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BDNFF - A Novel Bayesian Adaptive Filtering Algorithm for Removing Dynamic Pattern Noise in VHRI Satellite Images

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Abstract: One of the main challenges in remote sensing data is noise, which can negatively impact data quality and analysis results. Pattern noise can have different shapes in the Frequency domain which can be dynamic based on features. FFT thresholding may not suffice because of the difficulty in setting adaptive noise thresholds based on features in the image. There is a need for a methodology that automatically detects and corrects features based on dynamic noise frequency to improve the overall quality of data. This paper aims to explore the various challenges associated with noise removal in Cartosat 2 data, including methods for detecting and reducing noise, and current limitations in feature-dependent pattern noise correction. We propose a novel adaptive noise reduction algorithm for satellite images that can effectively reduce horizontal and vertical components of feature-based dynamic noise. The proposed Bayesian Dynamic Noise Filtering in Frequency domain (BDNFF) method consists of two stages: first, identification of noise was carried out using local statistical characteristics of the data, and second, denoising of the image is done using the Bayesian estimation technique to reduce the identified noise. The effectiveness of the proposed BDNFF method is evaluated using a set of satellite images with various levels and types of dynamic pattern noise. Traditional noise removal methods like using notch filters in the frequency domain introduce information loss due to frequency cutting which the BDNFF algorithm restores using Bayesian estimation. The proposed method has the potential to significantly improve the quality and accuracy of satellite imagery for various remote sensing applications. Analysis and results are presented in the paper in detail. These techniques will help to generate seamless products with a better signal-to-noise ratio (SNR) and modulation transfer function (MTF), which helps in ground segment remote sensing applications.

Keywords: Bayesian Estimation, FFT, Dynamic Pattern Noise, Noise Estimation, Noise Reduction, Image Enhancement.

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1. Introduction

The launch of various optical remote sensing satellites in recent years has made space-borne remote sensing images available on a global scale. Noise reduction [12] in satellite images is a critical step in ensuring high-quality and accurate data for remote sensing applications. The presence of noise can negatively impact the analysis and interpretation of the data, reducing the reliability and validity of the results. Noise [12] in satellite images can

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be introduced by various sources, including the sensor, atmospheric conditions, and electrical interference. Optical satellite images are susceptible to various types of noise that can degrade their quality and hinder analysis. These noises can arise from both internal and external factors. Internal noise, often referred to as sensor noise, is inherent to the imaging sensor itself and can be classified into several categories. Systematic noise and non-systematic noise are two major types of noise present in satellite images. Systematic noise [21], also known as structured noise, is predictable and consistent in its pattern. It is often introduced during the acquisition process, such as through sensor bias or calibration errors. In contrast, non-systematic noise [21], also known as random noise, is unpredictable and lacks a consistent pattern. It can be caused by factors such as atmospheric conditions, electrical interference, or sensor instability.

2. Related Work

Several techniques have been used for noise reduction in satellite images, including filtering, thresholding, regression, and others. Median filtering, Wiener filtering [7], and wavelet denoising [18] are some of the most commonly used methods. Each noise reduction technique has its own strengths and weaknesses. Median filtering is simple and effective for removing salt-and-pepper noise, but it can also lead to the blurring of fine details in the image. On the other hand, Wiener filtering [7] is more sophisticated and can yield better results for Gaussian noise, but it is computationally intensive and may result in over-filtering. Noise correction in the Fourier domain involves transforming the original image into the frequency domain using the Fourier transform and then removing or reducing the noise present in the image.

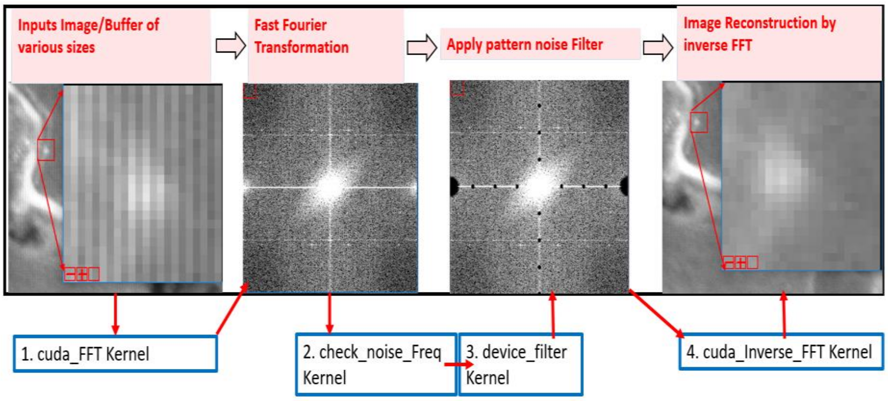

Figure 1 - Notch Filter Leaving Dark Spots in FFT. A – Input image , B – FFT of A, C – FFT after notch filter , D – Output after IFFT

Notch filters in the frequency domain [17] are a common technique for removing static pattern noise [16] from images. By identifying the frequency components associated with the noise, a narrow band can be created to eliminate those frequencies. This approach is particularly effective when the noise frequency remains consistent across multiple images. However, a limitation of notch filters is their inability to handle dynamic noise patterns, which can vary depending on the specific image content and features. In such cases, it can be difficult to distinguish between noise and genuine image details. Consequently, there is a pressing need for more advanced noise removal techniques that can address dynamic, feature-specific pattern noise [16].

