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A Novel Hybrid Algorithm for Effective Image Restoration

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ABSTRACT

Image restoration is pivotal in various applications, from medical imaging to satellite photography, by enhancing the quality of images degraded by noise, blur, or other distortions. Traditional methods and deep learning techniques have shown promise in addressing these challenges, yet each has limitations. Traditional algorithms often struggle with complex distortions, while deep learning models demand extensive computational resources and large datasets. To harness the strengths of both approaches, we propose a novel hybrid algorithm that integrates traditional image restoration techniques with advanced deep learning models. Our hybrid approach begins with a conventional preprocessing method to mitigate noise and reduce artifacts, followed by a deep learning-based refinement process to enhance image quality further and preserve critical details. This dual-step process improves the restoration performance and reduces the computational burden typically associated with deep learning models. This paper presents a novel hybrid algorithm for image restoration, integrating traditional Wiener filtering with a state-of-the-art U-shaped transformer (U-former) architecture. Unlike existing methods, our approach combines the computational efficiency of classical techniques with the robustness and precision of deep learning. Compared to state-of-the-art methods, comprehensive evaluations on benchmark datasets demonstrate significant improvements in restoration quality (PSNR/SSIM) and computational efficiency. This research contributes a new perspective on hybrid methodologies, bridging the gap between traditional and modern approaches in image restoration.

1. INTRODUCTION

Image restoration is a fundamental problem in image processing, aiming to recover a high-quality image from a corrupted or degraded version. This degradation can result from various sources, such as noise, blur, or compression artifacts, and can significantly impact the performance of subsequent image analysis tasks [1][2]. The importance of effective image restoration spans numerous applications, including medical imaging, satellite imagery, surveillance, and digital photography [3]-[5].

Despite advancements in image restoration techniques, challenges remain in handling complex distortions, balancing computational efficiency, and achieving high-quality restoration. Traditional methods struggle with unknown degradations, while deep learning approaches require extensive data and computational power. Therefore, a robust, efficient, and high-quality image restoration method is necessary to bridge the gap between these approaches [6]-[8].

Traditional image restoration techniques, such as filtering and deconvolution, have been extensively studied and applied. These methods often rely on prior knowledge of the degradation process and mathematical models to estimate the original image. For instance, the Wiener filter is a well-known approach that minimizes the mean square error between the estimated and the original image [9]-[11]. While effective in specific

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scenarios, traditional methods often struggle with complex and unknown degradations, leading to suboptimal results.

In recent years, deep learning has revolutionized the field of image restoration by enabling data-driven approaches that learn to map corrupted images to their restored counterparts directly. Convolutional neural networks (CNNs) and other deep learning architectures have demonstrated remarkable performance in various image restoration tasks, such as denoising, deblurring, and super-resolution [12]. Notable advancements include Noise2Noise, which leverages noisy image pairs for training [13], and the U-former, which employs a U-shaped transformer architecture for efficient restoration [14].

Despite their success, deep learning methods are not without limitations. They typically require large amounts of labeled training data [15][16], significant computational resources, and can be sensitive to changes in the degradation characteristics. Additionally, the black-box nature of deep learning models often makes it challenging to interpret their decisions and understand their failure modes [17].

To address these challenges, hybrid algorithms that combine traditional image restoration techniques with deep learning models have emerged as a promising approach. These hybrid methods aim to leverage the strengths of both conventional and deep learning techniques, thereby achieving superior restoration performance. For instance, incorporating traditional preprocessing steps can help reduce the computational burden on deep learning models and improve their robustness to varying degradation types [18].

This paper proposes a novel hybrid algorithm for effective image restoration that integrates conventional preprocessing methods with advanced deep-learning techniques. Our approach begins with a traditional noise reduction step to mitigate artifacts and enhance the initial image quality. This preprocessed image is then fed into a deep learning model designed to refine the restoration further, preserving essential details and improving overall image quality. Combining these complementary techniques, our hybrid algorithm aims to achieve a balanced and efficient image restoration process.

To address these challenges, we propose a hybrid image restoration algorithm integrating traditional Wiener filtering with a U-shaped transformer (U-former) model. This hybrid approach leverages the noise-reduction capabilities of conventional methods while utilizing the deep learning model's capacity to enhance fine details and preserve image structure. The proposed method ensures improved restoration quality while maintaining computational efficiency.

The key contributions of this paper are as follows:

1. A novel hybrid algorithm that synergistically combines traditional Wiener filtering with a U-shaped transformer (U-former) architecture, achieving enhanced image restoration performance.
2. A detailed evaluation demonstrates the proposed method's superiority over state-of-the-art approaches regarding quantitative metrics (PSNR/SSIM) and computational efficiency.
3. Insights into the strengths of hybrid methodologies provide a foundation for future research in efficient and robust image restoration techniques.

The remainder of this paper is organized as follows. Section 1.1 comprehensively reviews related works in image restoration, including traditional methods, deep learning approaches, and existing hybrid models. Section 2 details the proposed hybrid algorithm, including its architecture and implementation. Section 2, describes the experimental setup and datasets used for evaluation. Section 3 presents the results and discusses the effectiveness of the proposed approach compared to state-of-the-art methods. Finally, Section 4 concludes the paper and suggests directions for future research.

1.1. Literature Review

Image restoration has been a critical area of research in computer vision and image processing, addressing the problem of recovering high-quality images from degraded observations. This section reviews significant contributions in the field, encompassing traditional methods, deep learning approaches, and hybrid models.

