Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 10, 2025

INNOVATIVE APPROACHES IN APPLIED MATHEMATICS FOR ENHANCED IMAGE DENOISING AND NOISE REDUCTION

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DOI: https://doi.org/10.5281/zenodo.17474444

Keywords
Image denoising, Noise reduction, Optimization techniques, Machine learning, Deep learning, Convolutional neural networks (CNNs).

Article History
Submitted on 12 April 2025
Received on 20 September 2025
Re-Revised on 02 October
Accepted on 18 October
Published on 27 October

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Abstract
Image denoising and noise reduction are pivotal processes in various domains, including medical imaging, remote sensing, and digital photography. Recent advances in applied mathematics have notably enhanced the capabilities in this field. This review paper delves into contemporary developments and methodologies for image denoising and noise reduction, rooted in applied mathematics. It provides an extensive survey of both traditional and cutting-edge approaches, emphasizing their theoretical underpinnings, computational strategies, and practical applications. Special focus is given to innovative algorithms and mathematical models that exploit advanced concepts such as optimization, statistical inference, deep learning, and sparse representations. Furthermore, the paper addresses existing challenges, future directions, and emerging trends, offering researchers and practitioners a thorough understanding and insights into the progressive techniques shaping the future of image denoising and noise reduction.

INTRODUCTION

Image denoising is a fundamental task in digital image processing, crucial for removing noise originating from various sources such as sensor imperfections, environmental factors, or transmission errors[1]. This process enhances image quality and facilitates accurate analysis across a multitude of applications. The development of sophisticated algorithms and methodologies, deeply rooted in applied mathematics, has significantly propelled the field forward, enabling the creation of effective solutions to these challenges[2]. Leveraging machine learning techniques, particularly convolutional neural networks (CNNs), and utilizing metrics like peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) for performance evaluation, researchers have achieved superior denoising outcomes[3]. These modern techniques surpass traditional methods in preserving fine details and managing various noise types and levels with enhanced efficiency.

Common sources of noise in digital images include disturbances during image acquisition and transmission, leading to issues such as lens imperfections, uneven lighting, low contrast, and contamination from dirt[3, 4]. Noise can also arise from physical factors like optical interference or improper processing, resulting in artifacts such as salt-and-pepper noise. Additionally, noise during image sensor capture is influenced by the probability density functions associated with the image acquisition process and sensor properties[5]. Types of noise, such as impulsive noise and Gaussian noise, can degrade image quality, necessitating the use of noise removal techniques like weighted mean filters, fuzzy logic methods, and genetic algorithms to enhance image processing and preserve critical image features. Understanding these noise sources is essential for developing effective noise removal algorithms, thus improving image quality in fields such as robotics, biometrics, and medical imaging[6].

Sensor heat is a significant contributor to digital image noise, causing fluctuations in pixel values due to thermally generated currents, which increase noise levels in captured images. Heat in sensors, such as charge-coupled device (CCD) image sensors, generates noise that is subsequently processed by digital signal processing (DSP) systems, impacting processing time and memory usage[7]. Experimental studies reveal that camera noise characteristics are highly temperature-dependent, varying across different camera models and exhibiting unexpected traits. This underscores the importance of understanding and mitigating the effects of temperature on image noise to enhance image quality. Techniques such as cooling with Peltier devices and correcting for dark current have been explored to reduce sensor noise levels caused by thermal variations, demonstrating their effectiveness in noise reduction[8].

1. Literature Review

Liu, Yilin, et al. (2018) introduced the concept of non-convex total variation minimization, a prominent technique for analyzing the gradient field of cross-sectional images[9]. Their work focused on reconstructing MRI brain images using Fourier measurements, addressing the non-convex nature of the problem with the minimax-concave TV (MCTV) method. The MCTV method effectively captures the non-convexity parameter while maintaining convexity during each iteration step, ensuring efficient image reconstruction [10]. This approach holds significant promise for advancements in MRI image reconstruction within the field of neurology. Additionally, the authors proposed the Iterative Mean (IM) Filter for removing salt-and-pepper noise from medical images, particularly MRI images.

Thanh et al. (2019) proposed the IM Filter, which averages the gray values of noise-free pixels within a fixed-size window [11]. This method is notably more effective in preserving edges, image structure, and details compared to other denoising techniques. The authors addressed three types of noise: Gaussian noise, Rician noise, and Rayleigh noise, which commonly affect MRI images. Their research underscores the critical importance of noise management in medical image processing [12].

Rekha, Ch., Kranthi, K., et al. (2015) proposed an advanced method for speckle noise reduction in ultrasound image processing. They emphasized the importance of efficient preprocessing, accurate segmentation, and automatic registration to enable proper classification and diagnosis. Neural networks were highlighted for their significant potential in these steps, enhancing data classification and diagnostic precision [12]. Kohonen's Self-Organizing Maps (SOM) were noted for their effectiveness in image registration and dimensionality reduction, while Cohen-Grossberg neural networks were deemed ideal for noise removal using the Arnold transform in RGB space. Neural networks excel in nonlinear processing, learning input-output systems, and pattern recognition, making them valuable for noise recognition and diagnostic judgment. The proposed approach leverages the capabilities of neural networks in pattern recognition and signal processing, thereby improving the quality and diagnostic accuracy of ultrasound images.

