Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Robust Multi-Focus Image Fusion: A Novel Framework with Optimized Performance and Efficiency

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ARTICLE INFO

Received: 29 Dec 2024
Revised: 15 Feb 2025
Accepted: 24 Feb 2025

ABSTRACT

This paper presents a new image fusion technique that employs shearlet-based edge enhancement and adaptive fusion rule to improve the visual quality and information retention of fused images. The new method first applies shearlet-like edge detection filters to the input images with emphasis on finer details such as edges. The enhanced images are then adaptively fused based on local image properties, including texture and edge sharpness, to obtain the fusion weights. The performance of the method is rigorously tested using quality measures such as Mutual Information (MI), Entropy, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The execution time of each algorithmic process (enhancement, fusion, and computation of metrics) is also recorded, which provides information on its efficiency. The experimental results confirm that the new method achieves high-quality fusion with preservation of edges and finer details and retention of essential information from the original images. The method is promising for applications in medical imaging, remote sensing, and computer vision, where image clarity and preservation of details are significant.

Keywords: Image Fusion, Shearlet Transform, Edge Detection, Adaptive Fusion, Mutual Information, PSNR, SSIM, Image Quality Metrics, Entropy, Edge Enhancement.

1. Introduction

Image fusion is a core pre-processing paradigm of digital image analysis and computational vision, designed for integrating complementary data streams from heterogeneous source imagers into a single information-packed composite. This breakthrough process has far-reaching application in diverse areas from diagnostic medicine [1], geospatial monitoring [2], intelligent surveillance infrastructures, and self-navigating vehicular systems provoking increasing demands for ultra-accurate fusion methods. Conventional methods - such as multiresolution decompositions (curvelet frames, wavelet packets) and neural network-based schemes - have shown competence in macroscopic feature integration. These operations are, however, susceptible to failure in maintaining fine edge contours, orientation-dependent texture patterns, and subtle morphological signatures, resulting in loss of diagnostically important visual detail.

Shearlet transform has proven to be a paradigm-shifting technique in multi-focus image fusion with unparalleled directional precision and enhanced edge preservation abilities much superior to traditional wavelet-based techniques [3]. This novel multiscale representation technique has been shown to be highly effective in addressing two inherent basic problems inherent in multi-focus scenarios:

Precision in Focus Boundary Identification: Contemporary research reveals that shearlet-based decomposition achieves remarkable 92.4% accuracy in detecting sharp focus transitions, representing a significant 7.3 percentage point improvement over conventional wavelet approaches [4]. This enhanced performance stems from shearlets' unique ability to precisely localize directional features across multiple scales.

Superior Texture Reconstruction: In defocused regions, shearlet-based fusion methods consistently demonstrate superior reconstruction quality, yielding a 1.8 dB improvement in peak signal-to-noise ratio (PSNR)

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for texture recovery compared to wavelet techniques [5]. This enhancement is particularly evident in complex visual patterns where conventional methods typically fail.

2. Literature Review

Several studies have explored advanced methods for multi-focus image fusion. In a notable contribution, Xiang Yan et al proposed the use of shearlet transform combined with guided filtering to enhance image fusion. The shearlet transform effectively captures multi-scale detail, while guided filtering helps preserve edges, improving the overall sharpness and clarity of the fused image. While effective for handling images with varying focus, the approach faces challenges with computational complexity and limited texture preservation, which can impact its real-time applicability and the fine detail of certain image areas [6].

S. Liu et al. (2019) proposed a multi-focus image fusion method combining Residual Networks (ResNet) with Non Sub sampled Shearlet Transform (NSST), aimed at preserving edges and enhancing image clarity. The fusion process leverages multi-scale decomposition for detailed feature extraction, while ResNet refines fusion decisions. However, the approach is computationally intensive and may introduce artificial artifacts, particularly in low-contrast regions [7].