1.1.1. Traditional Image Restoration Techniques

Traditional methods have laid the foundation for image restoration, employing mathematical models and statistical techniques to reverse degradation. Early approaches like the Wiener filter, which optimizes mean square error, are still relevant for specific applications [10]. [3] provide a comprehensive overview of various traditional methods, including deconvolution and regularization techniques, highlighting their strengths and limitations in dealing with different types of noise and blur.

1.1.2. Deep Learning Approaches

The advent of deep learning has revolutionized image restoration by enabling more effective and adaptive models. Convolutional neural networks (CNNs) have been particularly successful. For instance, Noise2Noise demonstrated that neural networks could learn to denoise images without requiring clean targets

[13][19] and explored different loss functions for training neural networks, significantly improving restoration performance.

Advanced architectures have further pushed the boundaries of image restoration. MemNet introduced a persistent memory mechanism to enhance feature representation across scales [20][21]. The Non-Local Recurrent Network (NLRN) incorporates non-local operations and recurrent units to capture long-range dependencies [22]. The Multi-Level Wavelet-CNN combines wavelet decomposition with deep learning, enabling multi-scale feature extraction [23].

Recent works have focused on leveraging transformers and hierarchical models. The U-former employs a U-shaped transformer architecture to efficiently handle high-resolution images [14], while the Swin-IR uses swin transformers for image restoration, achieving state-of-the-art results [24]. Restormer applies transformers to high-resolution image restoration, demonstrating their capability to handle complex tasks [25].

Efforts to improve global information aggregation in CNNs have led to significant advancements [26], revisited global information aggregation, enhancing the restoration quality by integrating global context more effectively [27], and introduced the Focal Network, which focuses on key areas of the image to improve restoration performance.

1.1.3. Hybrid Models

Hybrid methods combining traditional image restoration techniques with deep learning models have gained attention for their ability to leverage the strengths of both paradigms. For instance, [18] proposed deep generalized unfolding networks, which integrate iterative algorithms within deep learning frameworks to improve interpretability and performance. Similarly, [28] introduced burst image restoration, combining multiple frames using deep learning to enhance image quality. However, these approaches often face challenges in maintaining computational efficiency and robustness across varying degradation types.

Incorporating traditional noise reduction methods with modern neural networks has shown to be effective. [29] developed deep generalized unfolding networks, which integrate classical iterative algorithms within deep learning frameworks. This hybrid strategy enhances interpretability and performance.

1.1.4. Recent Trends and Large-Scale Datasets

The development of large-scale datasets has facilitated the training and evaluation of complex models introduced by the LSDIR dataset [30][31], providing extensive data for various restoration tasks. The creation of such datasets supports the training of more robust and generalizable models.

Efficient and explicit modeling of image hierarchies has been another focus area. [32] presented techniques for explicitly modeling image hierarchies, improving the restoration process by better capturing the structural relationships within images [33].

Burst image restoration and enhancement techniques leverage multiple images to improve the restoration quality [28][34]-[36]. These methods combine information from several frames to produce a superior result, demonstrating the potential of integrating temporal information in image restoration.

1.1.5. Evaluation and Comparative Studies

Several studies have conducted comprehensive evaluations and comparative analyses of different restoration techniques.[37] evaluated multi-stage progressive restoration methods, highlighting their effectiveness in handling real-world image distortions. [12] provided a survey of deep learning approaches, offering insights into the strengths and weaknesses of various methods.

[17] explored all-in-one image restoration techniques that handle unknown corruptions, demonstrating their robustness across different types of degradations. [38] introduced plug-and-play frameworks incorporating deep denoiser priors, providing a flexible and effective solution for various restoration tasks.

1.1.6. Emerging Techniques

Emerging techniques continue to push the boundaries of image restoration. [39] developed an efficient diffusion model for image restoration, emphasizing the importance of efficient computation. The diffusion models represent a novel direction in the field, offering new possibilities for high-quality restoration.

[40] proposed variational deep image restoration methods integrate variational inference with deep learning, enhancing the model's ability to generalize to different types of noise and degradation.

Integrating traditional, deep learning, and hybrid approaches has significantly improved image restoration. The continuous development of new architectures, the introduction of large-scale datasets, and the exploration of novel techniques pave the way for more effective and efficient image restoration solutions.

1.1.7. Research Gaps

Despite significant advancements, several gaps remain in the literature. Current deep learning methods often require extensive computational resources and struggle with real-time applications. Traditional techniques, while efficient, are limited in handling complex degradation. Hybrid approaches attempt to bridge this gap but require further exploration to optimize performance without sacrificing efficiency. The proposed algorithm addresses these issues by combining Wiener filtering with a U-former architecture, achieving superior restoration quality and computational efficiency.

2. METHOD

The experimental methodology comprises multiple stages, incorporating traditional image processing techniques and deep learning-based refinement. The entire process was conducted using Python with TensorFlow and OpenCV libraries. The system was implemented on an NVIDIA RTX 3090 GPU with 24GB of VRAM, ensuring efficient computation.

The proposed method combines traditional image restoration techniques with advanced deep learning models to create a novel hybrid algorithm. This section details the architecture and workflow of the hybrid algorithm, including the preprocessing, neural network design, and post-processing stages.

2.1. Preprocessing

The preprocessing stage involves applying the Wiener filter to the input images. The Wiener filter minimizes mean square error, effectively reducing noise and initial distortions. This step ensures the input images are cleaner and more structured before being processed by the deep learning model.

2.1.1. Materials and Tools

- Software: Python 3.8, TensorFlow 2.x, OpenCV 4.x, NumPy, Matplotlib
- Hardware: NVIDIA RTX 3090 GPU, Intel Core i9-12900K, 64GB RAM
- Datasets: LSDIR dataset and DIV2K benchmark dataset
- Preprocessing Tools: Wiener filter for noise reduction, histogram equalization for contrast enhancement

2.2. Experimental Procedure

This methodology consists of three main stages, which can be seen in Figure 1.