There are various methods to estimate parameters based on the given input data. Given the evidence X, Maximum Likelihood (ML) [1][6] treats the parameter vector as a constant and seeks the value that provides maximum support for the observed data. Maximum A Posteriori (MAP) estimation [1] accounts for the fact that the parameter vector can take values from a distribution [2] representing prior beliefs about the parameters. MAP returns the value of θ that maximizes the posterior probability prob $(\theta \mid X)$

Both ML and MAP yield a single, specific estimate for the parameter. In contrast, Bayesian estimation is a statistical method that combines prior information with likelihood functions to estimate unknown parameters. It computes the full posterior distribution (Equation 1), allowing parameter estimation through Bayes' Rule.

$$P(\theta \mid D) = \frac{P(D|\theta)P(\theta)}{P(D)} \quad (1)$$

where P(θ|D) is the posterior distribution, P(D|θ) is the likelihood, P(θ) is the prior distribution, and P(D) is the marginal likelihood (or evidence). The denominator P(D) is often not easy to compute directly, so we typically choose our prior distribution P(θ) to facilitate this calculation. By choosing a prior that is conjugate to likelihood, computation of the posterior distribution is more straightforward, allowing us to avoid complex integrals [1].

3. Data Selection and Setup

The selection of appropriate data is paramount for the effective estimation and removal of noise in satellite images. Our dataset was sourced from the Cartosat 2 [5][8] series of satellites, encompassing all relevant imagery about our areas of interest. We focused on Level 0 data [8] with a Look-Up Table (LUT) applied due to its raw nature (L0+LUT), which is particularly useful for identifying and analyzing noise patterns. To isolate areas with prominent noise, we concentrated on homogeneous patches such as urban and playgrounds. For our experiments, we utilized 1024-scan by 1024-pixel panchromatic images. The proposed approach can be extended to multispectral images by processing each band individually. The input images were 16-bit unsigned integers with a resolution of 1024x1024 pixels. All experiments were conducted on a consistent hardware, featured 120 GB of RAM, a 60-core Intel Xeon processor, and an NVIDIA P100 graphics card with 16GB of memory, 3584 CUDA cores. Comparison of all images is done under the same 2% stretch conditions.

4. Methodology

In satellite imagery, pattern noise often manifests as sudden spikes or artifacts in specific frequency bands of the fast Fourier Transform (FFT) [17]. The algorithm designed implements a Bayesian-based algorithm for dynamic pattern noise removal, using prior information, and removes the identified horizontal, vertical, and diagonal pattern noise pattern from the imagery. The designed BDNFF algorithm contains two major components, dynamic pattern noise identification module and an identified noise correction module.

A. Dynamic Noise Identification: Noise is a sudden spike in the data. Nyquist frequency noise **[9]** is at a known location but to detect the other horizontal, vertical, and diagonal pattern noise **[16]**, we took a bin of 128 samples and based on mean and variance, a noise spike was identified. As real signal frequency transform is symmetric in nature, same noise spikes will be identified in both halves of FFT. Dynamic Noise Identification typically includes various steps including -

1. **Row-based Analysis**: Process each row of the image independently and carry out 1D FFT of each row.
2. **Spike Detection**: Use a suitable algorithm to identify sudden spikes in the FFT magnitude. We have used statistical tests of mean and variance with thresholding.
3. **Noise Region Definition**: Based on the identified spikes, define regions in the Frequency domain that are likely to contain noise. This is manually done for Nyquist frequency noise as its spread is constant. For Nyquist frequency noise [8], the region will have a range of nearly 100 pixels for Cartosat 2 images. For other, automatically identified noise frequencies region is set to be 1 pixel.

