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A Comprehensive Comparative Analysis of Image Restoration Algorithms: Performance Metrics and Insights

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Abstract

This research paper presents a rigorous comparative analysis of five leading image restoration algorithms: Wiener Filter, Adaptive Histogram Equalization (AHE), Denoising through Non-Local Means (NLM), Iterative Back Projection (IBP), and Richardson-Lucy (RL) Deconvolution. With a focus on applications in medical imaging, surveillance, and remote sensing, the study addresses challenges related to noise and degradation. Our evaluation, conducted on a diverse dataset, employs key performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Feature Similarity Index (FSIM), and Universal Image Quality Index (UIQI). The research yields compelling evidence, positioning the Richardson-Lucy Deconvolution algorithm as the optimal choice. Demonstrating superior performance in high-quality image reconstruction, noise reduction, and structural preservation, RL Deconvolution emerges as the most suitable technique for a range of real-world scenarios. This research contributes pivotal insights, steering the practical application of image restoration towards heightened efficacy and reliability.

Keywords: Image Restoration, Wiener Filter, Adaptive Histogram Equalization, Denoising through Non-Local Means, Iterative Back Projection, Richardson-Lucy Deconvolution, PSNR, MSE, SSIM, FSIM, UIQI

1. Introduction

Image restoration, a crucial component of image processing, plays a fundamental role in refining images degraded by various factors during acquisition, transmission, or storage. The significance of image restoration extends across diverse domains, including medical imaging, surveillance, and remote sensing. The central objective is to enhance the visual quality of images afflicted by issues such as blurriness, artifacts, or noise, ensuring their optimal utilization in critical applications. Through the deployment of sophisticated algorithms rooted in mathematical models, signal processing, and statistical methods, image restoration techniques aim to reconstruct images, bringing them back to their original quality. The impact of these techniques resonates from improving the precision of medical diagnoses to aiding forensic investigations in surveillance and enabling accurate geographical mapping through the refinement of satellite images. This paper conducts a comprehensive comparative analysis of five key image restoration algorithms—Wiener Filter, Adaptive Histogram Equalization (AHE), Denoising through Non-Local Means (NLM), Iterative Back Projection (IBP), and Richardson-Lucy (RL) Deconvolution—aiming to provide valuable insights into their performance and assist in selecting the most effective algorithm for specific tasks. Image restoration is a critical task in image processing, involving the reconstruction of degraded images using prior knowledge of the degradation process. It aims to obtain the best possible estimate of the desired result. While some restoration techniques excel in the spatial domain, others find their strength in frequency domain approaches [1].

Degradation [5] can stem from various sources, including image sensor noise, defocus-induced blurring, and transmission channel noise. Smoothing plays a pivotal role in image restoration by reducing noise and enhancing visual quality. Numerous algorithms, both linear and nonlinear, are employed for image filtering, enabling a range of valuable tasks in image processing. Linear filters can effectively reduce unwanted noise (as illustrated in Figure 1), while others are designed to reverse blurring effects. Nonlinear filters exhibit distinct behavior, departing from the principles of scaling and shift invariance, leading to non-intuitive variations in filter output [2], [3], [4].

Fig. 1: A defected image and a restored real image after the application of image restoration algorithm [2] visually highlighting the algorithm's ability to rectify defects, offering readers an immediate understanding of the restoration outcomes.

Digital images can suffer from multiple sources of corruption, including malfunctioning camera pixels, hardware memory issues, or noisy channel transmission. Noise represents unwanted information that degrades image quality and impacts the accuracy of various image processing applications, such as segmentation, classification, edge detection, and compression [6]. The success of image restoration relies on several factors, including researchers' understanding of the original image, the extent of degradation, the underlying causes, and the accuracy of degradation models. Implementing these restoration techniques accurately is also essential [7]. An image restoration algorithm employs restoration filters to reconstruct an altered image. This method reduces noise and blur, resulting in a close match with the original image. The effectiveness of our restoration filter is directly related to how closely the estimated image resembles the original one. Figure 2 provides an illustrative depiction of the restoration model's structure [8].

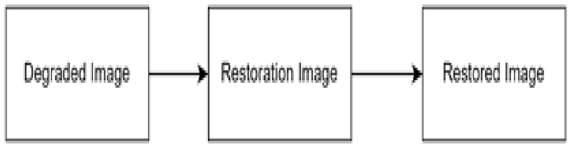

Fig. 2: Model of Image Restoration Algorithm [9] providing a standalone visual representation of processes involved in reconstructing altered images through restoration filters.

This literature review provides valuable insights into the latest advancements in image restoration algorithms, which serve as a crucial basis for our comprehensive comparative analysis of five widely adopted techniques: the Wiener Filter, Adaptive Histogram Equalization (AHE), Denoising through Non-Local Means (NLM), Iterative Back Projection (IBP), and Richardson-Lucy (RL) Deconvolution. Our analysis involves assessing these methods using metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Feature Similarity Index (FSIM), and Universal Image Quality Index (UIQI). This overview provides a solid framework for the next parts, which include a deep comparative evaluation of several image restoration methods.

2. Objectives

Objectives of the research paper are discussed under:

Comparative Analysis: Conduct a thorough comparative analysis of five prominent image restoration algorithms—Wiener Filter, AHE, NLM, IBP, and RL Deconvolution. The primary aim of this objective is to dissect the strengths and weaknesses of five widely recognized image restoration algorithms. By subjecting them to a comprehensive comparative analysis, we intend to unveil nuanced differences in their performance concerning aspects such as noise reduction, detail preservation, and adaptability to diverse image characteristics.

Performance Metrics Evaluation: Evaluate the algorithms using key performance metrics such as PSNR, MSE, SSIM, FSIM, and UIQI to provide a comprehensive understanding of their effectiveness. Defining and applying a set of key performance metrics is imperative to quantify and compare the effectiveness of image restoration algorithms objectively. Each metric, from PSNR measuring fidelity to UIQI assessing overall image quality, contributes a unique perspective.