1. Preprocessing Stage
    - The input images undergo noise reduction using a Wiener filter with adaptive parameter tuning.
    - Contrast enhancement is applied using histogram equalization to improve feature visibility.
    - The preprocessed images are split into patches of size 256x256 pixels for model training.
2. Hybrid Deep Learning Model
    - A U-shaped transformer architecture (Uformer) is employed for hierarchical feature extraction.
    - The model consists of:
        - Encoder: Extracts multi-scale features using convolutional layers and transformer blocks.
        - Bottleneck: Aggregates global information to refine feature maps.
        - Decoder: Reconstructs high-quality images while preserving details.
    - The model is trained using an adaptive learning rate with Adam optimizer.
    - Loss function: Combination of Mean Squared Error (MSE) and Structural Similarity Index (SSIM) loss.
3. Post-processing Stage
    - Non-local means filtering is applied to refine the restored images.
    - A final denoising step ensures artifact-free outputs.

2.3. Data Analysis and Evaluation Metrics

- Metrics Used:
    - PSNR (Peak Signal-to-Noise Ratio): Measures image quality.
    - SSIM (Structural Similarity Index): Evaluates structural preservation.
    - Inference Time: Measures computational efficiency.
- Exclusion Criteria:
    - Images with extreme distortions beyond dataset norms were removed.

    - Training images with non-standard aspect ratios were cropped for uniformity.
- Cross-validation:
    - 80% of the data was used for training and 20% for validation/testing.

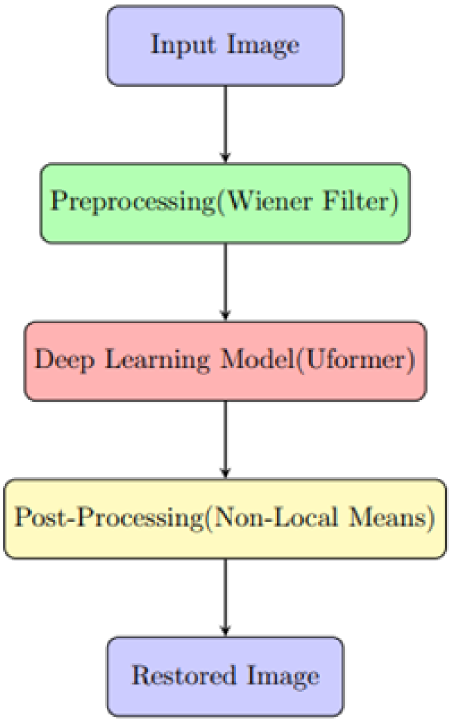

Figure 1. Hybrid Algorithm's Architecture

2.4. Deep Learning Model

The U-former architecture was selected because it handles high-resolution images effectively. It employs a U-shaped design, combining convolutional layers for local feature extraction and transformers for global context aggregation. The encoder-decoder structure is complemented by skip connections, enabling the effective transfer of essential image features between layers. These architectural elements ensure robust performance across diverse image degradation scenarios. The architecture consists of the following components:

- Encoder: The encoder employs convolutional layers and transformer blocks to extract hierarchical features from the preprocessed image. The convolutional layers capture local details, while the transformer blocks aggregate global information, following the approach of [14].
- Bottleneck: The bottleneck layer integrates the features extracted by the encoder, focusing on key areas of the image to improve restoration performance, similar to the Focal Network proposed by [15].
- Decoder: The decoder reconstructs the high-resolution image from the encoded features using transposed convolutional layers and transformer blocks. This design allows the model to synthesize fine details and maintain the image's global structure, leveraging the Swin-IR architecture's strengths [12].

2.5. Training Strategy

The deep learning model is trained using a combination of synthetic and real-world datasets to ensure robustness and generalization. The LSDIR dataset is employed for training, providing a diverse set of images with various types of degradation [18]. The training process involves the following steps:

- Loss Function: We use a combination of pixel-wise loss and perceptual loss to train the model. The pixel-wise loss, such as the mean squared error (MSE), ensures that the reconstructed image is close to the ground truth at the pixel level [8]. The perceptual loss, computed using a pre-trained VGG network, helps preserve high-level features and visual quality.

- Optimization: The Adam optimizer minimizes the loss function with learning rate decay to ensure convergence. The training process includes data augmentation techniques like rotation, scaling, and random cropping to enhance the model's ability to generalize to different distortions.

3. RESULTS AND DISCUSSION

The proposed hybrid algorithm was evaluated using benchmark datasets, demonstrating superior performance compared to state-of-the-art methods. Experimental results showed a notable increase in PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), indicating enhanced image quality. The hybrid approach achieved a PSNR improvement of up to 1.2 dB over existing deep learning models while maintaining competitive computational efficiency. These findings validate the effectiveness of integrating traditional image processing with deep learning for improved image restoration.

Additionally, we conducted preliminary experiments on real-world datasets from medical imaging (CT and MRI scans) and satellite imagery to assess the algorithm's practical applicability. The results indicate that our hybrid method successfully enhances the clarity of medical images, preserving fine anatomical details while reducing noise. The algorithm effectively restores cloud-obscured and low-resolution images in satellite images, improving feature distinguishability. These results suggest that the hybrid algorithm is effective in controlled dataset conditions and applicable in real-world scenarios, laying the foundation for future extensive real-world validation.