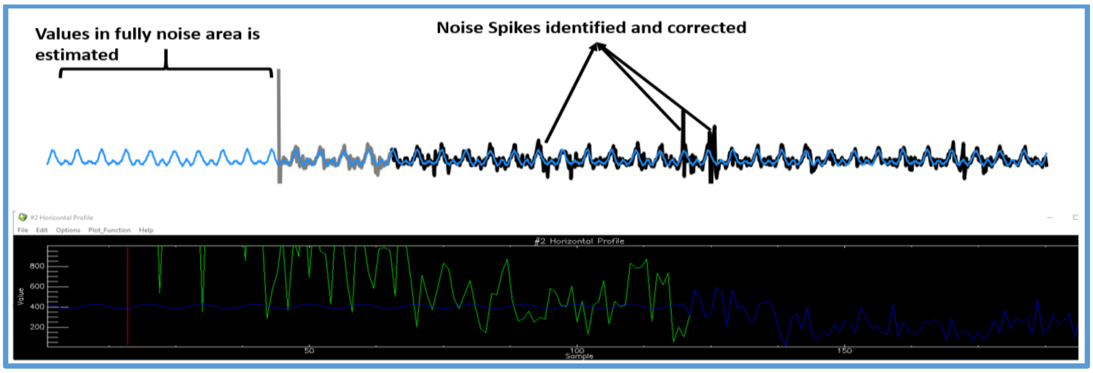

Figure 2- Nyquist frequency prediction using the Bayesian approach. A (top) – Illustration of noise detection and correction. B (bottom) - Corrected Nyquist Frequency

B. Bayesian Dynamic Noise Correction:

Noise will have horizontal component and vertical component which can be captured by vertical Column FFT and horizontal row FFT respectively. Once the noise is detected in the row data, It is removed using Bayesian approach. To remove the Nyquist frequency noise [8], we take the Nyquist noise region typically of nearly 100 pixels and use the posterior distribution from non-noisy values to estimate the missing values. We have Created

Prior and Likelihood Functions from row data of (L0+LUT) Level 0 products [8]. Prior and likelihood will be estimated for each line after identification of noise. Noise in Nyquist frequency is responsible for alternate column bias noise which is corrected by estimating the values using posterior probability. BDNFF Algorithm will estimate the diagonal frequency components by posterior estimation. It's particularly useful for interpolation, where the goal is to estimate values of a function between known data points.

Likelihood Function: The likelihood function specifies the probability of observing the existing curved data given a set of parameters. It's typically based on a noise model, such as Gaussian noise [9] for normally distributed errors. Satellite imagery data often assumes a Gaussian distribution [2] for pixel intensity values, especially when noise is present. The Gaussian model is widely used because it captures the central tendency of the data effectively, assuming that the noise is additive and follows a normal distribution as shown in the equation 6. Mean and variance of the likelihood distribution is calculated from the bin non-noisy samples.

$$P(D \mid \mu, \sigma^2) \sim \mathcal{N}(\mu, \sigma^2) \quad (2)$$

Prior Distribution:

If you have prior knowledge about the expected values of the pixel intensities or the expected range of values, a Gaussian prior can be effective. By choosing a prior that is conjugated to the likelihood, we make the computation of the posterior distribution more straightforward, allowing us to avoid complex integrals. This approach is particularly useful in practical applications where we want to update our beliefs with new data efficiently. we considered normal distribution as prior. we have chosen a prior distribution that is conjugate to the likelihood.

$$P(\mu) \sim \mathcal{N}(\mu_0, \tau^2) \quad (3)$$

Once the Prior and likelihood is estimated for each row of input image, each row data can be modelled using Bayesian approach. With Bayesian methods, as you observe new data points or if you want to estimate missing values, you can update your model using the prior and likelihood to obtain the posterior distribution estimate of the missing values.

C. BDNFF: Bayesian Dynamic Noise Filtering in Frequency domain

Bayesian Dynamic Noise Filtering in Frequency domain (BDNFF) algorithm is designed to identify and remove dynamic pattern noise from satellite images. Unlike traditional methods, BDNFF estimates the noise level for each individual line of the image based on the available non-noisy data. This localized approach ensures that the noise removal process is tailored to the specific characteristics of each image line, leading to more accurate and effective results. The following steps outline the implementation of the BDNFF algorithm:

Algorithm 1 BDNFF- Bayesian Dynamic Noise Filtering FFT

```
Create 1024*1024 size the tiles from noisy input image.
for each tile of 1024*1024 from Input Image,... do
    for each row line of a tile from 0 to ...1024 do
        Take FFT of row r.
        for each bin b of size 128 column FFT from 0 to ...8 do
            Noise Identification of Nyquist, dynamic pattern noise region
        end for—
        for each identified noise region in above for loop do
            Correct dynamic pattern noise using Bayesian interpolation.
            Correct Nyquist noise using Bayesian prediction.
        end for
        Take IFFT of row r.
    end for
end for
Combine the tiles to create noise corrected output image.
```

To remove dynamic pattern noise from the satellite image, we divided the L0+LUT image data into tiles of 1024x1024 pixels. For each tile, we processed each row individually. For each line of the data, the steps below are performed to eliminate and reduce the dynamic pattern noise. This typically includes various steps like –

1. **Fast Fourier Transform (FFT) of rows**: We applied a 1D-FFT to the row, transforming it from the spatial domain to the frequency domain to remove vertical component of the noise frequency.

2. **Binning:** We divided the FFT results into bins of 128 columns. This grouping helps to identify frequency patterns associated with noise in local region and prediction to the specific characteristics of each bin in row.

