

Despeckling Of Optically Fused SAR Image via PCA Analysis And Enhancement Using Genetic Algorithm

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Abstract— Despeckling Of Optically Fused SAR Image via PCA Analysis And Enhancement Using Genetic Algorithm was developed to attain the originality of the image and in order to obtain increased PSNR ratio. Initially it was fed into an adaptive Weiner filter, upon which logarithmic operations were performed in order to reduce the speckles. With the use of k-means clustering PSNR was improved. The image was further enhanced and the noises were eliminated using the Genetic algorithm, which served to overcome all the demerits of the already existing methods

Index Terms—SAR, PSNR, K-means clustering, Genetic algorithm, optical driven.

I. INTRODUCTION

A. OPTICALLY FUSED SAR IMAGE

Synthetic-aperture radar (SAR) is a form of radar which is used to create an image of an object, such as a landscape – these images can be 2D or 3D representations of the object. SAR uses the motion of the SAR antenna over a target region to provide finer spatial resolution than is possible with conventional beam-scanning radars. Optical imaging is an imaging technique. Optics usually describes the behavior of visible, ultraviolet, and infrared light used in imaging.

B. Despeckling Of Fused Image

Synthetic Aperture Radar (SAR) images are inherently affected by speckle noise which is due to the coherent nature of the scattering phenomena. Even though speckle carries itself information about the illuminated area, it degrades the appearance of images and affects the performance of scene analysis tasks carried out by computer programs (e.g., segmentation and classification) or even by human interpreters. To counter this problem, users resort often to the multilook, technique, which amounts to incoherently averaging a certain number (defined by the number of looks) of independent images, thus reducing noise intensity, but often at the cost of a clear loss in image resolution. Therefore, it is certainly preferable to develop suitable filtering techniques, which reduce noise significantly but, at the same time, preserve all the relevant scene features, such as radiometric and textural information. However, together with new problems, the abundance of remote sensing imagery offers new opportunities for all image processing tasks, particularly for despeckling. Given a multitemporal stack of coregistered

SAR images, for example, one can carry out filtering in the temporal domain [2], thus reducing speckle with no loss of spatial resolution. A step forward along this path is to exploit optical imagery to improve the despeckling of SAR images.



Figure 1. 3-D SAR image

II. RELATED WORK

A. Filtering

In signal processing, a filter is a device or process that removes from a signal some unwanted component or feature. Filtering is a class of signal processing, the defining feature of filters being the complete or partial suppression of some aspect of the signal. Most often, this means removing some frequencies and not others in order to suppress interfering signals and reduce background noise. However, filters do not exclusively act in the frequency domain; especially in the field of image processing many other targets for filtering exist. Correlations can be removed for certain frequency components and not for others without having to act in the frequency domain

B. Optical Driven Sar Image

We are going for optical driven SAR images in order to clarify the image the more even touch the SAR images are more than enough to be used for clear images in both 2-D and 3-D there may be some blurring of images due to the distance it travels and some other frequencies that it may unavoidable overcome. In order to overcome these types of image blurring we are going for optical driven SAR images where the blurring is reduced and leads to the multi speckles which are finally removed.

C. Spatial Domain Filters

These techniques are based on gray level mappings, where the type of mapping used depends on the criterion chosen for enhancement. As an eg. consider the problem of enhancing the contrast of an image. Let r and s denote any

gray level in the original and enhanced image respectively. Suppose that for every pixel with level r in original image we create a pixel in the enhanced image with level $S=T(r)$. If $T(r)$ has the form as shown

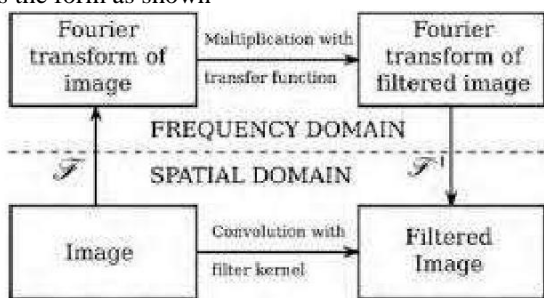


Figure 2. Block for the Spatial domain process.