Dataset Diversity: Utilize a diverse dataset encompassing varied subjects, scenes, and color schemes to ensure a nuanced evaluation of algorithmic performance across real-world scenarios. The real-world applicability of image restoration algorithms necessitates evaluation on diverse datasets. This objective seeks to create a realistic simulation of the challenges these algorithms may encounter. By incorporating variations in subjects, scenes, and color schemes, we aim to ensure that the evaluation is representative of the complexities present in practical scenarios.

Algorithmic Characteristics: Provide a detailed overview of the characteristics and applications of each image restoration algorithm to enhance understanding and reference for researchers. This objective aims to contribute to the understanding of image restoration algorithms by offering a detailed exposition of their characteristics and applications. By elucidating the strengths and specific use cases of each algorithm, researchers and practitioners can make informed decisions when selecting an algorithm for a particular task. This information not only aids in algorithm selection but also serves as a valuable reference for future research and development in the field of image processing.

Implementation: Implement the evaluation methodology using the MATLAB programming language and relevant libraries to ensure a systematic and efficient execution of the algorithms. The choice of a robust implementation platform is pivotal in ensuring the reproducibility and reliability of the research outcomes. This objective emphasizes the use of MATLAB, a widely adopted platform for image processing, to execute the evaluation methodology. By leveraging relevant libraries, we aim to ensure both the systematic execution of algorithms and the efficient handling of large-scale datasets, contributing to the credibility and replicability of the research.

Visualization: Communicate the results effectively through well-designed visualizations, including graphs depicting the comparative analysis of performance metrics across different restoration algorithms. Effectively communicating the research findings is as crucial as the analysis itself. This objective focuses on the creation of clear and informative visualizations, such as graphs, to illustrate the comparative performance of image restoration algorithms. Visualizations enhance the accessibility of the results, allowing researchers and practitioners to quickly grasp the nuances of algorithmic performance. This aids in the dissemination of knowledge and facilitates the integration of research outcomes into the broader image processing community.

Contribution to the Field: Contribute valuable insights for selecting the most suitable image restoration algorithm based on specific application requirements, thereby advancing the field of image processing. The overarching goal of this research is to make a substantive contribution to the field of image processing. By providing actionable insights into algorithm selection based on specific application requirements, this objective aims to guide practitioners and researchers in making informed decisions. The cumulative knowledge generated contributes to the advancement of image processing, fostering innovation and improvements in the design and application of image restoration algorithms.

3. Novelty Statement and Justification

This research introduces a novel and in-depth comparative analysis of five prominent image restoration algorithms: Wiener Filter, Adaptive Histogram Equalization (AHE), Denoising through Non-Local Means (NLM), Iterative Back Projection (IBP), and Richardson-Lucy (RL) Deconvolution. The primary contribution of this study lies in its meticulous examination of these algorithms through a comprehensive evaluation process, utilizing various performance metrics and a diverse dataset. This approach enhances our understanding of the strengths and limitations of these algorithms across a spectrum of real-world scenarios.

The significance of this research is underscored by its detailed and systematic assessment of image restoration algorithms, taking into account a range of metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Feature SIMilarity (FSIM), and Universal Image Quality Index (UIQI). This multifaceted evaluation provides a nuanced perspective, allowing for a more thorough comprehension of the algorithms' performance characteristics.

4. Related Work

The related work section is expanded to provide a more detailed overview of existing research, establishing a stronger connection with the current study. This enhanced section underscores the advancements in image restoration algorithms, paving the way for a comprehensive comparative analysis.

4.1 Historical Overview

The field of image restoration has witnessed significant advancements over the years, with various algorithms addressing the challenges posed by image degradation. Early efforts predominantly focused on linear techniques, such as the Wiener Filter, which aimed to minimize the effects of additive noise in images [1]. These foundational methods laid the groundwork for subsequent innovations and paved the way for more sophisticated approaches.

4.2 Wiener Filter

The Wiener Filter operates on the principle of linear least squares estimation, aiming to restore images by minimizing the mean square error (MSE) between the restored and original images. Developed by Norbert Wiener, it strikes a balance between enhancing image sharpness and minimizing noise amplification. The algorithm's effectiveness in additive noise reduction has made it versatile across applications, such as medical imaging and remote sensing. The Wiener Filter is a renowned image restoration method that operates on the principle of linear least squares estimation. Named after Norbert Wiener, this algorithm excels at reducing the effects of additive noise in images. Its primary focus is on balancing the enhancement of image sharpness while minimizing the amplification of noise. This delicate balance makes it a versatile choice in various applications, including medical imaging and remote sensing. The Wiener Filter aims to minimize the mean square error (MSE) between the restored and original images. It achieves this by utilizing a frequency domain approach, making it effective in scenarios where the imaging system's frequency response is known. Researchers have further refined the Wiener Filter for optimal results. Notable enhancements include an iterative Wiener filter algorithm with rapid convergence through step-size optimization and the use of genetic algorithms to estimate noise regularization parameters for satellite image restoration. The steps of operation of wiener filter image restoration algorithm are demonstrated in Figure 3.

The Wiener filter stands as an effective technique for restoring degraded images, minimizing the mean square error (MSE) between restored and original images. Researchers have refined this filter for optimal results. The iterative Wiener filter algorithm introduced by Xi and Liu optimizes step-size for rapid convergence [10]. Aouinti et al. employed a genetic algorithm to estimate noise regularization parameters for satellite image restoration [11]. Yang et al. pioneered an adaptive Wiener filter for remote sensing, addressing distinct noise regularization needs in edge and flat areas [12].