3. **Noise Region Identification:** Within each bin, we determined the regions corresponding to pattern noise using dynamic noise identification.

4. **Bayesian Noise Correction:**

4.1 Construct the Likelihood: As observations are non-noisy, we assume that the data is normally distributed around your model predictions.

4.2 Define the Prior: Based on trends in non- noisy data, we used normal distribution centered on that trend.

4.3 Perform Bayesian Updating and Interpolate Missing Values: Find the posterior distribution and use the posterior distribution for sampling to get a range of plausible values estimate for the missing values in FFT by Bayesian interpolation technique.

5. **Inverse FFT:** After correcting the noise in the frequency domain, we performed an inverse FFT to transform the data back into the spatial domain.

6. **Tile Combination:** Finally, we combined the processed tiles to create the vertically corrected input image.

7. **Fast Fourier Transform (FFT) of columns:** Once the image is reconstructed after step 7, repeat step 2 to 7 by taking columns FFT to remove horizontal component of the noise frequency. Horizontal component of the noise frequency is removed using 1D FFT of the rows and then corrected output is feed-in into 1D FFT of the columns to remove the vertical component of the noise frequency.

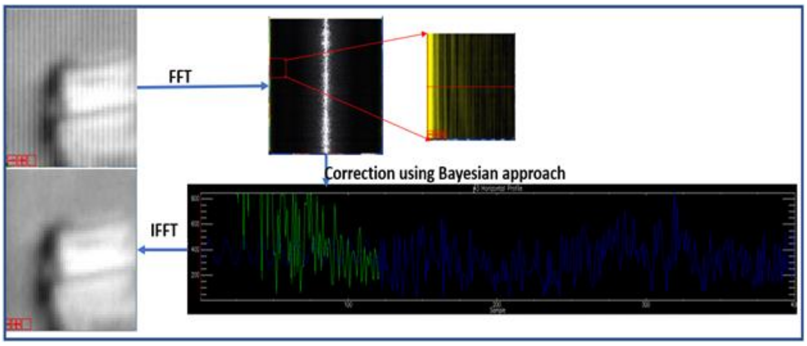

Figure 3 - Overview of BDNFF algorithm working. A(top-left) – Input image, B(top-right) – 1 D FFT of each row, C(bottom-right) – Corrected Nyquist Frequency, D(bottom-left) – Output Image.

As shown in the figure- 4, the BDNFF algorithm effectively corrects both Nyquist frequency and Nyquist/2 frequency components (Green is noise frequency). These frequencies are automatically detected and often associated with alternative column noise patterns in satellite images. To address Nyquist noise, we performed a multiple sampling of Bayesian estimate. The BDNFF algorithm successfully removes the undesirable effects of dynamic pattern noise.

Let's consider the example where bin size is 25 and 4 noisy frequencies are detected by noise identification, and we need to correct those 4 noisy frequencies using 21 non- noisy frequency data points in bin size of 25. One of the rows of 1-D FFT in our data is - 52, 60, 65, 48, 79, 59, 36, 59, 48, 35, 115 ,69, 50, 56, 58, 98,54, 51, 59, 62, 108, 64 ,61 ,51, 50, where bold numbers are noise frequency identified. To find the posterior distribution using a Normal likelihood and a Normal prior based on the input data, we will follow these steps below to correct dynamic noise: -

Step 1: Take each bin non-noisy data -

- Non-noisy data of 1D FFT: 52, 60, 65, 48, 59, 36, 59, 48, 35, 69, 50, 56, 58, 54, 51, 59, 62, 64 ,61 ,51, 50
- Non-Noisy Sample size in a bin: 21
- Likelihood: we considered normal distribution as likelihood.
- Prior: we considered normal distribution as prior.

Step 2: Calculate the Sample Mean and Sample Variance -

- Mean of the non-noisy data ($\bar{y}$):

$$\bar{y} = \frac{1118}{21} \approx 53.71 \tag{4}$$

- Sample Variance

$$s^2 = \frac{1}{n-1} \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{5}$$

Where the nominator term sums to ≈ 2.9041+39.4641 + 126.06 + 32.0641+ 28.2241+ 319.0641+ 28.2241+ 32.0641+ 356.0641+ 236.0641+ 13.0641+ 5.2561+ 18.4641+ 0.0841+ 7.3041+ 28.2241+ 68.0641+ 104.0641+ 73.8241+ 7.3041+ 13.0641 ≈ 1182.384

$$s^2 \approx \frac{1182.3841}{20} \approx 59.1192 \tag{6}$$

Step 3: Specify the Prior Distribution – we considered normal distribution as prior distribution.

- Prior Mean ($\mu0$): Mean of all non-noisy data points of full 1D -FFT.

μ_0=55.

- Prior Variance ($\tau2$): Variance of all non-noisy data points of full 1D -FFT.