The effect of this transformation will be to produce an image of higher contrast than the original by darkening the levels below a value m and brightening the levels above m in the original pixel spectrum. The technique is referred to as contrast stretching. The values of r below m are compressed by the transformation function into a narrow range of towards the dark end of the spectrum; the opposite effect takes place for values of r above m . In the limiting case shown in figure, $T(r)$ produces a 2-level (binary) image. This is also referred to as image thresholding. Many powerful enhancement processing techniques can be formulated in the spatial domain of an image.

D. WAVELET TRANSFORM FILTERS

In mathematics, a wavelet series is a representation of a square-integrable (real-or complex valued) function by certain orthonormal series generated by a wavelet. Nowadays, wavelet transformation is one of the most popular candidates of the time-frequency-transformations. This article provides a formal, mathematical definition of an orthonormal wavelet and of the integral wavelet transform equation. Recently, the use of wavelet transform has led to significant advances in image analysis. The main reason for the use of multiscale processing is the fact that many natural signals, when decomposed into wavelet bases are significantly simplified and can be modeled by known distributions. Besides, wavelet decomposition is able to separate noise and signal at different scales and orientations..The first multiscale speckle reduction methods were based on the thresholding of detail subband coefficients. [8] Wavelet thresholding methods have some drawbacks: (i) the choice of threshold is made in an ad hoc manner, supposing that signal and noise components obey their known distributions, irrespective of their scale and orientations; and (ii) the thresholding procedure generally results in some artifacts in the denoised image

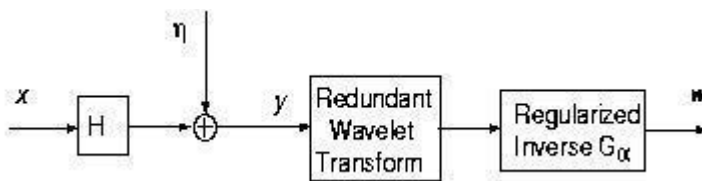


Figure 4. Block of wavelet domain filter.

E. NONLOCAL FILTERING

In existing approach The nonlocal means (NLM) techniques performed which mainly focused the high-frequency components. Also the Speckle noise is removed by probabilistic-patch-based (PPB) and SAR-BM3D process. The performance of denoising is very sensitive to patch-wise operation. This existing denoising process considered only for AWGN process not applied for signal-dependent noise. It achieved lesser PSNR for denoising result.

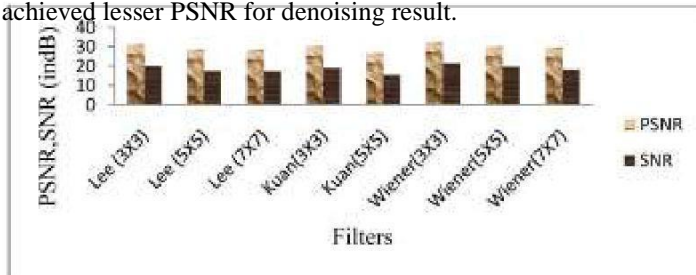


Figure 3. PSNR COMPARISON

III. OBJECTIVES & OVERVIEW OF THE PROPOSED SYSTEM

A. OBJECTIVES

In this paper, we propose to fuse the SAR image with an optical image which attains the originality of the image in the higher ratio. The concept of this system is important to increase the PSNR ratio. Here we reduce the dimensionality of the image after the transformation of the image from one form to another.

B. OVERVIEW OF THE PROPOSED SYSTEM

In the proposed system PCA technique to account for speckle noise. Here instead of using block matching approach used clustering approach. In this proposed use the combination of log-transformation, PCA and K-means methods for finding similar patches. Initially convert the image into patches. Log transformation was performed and then converted into PCA domain. Then applying Non local- Wiener filter to processing the denoise process and perform the inverse transformation. To overcome the limitations of the homomorphism approach for multiplicative noise. This method applicable for both preservation and speckle noise reduction. An improved PSNR can be gained from implementing this approach.

