International Journal of Research
Available at https://edupediapublications.org/journals
e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 04 Issue 14
November 2017

An Efficient Method for Seperated Component-Based Restoration of Speckled Sar Images

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ABSTRACT-*Many coherent imaging modalities such as synthetic aperture radar suffer from a multiplicative noise, commonly referred to as speckle, which often makes the interpretation of data difficult. An effective strategy for speckle reduction is to use a dictionary that can sparsely represent the features in the speckled image. However, such approaches fail to capture important salient features such as texture. In this paper, we present a speckle reduction algorithm that handles this issue by formulating the restoration problem so that the structure and texture components can be separately estimated with different dictionaries. To solve this formulation, an iterative algorithm based on surrogate functional is proposed. Experiments indicate the proposed method performs favorably compared to state-of-the-art speckle reduction methods.*

1.INTRODUCTION

Coherent imaging systems such as synthetic aperture radar (SAR), holography, ultrasound, and synthetic aperture sonar suffer from a multiplicative noise known as speckle. Speckle appears when objects illuminated by coherent radiation have surface features that are rough compared with the illuminating wavelength. It is caused by the constructive and destructive interference of the coherent returns scattered by many elementary reflectors within the resolution cell. Speckle can make the detection and interpretation difficult for automated as well as human observers. In some cases, it may be important to remove speckle to improve applications such as compression, target recognition, and segmentation. Many algorithms have been developed to suppress speckle noise . One of the simplest approaches for speckle noise reduction is known as multi-look processing. It involves non-coherently summing the independent images formed from L independent pieces of the phase history. The averaging process reduces the noise variance by a factor of L. However, this often results in the reduction of the spatial resolution.

Other types of speckle reduction methods are based on spatial local filtering performed after the formation of the SAR image. Various filters have been developed that avoid the loss in spatial resolution. Some of these methods are based on a window processing of the noisy image. Consequently, their performance depends significantly on the type, direction, and the size of the filter used. Furthermore, some of these filters often fail to preserve sharp features such as edges. To overcome some of these limitations, wavelet-

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based methods are often utilized , in which noise shrinkage is applied to the detailed wavelet coefficients of the noisy image . Since speckle is multiplicative in nature, some of these methods often apply the logarithm transform to SAR images to convert the multiplicative noise into additive noise. After applying soft or hard thresholding to the wavelet coefficients of the logarithmically transformed image, an exponential operation is employed to convert the logarithmically transformed image back to the original multiplicative format. It is well known that shrinkage-based denoising algorithms rely on the sparsity of the representation. A fixed transform such as a wavelet transform can represent a piecewise smooth image sparsely but it may also fail to represent an image with textures sparsely. As a result, the overall denoising performance of a fixed transform on an image containing both piecewise smooth and texture components can be inadequate.

2.RELATED WORK

2.1 Implementation of existing system

Image restoration concerns the removal or reduction of degradations which have occurred during the acquisition of the images. Such degradations may include noise. Imaging techniques using coherent illumination, such as synthetic aperture radar (SAR), ultrasound, holography, which generate coherent images are suffer from a multiplicative noise known as speckle . Speckle noise is generated due to constructive and destructive interference of multiple echoes returned from each pixel. Many attempts were made to reduce the speckle noise. An appropriate method for speckle reduction is multi-look processing. In this method the synthetic aperture is divided into some pieces. Each of these apertures is processed separately to obtain a pixel with a special along-track dimension. However this often results in the reduction of the spatial resolution. Many different types of speckle reduction approaches are based on spatial local filter formation of the SAR image. Different filters have been developed that avoid the loss in spatial resolution. These filters adapt themselves to the local texture information within a box surrounding a central pixel in order to calculate a new pixel value. Various wavelet-based transforms are used for the noisy image. The wavelet transform is used in many applications in signal and image processing as in data compression and signal de-noising, but also edge detection and texture characterization. Wavelet transform can represent a piecewise smooth image sparsely but it may also fail to represent an image with textures sparsely.