τ^2=10.

Step 4: Calculate the Posterior Distribution

The posterior distribution will also be normally distributed. The formulas for the posterior parameters are:

- Posterior Mean (μ_n):

$$\mu_n = \frac{\frac{\bar{y}}{s^2} + \frac{\mu_0}{\tau^2}}{\frac{1}{s^2} + \frac{1}{\tau^2}} \tag{7}$$

- Posterior Variance (σ_n^2):

$$\sigma_n^2 = \frac{1}{\frac{1}{s^2} + \frac{1}{\tau^2}} \tag{8}$$

Step 5: Perform the Calculations

- Calculate Posterior Variance:

$$\sigma_n^2 = \frac{1}{\frac{1}{s^2} + \frac{1}{\tau^2}} = \frac{1}{\frac{1}{59.1192} + \frac{1}{10}} \approx \frac{1}{0.0169 + 0.1} = \frac{1}{0.1169} \approx 8.55 \tag{9}$$

- Calculate Posterior Mean:

$$\mu_n = \frac{\frac{\bar{y}}{s^2} + \frac{\mu_0}{\tau^2}}{\frac{1}{s^2} + \frac{1}{\tau^2}} = \frac{\frac{53.71}{59.1192} + \frac{55}{10}}{\frac{1}{59.1192} + \frac{1}{10}} \tag{10}$$

$$\mu_n = \frac{0.9082+5.5}{0.0169+0.1} = \frac{6.4082}{0.1169} \approx 54.83 \quad (11)$$

Step 6: Posterior Distribution

Thus, the posterior distribution is

$$P(\mu \mid D) \sim \mathcal{N}(\mu_n, \sigma_n^2) \approx \mathcal{N}(54.83, 8.55) \quad (12)$$

This indicates that after observing the data, our updated belief about the mean value of the DN data is normally distributed with mean 54.83 and variance 8.55.

Step 7: Sample from posterior distribution to replace noisy frequency with new prediction: -

We have random samples from the normal distribution **[2]** N (54.83,8.55) to generate predicted values.

$$Prediction = random\ sampling\ from\ (\mathcal{N}(54.83, 8.55)) \quad (13)$$

The predicted values will normally distributed [2] around 54.83 with a standard deviation of approximately 2.93. The estimates will include some level of uncertainty due to the randomness inherent in sampling from a normal distribution. Since we have used normal distribution as likelihood and prior, our calculation for posterior is tractable and direct sampling is possible. When direct sampling is intractable and not possible, we can use MCMC and Variational Inference to approximate posterior distributions and can draw the samples.

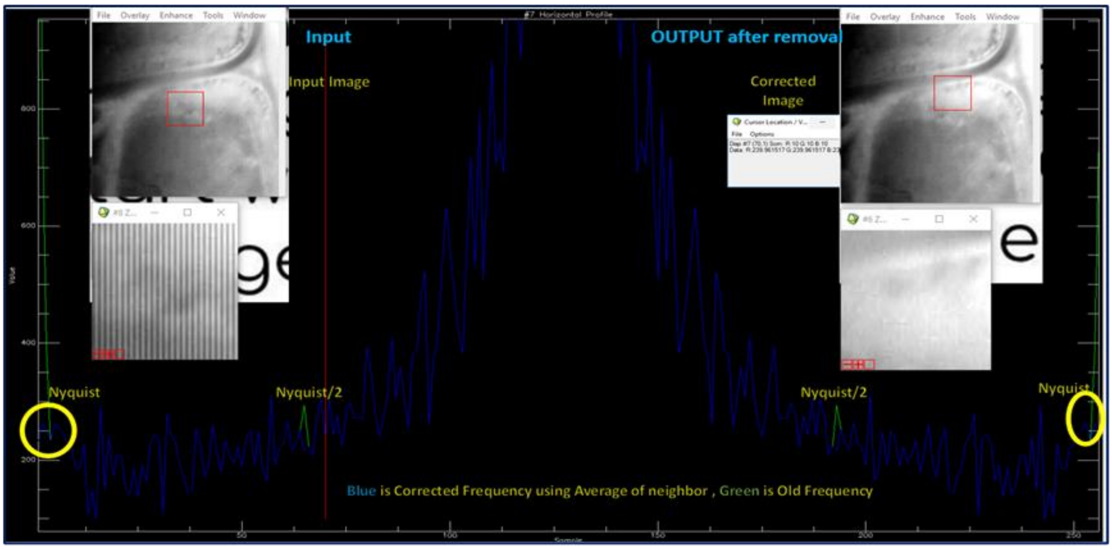

Figure 4 - Nyquist and Nyquist/2 Frequency removal using BDNFF. A (left) – Input image, B (middle – big image) - Corrected Noise (Green old frequency, Blue is corrected), C(right) – Output after correction

