SAR IMAGE DENOISING

Rajkishor Ranjan Kumar & Dr. Suman Kumar Maji
Computer Science and Engineering, IIT Patna
rajkishor.cs13@iitp.ac.in/1301CS35/Ph.+91-9661174964

Abstract
We have proposed a novel multifractal based image denoising technique. We tested the method over standard images of sipi database corrupted with high level of mixed Poisson-Gaussian noise and have shown the quality of improvement over the noisy versions. We have also tested the algorithm on real fluorescence microscopy aquisitions.

Introduction

- *Synthetic aperture radar (SAR)* is a form of radar that is used to create images of objects.
- These images are the satellite captured high resolution images which are having higher significance in various real time applications including water region identification, forest identification etc.
- *Benefits and Uses :* It can penetrate the cloud and collect data in bad weather persistent fog or smoke.
- The intensities of pixels in a SAR image are based on the spatial orientation, roughness, and dielectric constant of the surface imaged.
- SAR processing is the transformation of raw SAR signal data into a spatial image.

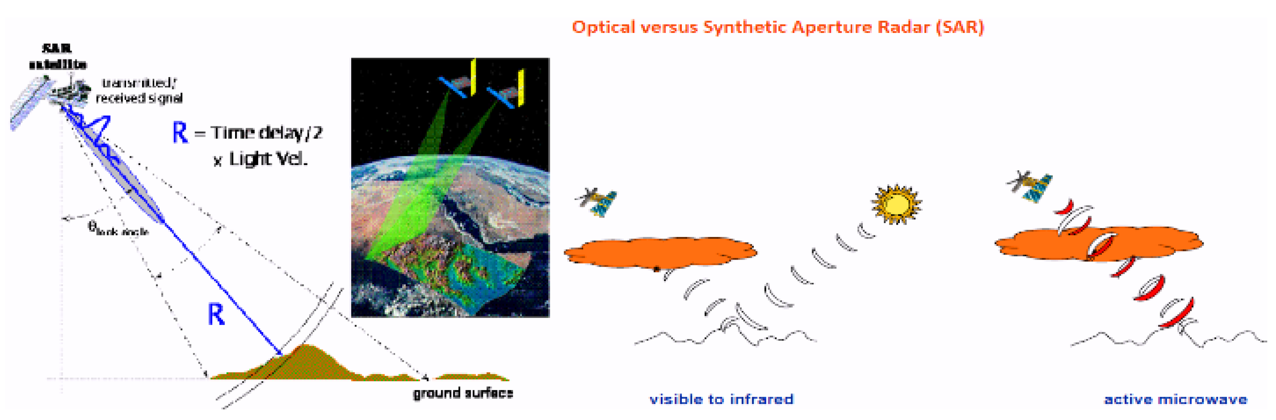

Figure 1: Fig. **Optical versus SAR**

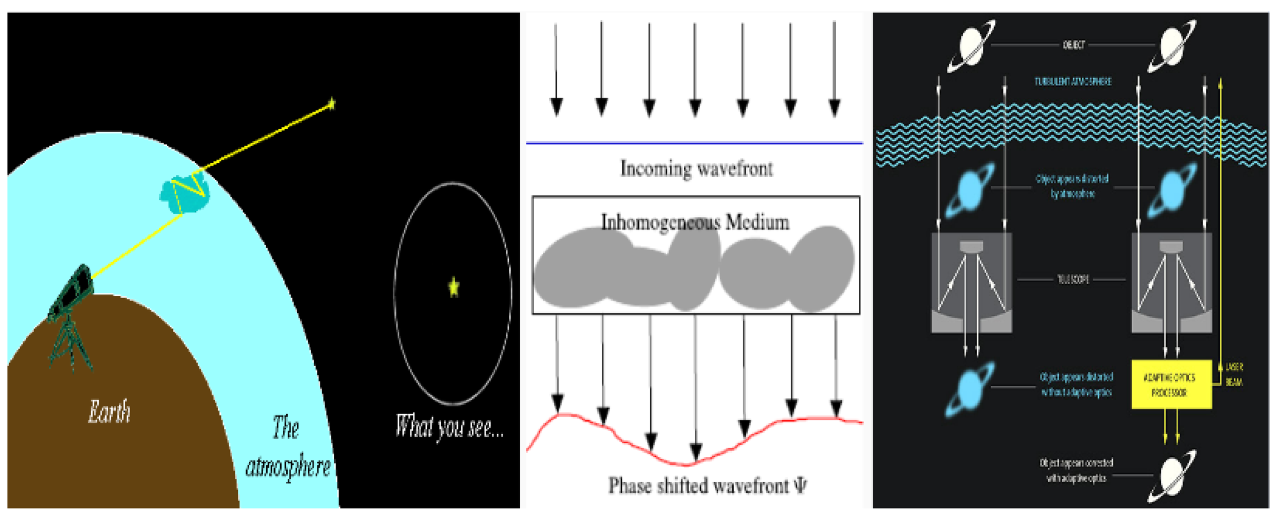

Figure 2: Fig. **Atmospheric Turbulence**