Total variation (TV) regularization, is an another approach for speckle noise removal. It is based on the principle that signals with excessive and possibly spurious details have high total variation. This noise removal technique has advantages over simple techniques such as linear smoothing or median filtering which reduce noise but at the same time smooth away edges to a greater or lesser degree. Many methods have been proposed for image restoration as use a combined dictionary.

Drawbacks

1.Multi-look processing often results in the reduction of the spatial resolution.

2.The wavelet transform is used in many applications in signal and image processing as in data compression and signal de-noising, but also fails in edge detection and texture characterization.

3.Wavelet transform can represent a piecewise smooth image sparsely but it may also fail to represent an image with textures sparsely.

4.The noise removal technique has advantages over simple techniques such as linear smoothing or median filtering which reduce noise but at the same time smooth away edges to a greater or lesser degree.

2.3 NEW SYSTEM

Many methods have been proposed for image restoration as use a combined dictionary. A classical approach consists in considering that an image f can be decomposed into two components u+v. This is called cartoon and texture image component based restoration for SAR image. The first component u is well-structured, and has a simple geometric description. The second component v contains both texture and noise. In proposed approach, u is estimated and is considered as the restored image and the texture components of v are not trying to be recovered. In this condition the texture components may result in the loss of important salient information in a SAR image. Fig.1 shows the example of structured and textured component based images.

Now, we present a separation based method that decompose image into a sum of piecewise smooth and textured elements. Our entire evaluation is based on finding spare representations of these elements dictionaries to compress them. Using help of sparse representation we are able to obtain important salient features and textured in the image.

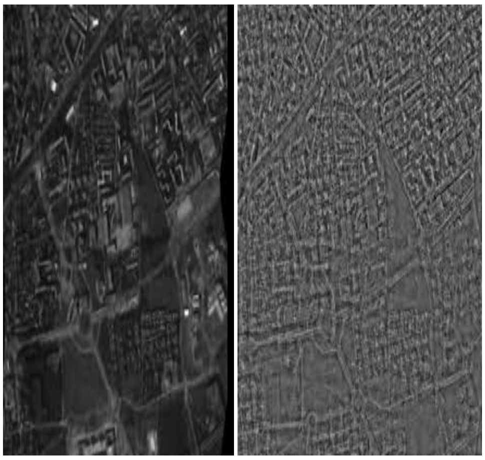

Fig 1: original image and its textural components

3.IMPLEMENTATION OF NEW SYSTEM

3.1 Separation of image

many statistical models have been proposed for sar images in this, we use the logarithmic transform to convert the multiplicative noise into additive noise and take appropriate model for that noise. let y, f and x denote the ordered vector of size n2 that is y, f and x respectively. now we assume that the sar image with two different signals that is

$$x = xp + xt$$

where xp denotes the piecewise smooth component and xt denotes the textured component of x. according to the logarithmic transformation, the additive model that can be written as

$$y = x + f$$

$$y = xp + xt + f$$

if we further assume that xp is compressed in a dictionary and represented in the form of a matrix dp and same for the xt is compressed in a dictionary that represented in the form of a matrix dt . for sparse representation of piecewise and texture components the dictionary dp ϵ rn2 $\times$ mp and dt ϵ rn2 $\times$ mt are selected where mp, mt $\geq$ n2 is given. there are coefficient vectors αp and αt so that

xp = dpαp and xt= dtαt . the texture dictionary dt have oscillatory nature and dp contains the structural feature such as edges. the piecewise smooth component xp and texture component xt are estimating for sar field x through αp and αt can recover the reflectivity of image. where tv is variations in image.

3.2 Iterative shrinkage algorithm

In this we present a fast convergent iterative shrinkage algorithm by using of separable surrogate functional (ssf). this method is solve the separation problem, for texture and piecewise smooth component posed. For dictionary we assume d = [dp, dt]. discard the tv component and equation can then be rewritten as where α holds both piecewise smooth and texture parts. let equations are added then surrogate function is we summarize the algorithm for restoring the two component of sar image .

input: y, c. initialization: initialize k = 1 and set .

repeat: 1.update the estimate of x and x as

2.update the residual as

3.upadate the shrinkage parameter as

until: stopping criterion is satisfied.

output: the two component is ssf iterative shrinkage algorithm to solve.

the final estimation of x is obtain to denoised components of x.