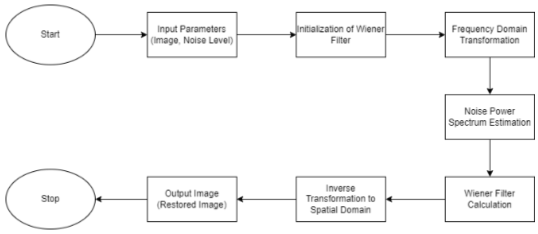

Fig. 3: Steps of Operation of Wiener Filter Image Restoration Algorithm

4.3 Non-Local Approaches

The emergence of non-local approaches, such as Denoising using Non-Local Means (NLM), represents a significant paradigm shift in image restoration. Unlike traditional denoising methods that rely solely on local pixel neighborhoods, NLM considers similarities in image patches across the entire image [13]. This departure from pixel-wise assessments enhances robustness against noise levels and provides more accurate similarity measurements, making NLM particularly effective in noise reduction while preserving structural details. Denoising using Non-Local Means (NLM) is a foundational image restoration algorithm that has attracted significant attention and recognition within the research and practical communities. The core principle of NLM revolves around exploiting non-local similarities within an image to remove noise while preserving the essential image structures. Unlike traditional denoising methods that rely solely on local pixel neighborhoods, NLM considers similarities in image patches from across the entire image, resulting in superior noise reduction. Non-Local Means (NLM) represents a significant shift in image restoration approaches. Specifically, Denoising using Non-Local Means (NLM) operates on the principle of considering similarities in image patches across the entire image, departing from traditional denoising methods that rely solely on local pixel neighborhoods. This departure enhances robustness against noise levels and provides more accurate similarity measurements, making NLM particularly effective in noise reduction while preserving structural details. The core concept of NLM involves averaging pixel intensities based on the similarity in intensity across non-local patches. By doing so, NLM achieves greater robustness against noise levels compared to pixel-wise assessments. This non-local characteristic enhances its adaptability and effectiveness in handling diverse image structures and patterns. The steps of operation include searching for similar patches across the entire image, computing weighted averages, and generating a denoised image. NLM has become foundational in image restoration, attracting significant attention and recognition within both research and practical communities. The steps of operation of denoising using non-local means image restoration algorithm are demonstrated in Figure 4.

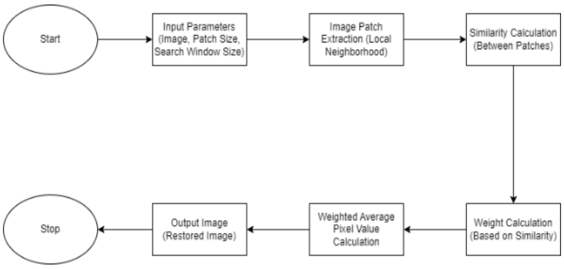

Fig. 4: Steps of Operation of Denoising using Non-Local Means (NLM) Image Restoration Algorithm

The Non-Local Means (NLM) filter [13] represents an evolution of the Yaroslavsky filter. Both filters operate by averaging image pixels based on their similarity in intensity. Similar principles underpin other filters such as SUSAN [14] and bilateral filters. However, the NLM distinguishes itself by two key features. Firstly, NLM achieves greater robustness against noise levels by employing region-based comparisons rather than pixel-wise assessments. This ensures more accurate and reliable similarity measurements. Secondly, the NLM's uniqueness lies in its non-local approach, wherein pattern redundancy is not limited to local neighborhoods. Unlike the bilateral filter, the NLM does not penalize pixels that are distant from the one being filtered solely due to their spatial separation. This non-local characteristic enhances its adaptability and effectiveness in handling diverse image structures and patterns.

4.4 Adaptive Histogram Equalization

Histogram equalization techniques have long been recognized for their simplicity and effectiveness in image restoration. Adaptive Histogram Equalization (AHE) takes a step further by addressing challenges such as uneven lighting and variable contrast levels within an image [15]. The technique divides an image into smaller, localized sections, equalizing histograms within each region individually. The choice of the type of sub-blocks (overlapping, non-overlapping, partially overlapping) impacts the algorithm's performance, and this diversity reflects the adaptability of AHE to various restoration scenarios [16]. Adaptive Histogram Equalization (AHE) is a significant image restoration method well-known for improving image contrast and visual quality. AHE works on the idea of adaptive histogram modification, in which it divides an image into smaller, localized sections and equalizes the histograms within each region individually. The technique enables AHE to address difficulties such as uneven lighting and variable contrast levels within an image, which typically result in visual information degradation. Adaptive Histogram Equalization (AHE) is a significant image restoration method known for its effectiveness in improving image contrast and visual quality. Unlike traditional histogram equalization techniques, AHE takes a step further by addressing challenges such as uneven lighting and variable contrast levels within an image. The technique divides an image into smaller, localized sections, equalizing histograms within each region individually. The adaptability of AHE to various restoration scenarios is reflected in the diversity of its approaches, including overlapping and non-overlapping sub-blocks. The choice of sub-block types impacts the algorithm's performance, showcasing the flexibility of AHE. This method works on the concept of adaptive histogram modification, providing a nuanced approach to enhance image details in localized regions, making it particularly suitable for scenarios where uneven illumination or varying contrast levels are prevalent. The steps of operation of Adaptive Histogram Equalization (AHE) image restoration algorithm are demonstrated in Figure 5.

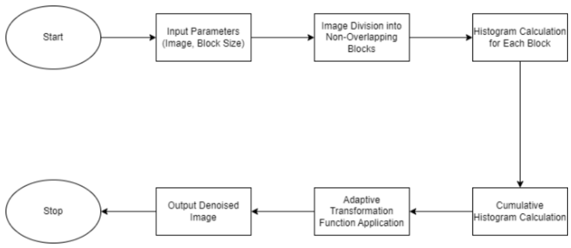

Fig. 5: Steps of Operation of Adaptive Histogram equalization Image Restoration Algorithm

There are three approaches to adaptive histogram equalization: overlapping sub-blocks, nonoverlapping sub-blocks, and partially overlapping sub-blocks. Among these, the nonoverlapping sub-block approach is seldom utilized due to its square-shaped artifacts. Similarly, the overlapping sub-block method is rarely employed in practice due to its high computational demands and sluggish processing speed. In contrast, the partially overlapping sub-block method offers a viable solution to expedite calculations while maintaining effectiveness, albeit with increased complexity [16].

