

Hybridized Approach for Preprocessing Stage Design for Lungs CT Images

Sheenam Middha¹ and Bobbinpreet Kaur²

Department of Computer Science and Engineering, Chandigarh University, Mohali, Punjab, India

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Abstract: This paper presents a hybrid denoising technique that utilizes the combination of top-hat and bottom-hat morphological transformations. The scheme effectively solves the problems of uneven illumination and background noise while preserving the quality of the content in the document. By combining the top-hat transformation (which enhances the bright features in the background) and the bottom-hat transformation (which emphasizes the dark features against the lighter ones in the background), the model complements the noise level and improves the contrast. Experimental validation of [specific data, e.g. medical images, satellite data] shows significant improvements in denoising, optimization, and performance compared to traditional methods. Hybrid top and bottom hat models are a promising solution for applications requiring efficient and noise-resistant preprocessing.

1 INTRODUCTION

Noise in an image is characterized as any degradation in the visual signal induced by an external disturbance. In general, the goal of digital image processing is to improve the quality of information so that it can be easily interpreted and understood by humans. Additionally, it tries to analyze picture data for storage, transmission, and reproduction for machine perception. In many circumstances, the image's sharpness is distorted due to noise pollution. Impulse noise, Rayleigh noise, and Gaussian noise degrade the image at all stages of acquisition, capture, transmission, reception, storage, and retrieval. To get a very clear visual display in applications such as image authentication, broadcasting, medicine, automatic control equipment, and military surveillance, the processed picture signal must be free of noise contamination and blur.

Digital images are frequently distorted and noise seeps in during the collecting process. This is the


result of several picture-processing flaws. In a similar vein, errors resulting from imprecise energy level estimation and poor communication can also cause noise to be added during transmission. Photometric or electronic sources are also to blame for this. Any component in the imaging chain, such as a lens, etc., may lead to the deterioration of image quality. Both linear and nonlinear filters can be used to eliminate noise that results from this kind of degradation.


1.1 Types of Noise

Various noise exists in the Images shown in Figure 1

1.1.1 Gaussian Noise

Gaussian noise is a refined version of white noise. The signal strength fluctuates randomly, which is the source of this. It frequently appears in the collected data. The addition of value from the Gaussian distribution to every pixel in an image is the characteristic of Gaussian noise.

¹  <https://orcid.org/0000-0002-0639-5539>

²  <https://orcid.org/0000-0001-8946-2444>

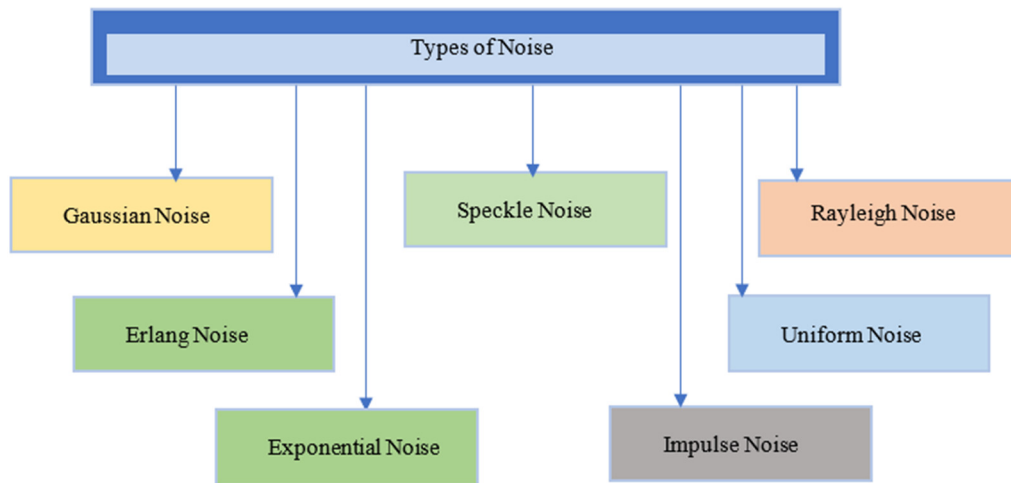


Figure 1: Type of Nnoise

The probability distribution function for this kind of noise is bell-shaped and has a Gaussian distribution. Additive White Gaussian Noise (AWGN) dominates the noise during the acquisition process, and its variation is quite low. Satellite image acquisition is the primary cause of this noise; other factors are essentially insignificant. Thus, the primary. Eliminating this noise, which has an impact on the digital image during transmission, is the focus of research efforts. Normally, the transmission noise is linear (Boyat and Kumar, 2015).