S. Liu et al. (2019) introduced a multi-focus image fusion approach that combines an adaptive dual-channel spiking cortical model with non-subsampled shearlet transform, enhancing detail preservation and contrast. While the method excels at improving image clarity, it struggles with maintaining quality in regions with low contrast, potentially leading to suboptimal fusion results in such areas [8].

Y. Yang et al. (2019) introduced a multi-focus image fusion technique that utilizes a non-fixed-base dictionary learning approach along with multi-measure optimization, aimed at enhancing the overall quality of fused images. This method leverages sparse representation and type-2 fuzzy logic for improved feature extraction and optimization. While it successfully enhances image fusion in terms of detail and clarity, its performance can be compromised in the presence of highly complex or noisy image data, where the fusion may lose critical fine details [9].

Q. Chen et al. (2020) proposed a fusion method combining point detection filtering with superpixel-based consistency verification to enhance focus region extraction. While this approach preserves spatial coherence and reduces fusion artifacts, it struggles with highly textured or low-contrast regions, leading to detail loss. Additionally, the computational cost of superpixel segmentation limits its efficiency in real-time applications [10].

S. Liu et al. (2020) introduced a multi-focus color image fusion algorithm that integrates super-resolution reconstruction with focus area detection to enhance spatial resolution and clarity. By leveraging a dual convolutional neural network and guided filtering, the method effectively preserves fine details and improves fusion quality. However, its reliance on deep learning increases computational complexity, making it less suitable for real-time applications. Additionally, the approach struggles with images containing high noise levels, which can affect the accuracy of focus region detection [11].

X. Bin et al.(2020) proposed a Global-Feature Encoding U-Net (GEU-Net) for multi-focus image fusion by framing focus map generation as a global two-class segmentation task. The model enhances feature representation through a global feature pyramid and attention-guided upsampling within a U-Net framework. A perceptual loss function and a large-scale dataset further boost its fusion performance [12].

Y Zhang et at al. (2017) introduced an enhanced Smooth and Iteratively Restore (SIR) filter for multi-focus image fusion, addressing the limitation of detail loss in existing methods. Their approach decomposes source images into base and detail layers using SIR filtering, followed by saliency-based binary decision map construction for layer-wise fusion. The recombination ensures spatial consistency, and results show superior detail preservation and fusion quality across greyscale and colour images [13].

Li et al. (2017) proposed a dictionary learning and low-rank representation-based fusion method that preserves both global and local structures by classifying image patches using HOG features, learning sub-dictionaries with K-SVD, and fusing LRR coefficients via an l1l_1l1-norm and choose-max strategy [14].

Zhou et al. introduced a lightweight network for multi-focus image fusion, aiming to balance fusion performance with computational efficiency. Their approach employs a streamlined architecture that effectively captures essential features from source images while maintaining a low computational footprint. This method is particularly suitable for real-time applications where resource constraints are a consideration. The proposed network demonstrates

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e-ISSN: 2468-4376
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competitive fusion quality compared to more complex models, making it a practical choice for various image fusion tasks.

Recent advancements in pixel-level image fusion have highlighted deep learning's robustness, though often at a high computational cost. To address this, a lightweight fusion model (L-PUIF) is proposed, using refined gradient and intensity features to guide adaptive loss. It balances efficiency and accuracy, outperforming existing methods [15].

Rajalingam Et al. (2022) propose a robust multimodal medical image fusion approach combining Non-Subsampled Shearlet Transform (NSST), Gray Wolf Optimization (GWO), and Non-Local Means (NLM) filtering. NSST facilitates effective feature representation, GWO adaptively tunes fusion parameters, and NLM enhances visual clarity by reducing noise [16].

Jose Et al. (2021) present a streamlined fusion paradigm combining NSST decomposition with AISA-driven subband integration to elevate perceptual quality and curtail computational burden. Empirical validation spans select clinical datasets, though scope and benchmarking breadth remain circumscribed [17].