By this algorithm, it gives good results to compare with competitive methods. in this equations k indicates the value for kth iteration and h is the undecimated haar wavelet transforms.

3.3 Degradation model

Given an ideal picture $f(x,y)$ and a degraded picture $g(x,y)$

We will assume *g* and *f* are related by,

$$g(x,y) = \int_{-\infty}^{\infty}\int h(x,y,x',y')f(x',y')dx'dy' + v(x,y)$$

where $h(x,y,x',y')$ is the degradation function and $v(x,y)$ is random noise.

In the absence of noise

1) The degraded image of a point source described by $f(x',y') = \delta(x'-\alpha, y'-\beta)$ would be given by $h(x,y,\alpha,\beta)$. Therefore $h(x,y,\alpha,\beta)$ is a PSF which in general is dependent on position (α,β) of the point in the ideal picture.

Note: The spatially continuum PSF $h(x,y)$ of any blur satisfies three constraints

- $h(x,y)$ takes on non -ve values only because of the physics of the underlying image formulation process.
- When real valued images are dealt with the PSF is real valued too.
- the imperfections in the image forming process are modeled as "passive" operations on data ie. no "energy" is absorbed or generated.

This means PSF is constrained to satisfy $\int_{-\infty}^{\infty}\int h(x,y))dxdy = 1$

2) The assumption that $g(x,y)$ is a linear function of $f(x,y)$ is approximately correct only over a small dynamic range of gray levels for eg. in a photographic system what is recorded is usually a non linear function of $f(x,y)$. If however the non linear characteristic of the film is known, it can be used to recover $f(x,y)$ from what is recorded on the film over a large dynamic range of gray levels.

3) The assumption noise is additive is also subject too criticism. Many noise sources may be individually modelled as additive. When however additive noise is followed by a non linear transformation its effect on function $g(x,y)$ can be assumed additive only over a small dynamic range. However as the assumption of additivity of noise makes the problem mathematically tractable, it is common to most work on picture restoration.

e-ISSN: 2348-6848
p-ISSN: 2348-795X
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If except for translation, the degraded image of a point is independent of the position of the point, then the PSF takes the form $h(x, y, x', y')$ and

$$g(x,y) = \iint h(x-x', y-y')\, f(x', y')dx'dy'.$$

In this case degradation is shift invariant. In our discussion we will restrict ourselves to pictures that have suffered this type of degradation i.e, point degradation.

In the absence of noise

$$g(x,y) = \iint h(x-x', y-y')\, f(x', y')dx'dy'$$

Fourier transforming both sides

$$G(u,v) = H(u,v)\, F(u,v)$$

where $H(u,v)$ is transfer function of system that transfers ideal picture *f* to degrade picture .

Advantages

The advantages of the iterative approach include improved insensitivity to noise and capability of reconstructing an optimal image in the case of incomplete data. The method has been applied in emission tomography modalities like SPECT and PET, where there is significant attenuation along ray paths and noise statistics are relatively poor.

As another example, it is considered superior when one does not have a large set of projections available, when the projections are not distributed uniformly in angle, or when the projections are sparse or missing at certain orientations. These scenarios may occur in intra operative CT, in cardiac CT, or when metal artifacts require the exclusion of some portions of the projection data.

In Magnetic Resonance Imaging it can be used to reconstruct images from data acquired with multiple receive coils and with sampling patterns different from the conventional Cartesian grid and allows the use of improved regularization techniques (e.g. total variation) or an extended modeling of physical processes to improve the reconstruction. For example, with iterative algorithms it is possible to reconstruct images from data acquired in a very short time as required for Real-time MRI.

In Cryo Electron Tomography, where the limited number of projections are acquired due to the hardware limitations and to avoid the biological specimen damage, it can be used along with compressive sensing techniques or regularization functions (e.g. Huber function) to improve the reconstruction for better interpretation.

Here is an example that illustrates the benefits of iterative image reconstruction for cardiac MRI.

