radar imagery. These pitfalls are eradicated by using DWT approach wherein the despeckled/deblurred HR image is recovered from the LR speckle/blurry corrupted radar image by applying some of the descriptive-experiment-design-regularization (DEDR) based re-constructive steps. Next, the multistage RE is consequently performed in each scaled refined SR frame via the iterative reconstruction of the upscaled radar images, followed by the discrete-wavelet-transform-based sparsity promoting denoising with guaranteed consistency preservation in each resolution frame. The performance of the method proposed is compared in terms of the number of iterations taken by it with other techniques existing in the literature.**

I. INTRODUCTION

In this work, a novel multistage iterative SR (MSISR) radar single image recovery technique is proposed. A feature enhanced despeckled high resolution (HR) image is first reconstructed from the LR input data. This is done by applying the variational analysis (VA) inspired descriptive experiment design regularization (DEDR) procedure that incorporates the convergence guaranteed projections onto convex sets (POCSs) [1]. At the consequent SR stages, the RE images are being super resolved from a coarser to finer nested up-sampled SR image grid with guaranteed sparsity and overall reconstruction consistency preservation. The HR initialization performs the spatially selective adaptive despeckling of the LR radar/fractional SAR image optimally balanced over the RE, making the overall unified DEDR MSISR technique well adapted to enhance the LR radar imagery with guaranteed sparsity and consistency preservation in the nested resolution scales. Our approach competitively performs with the state of the art SR methods, outperforming those in the speckle corrupted radar/SAR image recovery scenarios in terms of subjective perception and objective criteria, and, particularly, in the considerably speeded up convergence [12].

Modern approaches have failed to make use of scarcity and avoided the optimal balancing of speckle suppression during image reconstruction or recovery from a low resolution (LR) speckle corrupted image. This motivated us to make use of multi stage process with adaptive speckling over a DWT image recovery process. In this method, for reconstruction of high resolution (HR) image by speckle added low resolution (LR) image, we make use of descriptive experiment design regularization (DEDR) procedure which incorporates the convergence guaranteed projections onto convex sets (POCSs) [2].

We have separated the whole process into two parts. First part is deblurring and second part is of super resolution of the image [11]. The flow of the SR enhancement using the LR image is as shown in Fig 1.

Initially, we take a synthetic aperture radar (SAR) image of any resolution by saving the images in the same folder or by the MATLAB inbuilt function to select any image in any folder in the computer storage. The image is of good clarity/HR image. We resize the input image into 256 × 256 and then we add blur to the image in a controlled manner. We initialize DEDR process under state of art regularizations [3]. Generally, the images captured from a moving object are shaky in nature. The shaken quantity is known as blurriness in image processing. There are two types of blur as follows:

1. Uniform blur kernel [4]
2. Gaussian blur kernel [5]

The default blur kernel size is 9.

We selected Uniform blur kernel in our project, where the noise is distributed uniformly throughout the image taken. The blurring effect is removed using matched spatial filter (MSF) despeckling. To perform MSF, we convert the colour image to black and white image and later convert it back to the coloured image. The final image is saved in the output directory in jpeg format which is used for next process [5]. The output performance data of each iteration is noted down. Here we use 160 iterations, first it checks for 160 iterations completely and then it re-checks for double the iterations (320) and then it finally shows the peak SNR (PSNR), structural similarity index metric (SSIM) and the computational time taken to complete the iterations [6].

During recovery of the super-resolution image from the LR image, the SR image is recovered from the speckle corrupted LR image and the performance factors PSNR, SSIM and computational time is noted down. Wavelet based methods have and had a strong impact on the of image processing, especially in coding and denoising [10]. Their success is due the fact that the wavelet transforms of images tend to be sparse. This implies that image approximations based on a small subset of wavelets are typically very accurate, which is a key to wavelet-based compression [7]. The good performance of wavelet-based denoising is also intimately related to the approximation capabilities of wavelets. Thus, the conventional wisdom is that wavelet representations that provide good approximations will also perform well in estimation problems [9].

Resolution enhancement is the limiting factor for the utilization of remote sensing data. Spatial and spectral resolutions of satellite images (unprocessed) are related (a high spatial resolution is associated with a low spectral resolution and vice versa) with each other. Therefore, spectral and spatial, resolution enhancement (RE) is desirable. RE schemes (which are not based on wavelets) suffer from the drawback of losing high-frequency contents (which results in blurring) [10]. RE in the wavelet domain is a new research area. An RE scheme was proposed in using DT-CWT and bicubic interpolations, and results were compared with the conventional schemes. Note that, DWT is shift variant, which causes artefacts in the RE image, and has a lack of directionality; however, DT-CWT is almost shift and rotation invariant. DWT-based RE schemes generate artefacts [8].