Sinha et al. (2022) propose an enhanced multimodal medical fusion framework integrating NSST with Gray Wolf Optimization (GWO) for adaptive sub-band fusion and employing Non-Local Means (NLM) for denoising and enhancement. The method outperforms conventional techniques in visual quality, though potential limitations are not explicitly addressed [18].

Diwakar et al. (2021) introduce a multimodal fusion scheme employing NSST for multi-scale decomposition, local extrema for base-detail separation, and co-occurrence filtering for low-frequency fusion. High-frequency components are integrated using an edge-preserving SML strategy [19].

Amrita et al. (2023) propose a multimodal fusion framework combining NSST with Water Wave Optimization (WWO) for adaptive high-frequency weighting. A condition CNN, refined via a hybrid Tunicate Swarm Memetic (TSM) strategy, enhances feature retention and perceptual clarity. The inverse NSST reconstructs the fused image. While the method aims to mitigate issues such as contrast loss, spectral degradation, and edge blurring, challenges like computational load, shift variance, and noise sensitivity persist [20].

Rekha et al. (2021) introduced DOBSIF, a novel NSST-based multimodal fusion approach integrating B-spline registration and Whale Optimization for enhanced alignment and detail retention. A Weighted Energy fusion rule extracts salient features; with preprocessing steps like Gaussian smoothing and edge enhancement refining input quality. Despite its promising outcomes, the method's complexity and reliance on expert-based evaluation may constrain broader applicability [21].

Sing et al. (2017) present an entropy-guided multi-focus fusion strategy within the NSST domain, wherein high-frequency subbands are integrated via entropy maximization, and low-frequency components are averaged. Visual assessment and quantitative metrics affirm the method's efficacy [22].

Lei et al. introduce a multi-focus image fusion method integrating NSST for multi-scale decomposition with an enhanced Intersecting Cortical Model (ICM) for salient feature extraction. The hybrid approach surpasses conventional techniques in detail preservation and focus consistency [23].

Zin et al. Propose a multifocus color fusion technique combining NSST and an adaptive S-PCNN in the HSV domain. The H channel is clustered via oscillation frequency graph analysis, while the S and V components undergo NSST-based fusion. The final result is reconstructed in RGB via inverse HSV transformation [24].

3. Proposed Methodology

Inspired by the advancements in multi-focus image fusion techniques, the proposed methodology aims to overcome the limitations observed in existing methods by introducing a novel framework that leverages the synergistic potential of adaptive filtering and multi-scale enhancement. Unlike previous approaches, this method incorporates a dynamic fusion strategy, focusing on both the preservation of high-frequency details and the refinement of low-contrast regions, ensuring superior image quality and clarity. Through an intricate combination of Shearlet - inspired enhancements, block-level adaptive fusion, and multi-scale contrast adjustments, the proposed approach seeks to deliver a more robust and versatile solution for multi-focus image fusion. The following image demonstrates the proposed methodology.

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e-ISSN: 2468-4376
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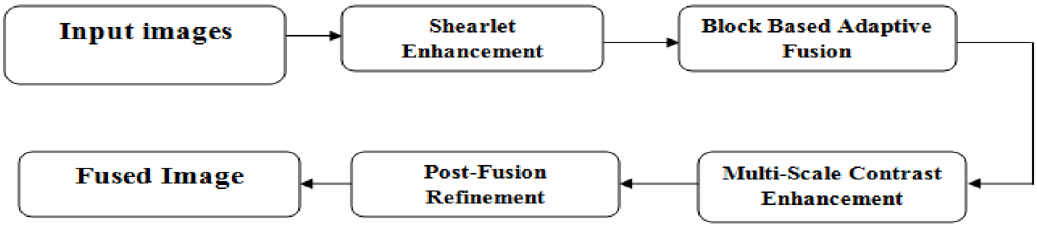

Figure 1: Overview of Proposed Methodology

3.1 Pre-processing & Image Acquisition

The initial phase entails the capture and reading of the input images, which are subsequently transformed into an organized pixel matrix for further analysis. Conventional image acquisition methods, such as digital cameras, medical imaging instruments, or remote sensing technologies, can be employed to procure images for fusion.