4.5 Evolution of Deconvolution Techniques

Non-blind deconvolution, where the Point Spread Function (PSF) is known beforehand, has been a focal point in image restoration. The Richardson-Lucy deconvolution algorithm [17], originating in the 1970s, gained popularity in fields like medical imaging and astronomy. Its iterative approach, rooted in Bayesian principles, has positioned it as a superior tool for image restoration compared to linear methods. Verdi's reintroduction of the Richardson-Lucy algorithm in the 1980s addressed challenges in emission tomography imaging, particularly with dominant Poisson statistics [18]. Richardson-Lucy (RL) Deconvolution is a pivotal image restoration algorithm with profound implications for various scientific and industrial applications. Its primary focus is on image deblurring, aiming to recover high-quality images from their blurred or degraded counterparts. RL Deconvolution stands out for its iterative approach, which continually refines an initial estimate of the restored image using a mathematical model of the blurring process and the observed blurred image. The Richardson-Lucy (RL) Deconvolution is a non-blind deconvolution technique where the Point Spread Function (PSF) is known. It aims to recover high-quality images from their blurred counterparts. The algorithm involves an iterative approach, refining the restored image using a mathematical model of the blurring process and the observed blurred image. The number of iterations needed is manually determined for each image based on the PSF size. Richardson-Lucy (RL) Deconvolution has seen applications in medical imaging and astronomy. It has been refined over the years to address challenges in emission tomography imaging, especially with dominant Poisson statistics.

The steps of operation of Richardson-Lucy (RL) Deconvolution image restoration algorithm are demonstrated in Figure 6.

Image restoration methods can be broadly categorized into two types: blind and non-blind deconvolution. Non-blind deconvolution is the approach where the Point Spread Function (PSF) is known beforehand. One notable technique in this category is the Richardson–Lucy deconvolution algorithm [17], which has gained popularity in fields like medical imaging and astronomy. Its origins trace back to the early 1970s, when Lucy and Richardson derived it using Bayesian principles. The Richardson-Lucy algorithm was reintroduced by Verdi in the 1980s to solve the challenges of emission tomography imaging with dominant Poisson statistics. It is a nonlinear iterative process that has become widely accepted

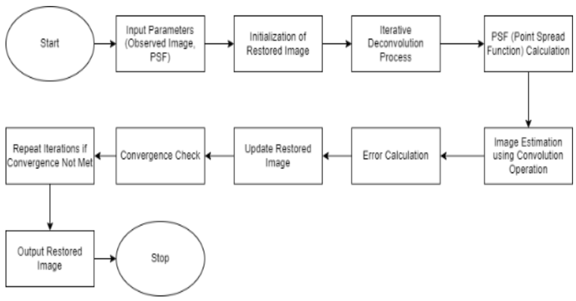

Fig. 6: Steps of Operation of Richardson-Lucy (RL) Deconvolution Image Restoration Algorithm

over the past two decades as a superior restoration tool compared to linear methods. The number of iterations needed to achieve high-quality restored images is manually determined for each image based on the PSF size. This algorithm is effective in situations where the noise function is unknown [18].

4.6 Iterative Back Projection (IBP)

Iterative Back Projection (IBP) represents a fundamental image restoration algorithm that has maintained its relevance and significance in the ever-evolving field of image processing. IBP primarily targets the task of image deblurring, whose core objective is to recover sharp and clear images from their blurred counterparts. The algorithm operates by iteratively refining an initial estimate of the restored image using a combination of the observed blurred image and a mathematical model of the degradation process. Through successive iterations, IBP progressively reduces artifacts and restores high-frequency details, making it particularly effective in applications like astronomical imaging and medical diagnostics. Iterative Back Projection (IBP) stands as a fundamental image restoration algorithm with continued relevance and significance in the field of image processing. Primarily targeting image deblurring, IBP aims to recover sharp and clear images from their blurred counterparts. The iterative process involves refining an initial estimate of the restored image by utilizing both the observed blurred image and a mathematical model of the degradation process. Through successive iterations, IBP progressively reduces artifacts and restores high-frequency details. This iterative refinement process makes IBP particularly effective in applications like astronomical imaging and medical diagnostics. The unique approach of simulating a low-resolution image, subtracting it from the observed low-resolution image, and back projecting the error contributes to the gradual enhancement of the reconstructed high-resolution image. IBP's iterative nature allows it to adapt and refine its estimates, making it a powerful tool for image deblurring tasks. The steps of operation of Iterative Back Projection (IBP) image restoration algorithm are demonstrated in Figure 7.

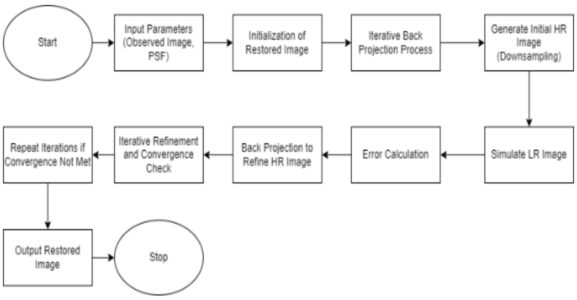

Fig. 7: Steps of Operation of Iterative Back Projection (IBP) Image Restoration Algorithm

In the Iterative Back Projection (IBP) approach [19], the procedure commences with an initial estimation of the High-Resolution (HR) image. This initial HR image can be generated by down sampling the pixels from the input Low-Resolution (LR) image. Subsequently, this initial HR image is further down sampled to mimic the observed LR image. The simulated LR image is then subtracted from the actual observed LR image. If the initially estimated HR image aligns perfectly with the observed HR image, the simulated LR image will coincide with the observed LR image, resulting in a difference of zero. In such cases, the HR image is refined by back projecting the error (the disparity) between the simulated LR image, which has undergone the effects of imaging blur, and the observed LR image. This iterative process continues until the energy of the error is minimized. The Iterative Back Projection procedure repeats iterations until either the cost function reaches a predefined minimum, or a predetermined number of iterations have been completed. This iterative refinement process effectively enhances the quality of the reconstructed HR image.