Objectives

1. Image Noising (Change in phase of light source, Speckle Noise)
2. Multifractal System (Microcanonical Multiscale Formalism (MMF), Singularity Exponent (SE))
3. Multifractal Based Denoising (Feature Extraction, Noise Separation ,Image Reconstruction, PSNR)
4. MSM result, SARBM3D result, Comparison b/w them

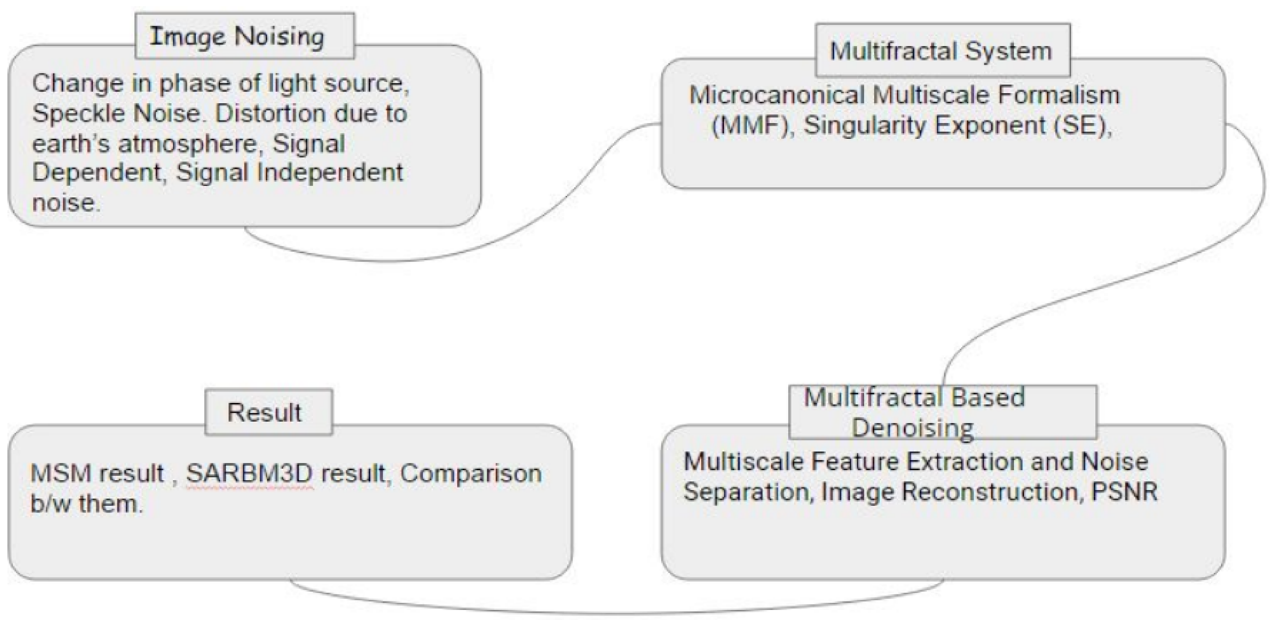

Figure 3: Fig. **Work Flow**

Restoration of SAR Images

According to SAR image model, $v(\vec{x},\vec{y}) = H(\vec{x},\vec{y}) * u(\vec{x},\vec{y}) + n$ where $u(\vec{x},\vec{y})$: original image, $v(\vec{x},\vec{y})$: observed image, $H(\vec{x},\vec{y})$: degradation or distortion matrix and n : noise. For image restoration, we have to find u given v and H. if we remove the noise from the image then original image becomes $u(\vec{x},\vec{y}) = H^{-1}(\vec{x},\vec{y}) * v(\vec{x},\vec{y})$.

Methods and Approach

1. **Multifractal System and MMF**
   - Novel denoising technique based on Microcanonical Multiscale Formalism (MMF)
   - In multifractal systems, a local power-law governs the behavior of objects at different scales
   - **Singularity Exponents (SE) :** This leads to a set of pixels known as the most singular manifold (MSM)
   - MMF is a model which quantitatively evaluates the parameters associated to a multifractal system.