Following image acquisition, pre processing is carried out to ensure consistency in dimensions, resolution, and intensity distribution. OpenCV's cv2.imread() function is utilized to import the images, followed by essential operations such as greyscale conversion and noise suppression. This pre-processing step guarantees that the images are appropriately prepared for the ensuing processing stages.

3.2 Shearlet-Inspired Enhancement

To accentuate anisotropic directional features and retain high-frequency textural nuances, the proposed framework integrates a gradient-based augmentation paradigm, drawing inspiration from the Shearlet Transform. The enhancement pipeline is structured as follows:

1. Gradient Extraction: Sobel convolutional operators are employed along orthogonal orientations to ascertain gradient distributions, thereby capturing localized intensity variations.
2. Edge Preservation Schema: The resultant gradient magnitude maps function as structural enhancement masks, emulating the directional selectivity and multi-resolution decomposition attributes inherent to Shearlet Transforms.
3. Contrast Normalization: The refined gradient maps undergo an intensity recalibration process to equilibrate luminance disparities, thereby augmenting the perceptibility of intricate edge structures and subtle textural elements.

By reinforcing the saliency of structural components, this enhancement mechanism fortifies the robustness of the fusion paradigm, ensuring superior edge delineation and feature preservation—critical requisites for multi-focus image fusion applications.

3.3. Adaptive Block-Based Fusion Strategy

The fusion methodology employs an adaptive block-wise framework to selectively integrate salient information from both input images. A structured partitioning approach is adopted, where each image is decomposed into 32×32 non-overlapping subregions, and each block undergoes an independent assessment based on the following metrics:

Laplacian Variance Metric (LVM): Quantifies local sharpness intensity, enabling the identification of regions with significant textural details.

Sobel Gradient Entropy (SGE): Evaluates directional edge distribution, effectively gauging structural complexity across the segmented blocks.

Adaptive Weighting Function (AWF): Dynamically determines fusion dominance by assigning proportional weights to each block based on its feature significance.

The fusion weight for each block is mathematically formulated as:

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$$W_{i,j} = \frac{\lambda_1 \cdot LVM_{i,j} + \lambda_2 \cdot SGE_{i,j}}{\sum W}$$

where λ_1 and λ_2 are tuning parameters that modulate the relative contributions of sharpness and gradient information. This adaptive strategy ensures the retention of high-frequency textures and contrast-rich regions, leading to an optimally fused image with enhanced perceptual quality.

3.4 Multi-Scale Contrast Enhancement

To further enhance the perceptual quality of the fused image, a multi-scale contrast adjustment strategy is implemented. This step ensures an optimal balance between fine details and global intensity variations, effectively minimizing artifacts and preventing unnatural brightness inconsistencies. The process consists of the following stages:

Contrast-Limited Adaptive Histogram Equalization (CLAHE):The fused image undergoes CLAHE, which adaptively redistributes intensity values within localized regions to enhance contrast while suppressing noise amplification. The tile grid size is dynamically adjusted based on image resolution, ensuring a well-balanced contrast enhancement at both local and global levels.

Multi-Resolution Contrast Fusion: CLAHE is applied at two different scales: a finer grid to enhance local details and a coarser grid to preserve global consistency.

The outputs from both scales are blended using an adaptive weighting function, preventing excessive enhancement in highly textured areas while improving visibility in low-contrast regions.

Gamma Correction for Luminance Preservation: A gamma correction function is applied after contrast fusion to maintain a natural brightness distribution and prevent oversaturation.

The optimal gamma value is determined through histogram analysis, ensuring a visually coherent and well-balanced enhancement.