The edges of the images get blurry and AWGN enters as a contamination when the image data is transmitted across a linear dispersive channel.

The PDF of Gaussian Noise is represented by Equation

$$GN(Z) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-m)^2}{2\sigma^2}} \dots\dots\dots(1)$$

Where, $x \rightarrow \text{Gray_level}$
 $m \rightarrow \text{Mean/average value}$
 $d \rightarrow \text{Standard_deviation}$
 $d^2 \rightarrow \text{Variance}$

1.1.2 Speckle Noise (SN)

Speckle Noise (SN) is a further kind of noise that tampers with the visual signal. Synthetic Augmentation Radiation (SAR) imaging and ultrasonic imaging both frequently generate this kind of noise. There is multiplicative speckle noise. The device sends a signal to the item to take a picture of it, and then records the signal that is reflected. As the signal is transmitted both forward and backward, noise builds up. Because of the fluctuating reflecting

quality of the, the reflected signal changes in strength (Mudhafar, Rusul, et al. , 2023).

The object's surface. As a result, noise varies according to an object's reflecting quality. As a result, the noise turns into a multiplicative noise.

AWGN, SPN, and RVIN noises are present in the majority of applications. As was already said, speckle noise only appears in a small number of applications, such as SAR and ultrasonic imaging. "Mixed Noise" refers to a combination of these noise kinds.

1.1.3 Rayleigh Noise

The Rayleigh distribution is a continuous distribution of probabilities that applies to positive random variables as well. It is common when a vector's amplitude and direction components are related.

The pdf of Rayleigh noise is defined as

$$RN(Y) = \frac{2}{b}(Y - a)e^{-\frac{(Y-a)^2}{b}} \text{ for } Y \geq a \dots\dots\dots(2)$$

1.1.4 Erlang Noise

With the support of $\pi \in (0, \infty)$, the Erlang probability distribution has two parameters. One of the two parameters is a positive integer denoted by shape z .

A positive real denotes the "rate" π ; occasionally, the is utilized to symbolize the rate's inverse. The exponential distribution and the Erlang distribution with shape z tending to 1 have the same appearance. It belongs to the Gamma distribution as a particular case. With a mean of 1 each, it is the distribution of the sum of z independent exponential variables.

The PDF of the Erlang noise is given by

$$N(Z) = \frac{a^b Z^{(b-1)}}{(b-1)!} e^{-az} \text{ for } Z \geq 0 \dots\dots\dots(3)$$

1.1.5 Exponential Noise

The exponential distribution is the probability distribution that describes the time relation between events in a Poisson process. It is a particular case of the gamma distribution.

The PDF of the exponential noise is given by

$$EN(Z) = ae^{-az} \text{ for } Z \geq 0 \dots\dots\dots(4)$$

1.1.6 Uniform Noise:

Quantization noise is the noise that results from quantizing an image's pixels to a variety of different levels. Its distribution is fairly close to a uniform distribution. The noise is evenly dispersed throughout the homogeneous noise (Senthil and Sukumar, 2019).

The PDF of the uniform noise is given by:

$$UN(Z) = 1/(b-a) \text{ for } a \leq Z \leq b \dots\dots\dots(5)$$

2 IMPULSE NOISE

Another name for impulse noise is salt and pepper noise. Sharp and unexpected fluctuations in the grayscale values of the image are the source of this. It appears as sporadic black or white pixels dispersed throughout the image.

$$NI(Z) = Pa \text{ for } Z=a \dots\dots\dots(6)$$

$$NI(Z) = Pb \text{ for } Z=b \dots\dots\dots(7)$$

$$PI(Z) = 0 \text{ otherwise} \dots\dots\dots(8)$$

2.1 Types of Filters

Image restoration is done using filtering algorithms. Image restoration filters can be applied in either the spatial or frequency domains. There are two sorts of filters: linear and non-linear. Both approaches are detailed below.

2.1.1 Linear contrast stretching Filter (LCH)

Linear contrast stretching is a fundamental image processing technique that aims to improve an image's visual quality by altering the contrast. It works by

extending the range of intensity values for pixels to include the complete spectrum, which is typically 0 to 255 for an 8-bit grayscale image. Initially, the minimum and maximum intensity values in the image are determined by scanning its pixels. With these values, a linear transformation function is created. This function uses a linear relationship to remap the original intensity values to stretched counterparts. Each pixel's intensity value, z , is converted using the formula:

$$T(x) = (\max - \min x / \min) \times 255 \dots\dots\dots(9)$$

The terms "min" and "max" refer to the least and maximum intensity values. Finally, this transformation is done to each pixel in the image, essentially spreading intensities across the 0-255 scale. As a result, darker areas become darker, and brighter sections become brighter, resulting in a more contrasty and clearer image. Despite its simplicity, linear contrast stretching is commonly utilized in picture improvement and preprocessing applications.