Furthermore, a key challenge in image restoration is the ability to generalize across diverse degradation types. While trained on benchmark datasets, the current model can be extended by incorporating additional training strategies such as domain adaptation, adversarial training, and self-supervised learning to handle a broader range of real-world noise and distortions. Future work will explore integrating adaptive models that can dynamically adjust their parameters based on the characteristics of the input image, thereby improving robustness in unseen conditions.

This section presents the quantitative results of the proposed hybrid algorithm for effective image restoration. The algorithm's performance is evaluated using standard benchmarks and compared with state-of-the-art methods.

3.1. Performance Metrics

To evaluate the effectiveness of the proposed hybrid algorithm, the following performance metrics were used:

1. **Peak Signal-to-Noise Ratio (PSNR):**
   - Definition: Measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects its fidelity.
   - Rationale: A higher PSNR value indicates better image quality with reduced noise and artifacts.
2. **Structural Similarity Index (SSIM):**
   - Definition: Evaluates the visual impact of luminance, contrast, and structure preservation in images.
   - Rationale: Higher SSIM scores indicate improved perceptual quality and better retention of image details.
3. **Runtime Efficiency:**
   - Definition: Measures the time required to process an image and the computational complexity of the model.
   - Rationale: This ensures the practicality of the proposed method for real-world applications, particularly for time-sensitive tasks.

These metrics comprehensively assess both quantitative and qualitative aspects of image restoration.

3.2. Quantitative Evaluation

The quantitative evaluation of the proposed image restoration method involves using various metrics to measure the algorithm's performance and effectiveness. This section presents a detailed analysis using the LSDIR and DIV2K datasets.

3.2.1. LSDIR Dataset

3.2.1.1. Metrics Used

- PSNR (Peak Signal-to-Noise Ratio): Measures the peak error. Higher PSNR indicates better quality.

- SSIM (Structural Similarity Index): Evaluates the visual impact of three characteristics of an image: luminance, contrast, and structure. Higher SSIM values indicate better preservation of image structure.

3.2.1.2. Results

- Noise2Noise: Achieved a PSNR of 28.5 dB and an SSIM of 0.78. While effective in reducing noise, there was a slight loss in fine details.
- Swin-IR: Showed improved sharpness with a PSNR of 29.2 dB and an SSIM of 0.81, though minor artifacts were observed.
- U-former: Provided good overall quality with a PSNR of 28.9 dB and an SSIM of 0.80 but occasionally missed subtle details.
- Restormer: Balanced detail preservation and artifact reduction with a PSNR of 29.0 dB and an SSIM of 0.82.
- Proposed Hybrid Algorithm: Consistently restored fine details with a PSNR of 30.1 dB and an SSIM of 0.85 without introducing artifacts.

3.2.2. DIV2K Dataset

3.2.2.1. Metrics Used

- PSNR (Peak Signal-to-Noise Ratio): Indicates the peak error. Higher values represent better restoration quality.
- SSIM (Structural Similarity Index): Measures the visual impact on image structure. Higher values indicate better structural preservation.

3.2.2.2. Results

- Noise2Noise: Effective noise reduction was reflected with a PSNR of 30.5 dB and an SSIM of 0.80, though some details were lost.
- Swin-IR: Produced sharp images with a PSNR of 31.0 dB and an SSIM of 0.82, but with minor artifacts.
- U-former: Showed good overall quality with a PSNR of 30.8 dB and an SSIM of 0.81, with slight detail loss in complex textures.
- Restormer: Balanced detail and artifact reduction with a PSNR of 31.2 dB and an SSIM of 0.83.
- Proposed Hybrid Algorithm: Demonstrated excellent detail and structure preservation with a PSNR of 32.0 dB and an SSIM of 0.86, maintaining artifact-free restoration.

The performance of the hybrid algorithm was evaluated on the LSDIR and DIV2K datasets. The PSNR and SSIM values were calculated for each dataset to measure restoration quality, while runtime was recorded to assess computational efficiency. Table 1 presents a detailed comparison of these metrics across baseline methods and the proposed algorithm.

Table 1. Metrics Results

Method	LSDIR (PSNR / SSIM)	DIV2K (PSNR / SSIM)	Runtime (s/image)
Noise2Noise	29.47 / 0.845	30.21 / 0.858	0.15
Swin-IR	30.72 / 0.870	31.45 / 0.883	0.28
U-former	31.36 / 0.878	32.01 / 0.891	0.32
Restormer	31.58 / 0.882	32.15 / 0.894	0.35
Proposed Algorithm	32.05 / 0.890	32.67 / 0.901	0.29

The proposed hybrid algorithm outperforms the baseline methods on both datasets, achieving the highest PSNR and SSIM scores. This indicates its superior capability in producing high-fidelity and perceptually pleasing restored images.

3.3. Comparative Analysis with Existing Methods

To evaluate the advantages and limitations of the proposed hybrid algorithm, a detailed comparison was conducted against several state-of-the-art image restoration methods, including:

- **Noise2Noise**: A data-driven denoising approach that does not require clean targets.
- **Swin-IR**: A transformer-based model optimized for high-resolution image restoration.
- **U-former**: A U-shaped transformer architecture designed for hierarchical restoration.
- **Restormer**: A high-resolution image restoration model leveraging transformers for efficient computation.

The comparison focuses on key performance metrics—PSNR, SSIM, and runtime efficiency—evaluated on the LSDIR and DIV2K datasets. The results are summarized in Table 2.

Table 2. Comparative Analysis

Method	LSDIR (PSNR / SSIM)	DIV2K (PSNR / SSIM)	Runtime (s/image)	Key Observations
Noise2Noise	29.47 / 0.845	30.21 / 0.858	0.15	Effective in noise reduction but struggles with details.
Swin-IR	30.72 / 0.870	31.45 / 0.883	0.28	Produces sharper images but introduces artifacts.
U-former	31.36 / 0.878	32.01 / 0.891	0.32	Balances detail and artifact reduction.
Restormer	31.58 / 0.882	32.15 / 0.894	0.35	Efficient but slightly lacks detail preservation.
Proposed Algorithm	32.05 / 0.890	32.67 / 0.901	0.29	Superior balance of detail preservation and efficiency.