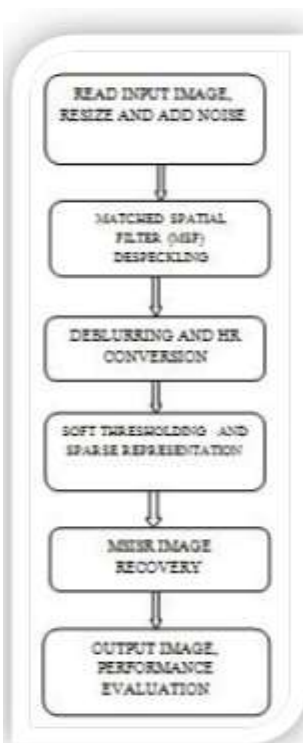

Fig 1: Flow of the deblurring and SR recovery.

II.PROBLEM PHENOMENOLOGY

In the discrete-form model representation, the radar/fractional SAR complex trajectory data signal vector u is related to the complex random scene reflectivity e and additive observation noise n via the coherent equation of observation, i.e., $u = Se + n$, where the regular $L \times K$ matrix-form signal formation operator S ($L < K$ for compressed sensing scenarios) is specified by the employed signal modulation format, and e, n, u represent complex random Gaussian zero-mean vectors composed of decomposition coefficients $\{e_k\}_{k=1}^{K}, \{n_l\}_{l=1}^{L}$, and $\{u_l\}_{l=1}^{L}$, respectively. These vectors are characterized by correlation matrices, i.e., $R_e = D(b) = diag(b)$, $R_n = N_0 I$, and $R_u = SR_eS^+ + N_0 I$, respectively [10]. The superscript $^+$ stands for the adjoint (Hermitian conjugate), and N_0 is the white observation noise power. Vector b composed of averages $\{b_k = <|e_k|^2>\}_{k=1}^{K}$ is a vector-form representation of the spatial spectrum pattern (SSP) of the power reflectivity map over the $K_y \times K_x$ pixel-framed 2-D scene $\{k_x = 1, \dots, K_x; k_y = 1, \dots, K_y; k = 1, \dots, K = K_y \times K_x\}$ lexicographically ordered by multiindex $k = (k_x, k_y)$. Hence, if we are given the data records, u, the need is to form an SR estimate $\hat{b}_{SR}$ of the of the scene SSP b. $\hat{b}_{SR}$ is called the feature enhanced recovered pixel-framed power reflectivity map [11]. Mathematically, this corresponds to the second-order statistics of the complex random reflectivity field e.

III. MULTISTAGE ITERATIVE SR IMAGE RECOVERY

The proposed MSISR algorithm is different from the referenced SR techniques in three aspects. First, it is adapted to tackle with the speckle-corrupted LR images due to HR initialization. Second, it makes use of the properties of DWT in image upsampling, decomposition, and SR processing. Third, it exploits the multiscale fine features of the images recovered in each of the nested resolution scales at different SR recovery stages, i.e., $m = 2, \dots, M$ [9].

Let W denote the (inverse) DWT. Then, any image vector v (in any resolution scale) can be reexpressed in terms of its WT expansion $v = W\alpha$, where α represents a vector of the wavelet coefficients defined as $\alpha = W^T v$. Typically, despeckled radar/SAR images manifest sparse representations in the WT space with a few large coefficients and many very small coefficients [12].

In such a representation, the SR level of the overall image recovery problem can be recast as the multistage task as follows:

$$\hat{v}_{(m)}^{[t+1]} = \mathcal{J}_{(m)}\left\{\hat{v}_{(m)}^{[t]}\right\}, m = 2, \dots, M; t = 1, \dots, T_m$$

to be resolved over $m = 2, \dots, M$ recovery stages, where, $\mathcal{J}_{(m)}\left\{\hat{v}_{(m)}^{[t]}\right\} = W_{(m)}\mathcal{D}_{\gamma(m)}\{W_{(m)}^T \hat{v}_{(m)}^{[t]}\}$ defines the WT based sparsity-promoting SR recovery operator, in which $W_{(m)}$

denotes the DWT in the mth refined resolution scale ($m = 2, \ldots, M$), $\hat{v}_{(m)}^{[t]}$ defines the image recovered at the tth iteration in the m th scale, and $\mathcal{D}_{\gamma(m)}\{.\}$ is the Donoho's softthresholding (denoising) operator with a shrinkage parameter γ. The recovery performed in the finest (Mth) resolution scale is expected to yield the desired SR radar image $\hat{b}_{SR} = \hat{v}_{(M)}^{[T_M]}$. This approach suggest to recover the SR image with the guaranteed sparse representation in the WT space via running the sparsity-promoting DWT-based denoising step. We propose to apply such iterative processing in each nested scale (subband). Finally, we incorporate into the overall SR recovery process the procedure that guarantees the nonnegativity and consistency preservation in the recovered SR radar image [10].

