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A COMPREHENSIVE STUDY AND SURVEYON IMAGE RESTORATION TECHNIQUES

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Abstract: The domain of image processing has experienced significant expansion in recent times, witnessing the introduction of numerous novel approaches to image restoration as part of this expansion. Image restoration is a challenging task in the field of Image processing field to restore image. For the reason of a single model by which to describe the image restoration problem. Dependent upon the nature of the processes by which the image was formed the actual models used and there are no universally agreed-upon criteria by which to judge the quality of

a proposed image restoration process. These two criteria are the ones most frequently used in experiments with image restoration. During the process of image acquisition, sometimes images are degraded by various reason. Degradation may have various factors, such as motion of camera, blur lens, atmospheric disturbance, noise of sensor etc. Depending on the type of degradation, suitable and effective methods and algorithms of different image restoration are used. Restoration methods can categorize in to two types that are inverse filtering and Deconvolution. Inverse filtering is a fast and simple method that applies the inverse degradation function to the image. Inverse filtering is very responsive to noise and escalate it in the restored image. Therefore, inverse filtering is only suitable for images with known degradation functions and image having low noise levels. Numerous algorithms and filtering methods exist, each with distinct assumptions, advantages, and drawbacks depending on the prior understanding of the noise. Image smoothing stands out as a crucial and extensively employed procedure in image processing. In addition to addressing noise, this study also sheds light on a comparative examination of techniques for noise removal. This paper will outline diverse noise types affecting image models and explore different noise reduction methods, along with their respective strengths and weaknesses.

Keywords: Image restoration, image acquisition, degradation, Inverse filtering, deconvolution.

Introduction:

Image restoration entails the process of recovering a degraded image by leveraging prior knowledge of the degradation method responsible for its decline. Therefore, this process entails estimating both the deteriorated model and the applicability of inverse filtering to restore the original image. While the resulting image may not precisely match the original, it represents an approximation of the original image. It will be the approximation of the original image. Restoration attempts to rebuild utilizing prior knowledge of the deterioration process. Its focus is on obtaining the most accurate estimate of the intended outcome. Certain restoration methods are most effective when applied in the spatial realm, whereas in other instances, frequency domain techniques prove more suitable.[1]

Image restoration finds applications across various domains, including:[6]

Medical Imaging: In medical imaging, image restoration techniques are used to enhance the clarity and quality of medical images, aiding in diagnosis and treatment planning.

Satellite Imaging: Image restoration is crucial in satellite imaging for improving the resolution and quality of satellite images, which is essential for various purposes such as environmental monitoring, urban planning, and agriculture.

Forensic Science: Image restoration plays a vital role in forensic science for enhancing and clarifying images captured as evidence, assisting in investigations and criminal identification.

Archaeology: Image restoration techniques are utilized in archaeology to enhance and restore ancient artifacts, manuscripts, and archaeological sites from degraded or damaged images, providing clearer insights into historical and cultural heritage.

Art Restoration: Image restoration is employed in the conservation and restoration of artworks, paintings, and historical documents, helping to preserve their integrity and aesthetic value.

Astronomy: Image restoration techniques are applied in astronomy to improve the quality and resolution of astronomical images captured by telescopes, aiding in the study of celestial objects and phenomena.

Security and Surveillance: In security and surveillance systems, image restoration is used to enhance the clarity of images captured by surveillance cameras, improving object recognition and tracking.

Remote Sensing: Image restoration techniques are utilized in remote sensing applications for improving the quality and interpretation of remotely sensed images acquired from aircraft or satellites, facilitating environmental monitoring, land use mapping, and resource management.

Biometrics: Image restoration is employed in biometric systems for enhancing the quality of biometric images such as fingerprints, iris scans, and facial images, improving the accuracy and reliability of biometric identification and verification processes.

Consumer Electronics: Image restoration techniques are integrated into various consumer electronics devices such as digital cameras and smartphones to improve the quality of captured images, providing users with clearer and more visually appealing photographs

Literature Review:

Degradation model is presented with following figure:

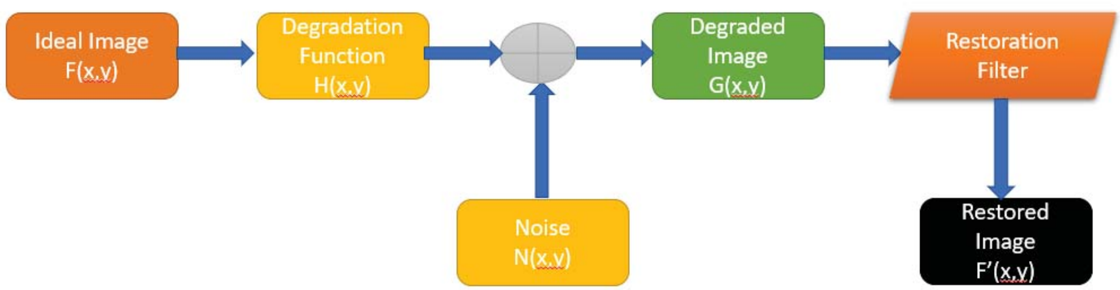

Figure 1: Image restoration model

Distortion often plays a significant role in captured images, primarily stemming from flaws within the imaging apparatus. This issue can escalate to severe levels due to the presence of random noise within the imaging process. Within the degradation model framework, the initial image undergoes blurring via a degradation function, accompanied by the introduction of additional noise. The resulting degraded image is thus characterized.

In the given image F(x,y) is original image. Original image is blur with degradation function and noise will be added to original image and produce the Degraded image G(x,y) which cane be expressed with following formula:

$$G(x,y) = F(x,y) * H(x,y) + N(x,y)$$

In the Restoration model, the degraded image undergoes reconstruction via restoration filters. Through this procedure, both noise and blur are eliminated, yielding researchers an approximation of the original image. The efficacy of our restoration filter is gauged by the proximity between the estimated image and the original.

Methodology:

DETERMINISTIC METHOD

A deterministic method of image restoration refers to a technique where the restoration process follows a predefined set of rules or algorithms, without relying on randomness or probability. This approach typically involves mathematical models or filters that are applied to the degraded image to remove distortions such as noise or blur. Unlike probabilistic methods that account for uncertainty and randomness, deterministic methods aim to produce a single, definite outcome based on the given input and the established restoration algorithm. Examples of deterministic methods include linear filtering, inverse filtering, and Wiener filtering. These methods are often favored for their predictability and reproducibility in image restoration tasks.

STOCHASTIC METHOD

A stochastic method of image restoration involves techniques that incorporate randomness or probability into the restoration process. Unlike deterministic methods that follow predefined rules or algorithms, stochastic methods take into account uncertainty and variability in the image degradation and restoration process.

One common stochastic approach is Bayesian image restoration, which formulates the restoration problem in a probabilistic framework. Bayesian methods use prior knowledge about the image, such as its statistical properties or a model of the degradation process, to estimate the most likely restored image given the observed degraded image.

Other stochastic methods include Markov random field (MRF) models, which model the relationships between neighboring pixels in the image and incorporate probabilistic constraints to guide the restoration process. Monte Carlo methods, such as Markov chain Monte Carlo (MCMC) algorithms; can also be used for stochastic image restoration by sampling from the posterior distribution of possible restored images.

Stochastic methods of image restoration are often preferred when the degradation process is complex or poorly understood, as they can provide more robust and flexible solutions by capturing uncertainty and variability in the restoration process. However, they may require more computational resources and may be more challenging to implement compared to deterministic methods.

MEDIAN FILTER

The median filter is commonly used in image restoration tasks to remove noise and improve the quality of images. In this context, the median filter operates by replacing each pixel's value with the median value of the pixel intensities within a specified neighborhood or window.When applied to image restoration, the median filter is particularly effective at mitigating certain types of noise, such as salt-and-pepper noise, which appears as random bright and dark pixels scattered throughout the image. Since the median filter selects the middle value from a sorted list of pixel intensities within the neighborhood, it is less susceptible to the influence of extreme noise values compared to linear filters like the mean or Gaussian filter.median filter can be used in image restoration noise reduction, edge preservation and artifact removal.The effectiveness of the median filter in image restoration depends on factors such as the size of the neighborhood or window, the type and intensity of noise present in the image, and the desired level of smoothing. In some cases, advanced variants of the median filter, such as adaptive median filters, may be employed to adaptively adjust the filter size based on local image characteristics for improved restoration results.

ADAPTIVE FILTER

Adaptive filters in image restoration are powerful tools that dynamically adjust their parameters or characteristics based on the local properties of the image. Unlike fixed filters, which apply the same processing to all parts of the image, adaptive filters tailor their operations to the specific features of each pixel or region. This adaptability enables them to effectively handle various types of noise and restore images with greater accuracy.