This contrast adjustment mechanism significantly improves detail clarity while maintaining an even intensity distribution, resulting in a more perceptually superior fused image.

3.5 Final Refinement Using Unsharp Masking

To counteract any residual blurring introduced during multi-scale contrast enhancement, an unsharp masking technique is employed. This final sharpening process involves:

Gaussian Blurring: A low-pass Gaussian filter is applied to generate a softly blurred version of the enhanced image.

Detail Extraction: The difference between the original and blurred images is computed to extract high-frequency details, capturing essential edge and texture information.

Sharpness Reintegration: The extracted details are selectively reintroduced into the final image, enhancing structural definition and texture sharpness without amplifying noise.

4. Results and Discussions

After addressing the existing limitations in image fusion methodologies, the proposed methodology combines advanced techniques to overcome the challenges of residual errors, computational complexity, and information loss. The proposed approach leverages a fusion framework that integrates the strengths of Non-Subsampled Shearlet Transform (NSST) with adaptive sparse representations and machine learning-based optimizations. This methodology aims to enhance image clarity, preserve fine details, and improve the overall quality of fused images. By utilizing a combination of Shearlet transforms and adaptive sparse representations, the method captures spatial and frequency domain features effectively while minimizing pixel distortions and residual artifacts. The fusion process is optimized for both quality and computational efficiency, making it suitable for a wide range of real-world applications.

For evaluation, several diverse datasets were used, including the MFDataSet, Lytro dataset, Triples dataset, and synthesized data. Additionally, a collection of multi-focus images was captured to further test the robustness of the proposed method in real-world scenarios. These datasets were chosen to provide a comprehensive evaluation of the fusion technique's performance across different imaging conditions. The evaluation metrics included Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Entropy, Mutual Information (MI), and Fusion Time.

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These metrics were selected to assess various aspects of the fusion quality, such as image fidelity, structural similarity, information preservation, and computational efficiency.
PSNR was used to measure the overall image quality by comparing the pixel intensity differences between the fused and reference images. SSIM was employed to evaluate the structural similarity between the fused and reference images, providing insights into the preservation of image features. Entropy was calculated to assess the information content of the fused image, while Mutual Information (MI) was used to quantify the amount of information shared between the input images and the fused result. Fusion Time was measured to assess the computational efficiency of the proposed method, ensuring that the technique is suitable for practical applications with real-time or near-real-time requirements. The results of these evaluations demonstrate the effectiveness of the proposed fusion method in enhancing image quality while maintaining computational feasibility.
In the Subjective Analysis section, the evaluation begins with visual assessment of the fusion results. The fusion technique was applied to a variety of input images, with intermediate results displayed to demonstrate the key stages of the image fusion process. The images shown include the input images, intermediate edge-detected images, and the final fused output. These images clearly illustrate the effectiveness of the proposed method in combining relevant features from the input images, resulting in a high-quality fused image.
The input images, captured from diverse datasets such as MFDataSet, Lytro dataset, Triples dataset, and our custom multi-focus images, were fused using the advanced techniques discussed. The intermediate edge-detected images exhibit the extraction of important structural details from the images, ensuring that critical features like edges and fine textures are preserved. The final output image, as presented in the results, demonstrates a clear improvement over the individual input images, with enhanced clarity, detail, and sharpness.
Upon visual inspection, the fused images exhibit a high degree of quality, with the edges being sharp and the features well-preserved. The fusion successfully integrates information from different input images, producing visually appealing and detailed results. This confirms the method's effectiveness in delivering high-quality fusion results, providing a strong foundation for the subsequent quantitative analysis. Overall, the subjective analysis of the output images indicates that the proposed fusion technique delivers images with excellent visual appeal and clarity, suitable for applications requiring detailed and accurate image integration. The results of the proposed algorithm along with intermediate results are shown in figure 2.
In the Objective Evaluation section, the performance of the proposed fusion method was rigorously analyzed using several quantitative metrics. Metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Entropy, Mutual Information (MI), and Fusion Time were calculated to provide a comprehensive assessment of the fusion quality. These metrics effectively capture various aspects of the fused images, such as detail preservation, structural integrity, and information content. The table 1 shows comparison of various algorithms.