5. Results and Experiments

To evaluate the effectiveness of our proposed algorithm, we applied it to 1200 image patches, (each of 1024 rose by 1024 columns),extracted from diverse geographic locations, including deep sea, deserts, and urban areas. We observed significant improvements in noise reduction, particularly for horizontal, vertical, and diagonal noise patterns that arise from dynamic factors present in the satellite data. To remove alternate column, diagonal, or full-image pattern noise, we can use simple notch filters if the noise's location in the frequency domain is static. Once the noise regions are identified, noise correction can be achieved using predefined notch filters like Gaussian or Butterworth notch filters **[20]**. These filters are designed to attend specific frequency components associated with noise. However, if the noise location is dynamic and depends on the characteristics of the objects in the image, a more flexible approach is needed. Moreover, elliptical noise frequency spikes in 2D-FFT cannot be removed using notch filters. Our proposed Bayesian Dynamic Noise Filtering in Frequency domain (BDNFF) algorithm is well-suited for these dynamic noise scenarios. Unlike static notch filters, BDNFF can effectively correct pattern noise, regardless of its location and shape in the frequency domain (figure 5). This adaptability is crucial for handling noise patterns that vary across different parts of the image. Figure 5 illustrates the effectiveness of our Bayesian noise removal technique BDNFF. The first image in Figure 5 depicts an airport scene, with alternative pixel noise and diagonal noise. The yellow line in the image highlights the diagonal noise pattern. The second image shows the results of applying our Bayesian method to the same airport scene. Both types of noise have been significantly reduced.

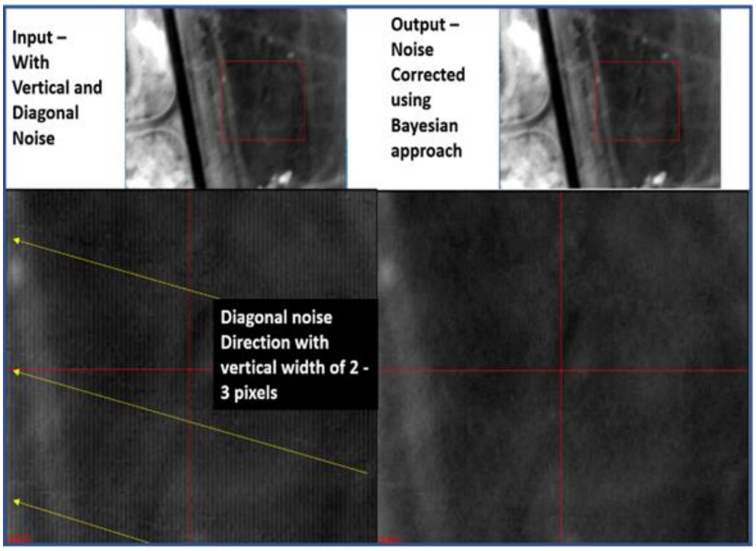

Figure 5 - Input patch near airport area. A (left) – Input image with Nyquist noise and diagonal noise, yellow arrows annotated for direction of diagonal noise. B (right) Output image of BDNFF algo.

Image A of figure 6 represents the 2D FFT of input image, B represents the 2D FFT of BDNFF output and C represents the subtraction of A and B. The black regions in image C represent the areas where noise was successfully eliminated. We observed that the algorithm effectively removed diagonal noise frequencies and horizontal lines near the center of the FFT spectrum. Importantly, BDNFF does not modify the DC component of the image. This is achieved by restricting the algorithm's operation in the vicinity of the DC component.

There are several approaches to correcting noise within the Nyquist noise region and dynamic pattern noise in the Frequency domain. We have compared various methods to determine the most effective techniques. For dynamic pattern noise, a simpler method involves taking the average of the nearest non-noisy neighbors. This approach assumes that neighboring pixels are likely to have similar values, and averaging can help to smooth out noise fluctuations. For our noise correction experiments, we implemented three methods:

Method 1- Average in neighbor – replacement of noisy pixels with average of 3 nearest non-noisy values.

Method 2 Linear regression - replacement of noisy pixels with linear regression [14] curve fitting of nearest non-noisy values.

Method 3 - Bayesian Estimation - replacement of noisy pixels with Bayesian estimation [15] regression fitting of nearest 128 (bin size) non-noisy values.