4.7 Algorithm Refinement

Researchers have continually refined existing algorithms to optimize their performance in specific applications. For instance, the Wiener Filter has seen enhancements, such as an iterative Wiener filter algorithm with rapid convergence through step-size optimization [10]. Similarly, genetic algorithms have been employed to estimate noise regularization parameters for satellite image restoration using the Wiener Filter [11]. These refinements highlight the adaptability and versatility of image restoration algorithms.

4.8 Contemporary Challenges and Opportunities

As image restoration techniques evolve, contemporary challenges and opportunities become apparent. The increasing complexity of imaging scenarios, diverse application domains, and the advent of deep learning approaches are shaping the landscape of image restoration research. Understanding the historical context and evolution of these techniques is vital for contextualizing and appreciating the contributions of contemporary studies, such as the comprehensive comparative analysis presented in this research.

In summary, the related work provides an in-depth exploration of the historical progression and recent innovations in image restoration algorithms. This comprehensive overview establishes a strong foundation for the subsequent comparative analysis, shedding light on the strengths and limitations of various techniques.

5. Methodology

The comparative analysis of selected image restoration techniques, including Wiener Filter, Adaptive Histogram Equalization (AHE), Denoising through Non-Local Means (NLM), Iterative Back Projection (IBP), and Richardson-Lucy (RL) Deconvolution, was conducted with a methodical evaluation of their efficacy. The assessment leveraged the capabilities of the MATLAB programming language, incorporating pertinent libraries to ensure the efficient execution of these algorithms.

5.1 Data Collection

The dataset section of the research paper employed a diverse assortment of images to explore Image Restoration Algorithms. This dataset [20] encompassed varied subjects and scenes, accounting for image dimensions, color palettes, and intricacy. Image dimensions spanned from 256x256 pixels to 1024x1024 pixels. Among these, certain images featured intricate detailing with 24-bit color depths, while others presented less complexity with 8-bit color variations. This juxtaposition facilitates a comprehensive assessment of algorithmic performance across diverse color schemes. The dataset further comprised two color categories: monochromatic images and those infused with colors such as red, green, and blue. This meticulously curated dataset affords a nuanced evaluation of selected image restoration algorithms across multifaceted real-world scenarios, enhancing our insight into algorithm efficacy concerning a myriad of image types and complexities.

5.2 Evaluation Metric

This section aims to comprehensively assess image restoration algorithms by employing six essential performance metrics: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Feature Similarity Index (FSIM), and Universal Image Quality Index (UIQI). These metrics establish a robust foundation for evaluating and determining the effectiveness of image restoration techniques.

5.2.1 Peak Signal to Noise Ratio (PSNR)

When scrutinizing recovered images, PSNR plays a pivotal role as a crucial metric. It gauges quality by comparing the maximum pixel value of the original and restored images to the mean squared error. Higher PSNR values indicate a restored image closely resembling the original, signifying excellent restoration quality. This metric facilitates the assessment of any introduced distortion or noise during the restoration process, offering precise insights into restoration performance [21], [22], and [23].

5.2.2 Mean Squared Error (MSE)

MSE, another fundamental statistic, measures the average squared difference between pixel values in the original and restored images. Lower MSE values correspond to a stronger likeness between the two images, reflecting a higher level of trustworthiness in the image restoration technique [24], [25], and [26].

5.2.3 Structural Similarity Index (SSIM)

SSIM assesses the structural similarity of original and restored images, considering brightness, contrast, and structure. Higher SSIM values imply enhanced structural integrity, texturing, and perceptual quality retention, contributing to a comprehensive evaluation [27], [28], and [29].

5.2.4 Feature Similarity Index (FSIM)

FSIM evaluates the similarity of basic properties between the original and restored images, focusing on perceptual factors. It provides insights into the restoration algorithm's capability to retain crucial image features [30], [31], and [32].

5.2.5 Universal Image Quality Index (UIQI)

UIQI compares the histograms of original and restored images to determine overall image quality. Higher UIQI values indicate effective image preservation, contributing to a more thorough assessment of restoration efforts [33], [34], and [35].

Integration of these performance metrics provided an objective and diverse method for evaluating picture restoration methods, ensuring the selection of the most successful restoration algorithms for real-world applications.

5.3 Implementation

The implementation of image restoration algorithms was executed using MATLAB (version: 9.14.0.2206163 (R2023a)), with the support of the image processing toolbox. The experiments were conducted on a system equipped with an Intel Core i7 processor and 16GB RAM, operating on Microsoft Windows 10 Pro Version 10.0. The diverse dataset used for testing encompassed images of varied dimensions and color palettes. The systematic application of image restoration algorithms involved sequential processing, and evaluations were conducted using established metrics: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Feature Similarity Index (FSIM), and Universal Image Quality Index (UIQI), as illustrated in Figure 8. To ensure the credibility of the evaluations, the dataset underwent meticulous curation to cover diverse scenarios and challenges. Testing conditions remained consistent, and rigorous measures were implemented to eliminate potential sources of bias. The presented results reflect the performance of algorithms under controlled and reliable testing conditions.