4.RESULTS & ANALYSIS

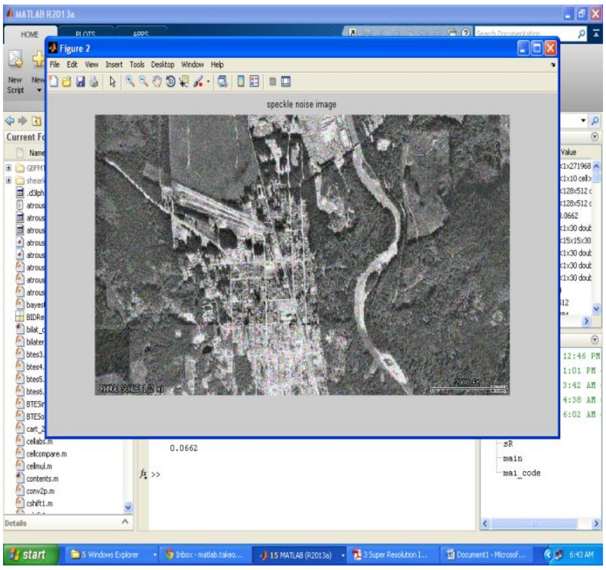

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Fig 2: The above figure shows the speckle noise image.

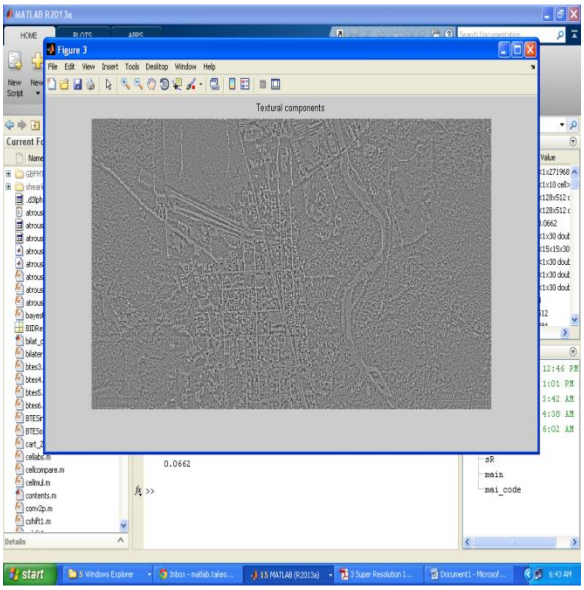

Fig 3: The above figure shows the textural components of the speckle noise image.

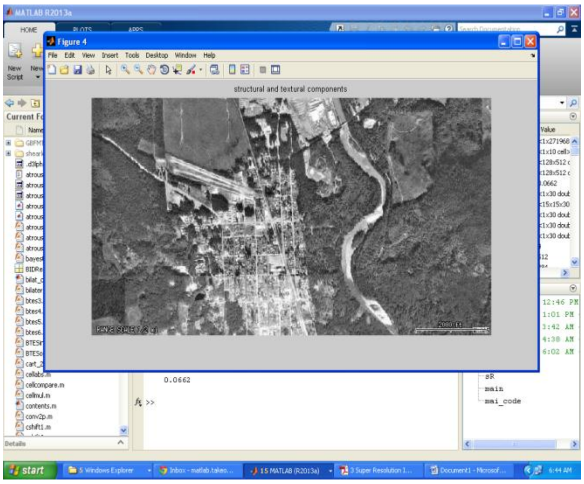

Fig 4: The above figure represents the output which is a combination of both structural and textual components of the speckle noise image.

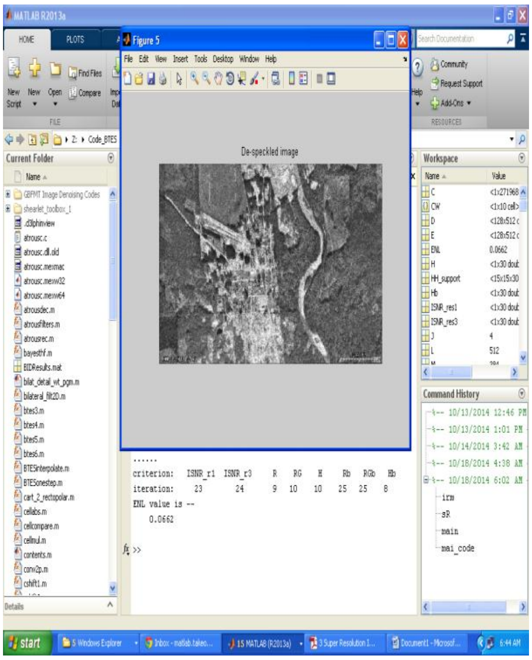

Fig 5: The above figure represents the output of the de-speckled image.