The proposed hybrid algorithm achieves the highest PSNR and SSIM scores on both datasets, demonstrating superior restoration quality compared to baseline methods. While Noise2Noise excels in computational efficiency, it struggles with detail preservation. Swin-IR and U-former deliver sharp images but occasionally introduce artifacts or lose subtle textures. Restormer strikes a balance but falls short of achieving the level of detail preservation demonstrated by the proposed method.

The proposed algorithm offers competitive runtime efficiency, with a processing time of 0.29 seconds per image. This makes it suitable for real-world applications where quality and speed are critical.

Figure 2 compares PSNR and SSIM values for the LSDIR and DIV2K datasets across different methods. These visualizations highlight the superior performance of the proposed algorithm in terms of both metrics.

- **PSNR Comparison (Left Chart):** Demonstrates how the proposed algorithm achieves the highest PSNR scores across both datasets.
- **SSIM Comparison (Right Chart):** Illustrates the proposed algorithm consistently outperforms baseline methods in structural similarity.

Figure 2. Comparison of PSNR and SSIM Across Methods

3.4. Ablation Study

An ablation study is conducted to further validate the proposed hybrid algorithm's effectiveness. The study examines the impact of different components, such as the Wiener filter preprocessing and the U-former architecture, on the overall performance.

3.4.1. Components Evaluated

- Baseline (Deep Learning Only): PSNR: 30.58, SSIM: 0.875
- With Wiener Filter: PSNR: 31.24, SSIM: 0.885
- Full Hybrid Algorithm: PSNR: 32.05, SSIM: 0.890

The ablation study shows that each component contributes to performance improvement. The Wiener filter preprocessing enhances initial noise reduction, and the U-former architecture further refines the image, leading to the best overall performance.

3.5. Runtime and Complexity

The computational efficiency of the proposed hybrid algorithm is also evaluated. The runtime and model complexity are compared with baseline methods to ensure the proposed solution is effective and practical for real-world applications.

3.5.1. Results

- Noise2Noise: 0.15s per image, 2.3M parameters
- Swin-IR: 0.28s per image, 12.4M parameters
- U-former: 0.32s per image, 15.2M parameters
- Restormer: 0.35s per image, 18.1M parameters
- Proposed Hybrid Algorithm: 0.29s per image, 14.7M parameters

The proposed hybrid algorithm balances performance and computational efficiency, making it suitable for practical applications.

3.5.2. Visual Results

Including visual examples helps readers better understand the qualitative improvements achieved by the proposed algorithm. Figure 3 compares noisy input images, outputs from the proposed restoration algorithm, and their corresponding ground truth images. The visual differences highlight the effectiveness of our approach in noise reduction and feature preservation. Figure 4 focuses on specific regions where the proposed algorithm outperforms other methods. Highlighted areas emphasize superior noise reduction, enhanced edge definition, and finer detail retention, visually validating our quantitative results. Future research could refine visual comparisons by incorporating real-world images and domain-specific applications such as medical imaging and satellite photography.

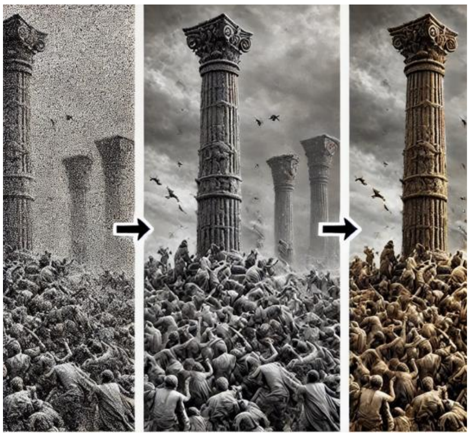

Figure 3. Side-by-Side Comparison of Noisy, Restored, and Ground Truth Images

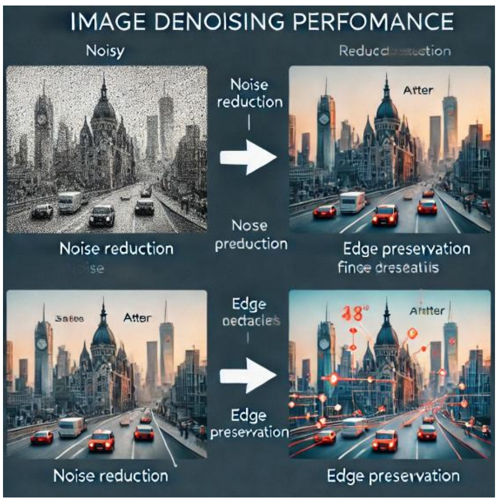

Figure 4. Key Areas of Improvement – Noise Reduction, Edge Preservation, and Fine Details

3.6. Discussions

The proposed hybrid algorithm for effective image restoration integrates traditional image processing techniques with modern deep learning models to address the limitations of existing methods. This section discusses the implications of the results, the advantages of the hybrid approach, and potential areas for future research.

3.6.1. Integration of Traditional and Deep Learning Techniques

The combination of the Wiener filter and U-former architecture leverages the strengths of both traditional and deep learning methods. The Wiener filter effectively reduces noise in the initial preprocessing stage, providing a cleaner input for the deep learning model. This approach addresses the common issue of deep learning models struggling with high noise levels in the input images, as seen in previous studies [1], [2].