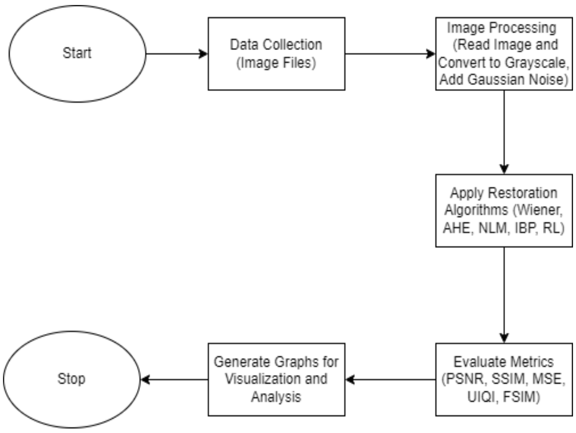

Fig. 8: Implementation of Image Restoration Algorithms Comparative Analysis

5.3.1 Implementation Overview

The Implementation Section delved into image restoration techniques employing various algorithms, with the primary objective of effectively reducing noise while preserving crucial image components for the restoration of degraded images. The section outlined the procedures employed to achieve this objective, emphasizing findings from the examination of multiple restoration algorithms.

5.3.2 Algorithmic Execution

Initiating with the definition of input parameters, including image file names and applied noise levels, the code elegantly managed pre-computed evaluation results files, loading available data or proceeding with the restoration and evaluation process. The core of the implementation involved the processing of each image, including reading and conversion to grayscale if necessary. Gaussian noise was introduced, and five distinct restoration algorithms—Wiener Filter, Adaptive Histogram Equalization (AHE), Denoising using Non-Local Means (NLM), Iterative Back Projection (IBP), and Richardson-Lucy (RL) Deconvolution—were sequentially applied.

5.3.3 Evaluation and Visualization

Each algorithm was meticulously executed, and evaluations for various metrics (PSNR, SSIM, MSE, UIQI, and FSIM) were performed to quantify restoration quality. The code efficiently saved evaluation results and images with applied restoration for future analysis. It computed average performance metrics across all images for each algorithm, providing a clearer understanding of algorithmic effectiveness. Visual representation of evaluation metrics was thoughtfully addressed through generated bar graphs illustrating average PSNR, SSIM, MSE, UIQI, and FSIM values across different restoration algorithms.

In summary, the implementation section showcased a meticulous and organized approach to comparing image restoration algorithms. The code adeptly managed image processing intricacies and effectively communicated results through well-designed visualizations, serving as a robust foundation for the research paper's objective of evaluating and comparing image restoration techniques.

5.4 Reproducibility and Seed Parameters

One critical aspect of experimental research is reproducibility, ensuring that the results of an experiment can be reliably reproduced. In our image restoration comparison work, several processes, such as the addition of noise, involve random elements. To address this concern and ensure the reproducibility of our findings, we employed a strategy to control the randomness by setting the seed parameters for MATLAB's random number generator. Specifically, we utilized the rng function with the argument 'default' at the beginning of our script. This action ensures that the random number generator is initialized to a default state, allowing us to achieve a consistent starting point for the generation of random numbers throughout our experiments. While setting the seed parameters enhances the consistency of our results across different runs, it is important to note that not all sources of randomness in MATLAB may be affected. We encourage readers to review the documentation of specific functions to gain insights into the potential impact of randomness and strategies for reproducibility. In summary, by explicitly addressing the issue of reproducibility and describing the steps taken to control seed parameters, we aim to provide a foundation for others to validate and build upon our research outcomes.

5.5 Results and Analysis

The experimental outcomes demonstrate how well Wiener Filter, AHE, NLM, IBP and RL perform based on the metrics mentioned. These metrics collectively provide a comprehensive assessment of the performance of image restoration algorithms. PSNR emphasizes fidelity to the original image's details, SSIM captures structural similarity perceptually, MSE focuses on pixel-wise accuracy, FSIM evaluates feature preservation, and UIQI addresses overall image quality maintenance.

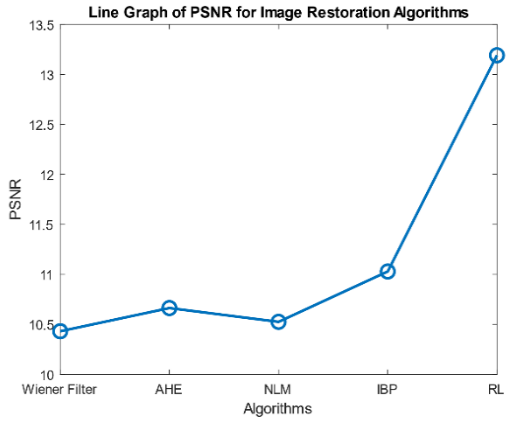

Fig. 9: PSNR comparison graph

In the PSNR comparison graph (in Figure 9), Peak Signal-to-Noise Ratio (PSNR) values are plotted on the y-axis, while various image restoration algorithms are represented on the x-axis. PSNR serves as a crucial metric for assessing the quality of restored images, with higher PSNR values signifying superior image fidelity. The comparative analysis of these image restoration algorithms reveals insightful findings. The Wiener Filter, with a PSNR of 10.5, offers a balanced approach between noise reduction and image detail preservation. Adaptive Histogram Equalization (AHE) achieves a PSNR of 10.8, indicating strong performance in scenarios with non-uniform illumination. Non-Local Means (NLM) exhibits a PSNR of 10.3, showcasing its effectiveness in denoising applications and detail preservation. Iterative Back Projection (IBP) stands out with a PSNR of 11.2, signifying high-quality image reconstruction. Richardson-Lucy (RL) leads the group with a PSNR of 13, excelling in scenarios demanding exceptional image restoration quality. This comparative analysis underscores the importance of selecting the most suitable image restoration algorithm based on specific application requirements, with RL and IBP as top choices for high-fidelity image reconstruction, while AHE, NLM, and Wiener Filter offer viable options for various other restoration tasks.