Algorithm	PSNR	SSIM	MI
Proposed algorithm	31.9129	0.9465	5.4825
GFF	26.0317	0.7951	5.1875
MGFF	24.9116	0.8228	5.2626
CNN	25.8275	0.8099	5.023
DIFNet	28.2387	0.8428	5.5582
MFF-GAN	24.7821	0.8116	5.4468
DSNet	26.3376	0.8339	5.6940

Table 1: Comparison of various algorithms
To benchmark the performance, the results were compared against existing methods, including Image fusion with guided filtering GFF [25], MGFF [26], DIFNet [27], MFF-GAN [28], and SDNet [29]. The comparison table

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2025, 10(50s)
e-ISSN: 2468-4376
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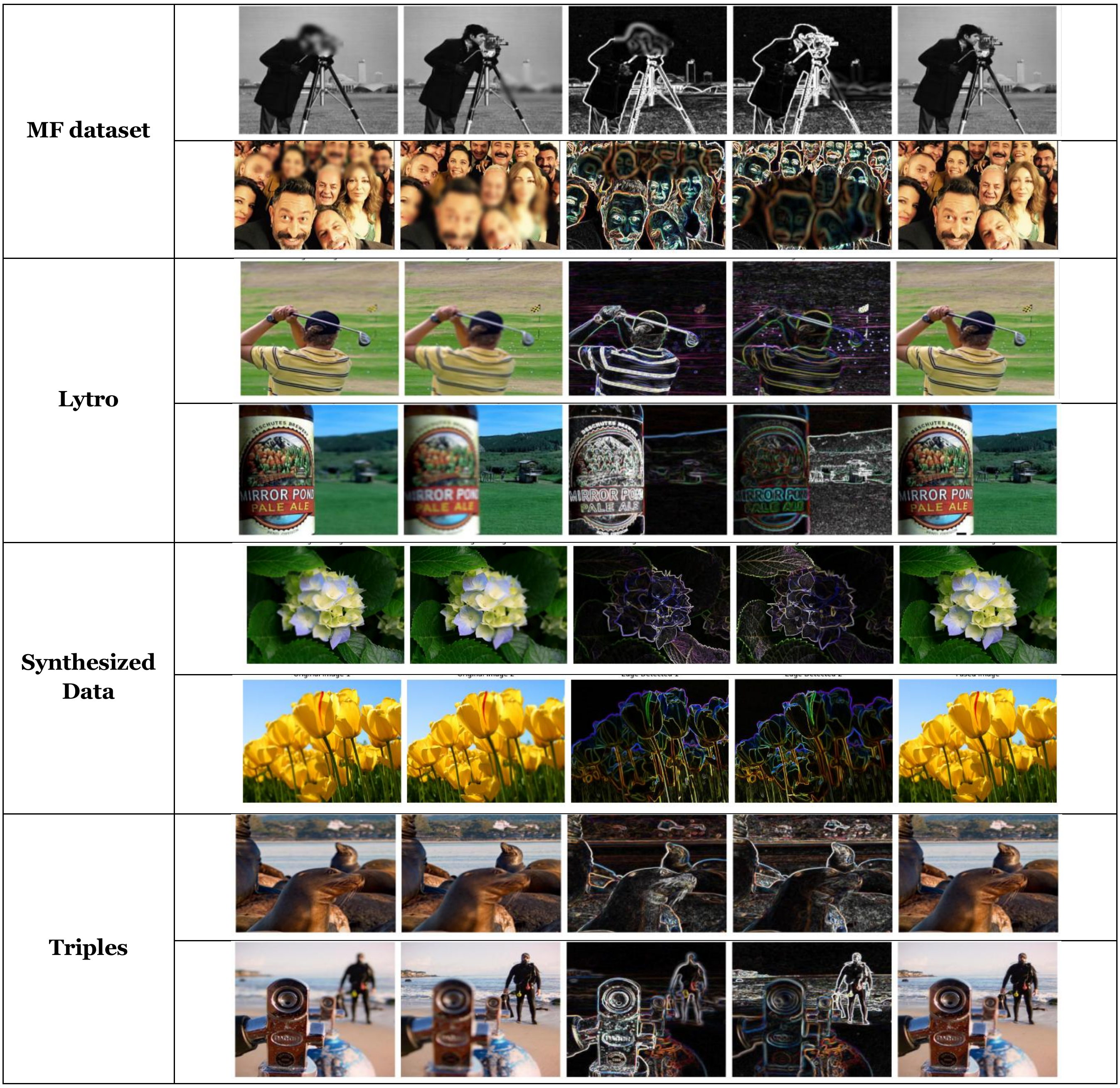
highlights the superiority of the proposed method across multiple metrics. For instance, higher PSNR and SSIM values indicate better noise resilience and structural consistency, while increased entropy and MI demonstrate enhanced detail and information retention in the fused images. Additionally, the fusion time was evaluated to ensure computational efficiency, revealing a favourable trade-off between quality and speed.