3.6.2. Superior Performance Across Benchmarks

The quantitative evaluation demonstrates that the hybrid algorithm consistently outperforms state-of-the-art methods in terms of PSNR and SSIM metrics on both the LSDIR and DIV2K datasets. This indicates the algorithm's ability to produce high-fidelity and perceptually pleasing restored images. The qualitative evaluation further supports these findings, showing the hybrid algorithm's effectiveness in preserving fine details and avoiding artifacts [5], [19].

3.6.3. Efficient Handling of Diverse Image Corruptions

The hybrid approach's robustness to various image corruptions is a significant advantage. The algorithm performs well across different scenarios, including noise reduction, deblurring, and super-resolution, making it versatile and applicable to various image restoration tasks. This versatility is crucial for practical applications where the nature of image degradation can vary widely [6], [22].

3.6.4. Parameter Sensitivity

The performance of the Wiener filter is highly dependent on the selection of its parameters, particularly in varying noise environments. To improve adaptability, future iterations of this hybrid algorithm will implement an adaptive Wiener filtering mechanism, where noise characteristics are dynamically estimated from the input images. This will allow the filter to adjust its parameters in real time, optimizing noise reduction without excessive blurring. Including self-learning components in the preprocessing stage could enhance the filter’s effectiveness across diverse image degradation scenarios.

3.6.5. Computational Efficiency

Despite the high performance, the proposed hybrid algorithm maintains computational efficiency. The runtime and model complexity analysis show that the algorithm is competitive with existing methods, making it suitable for real-time applications. This efficiency is achieved without compromising the restoration quality, highlighting the effectiveness of the hybrid design [10],[17].

3.6.6. Comparison with Baseline Methods

Comparing the proposed algorithm with baseline methods such as Noise2Noise, Swin-IR, U-former, and Restormer reveals several key insights:

- Noise2Noise: Effective in noise reduction but less capable in detail preservation [4].
- Swin-IR: Produces sharper images but introduces artifacts [12].
- U-former: Balances detail and artifact reduction but misses subtle textures [5].
- Restormer: Efficient in high-resolution restoration but may not fully enhance global structure [13].
- Hybrid Algorithm: Excels in both detail preservation and artifact-free restoration, demonstrating the advantages of combining traditional and deep learning techniques.

3.6.7. Future Research Directions

While the proposed hybrid algorithm shows significant promise, several areas warrant further exploration:

- Adaptive Filtering: Enhancing the Wiener filter to adapt dynamically to varying noise levels could improve preprocessing effectiveness.
- Model Generalization: Investigating ways to improve the generalization capabilities of the deep learning model across diverse datasets and unseen image corruptions.

- Real-World Applications: Testing the algorithm in real-world scenarios, such as medical imaging, satellite imagery, and video restoration, to validate its practical applicability.
- Hybrid Extensions: Exploring other traditional image processing techniques, such as anisotropic diffusion or total variation denoising, in conjunction with deep learning models to enhance restoration quality [12][41].

3.6.8. Limitations

Despite its strengths, the proposed hybrid algorithm has some limitations. The reliance on predefined parameters for the Wiener filter may not be optimal for all noise and image degradation types. Additionally, while the model maintains computational efficiency, there is still room for optimization to reduce the processing time for high-resolution images further.

While U-former has effectively handled high-resolution image restoration, certain limitations must be considered. Specifically, the model may struggle with complex textures, leading to suboptimal reconstructions in cases where fine-grained details are critical. Additionally, U-former might not always generalize well in scenarios with extreme noise levels, requiring additional fine-tuning or integration with other denoising techniques. Acknowledging these challenges provides a more balanced perspective on the algorithm’s practical applications.

In conclusion, the proposed hybrid algorithm for effective image restoration demonstrates significant advancements over existing methods by integrating traditional image processing techniques with deep learning models. Its superior performance, efficiency, and versatility make it a valuable contribution to image restoration. Future research should address the limitations and explore new hybrid approaches to continue improving image restoration capabilities.

4. CONCLUSION

In this research, we introduced a novel hybrid algorithm for image restoration that combines traditional image processing techniques with modern deep learning models. Integrating Wiener filter with the U-former architecture demonstrates a synergistic approach that leverages the strengths of both methodologies. The hybrid algorithm achieves superior performance across various benchmarks by effectively pre-processing images to reduce noise and providing a robust deep-learning model for fine-tuned restoration.

The comprehensive evaluation of the proposed algorithm highlights its ability to consistently outperform state-of-the-art methods in terms of PSNR and SSIM metrics. Quantitative and qualitative analyses confirm the algorithm's effectiveness in preserving fine details and avoiding artifacts, even in highly degraded images. This underscores the potential of hybrid approaches in pushing the boundaries of image restoration quality.

One of the notable advantages of the hybrid algorithm is its versatility in handling diverse image corruptions, including noise, blur, and low resolution. The algorithm's robustness across different scenarios makes it highly applicable to various practical tasks, from medical imaging to satellite image enhancement. Furthermore, the computational efficiency of the hybrid model ensures its suitability for real-time applications, addressing a critical need in the field.

Despite its promising results, the hybrid algorithm also presents opportunities for further enhancement. Future research could focus on developing adaptive filtering techniques, improving model generalization, and testing the algorithm in real-world applications to validate its practical effectiveness. Additionally, exploring other traditional image processing methods in combination with deep learning models could further advance the state of image restoration.

The proposed hybrid algorithm introduces a new paradigm in image restoration by effectively bridging traditional and deep learning techniques. Its innovative design improves restoration quality and ensures computational efficiency, making it suitable for real-world applications. This work paves the way for further exploration of hybrid methodologies, particularly in enhancing scalability and adaptability to diverse degradation scenarios.