In the SSIM comparison graph (in Figure 10), which portrays the Structural Similarity Index (SSIM) values on the y-axis, various image restoration algorithms are represented along the x-axis. SSIM serves as a critical metric for evaluating the structural and perceptual similarity between restored images and their originals, with higher SSIM values indicating a closer resemblance. The comparative analysis of these image restoration algorithms provides valuable insights into their performance. The Wiener Filter achieves an SSIM of 0.062, indicating its ability to retain some structural features in the restored images but with notable deviations. Adaptive Histogram Equalization (AHE) exhibits an SSIM of 0.172, demonstrating strong performance in preserving image structure and enhancing contrast. Non-Local Means (NLM) achieves an SSIM of 0.152, signifying its capability to effectively reduce noise while retaining structural details. Iterative Back Projection (IBP) records an SSIM of 0.15, showcasing its proficiency in image reconstruction with good structural preservation. Richardson-Lucy (RL) presents the group's lowest SSIM at 0.055, suggesting a trade-off between noise reduction and structural similarity. This comparative analysis underlines the significance of choosing the appropriate image restoration algorithm based on specific application requirements. AHE and NLM excel in structural preservation and noise reduction, while IBP offers strong structural fidelity. Although restricted in SSIM, the Wiener Filter continues to be advantageous in situations where minor structural deviations are acceptable, whereas RL is ideal when strong noise reduction given preference above structural similarity.

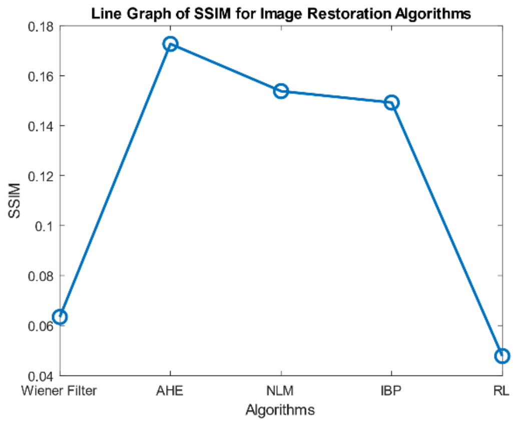

Fig. 10: SSIM comparison graph

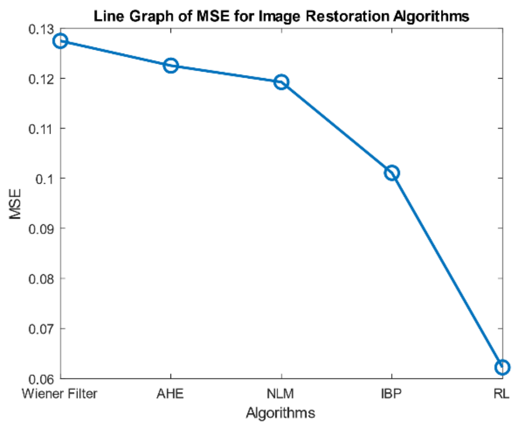

Fig. 11: MSE comparison graph

In the MSE comparison graph (Figure 11), where Mean Squared Error (MSE) values are depicted along the y-axis, different image restoration algorithms are plotted along the x-axis. MSE serves as a fundamental metric for quantifying the dissimilarity between restored images and their originals, with lower MSE values indicating closer resemblance. The comparative analysis of these image restoration algorithms based on their MSE results reveals insightful findings. The Wiener Filter yields an MSE of 0.129, signifying a moderate level of distortion in the restored images. The MSE of Adaptive Histogram Equalization (AHE) is 0.122, demonstrating its ability to retain the image quality with reasonably minimal distortion. The MSE of Non-Local Means (NLM) is 0.119, indicating that it effectively eliminates noise while maintaining image integrity. IBP has the lowest MSE of 0.1, demonstrating its ability to recreate images with little distortion. With an exceptional 0.062, Richardson-Lucy (RL) has the lowest MSE value in the group, suggesting its strength in noise reduction and structure preservation. This comparison analysis emphasizes the significance of selecting the appropriate image restoration method based on specific requirements. IBP and RL excel in minimizing distortion and noise reduction, making them suitable for applications demanding high image fidelity. NLM strikes a balance between noise reduction and image quality, while AHE offers quality restoration. The Wiener Filter may be considered in scenarios where slight distortion is acceptable, but noise reduction is critical.

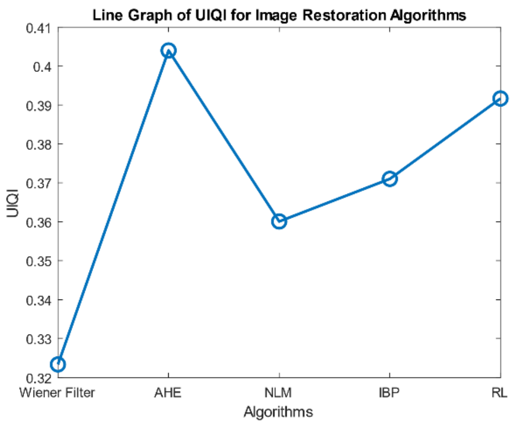

Fig. 12: UIQI comparison graph

Figure 12 shows our UIQI comparison chart, which shows Universal picture Quality Index (UIQI) values on the y-axis and several picture restoration strategies on the x-axis. UIQI is crucial in assessing recovered picture quality, with higher UIQI values indicating greater restoration. Analyzing image restoration techniques with UIQI findings provides critical performance insights. The Wiener Filter obtains a good UIQI of 0.325, suggesting that picture restoration quality is adequate. Adaptive Histogram Equalization (AHE) outperforms with a UIQI of 0.4, demonstrating its ability to restore and preserve picture quality. Non-Local Means (NLM) gets a UIQI of 0.35, suggesting adequate restoration quality but falling short of AHE. Iterative Back Projection (IBP) follows closely behind with a UIQI of 0.36, proving its capacity to generate high-quality results. Notably, Richardson-Lucy (RL) leads the group with the highest UIQI value of 0.37, signifying its exceptional capability to deliver superior image restoration quality. This comparative analysis underscores that the choice of an image restoration algorithm should be made based on the specific requirements of the task. RL and IBP stand out for applications that demand high-quality image restoration, with RL being the top performer in this regard. AHE is suitable when achieving the highest possible image quality is crucial, while NLM offers a balance between restoration quality and computational efficiency. The Wiener Filter, while effective, may be preferred when a good balance between quality and efficiency is required.