a. Fuzzy Filters

$$[(+ , +)] \quad (1)$$

Noise reduction is the very important stage of image processing and pattern reorganization. Many researches find new tools and filters for noise reduction. This paper proposed a fuzzy based adaptive filter. The proposed filter is composed with the existing filter like VDF, VMF and VRF with Gaussian noise, impulse noise and mixed Gaussian Noise. Median filter effectively suppresses the speckle noise but the edges are not well preserved. Fuzzy filters with median center preserve image sharpness, when used for additive noise reduction. The median value based on fuzzy triangulation membership function with median center (TMED) [28, 29] is defined by (5) with different window and padding size. The maximum, minimum, median, and moving average values are, respectively

b.Adaptive Wiener Filter

Consider the filtering of images corrupted by signal independent zero-mean white Gaussian noise. The problem can be modeled as

$$Y(i, j) = z(i, j) + n(i, j) \quad (2)$$

where $y(i, j)$ is the noisy measurement, $z(i, j)$ is the noise free image and $n(i, j)$ is additive Gaussian noise. The goal is to remove noise, or "denoise" $y(i, j)$, and to obtain a linear estimate $\hat{z}(i, j)$ of $z(i, j)$ which minimizes the mean squared error (MSE), N , where N is the number of elements in $x(i, j)$. When $z(i, j)$ and $n(i, j)$ are stationary Gaussian processes the Wiener filter is the optimal filter. Specifically, when $x(i, j)$ is also a white Gaussian process the Wiener filter has a very simple scalar form: where u_2 , p are the signal variances and means, respectively, and where we will normally assume the mean of the noise to be zero. The effectiveness of the simple form Wiener filter (3) was documented in . In particular, Kuan proposed a non stationary mean and non stationary variance (NMMNV) image model; conditioned on this model, for natural images the residual process can be well treated as white Gaussian processes. To use this we need to determine $p z(i, j)$, $uz(i, j)$ and $u:(i*j)$. We will assume that the noise mean and variance are known (for the well-established problem of noise variance estimation readers are referred to and references therein). Instead, we focus on the local estimation of $p z(i, j)$ and $u ;(i, j)$. Normally the local mean and local variance are calculated over a uniform moving average window of size $(27 + 1) \times (27- + 1)$ As discussed in the Introduction, they tend to blur the mean and increase the variance near edges. Thus, the resulting denoised image is poor and looks noisy.

C. GEOMETRIC FILTERING

The geometric filter works by increasing or decreasing the pixel values in the neighborhood based on their comparative value. The intensity of the pixel located at the center of 3×3 window is compared with eight neighbors. Depending on the intensity values of neighborhood pixels, the value are either incremented or decreased so that the values stand out compared to theirs. The size of moving window in this study is set to 3×3 with number of iteration being equal to 2. The visual quality of the image improves on using geometric filter but at the same time the image is smoothed considerably also with some noisy edge retained. Some of the edges and finer details are mostly lost.

D. GENETIC ALGORITHM

In the field of artificial intelligence, a genetic algorithm (GA) is a search heuristic that mimics the process of natural selection. This heuristic (also sometimes called a met heuristic) is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. Genetic algorithms find application in bioinformatics, phylogenetics, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics, pharmacometrics and other fields. A typical genetic algorithm requires:

- a genetic representation of the solution domain,
- a fitness function to evaluate the solution

domain Basic Genetic Algorithm

```
{
    Initialise Population;
    Calculate fitness function;
    While { fitness value != Termination criteria}
    {
        Selection;
        Crossover;
        Mutation;
        Calculate fitness function
    }
}
```

A standard representation of each candidate solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming; a mix of both linear chromosomes and trees is explored in gene expression programming. Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators.



Figure 5. Comparison of Canny edge maps for clip 3. From left to right: De Grandi (reference), enhanced Lee, SRAD, PPB, SAR-BM3D, and proposed.

IV PROPOSED WORK TECHNIQUES

A. PCA

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation. It is used to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This transformation is defined in such a way that the first principal component has the largest possible variance. PCA is the simplest of the true eigenvector-based multivariate analyses.