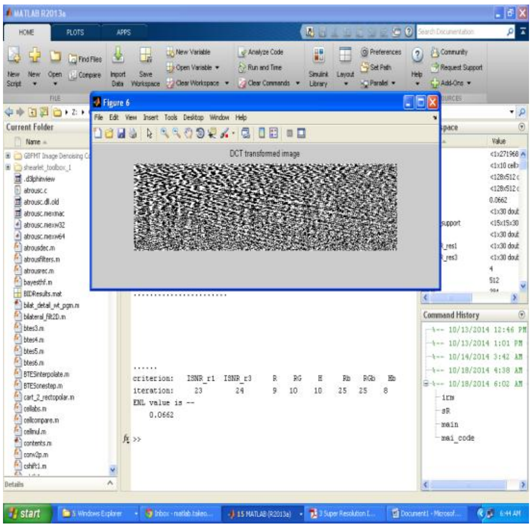

Fig 6: the above figure represents the output of DCT transform image.

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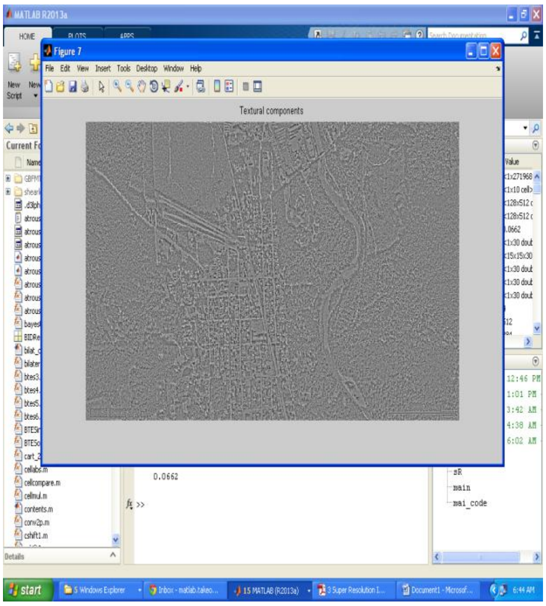

Fig 7: The above figure shows the textural components of the speckle noise image.

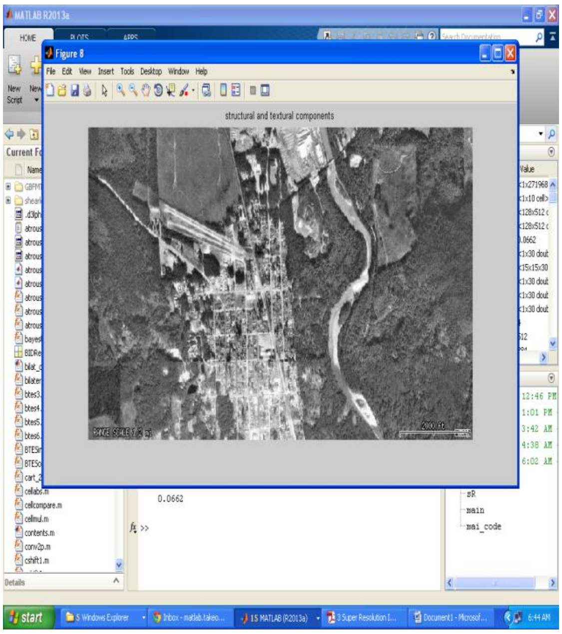

Fig 8: The above figure represents the output which is a combination of both structural and textual components of the speckle noise image.