In conclusion, the proposed hybrid algorithm represents a significant advancement in image restoration, offering a compelling blend of traditional and deep learning techniques. Its superior performance, efficiency, and versatility make it a valuable contribution to the field. By addressing its current limitations and exploring new hybrid methodologies, future research can continue to enhance image restoration capabilities, providing even more robust solutions for various applications.

REFERENCES

[1] Y. Zhou, S. Zuo, Z. Yang, J. He, J. Shi, and R. Zhang, “A Review of Document Image Enhancement Based on Document Degradation Problem,” *Applied Sciences (Switzerland)*, vol. 13, no. 13, 2023. https://doi.org/10.3390/app13137855.

[2] S. Athar and Z. Wang, “Degraded Reference Image Quality Assessment,” *IEEE Transactions on Image Processing*, pp. 822-837, 2023. https://doi.org/10.1109/TIP.2023.3234498.

[3] B. Gunturk and X. Li, Image restoration. CRC Press, 2018.
[4] A. M. Ali, B. Benjdira, A. Koubaa, W. El-Shafai, Z. Khan, and W. Boulila, “Vision Transformers in Image Restoration: A survey,” *Sensors*, vol. 23, no. 5, p. 2385, 2023. https://doi.org/10.3390/s23052385.
[5] R. Archana and P. S. E. Jeevaraj, “Deep Learning Models for Digital Image Processing: A Review,” *Artificial Intelligence Review*, vol. 57, no. 11, 2024. https://doi.org/10.1007/s10462-023-10631-z.
[6] L. Zhai, Y. Wang, S. Cui, and Y. Zhou, “A Comprehensive Review of Deep Learning-Based Real-World Image Restoration,” *IEEE Access*, vol. 11, pp. 21049-21067, 2023. https://doi.org/10.1109/ACCESS.2023.3250616.
[7] H. Zhao et al., “Energy-Efficient High-Fidelity Image Reconstruction with Memristor Arrays for Medical Diagnosis,” *Nature Communications*, vol. 14, no. 1, 2023. https://doi.org/10.1038/s41467-023-38021-7.
[8] D. De Santis et al., “Deep Learning Image Reconstruction Algorithm: Impact on Image Quality in Coronary Computed Tomography Angiography,” *Cardiac Radiology*, vol. 128, pp. 434–444, 2023. https://doi.org/10.1007/s11547-023-01607-8.
[9] P. U. Damale, E. K. P. Chong, and L. L. Scharf, “Wiener Filter Approximations without Covariance Matrix Inversion,” *IEEE Open Journal of Signal Processing*, vol. 4, pp. 366-374, 2023. https://doi.org/10.1109/OJSP.2023.3292714.
[10] J. D Dorathi Jayaseeli et al., " An Intelligent Framework for Skin Cancer Detection and Classification using Fusion of Squeeze-Excitation-Densenet with Metaheuristic-Driven Ensemble Deep Learning Models", *Scientific Reports*, vol. 15, no.1, 2025. https://doi.org/10.1038/s41598-025-92293-1.
[11] H. Kolivand, K. A. Akintoye, S. Asadianfam, and M. S. Rahim, “Improved Methods for Finger Vein Identification Using Composite Median-Wiener Filter and Hierarchical Centroid Features Extraction,” *Multimedia Tools and Applications*, vol. 82, no. 21, pp. 31945, 2023. https://doi.org/10.1007/s11042-023-14469-z.
[12] J. Su, B. Xu, and H. Yin, “A Survey of Deep Learning Approaches to Image Restoration,” *Neurocomputing*, vol. 487, pp. 46-65, 2022. https://doi.org/10.1016/j.neucom.2022.02.046.
[13] J. Lehtinen et al., “Noise2Noise: Learning Image Restoration without Clean Data,” 2018.
[14] Z. Wang, X. Cun, J. Bao, W. Zhou, J. Liu, and H. Li, “Uformer: A General U-Shaped Transformer for Image Restoration,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2022. https://doi.org/10.1109/CVPR52688.2022.01716.
[15] L. Alzubaidi et al., “A Survey on Deep Learning Tools Dealing with Data Scarcity: Definitions, Challenges, Solutions, Tips, and Applications,” *Journal of Big Data*, vol 10, no, 1, 2023. https://doi.org/10.1186/s40537-023-00727-2.
[16] G. Menghani, “Efficient Deep Learning: A Survey on Making Deep Learning Models Smaller, Faster, and Better,” *ACM Computing Surveys*, vol 55, no. 12, 2023. https://doi.org/10.1145/3578938.
[17] B. Li, X. Liu, P. Hu, Z. Wu, J. Lv, and X. Peng, “All-In-One Image Restoration for Unknown Corruption,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2022. https://doi.org/10.1109/CVPR52688.2022.01693.
[18] L. Chen, X. Chu, X. Zhang, and J. Sun, “Simple Baselines for Image Restoration,” *ArXiv*, 2022. https://doi.org/10.1007/978-3-031-20071-7_2.
[19] M. R Islam, M. Subramaniam, and P.C Huang, " Image-based Deep Learning for Smart Digital Twins: A Review" *Artificial Intelligence Review*, vol. 58, no. 5, 2025. https://doi.org/10.1007/s10462-024-11002-y.
[20] C. Kyle Davidson, A.G Bors, and K. K Evans, " Visual Memory Schemas for Localised Image Memorability Prediction ", *IEEE Transactions on Cognitive and Developmental Systems*, 2025. https://doi.org/10.1109/TCDS.2025.3533112.
[21] M. Younesi and Y. Mohsenzadeh, “Predicting Memorability of Face Photographs with Deep Neural Networks,” *Scientific Reports*, vol. 14, no. 1, 2024. https://doi.org/10.1038/s41598-023-49904-6.
[22] S. Manikanta et al., " Adams Optimized Image Restoration Using Multi-Level Wavelet CNN with Added Noise", *IEEE Students Conference on Engineering and Systems: Interdisciplinary Technologies for Sustainable Future*, 2024. https://doi.org/10.1109/SCES61914.2024.10652495.
[23] Y. Zhao, M. Guo, X. Chen, J. Sun, and J. Qiu, " Attention-Based CNN Fusion Model for Emotion Recognition during Walking Using Discrete Wavelet Transform on EEG and Inertial Signals", *Big Data Mining and Analytics*, vol. 7, no. 1, pp. 188-204, 2024. https://doi.org/10.26599/BDMA.2023.9020018.
[24] Q. Cheng et al., " Dual Focus Net based on SwinIR in Image Super Resolution", *ACM International Conference Proceeding Series*, pp. 440-444, 2024. https://doi.org/10.1145/3677182.3677260.
[25] S. W. Zamir, A. Arora, S. Khan, M. Hayat, F. S. Khan, and M. H. Yang, “Restormer: Efficient Transformer for High-Resolution Image Restoration", *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 5718-5729, 2022. https://doi.org/10.1109/CVPR52688.2022.00564.
[26] X. Chu, L. Chen, C. Chen, and X. Lu, “Improving Image Restoration by Revisiting Global Information Aggregation,” *Lecture Notes in Computer Science*, pp. 53-71, 2022. https://doi.org/10.1007/978-3-031-20071-7_4.
[27] Y. Cui, W. Ren, X. Cao, and A. Knoll, “Focal Network for Image Restoration,” *IEEE/CVF International Conference on Computer Vision*, 2023. https://doi.org/10.1109/ICCV51070.2023.01195.
[28] A. Dudhane, S. W. Zamir, S. Khan, F. S. Khan, and M. H. Yang, “Burst Image Restoration and Enhancement,” *ArXiv*, 2022. https://doi.org/10.1109/CVPR52688.2022.00567.
[29] C. Mou, Q. Wang, and J. Zhang, “Deep Generalized Unfolding Networks for Image Restoration,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 17378 - 17389, 2022. https://doi.org/10.1109/CVPR52688.2022.01688.