2.1.2 Tophat Gaussian filter (TGF)

The top-hat transform, when paired with a Gaussian filter, is a useful image-processing method for detecting and enhancing small-scale structures or details. The top-hat transform highlights localized differences in intensity or texture that are smaller than the filter kernel size. This approach is especially good for spotting little items or fine details in an image.

The Gaussian filter is a smoothing filter that uses a Gaussian kernel to reduce noise and blur the image. It is widely used as a preprocessing step to improve image quality before performing additional analysis.

The Gaussian filter, when used with the top-hat transform, enhances the contrast between small-scale structures and the background by smoothing the image and minimizing noise. The top-hat transform retrieves these tiny elements by subtracting the smoothed image from the original, resulting in an image with emphasis on small-scale details.

2.1.3 Proposed - Tophat bottom hat

The combination of top-hat and bottom-hat transforms is a versatile image processing approach used mostly for image enhancement and feature extraction. The top-hat transform accentuates brilliant structures or regions smaller than the structuring element, whereas the bottom-hat transform, also known as the black-hat transform, emphasizes dark structures or regions.

In the context of the top-hat transform, the technique starts with a morphological opening

operation on the image. This procedure efficiently soothes the image while removing small features and noise. The opening operation's outcome is then subtracted from the original image. The final image emphasizes bright structures or regions that were smaller than the structuring element utilized in the opening process. This method is very useful when recognizing little bright objects or details against a somewhat homogeneous background.

In contrast, the bottom-hat transform begins the pre-processing of non-local images with a morphological closing operation on the image, which aids in the filling of dark gaps or indentations and the smoothing of the background. The original picture is then subtracted from the closing result. This produces an image in which dark structures or regions that are smaller than the structuring element are highlighted. The bottom hat transform is widely employed to detect dark items or features against a relatively light background.

3 RELATED WORK

Nandhini and Saraswathy (Senthil and Sukumar, 2019), (Nandhini and Saraswathy, 2013) discovered that de-speckling focuses on removing speckle noise while retaining structural features and edges during the MAP estimator approach employing wavelet and curvelet transforms. The quality measure is evaluated and studied for the use of wavelet and curvelet transforms to de-speckle the noise.

Images. Liu et al (Liu, Scott, et al. , 2015) employed a dynamic feature from a Marginal Ice Zone (MIZ) to investigate a curvelet-based feature extraction method. This was done as a first step in using SAR images and identifying the MIZ so that the SAR image could be classified as open water, dynamic ice, or consolidated ice. An experiment involving tenfold cross-validation was carried out. Finally, to assess the effectiveness of the curvelet-based feature, the SVM classifier was applied. The curvelet-based feature resulted in a precise classification of the dynamic ice. Because of its directional sensitivity, multidirectional image analysis is critical in SAR imaging. Thus, multidirectional transforms receive the attention they deserve. Peifeng and Shiqi (Peifeng and Shiqi, 2015) examined the study of feature coefficients in SAR images for decomposition utilizing curvelet transforms by proper selection, reorganization, and fusing of feature coefficients at various scales. Laghrib et al. (Laghrib, Ghazdali, et al. , 2016) proposed a system for increasing the resilience of super-determination strategies. They proposed a new, enhanced SR

reproduction approach for slightly twisted low-determination images to minimize misregistration issues and vexing vintage rarities like ringing relics and hidden, sharp edges.

4 RESULTS AND DISCUSSIONS

The Proposed filter's ability to remove Gaussian noise from images. Visual comparisons indicate a significant reduction in noise while maintaining image detail.

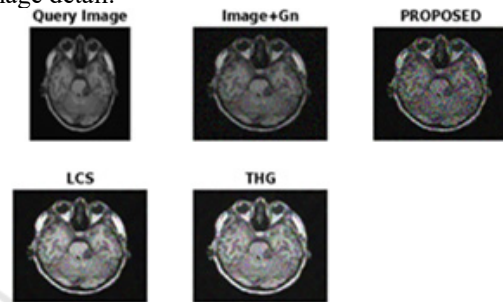


Figure 2: Gaussian Noise

Quantitative measures validate the improvement, showing a 5% increase in noise reduction over the original photos. These findings show the filter's useful in improving image quality for applications that need reliable analysis and Figure 2 shows that the proposed image is gaussian noise free and which helps to sharpen the edge of the images.