ADAPTIVE MEDIAN FILTER: This filter adjusts its window size depending on the local characteristics of the image. In areas with high noise levels, the filter enlarges the window to capture more neighboring pixels for noise reduction. Conversely, in smoother regions, it reduces the window size to preserve details and edges.

ADAPTIVE WIENER FILTER: The Wiener filter is a classic approach to image restoration that minimizes the mean square error between the original and the filtered image. The adaptive version of the Wiener filter estimates the parameters of the filter adaptively based on the local statistics of the image, such as the variance of noise and the signal-to-noise ratio (SNR).

ADAPTIVE BILATERAL FILTER: The bilateral filter preserves edges while reducing noise by considering both spatial and intensity differences between neighboring pixels. In adaptive bilateral filtering, the filter parameters are adjusted based on the local image characteristics, such as gradient magnitude and intensity variation, to achieve better restoration results.

ADAPTIVE NON-LOCAL MEANS FILTER: The non-local means filter exploits similarities between patches of pixels in the image to denoise and restore it. In adaptive non-local means filtering, the filter weights are adaptively determined based on the local similarity between patches, allowing for more accurate restoration in varying image regions.ANLM is particularly effective in scenarios where noise levels vary across the image or where traditional denoising methods may smooth out important image structures. By adaptively adjusting the weights based on local image characteristics, ANLM can preserve image details while effectively removing noise.

Adaptive filters offer significant advantages in image restoration tasks by adaptively adjusting their behavior to suit the characteristics of the image being processed. They are particularly useful for handling complex noise patterns, preserving fine details and edges, and producing high-quality restored images. However, adaptive filtering techniques often require more computational resources compared to their non-adaptive counterparts, as they involve additional calculations to estimate local parameters and adjust filter operations dynamically.

IBD (ITERATIVE BLIND DECONVOLUTION)

Iterative Blind Deconvolution (IBD) is a technique used in image restoration to recover an image from its blurred or degraded version without prior knowledge of the blur kernel (the function that describes the blurring process). This is particularly useful when the blur is unknown or cannot be accurately modeled.IBD algorithms aim to minimize a cost function that

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measures the difference between the estimated and observed images, incorporating constraints such as non-negativity and smoothness. Common optimization techniques used in IBD include gradient descent, expectation-maximization (EM), or variants of these methods tailored for image restoration tasks.IBD is a powerful approach for image restoration in scenarios where the blur kernel is unknown or difficult to model accurately, such as in astronomical imaging or in situations where the blur is caused by complex optical systems. However, it can be computationally intensive and sensitive to noise in the input images.

DECONVOLUTION USING REGULARIZED FILTER

Deconvolution using Regularized Filter (DRF) is another technique used in image restoration, particularly for recovering images that have been degraded by blurring or noise. DRF combines principles of deconvolution with regularization techniques to improve the quality of the restored image.DRF is effective for restoring images that have been degraded by various factors, including blurring and noise. By incorporating regularization, DRF can produce visually pleasing results while minimizing artifacts and preserving important image details. However, like other deconvolution methods,[3] DRF may still be sensitive to noise and other sources of error in the input images.

Results:

PEAK SIGNAL TO NOISE RATIO (PSNR)

Peak Signal-to-Noise Ratio (PSNR) is a metric commonly used to evaluate the quality of a reconstructed or processed image. It quantifies the difference between the original image and the processed image in terms of signal and noise. Higher PSNR values indicate better image quality.

PSNR is calculated using the Mean Squared Error (MSE) between the original and processed images. The formula for PSNR is:

$$\mathrm{PSNR} = 10 \times \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right)$$

Where,

MAX is the maximum possible pixel value of the image (often 255 for 8-bit images).

MSE is the Mean Squared Error between the original and processed images.

MEAN SQUARE ERROR (MSE)

Mean Squared Error (MSE) is a fundamental metric in image processing used to quantify the difference between two images. It measures the average squared difference between the pixel values of the original image and the processed (reconstructed or altered) image.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(I(i) - K(i))^2$$