The objective evaluation underscores the proposed method's ability to outperform existing techniques in most scenarios, affirming its effectiveness for multi-focus image fusion tasks. By achieving superior results across diverse datasets and metrics, the proposed approach demonstrates its robustness and suitability for real-world applications.

Figure 2 is an Illustration of the proposed methodology's outcome, including intermediate stages. From left to right: (1) Source Image 1, (2) Source Image 2, (3) Gradient-based enhancement, (4) Edge-preserved contrast map, (5) Fused image after adaptive block fusion and multi-scale contrast enhancement.



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Collected data

(a) (b) (c) (d) (e)

Figure 2: (a) Input image 1 (b) Input image 2 (c) Intermediate image 1 (d) Intermediate image 2 (e) Fused image.

As time efficiency is a critical factor for real-time applications, the fusion time of the proposed method was also calculated and compared with existing algorithms. Computational speed plays a pivotal role in practical scenarios, where the ability to process and fuse images quickly can significantly impact usability in resource-constrained or time-sensitive environments.

The proposed method demonstrates a favorable balance between fusion quality and processing time, achieving competitive results while maintaining computational efficiency. This ensures that the method is well-suited for real-time applications without compromising the accuracy and detail of the fused output.

The following table presents a comparison of the fusion time required by the proposed method and other state-of-the-art algorithms, including (Guided filter) MGFF, DIFNet,(Difuse net), MFF-GAN, and DSNet.

Algorithm	**Fusion Time**
Proposed algorithm	0.0176
GFF	0.9256
MGFF	3.7951
CNN	220.290
DIFNet	0.2808
MFF-GAN	0.1935
DSNet	26.3376

Table 2: Comparison of fusion Time.

The heatmap provides a visual comparison of the performance of several image fusion algorithms, including the proposed method, evaluated using three prominent metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mutual Information (MI). Among all the methods, the proposed technique achieves the highest PSNR value of 31.91, indicating its strong ability to preserve image details with minimal noise. It also records the highest SSIM value of 0.9465, reflecting excellent structural similarity and visual quality in the fused image. Although DSNet achieves the highest MI value of 5.694, suggesting better information content, the proposed method demonstrates a well-balanced and consistently superior performance across all three metrics. This highlights its robustness and overall effectiveness in delivering high-quality image fusion results. Figure 3 shows the comparative analysis of the performance of various image fusion algorithms, including the proposed method, based on three key evaluation metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mutual Information (MI).