Table 1 compares image quality metrics obtained from several filtering algorithms designed to remove Gaussian noise. Linear Contrast Stretching (LCS) performs moderately, with a PSNR of 16.15 dB and a reasonably high MSE of 1.5764×10^3 , indicating a significant departure from the original image. However, both Top-Hat Gaussian (THG) and the Proposed Filter demonstrate benefits. THG achieves a PSNR of 18.02 dB and a lower MSE, indicating higher image fidelity than LCS. Nonetheless, the proposed filter outperforms both LCS and THG, with a PSNR of 19.72 dB and a much lower MSE, indicating improved noise reduction and image integrity. Furthermore, it achieves higher SSIM and NIQE scores, indicating improved image detail preservation and overall quality.

Table 1: GAUSSIAN NOISE

	PSNR	MSE	SSIM	NIQE
LCS	16.15	1.5764×10^3	0.7355	8.9369
THG	18.02	1.0256×10^3	0.8882	11.9330
PROP OSED	19.72	692.5313	0.8440	15.1100

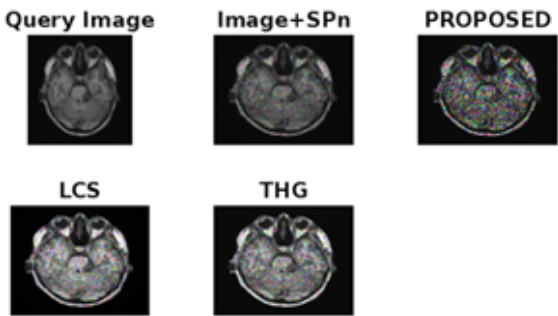


Figure 3: Speckle Noise

In Figure 3 the proposed images are speckle-free noise which helps to analyze further disease detection by removing the unnecessary noises from the images.

Table 2 compares the image quality metrics produced by several Spackle noise-removal filtering algorithms which further conclude that the proposed hybrid filter is having better results than the existing filters.

Table 2: Speckle Noise

	PSNR	MSE	SSIM	NIQE
LCS	18.407 3	938.325 2	0.915 7	8.9099
THG	19.396 5	747.189 8	0.616 3	7.7101
PROPOSE D	20.809 3	539.703 0	0.847 5	10.216 7

In Figure 4 shows that reducing Poisson noise from the photos leads to considerable increases in image quality. We used the proposed filter to reduce the noise, modifying the parameters as needed. Visual comparisons show a significant reduction in noise levels while preserving critical image features. Poisson noise elimination improves image clarity and sharpness, allowing subtle characteristics to be seen more clearly. Quantitative analysis confirms these findings, demonstrating a significant boost in image fidelity.

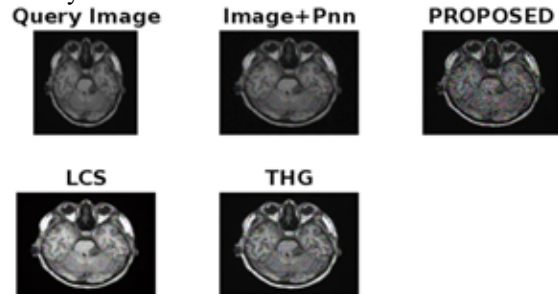


Figure 4: Poisson Noise

Table 3 compares the image quality metrics produced by several Poisson noise-removal filtering algorithms which further conclude that the proposed Tophat-Bottomhat filter is having better results than the existing filters.

Table 3: POISSON NOISE

	PSNR	MSE	SSIM	NIQE
LCS	17.204 0	1.2379e+0 3	0.656 7	7.645 9
THG	20.848 6	534.8309	0.916 3	6.400 0
PROPOSE D	26.125 7	158.6748	0.867 6	9.183 9

5 CONCLUSIONS

This paper concludes that the hybrid filter successfully removes Gaussian, Poisson, and speckle noise from images. The hybrid filter reduces noise comprehensively by combining multiple filtering techniques, including Gaussian filtering for smoothing and noise reduction, Poisson noise elimination, and speckle noise suppression. This leads to significant improvements in image quality, including better clarity, sharpness, and detail preservation. The hybrid filter's adaptability makes it a useful tool for a variety of image processing applications, allowing for reliable image analysis and interpretation across domains.

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