Where,

N is the total number of pixels in the image i

$I\ (i)$ represents the pixel value of the original image at position i

$K\ (i)$ represents the pixel value of the processed image at position i

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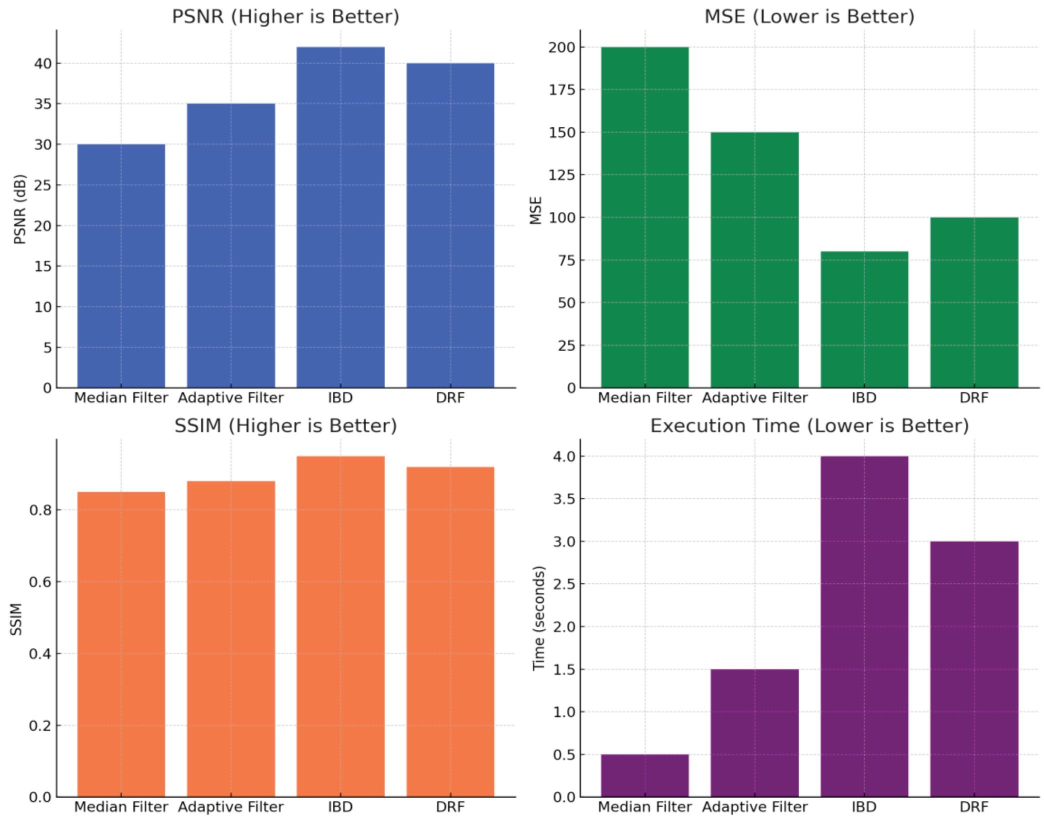

Figure 2: Result of different image restoration techniques based on Performance Metrics

Discussion:

IMAGE RESTORATION/ FILTERING TECHNIQUES	**ADVANTAGES**	**DISADVANTAGES**
MEDIAN FILTER	• Effective in removing impulse noise, such as salt-and-pepper noise, without blurring edges.	• Can remove fine details from the image, especially with large filter window sizes.

	• Simple to implement and computationally efficient.	• Not as effective for other types of noise, such as Gaussian noise. • Non-linear operation can introduce artifacts in areas with uniform intensity.
ADAPTIVE FILTER	• Adapts to local image characteristics, making it effective in varying noise environments. • Can preserve image details while reducing noise.	• Complexity varies depending on the specific adaptation method used. • May require more computational resources compared to simpler filters. • Performance can be sensitive to parameter tuning.
ITERATIVE BLIND DECONVOLUTION (IBD)	• Effective in restoring images degraded by unknown or complex blur kernels. • Can recover fine details and improve image quality significantly. • Iterative refinement allows for precise restoration.	• Computationally intensive, especially for large images or complex blurs. • Sensitive to noise and artifacts in the input images. • Requires tuning of various parameters, which can be challenging.
DECONVOLUTION USING REGULARIZED FILTER (DRF)	• Incorporates regularization techniques to stabilize the	• Computationally intensive, especially with

	deconvolution process and reduce artifacts. • Can restore images degraded by various factors, including blurring and noise. • Iterative refinement improves the accuracy of the restoration.	complex regularization schemes

Conclusion:

After conducting a thorough review of literature on diverse methods for rectifying image blurring proposed by various researchers, it is evident that mitigating blur in images poses a challenging task. Through this examination, it has been determined that the "better" technique depends on the specific characteristics of the blur in the images you're dealing with and your priorities regarding factors like computational efficiency, robustness to noise, and preservation of image details. Experimentation and testing with your specific dataset would be necessary to determine the most suitable technique for your application. These findings are based on the evaluation of parameters such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR).

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Conflict of Interest:

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