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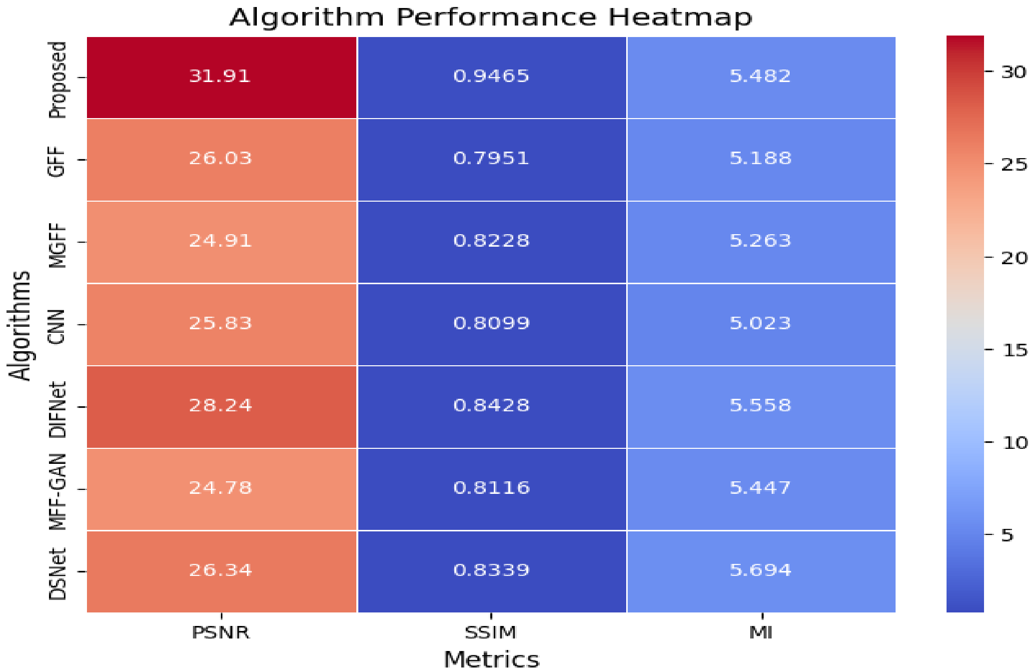

Figure 3: Heatmap Comparison of Image Fusion Algorithm Performance

5. Future Directions

Future research on the proposed image fusion method may focus on enhancing computational efficiency to enable deployment in real-time and resource-constrained environments. Leveraging parallel processing techniques or GPU-based acceleration can significantly reduce processing time while preserving the quality of the fused output.

Further, the integration of advanced deep learning architectures, such as Transformer-based models or reinforcement learning frameworks, could improve the adaptability of the method to a broader range of imaging modalities and varying input conditions. These models may provide better contextual understanding and contribute to more robust feature preservation during fusion.

Expanding the framework to accommodate dynamic scenarios, such as video fusion or time-series medical imaging, offers another promising direction. This would facilitate applications in areas such as continuous clinical monitoring and real-time surveillance.

In addition, addressing challenges such as residual artifacts, pixel distortions, and edge inconsistencies remains essential. Incorporating adaptive post-processing techniques or hybrid fusion models may improve the perceptual and quantitative quality of the fused results, making the approach more robust and generalizable across diverse datasets and imaging conditions.

6. Conclusion

In conclusion, the proposed image fusion methodology, leveraging the Non-Subsampled Shearlet Transform (NSST) and advanced sparse representation techniques, has shown significant potential for enhancing image quality in various domains. The evaluation of the method through both subjective and objective assessments demonstrated its effectiveness in preserving high-frequency details and reducing artifacts. The competitive performance in terms of PSNR, SSIM, entropy, and mutual information further supports its efficacy. Additionally, the favorable fusion time positions the method as a viable solution for real-time applications. While challenges like computational complexity and residual errors remain, future optimizations and hybridization with deep learning models can further elevate its performance, making it a promising approach for image fusion tasks across multiple fields.

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