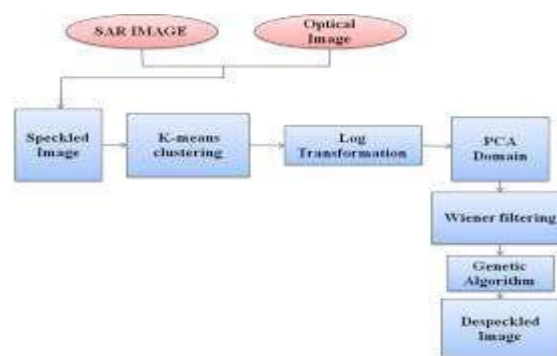


Figure 6. Proposed Technique

B. K-Mean Clustering

k-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. The algorithm is often presented as assigning objects to the nearest cluster by distance.

C. Logarithmic Transform

The logarithm and square root transformations are commonly used for positive data, and the multiplicative inverse (reciprocal) transformation can be used for non-zero data.

Despeckling methods	Test Image 1	
	MSE	PSNR
Lee Filter	1180.68	15.71
Median Filter	1059.34	17.30
Mean Filter	847.10	17.64
Frost Filter	773.87	19.25
Hard Threshold in curvelet transform	677.81	25.58
Soft Threshold in curvelet transform	365.05	28.57
Hard Threshold in shearlet transform	246.76	30.57
Hard Threshold in shearlet transform	145.89	35.53
Wavelet Transform	89.53	39.53
Weiner with Genetic Algorithm (Proposed)	71.26	44.93

Table I Comparison of MSE and PSNR

V. RESULTS

The performance of k-means clustering, log transformation, Wiener filtering and genetic algorithm is analyzed in terms of IQM followed by visual assessment. Improvement in image quality metrics is observed using the integration of wiener filter along with genetic algorithm. Enhancement is observed. The results suggest that proposed methods are superior compared to others.

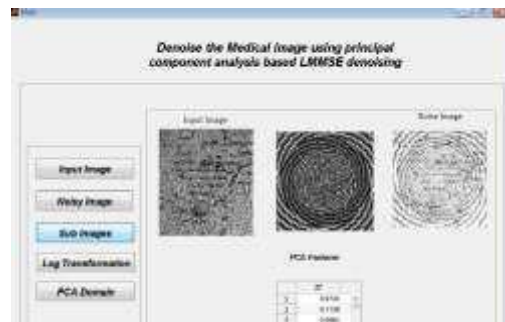


Figure 7. Output(1)

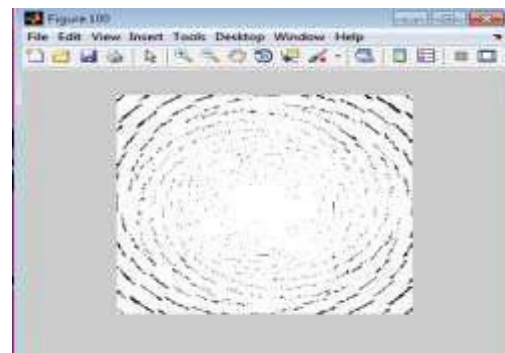


Figure 8. Output(2)

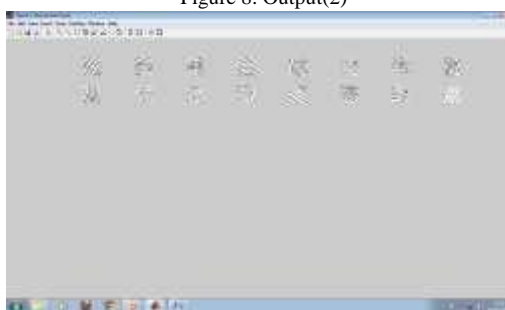


Figure 9. Output (3)



Figure 10. output (4)

VI. CONCLUSION

We proposed a new SAR despeckling technique that exploits information drawn from a coregistered optical image. Using optical data to increase despeckling power is certainly appealing but can cause a loss of fidelity. We avoid this drawback by resorting to nonlocal filtering and to a suitable soft classification of the image, obtaining very good results in all experiments. With the increasing diffusion of remote-sensing imagery, the joint availability of optical and SAR data is becoming more and more frequent, making the proposed approach very relevant for the applications. In future research,

we will further explore the potential of this approach and consider more sophisticated filters and fusion techniques.

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