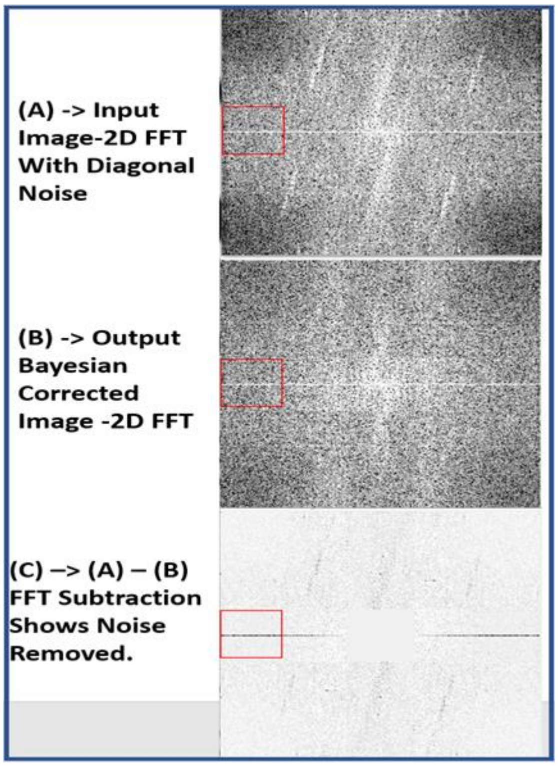

Figure 6 - Image A represents the 2D FFT of input image, B represents the 2D FFT of BDNFF output, C = A-B represents the subtraction of A and B.

We evaluated the performance of various methods for removing Nyquist vertical noise and other dynamic pattern noise from multiple datasets. Our results demonstrate that Bayesian estimation is particularly effective at eliminating complex dynamic patterns, even when these patterns are localized within specific regions of the image rather than being present throughout the entire image.

Figures 7 and 8 illustrate a comparative analysis of different methods for removing noisy data from images. The first column presents the original input image, along with a zoomed-in portion. The second column, titled "Method 1 - Average," demonstrates the results of replacing noisy pixels with the average of the three nearest non-noisy pixel values. In the third column, labeled "Method 2 - Linear," noisy pixels are replaced using linear regression [14] curve fitting based on the 128 nearest non-noisy values (bin size). Finally, the fourth column, "Method 3 - Bayesian," showcases the application of Bayesian estimation regression fitting to replace noisy pixels, utilizing the same 128-pixel bin size. Figure 7 demonstrates dynamic pattern noise near a building. We observe that this type of noise is highly localized, affecting only small regions of the image. As illustrated by method 3, effective noise removal techniques can completely eliminate dynamic pattern noise from these localized areas, resulting in a cleaner and more accurate representation of the building and its surroundings. Figure 8 illustrates a challenging image with severe dynamic pattern noise, obscuring the underlying buildings almost entirely. To demonstrate the effectiveness of different noise removal methods, we compared their performance on this image. Our results revealed that Bayesian estimation outperformed other techniques in significantly reducing complex dynamic pattern noise, resulting in a clearer and more discernible representation of the hidden structures.

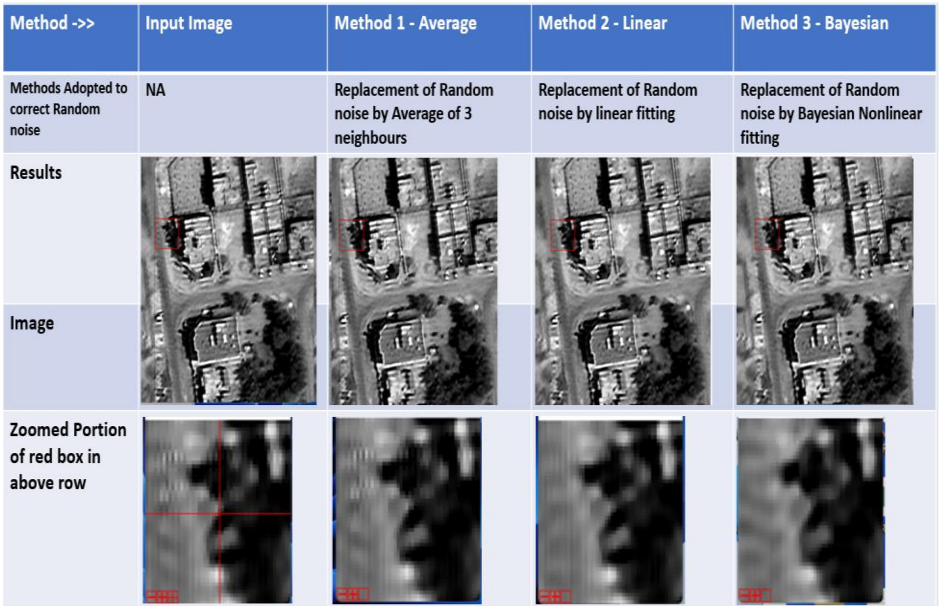

Figure 7- Comparison of various methods for dynamic pattern noise. Method 3, Bayesian approach shows correction of horizontal and vertical local pattern of noise.