   According to MMF, a signal $s(\vec{x})$ is multifractal, if the following relation holds :
   $T_r s(\vec{x}) = \alpha(\vec{x}) * r^{h(\vec{x})} + o(r^{h(\vec{x})})$ where $s(\vec{x})$: signal, $T_r s(\vec{x})$: Signal Function, $h(\vec{x})$: SE, $\alpha(\vec{x})$: Signal dependent amplitude pre-factor. when $r \Rightarrow 0$ then $T_r s(\vec{x}) = \alpha(\vec{x}) * r^{h(\vec{x})}$.

   For small number of r , the above equation satisfies the equality criteria and the SE $h(\vec{x})$ can be computed through a log-log regression of above equation and is equal to,

   $h(\vec{x}) = \lim_{r\to 0}(\frac{\log \frac{T_r s(\vec{x})}{\alpha(\vec{x})}}{\log r})$, $T_\psi s(\vec{x}, r) = \int ||\Delta s||(\vec{y}) \frac{1}{r^d} \psi(\frac{\vec{x}-\vec{y}}{r}) d\vec{y}$

   where d : is dimension of signal domain (d=2 for image), and $\psi(\vec{x})$ is a wavelet function which is defined as $\psi(\vec{x}) = \psi^\beta(\vec{x}) = \frac{1}{(1+|\vec{x}|^2)^\beta}$
   - The choice of the functional T plays an important role in estimating the **SE**.
2. **Multifractal Based Denoising**
   - Singularity Exponent for every point has a fractal component . Once we compute the SE , we move our attention towards the derivation MSM set. $f_h = [\vec{x} : h(\vec{x}) = h]$
   - The MSM points are the components associated with the smallest possible value of SEs (Threshold). $f_\infty = [\vec{x} : h(\vec{x}) = h_\infty = min(h(\vec{x}))]$
   - After extracting noise-free features from the image, reconstruct an image at every point in the image domain from the gradient of SEs evaluated over the MSM.
   - **Universal Reconstruction Kernel (g) :** Capable of reconstructing the signal from its gradient measurement restricted to the MSM.
   $s(\vec{x}) = g * \Delta f_\infty s(\vec{x})$, $\Delta f_\infty s(\vec{x}) = \Delta s(\vec{x}) \delta f_\infty(\vec{x})$ where (*) denotes convolution
   Converting Above equation in fourier domain is given by : $s(\vec{w}) = g(\vec{w}).\Delta f_\infty s(\vec{w})$, and $g(\vec{w}) = \frac{\vec{w}}{||\vec{w}||^2}$
   - The final expression of the reconstruction formula in the Fourier domain, is: $s(\vec{w}) = \frac{\vec{w}.\Delta f_\infty s(\vec{w})}{||\vec{w}||^2}$ Fourier inversion of this formula gives the reconstruction of the image from the restriction of the gradient field to the MSM.

Results

- We are doing our experiment over sipi dataset . We tested the method over standard images corrupted with high level of mixed Poisson-Gaussian noise and have shown the quality of improvement over the noisy versions.
- **Peak Signal to Noise Ratio (PSNR) :** We evaluate PSNR for quantitative evaluation of the denoising algorithm.
  PSNR $= 20{*}\log\frac{max(s(\vec{x}))}{\sqrt[2]{MSE}}$ where $MeanSquareError(MSE) = \frac{1}{M*N}\sum_{i,j}|s(\vec{x}) - s_r(\vec{x})|^2$
  where $M * N$ = size of image, $s(\vec{x})$ represents noise image and $s_r(\vec{x})$ represents denoised image.
- Experiment has been carried over a set of different images, of different sizes, from SIPI image database. Tests were performed after adding high noise using a mixed Poisson-Gaussian noise model. The metric used for quantitative evaluation of the denoising algorithm is **PSNR** (expressed in dB).

Image	PSNR(MSM)
4.2.07.tiff	23.32
4.2.06.tiff	21.40
5.1.09.tiff	23.09
7.1.01.tiff	19.44
7.1.04.tiff	24.32
7.2.01.tiff	25.80
7.2.04.tiff	18.05
7.1.04.tiff	24.32
5.1.09.tiff	23.09

Table 1: Calculated Data

Conclusions

- In this paper, we have proposed a novel multifractal based image denoising technique for fluorescence microscopy.
- We tested the method over standard images corrupted with high level of mixed Poisson-Gaussian noise and have shown the quality of improvement over the noisy versions.
- We have also tested the algorithm on real fluorescence microscopy aquisitions.

References

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