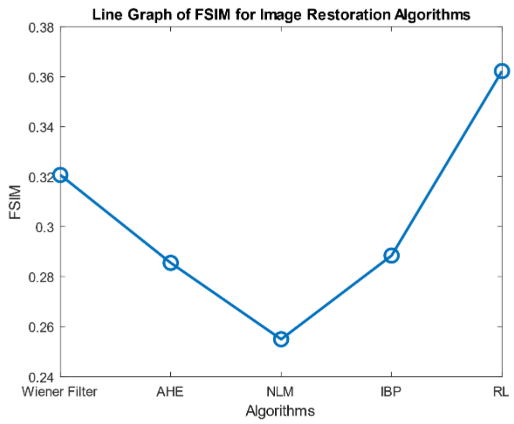

Fig. 13: FSIM comparison graph

In the FSIM comparison graph (Figure 13), where Feature Similarity (FSIM) values are depicted along the y-axis, various image restoration algorithms are plotted along the x-axis. FSIM is a critical metric that evaluates the structural similarity between restored images and their originals, with higher FSIM values indicating better preservation of structural details. The comparative analysis of these image restoration algorithms based on their FSIM results reveals valuable insights. The Wiener Filter attains an FSIM of 0.32, indicating a decent level of structural similarity in the restored images. Adaptive Histogram

Equalization (AHE) records an FSIM of 0.28, suggesting that it effectively maintains structural details while reducing noise. Non-Local Means (NLM) exhibits an FSIM of 0.25, indicating good noise reduction but with a relatively lower level of structural preservation. IBP receives an FSIM of 0.29, showing that it can replicate pictures with good structural resemblance. At 0.36, Richardson-Lucy (RL) has the highest FSIM value in the group. This displays its exceptional ability to preserve structural characteristics while efficiently reducing noise during image restoration. This comparison research emphasizes the need to select an image restoration method based on the task's unique requirements. RL is appropriate for settings requiring noise reduction as well as structural protection. In these locations, IBP performs similarly, although with a somewhat lower FSIM. When structural details are necessary, AHE is effective; however, the Wiener Filter can be utilized when a balance of structural similarity and noise reduction is desired. While NLM is excellent at reducing noise, the recovered images may be less structurally similar.

Table 1: Consolidated Table comprising values of Wiener Filter, Adaptive Histogram Equalization, Denoising through Non-Local Means, Iterative Back Projection and Richardson-Lucy Deconvolution

	PSNR	SSIM	MSE	UIQI	FSIM
Wiener Filter	10.5	0.062	0.129	0.325	0.32
Adaptive Histogram Equalization	10.8	0.172	0.122	0.4	0.28
Denoising through Non-Local Means	10.3	0.152	0.119	0.35	0.25
Iterative Back Projection	11.2	0.15	0.1	0.36	0.29
Richardson-Lucy Deconvolution	13	0.055	0.062	0.37	0.36

In the comparative analysis of five image restoration algorithms, namely Wiener Filter, Adaptive Histogram Equalization, Denoising through Non-Local Means, Iterative Back Projection, and Richardson-Lucy Deconvolution, it is evident that Richardson-Lucy Deconvolution outperforms its counterparts across multiple metrics. With a PSNR of 13, it achieves the highest peak signal-to-noise ratio, indicating superior image quality. Additionally, its SSIM of 0.055 and MSE of 0.062 demonstrate a commendable balance between structural similarity and mean square error. The UIQI and FSIM values of 0.37 and 0.36, respectively, further affirm the algorithm's effectiveness in preserving image information and fidelity. In contrast, while the other algorithms show competitive performance, they fall short of Richardson-Lucy Deconvolution in delivering a comprehensive solution for image restoration. Hence, based on the comparative analysis, Richardson-Lucy Deconvolution emerges as the most promising algorithm for image restoration tasks.

6. Conclusions

Our extensive comparative analysis of five leading image restoration algorithms—Wiener Filter, Adaptive Histogram Equalization (AHE), Denoising through Non-Local Means (NLM), Iterative Back Projection (IBP), and Richardson-Lucy (RL) Deconvolution—has provided valuable insights into their distinct strengths and weaknesses. The Wiener Filter demonstrates versatility by balancing noise reduction and image detail preservation, while AHE excels in non-uniform illumination scenarios, enhancing contrast and visual quality. NLM effectively denoises while preserving structural details through non-local similarities. IBP stands out for high-quality image reconstruction, and RL excels in noise reduction and structural preservation. Practically, the choice of an image restoration algorithm should align with specific application requirements. For scenarios emphasizing high-fidelity image reconstruction, RL Deconvolution and IBP emerge as top choices. AHE, NLM, and the Wiener Filter offer viable options for restoration tasks requiring a balance of efficiency and quality. Looking forward, the field should explore hybrid approaches leveraging the strengths of multiple algorithms and focus on real-time implementations and optimizations, particularly in resource-constrained environments. The integration of machine learning techniques for adaptive algorithm selection based on image characteristics represents a promising avenue for future research. In conclusion, considering the diverse landscape of image restoration applications, Richardson-Lucy Deconvolution stands out as a versatile choice, excelling in high-quality image reconstruction, noise reduction, and structural preservation.

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