IV.SIMULATIONS

First, we take 256×256 pixel framed SAR image then it is down-sampled by an integer factor 2. The input image is a RADARSAT – 2 image captured on May 15, 2007 of the city of New York, U.S.A. For the LR image is then added blurr-noise in a limited quantity and it is later filtered using MSF. The deblurred image is then super-resolved using MSISR single image technique. We have tested the most widely used Haar wavelet in this work. The results are reported. In tests, the MSISR iterative processes were terminated at $t = Tm, m = 2, 3$, after attaining by the adopted performance criterion, which, in our case, is the structural similarity index metric (SSIM) change threshold. We compared the proposed DEDR- MSISR approach with the most competing predecessors, namely: 1) the DEDR-related robust adaptive spatial filtering (RASF) HR reconstruction; 2) the HR $l_2 - l_1$ -structured DEDR-VA recovery; 3) the NLF-DWT variant of the DT-CWT method; 4) the Papoullis–Gerchberg (P–G) SR algorithm; and 5) the most prominent competing BM3D. In the simulations, we have observed that compared SR methods steps 3–5 are failed to recover the single-look SAR images; thus, the LR despeckled MSF image $\hat{b}_{MSF}$ was used as an input to all those algorithms. The method proposed has outshined the methods existing in the literature w.r.t the PSNR (Peak Signal to Noise Ratio) and computation time needed for its implementation. The results are tabulated below.

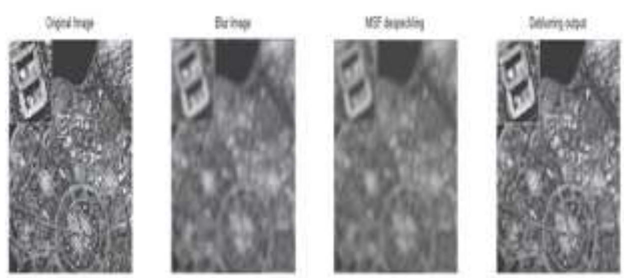

Fig 2: De blurred output image

The PSNR of the blurred image = 19.128936

MSISR deblurring: iter. 40 : PSNR = 21.405415

MSISR deblurring: iter. 80 : PSNR = 21.510360

MSISR deblurring: iter. 120 : PSNR = 21.540123

MSISR deblurring: iter. 160 : PSNR = 21.551052

MSISR deblurring: iter. 200 : PSNR = 21.640924

MSISR deblurring: iter. 240 : PSNR = 21.645695

MSISR deblurring: iter. 280 : PSNR = 21.647518

MSISR deblurring: iter. 320 : PSNR = 21.648281

Total elapsed time = 3.854867 min

PSNR = 21.65, SSIM = 0.540714

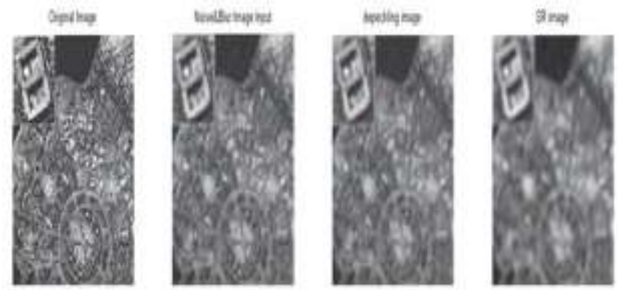

Fig 3: SR output image

MSISR SR, iter. 40 : PSNR = 19.389984

Total elapsed time = 0.615167 min

PSNR = 19.39, SSIM = 0.277741

The reported simulations corroborate that the best perceptual SR enhancement performance of the fractional SAR image recovery and the quantitative enhancement measures evaluated via the peak SNR (PSNR) and SSIM, metrics and the convergence rates were attained with the proposed MSISR technique that employs the Haar DWT.

V.CONCLUSION

We have exhibited a novel method for the SR recuperation of LR radar/SAR pictures that binds together the VA-roused HR picture recreation with the multi scale iterative SR that substitutes between wavelet-area up scaling and DWT-based picture recuperation by means of meager portrayal in the WT space. The HR introduction plays out the spatially specific versatile despeckling of the LR radar/partial SAR picture ideally adjusted over the RE, making the general brought together DEDR-MSISR strategy all around adjusted to upgrade the LR radar symbolism with ensured sparsity and consistency conservation in the settled determination scales. Recreations highlight that our approach aggressively performs with the best in class SR techniques, pulses those in the spot adulterated radar/SAR picture recuperation situations as far as subjective discernment and target criteria, and, especially, in the extensively speeded-up union.

ACKNOWLEDGMENT

The authors are grateful to Dr. Mohan Manghnani, Chairman, New Horizon Educational Institution, Bengaluru, for his encouragement for carrying out his work. They are thankful to Dr. Manjunatha, Principal, New Horizon College of Engineering (NHCE), Bengaluru, for his encouragement for this research work. They are also very grateful to Dr. Sanjay Jain, former Professor and HOD, ECE Dept., New Horizon College of Engineering, Bengaluru, for providing necessary backbone support to proceed on this endeavor. Finally, we are highly indebted to our parents for encouraging us to excel in our chosen fields.

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