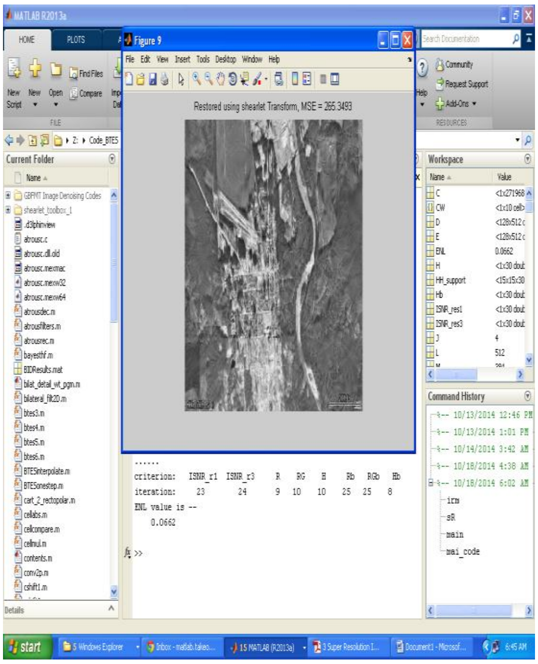

Fig 9: the above figure shows the restoration of image using wavelet transform.

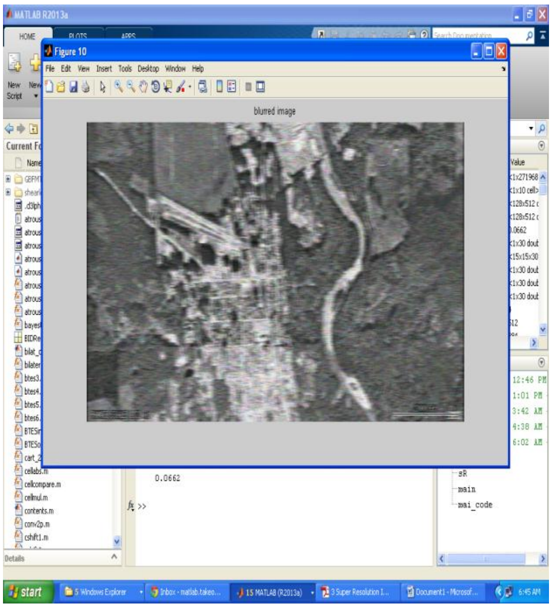

Fig 10: The above figure shows the appearance of blurre in the image.

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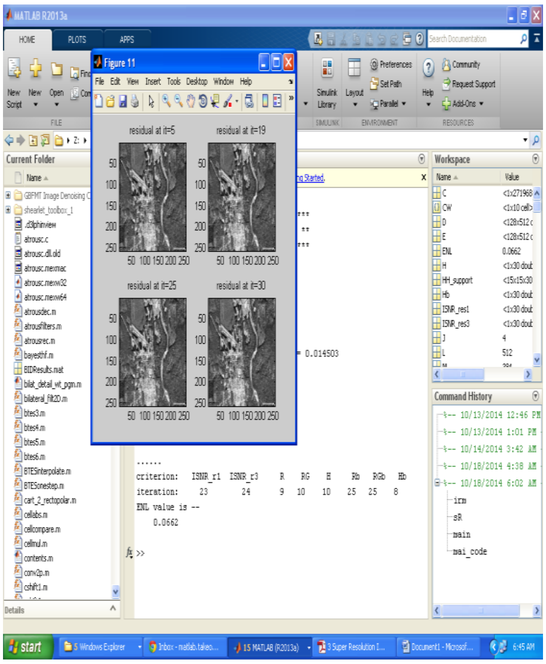

Fig 11: the above figure shows the images at different modules.