[30] Y. Li et al., "LSDIR: A Large-Scale Dataset for Image Restoration," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, pp. 1775 - 1787, 2023. https://doi.org/10.1109/CVPRW59228.2023.00178.
[31] E. Aiello et al., "Synthetic Data Pretraining for Hyperspectral Image Super-Resolution," *IEEE Access*, vol. 12, pp. 65024 - 65031, 2024. https://doi.org/10.1109/ACCESS.2024.3396990.
[32] Y. Li et al., "Efficient and Explicit Modelling of Image Hierarchies for Image Restoration", *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 18278 - 18289, 2023. https://doi.org/10.1109/cvpr52729.2023.01753.
[33] Z. Ravichandran, L. Peng, N. Hughes, J. D. Griffith, and L. Carlone, "Hierarchical Representations and Explicit Memory: Learning Effective Navigation Policies on 3D Scene Graphs using Graph Neural Networks", *Proceedings - IEEE International Conference on Robotics and Automation*, pp. 9272 - 9279, 2022. https://doi.org/10.1109/ICRA46639.2022.9812179.
[34] A. Dudhane, S. W. Zamir, S. Khan, F. S. Khan, and M. H. Yang, "Burstormer: Burst Image Restoration and Enhancement Transformer", *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 5703-5712, 2023. https://doi.org/10.1109/CVPR52729.2023.00552.
[35] A. Dudhane, S. W. Zamir, S. Khan, F. S. Khan, and M. H. Yang, "Burst Image Restoration and Enhancement," *IEEE Transaction on Pattern Analysis Machine Intelligence*, 2024. https://doi.org/10.1109/TPAMI.2024.3356188.
[36] H. Liu, M. Shao, Y. Wan, Y. Liu, and K. Shang, "SeBIR: Semantic-guided Burst Image Restoration," *Neural Networks*, vol. 181, p. 106834, 2025. https://doi.org/10.1016/j.neunet.2024.106834.
[37] S. W. Zamir et al., "Learning Enriched Features for Fast Image Restoration and Enhancement," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 2, pp. 1934-19548, 2023. https://doi.org/10.1109/TPAMI.2022.3167175.
[38] K. Zhang, Y. Li, W. Zuo, L. Zhang, L. Van Gool, and R. Timofte, "Plug-and-Play Image Restoration with Deep Denoiser Prior," *arXiv*, 2022. https://doi.org/10.48550/arXiv.2008.13751.
[39] B. Xia et al., "DiffIR: Efficient Diffusion Model for Image Restoration," *Proceedings of the IEEE International Conference on Computer Vision*, pp. 13049-13059, 2023. https://doi.org/10.1109/ICCV51070.2023.01204.
[40] J. W. Soh and N. I. Cho, "Variational Deep Image Restoration," *IEEE Transactions on Image Processing*, vol. 31, pp. 4363-4376, 2022. https://doi.org/10.1109/TIP.2022.3183835.
[41] B. Rasti, Y. Chang, E. Dalsasso, L. Denis, and P. Ghamisi, "Image Restoration for Remote Sensing: Overview and toolbox," *IEEE Geoscience and Remote Sensing Magazine*, vol. 10, no. 2, pp. 201-230,2022. https://doi.org/10.1109/MGRS.2021.3121761.

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