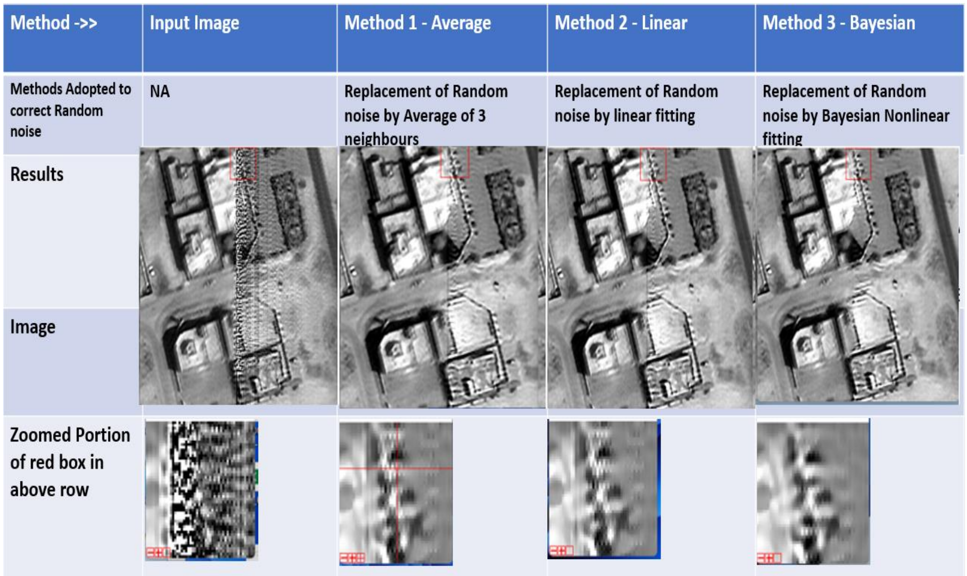

Figure 8- Comparison of various methods of removing complex dynamic pattern noise. Method 3 - Bayesian estimates perform the best corrected the mixture of vertical and horizontal complex noise.

6. Assessment

We applied BDNFF to 1200 image patches, each measuring 1024 rows by 1024 columns. We evaluated BDNFF by comparing it with our other methods (e.g., averaging, linear regression [14]) on multiple datasets containing diverse noise patterns. Quantitative metrics like FWHM [13], and PSNR [10] were calculated for BDNFF. Visual inspection of the corrected denoised images was conducted to assess the preservation of image details. BDNFF have significantly improve PSNR compared to the other methods, indicating better noise reduction. BDNFF have the lowest RMSE, indicating a smaller average error between the original input and denoised images. BDNFF have a smaller FWHM [13] at noise-corrected location as compared to the other methods, suggesting less image blurring and better preservation of fine details.

TABLE 1 - Quantitate analysis of various methods implemented

1024*1024 input size	**Avg PSNR** (dB)	**Avg FWHM** (pixels)
Method 1 – Average	20	4.5
Method 2 – Linear	25	3.0
Method 3 Bayesian (BDNFF)	**28**	**2.5**

7. Conclusion

Dynamic pattern noise removal is a crucial pre-processing step for satellite images, ensuring the accuracy and reliability of subsequent analyses. This research paper provides a comprehensive overview of existing noise reduction techniques, highlighting their advantages and limitations. The selection of an appropriate method depends on the specific characteristics of the image and the desired level of noise reduction.

The proposed Bayesian Dynamic Noise Filtering in Frequency domain (BDNFF) algorithm effectively addresses the challenge of dynamic pattern noise in satellite images. By combining Bayesian estimation with FFT techniques, our approach leverages prior knowledge and likelihood models to accurately estimate and remove noise while preserving essential image features. While the BDNFF algorithm provides excellent results, its computational efficiency can be a limitation, particularly on low-resource hardware. To improve speed, future work could explore techniques to estimate prior and likelihood distributions for the set of rows in an image rather than line-by-line, potentially sacrificing some noise reduction performance but achieving significant computational gains.

The results are expected to demonstrate that BDNFF achieves:

- Higher SNR values compared to other methods, indicate more effective noise reduction.
- Lower RMSE values, signifying a smaller average difference between the original and denoised images.
- Smaller FWHM **[13]** values, indicate a sharper PSF and less image blurring compared to other methods.
- Visually improved images with reduced noise artifacts while maintaining essential details.

In conclusion, the BDNFF algorithm offers a promising solution for dynamic pattern noise removal in satellite images. Its effectiveness in preserving image quality and enhasncing the accuracy of remote sensing applications offers both quantitative and qualitative benefits. Although the algorithm's computational demands pose challenges for low-resource hardware, future research may focus on optimizing efficiency by refining estimation techniques.

8. Future Work

While BDNFF offers a promising approach to removing dynamic pattern noise in very high-resolution imagery (VHRI), further research is needed to explore more innovative and efficient techniques. To enhance the computational speed of BDNFF, one potential avenue is to consider averaging bins in the vertical direction. This would leverage the spatial relationships between neighboring pixels to reduce the computational burden. Future research directions also include optimizing the algorithm for even greater efficiency, potentially through parallel processing or hardware acceleration.

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10. Conflict of Interest

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12. Author Biography

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