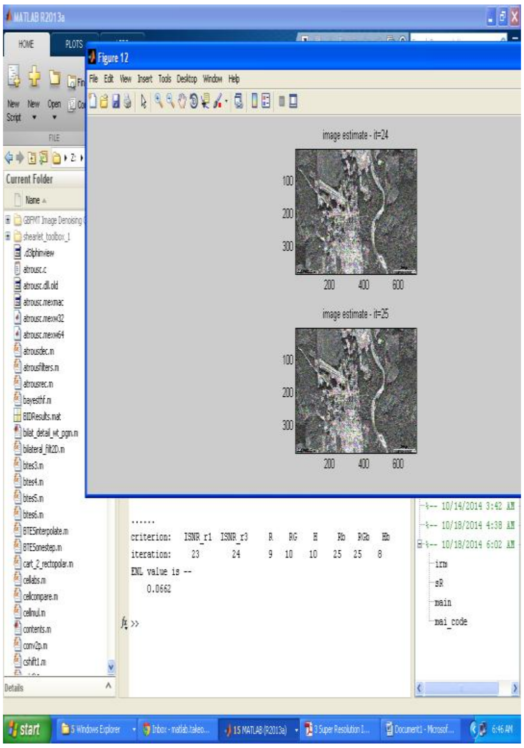

Fig 12: The above figure shows how the satellite images are estimated.

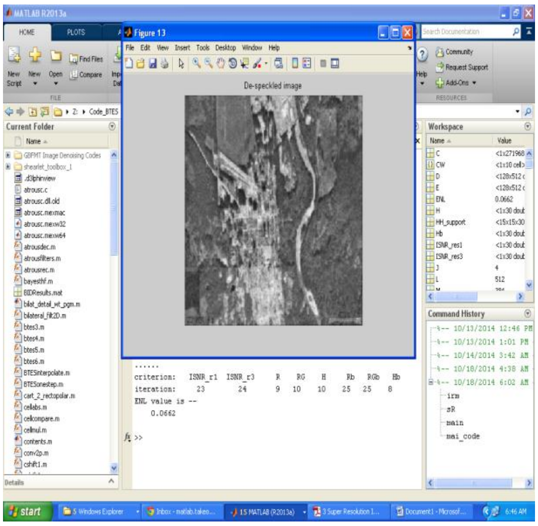

Fig 13: The above figure shows the output which is a de-speckled image.

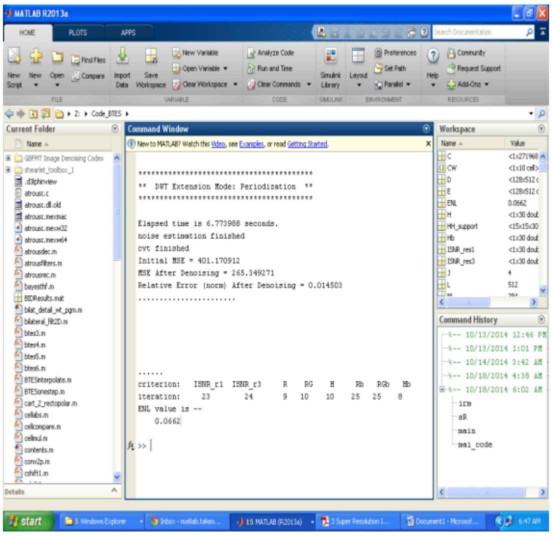

Fig 14: the above figure shows the command window in which the program is being written.

4. CONCLUSION

In this paper, we discussed new component based method for the reduce speckle noise in SAR images. The proposed new method consists a specific dictionaries for structural and texture components. This dictionary represents the separation with an fast convergent iterative shrinkage scheme. It contains important salient features for SAR image. This paper also shows that comparison between proposed approach and various recent methods and obtained better **4** results. The proposed method also valuable for many SAR images such as volcano scenes, coastline detection, road detection, railway detection and agricultural scenes.

We proposed a new method of speckle reduction in SAR imagery based on separating an image into various components. Unique to this approach is the ability to use specific dictionaries of representations suited for separation with an iterative scheme that is able to retain important features. Matlab results showed that this method performs favorably compared to other competitive methods. This new process is also valuable for many SAR image understanding tasks such as road detection, railway detection, ship wake detection, texture segmentation for agricultural scenes, and coastline detection. In addition, specific dictionaries could be designed to be used with this procedure to capture unique signatures while dealing with speckle removal. Likewise, particular lexicons could be intended to be utilized with this system to catch one of a kind marks while managing with dot evacuation.

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