Sudha, Suresh, G. R., et al. (2009) emphasized the importance of speckle reduction methods in enhancing the interpretation of diseased tissue in medical imaging, improving segmentation and registration processes, and increasing the Peak Signal-to-Noise Ratio (PSNR) of images. Various approaches, including Fourier and wavelet transform methods, have been explored, although they lack data adaptiveness[13]. Independent Component Analysis (ICA) has been utilized for Gaussian noise reduction, and Principal Component Analysis (PCA) has been applied for speckle noise removal in ultrasound images. Additionally, Fourth-order Partial Differential Equations (PDEs) have been used alongside speckle reduction filters such as SRAD, Kaun, and LEE filters. While diffusion filters based on partial differential equations are effective for Gaussian noise reduction, they often struggle with adequate speckle removal. Techniques like pixel compounding, which synthesize image sequences, show promise in reducing speckle and enhancing image details in ultrasound imaging. Collectively, these methods aim to address the challenges posed by speckle noise in medical imaging, thereby improving diagnostic accuracy and image quality[14].

2. Classical Approaches

Classical image denoising techniques such as median filtering, Gaussian smoothing, and Wiener filtering have been fundamental in the field. These methods rely on statistical noise models and image priors to minimize mean square error for image restoration. Despite their foundational role, traditional methods often struggle with intricate noise patterns and risk oversmoothing image features, limiting their effectiveness in certain scenarios. The evolution toward deep learning-based approaches, including the U-Net architecture, has demonstrated remarkable performance in handling various image types and complex noise patterns. These approaches leverage geometry-adaptive harmonic bases to offer adaptability and superior results, showcasing significant improvements over classical methods[15].

Median filtering is a common technique in image processing for denoising, particularly effective against salt-and-pepper noise. However, it faces limitations when dealing with outliers and significant variations in noisy data, which can impact the selection of the median value and result in suboptimal denoising outcomes. While effective in reducing certain types of noise, such as salt-and-pepper, median filters may struggle with other types like Poisson, white Gaussian, and speckle noise commonly found in medical images[16]. This limitation poses challenges in preserving fine details and image features during the denoising process. Nonetheless, the median loss function associated with median filtering enhances robustness and computational efficiency in optimizing machine learning models for various applications.

In scenarios where images are corrupted by salt-and-pepper noise, median filtering replaces noisy pixels with the median intensity value of neighboring pixels, effectively reducing noise while preserving edge information. Despite traditional median filters struggling with high-density salt-and-pepper noise, innovative approaches like Recursive Weighted Myriad Filtering (RWMyF) have been proposed to enhance the performance of deep learning convolutional neural networks (CNNs) in image classification tasks affected by such noise interference[17]. The effectiveness of median filtering in noise reduction has been compared with other standard filters, highlighting its importance in improving image quality by eliminating salt-and-pepper noise.

Median filtering is widely used in various applications, such as medical imaging and document scanning, for noise reduction. It replaces pixel values with the median of neighboring pixels, enhancing image clarity and facilitating feature extraction, segmentation, and object classification processes[18]. Leveraging innovative algorithms and parallel processing techniques, median filtering not only enhances image quality but also contributes to real-time processing capabilities, making it a fundamental tool in digital image processing applications.

Traditional median filters can be computationally slow, especially with larger kernel sizes. However, novel approaches, such as the wavelet matrix data structure, enable constant complexity filtering for faster processing, even with high pixel depth images[19]. In digital color images, peer group filters are found to be more robust to noise compared to vector median filters, as they consider a set of pixels rather than just one, enhancing noise reduction and structural similarity without the need for thresholding[20]. Additionally, efficient methods for reducing impulse noise in color images involve slicing rows of the image, identifying anomalies, and applying corrective median filtering, leading to effective noise reduction with reduced computational overhead.

Median filtering offers several key benefits in fields such as image processing, signal processing, and medical imaging. It is a powerful noise reduction technique that effectively removes impulsive noise like salt-and-pepper noise while preserving image content[20]. The filter is known for its simplicity and ability to maintain image integrity by taking the median of neighboring pixels. This makes it ideal for tasks such as image restoration, facial beautification, and artifact removal in ECG signals. Additionally, median filtering aids in reducing noise from medical images, enhancing segmentation processes for accurate diagnosis, particularly in detecting early stages of diseases like Alzheimer's. Its applications extend to real-time operations without significant time delays, showcasing its computational simplicity and effectiveness in various domains[21].

Advancements in median filtering techniques include modified median filters with improved root mean square error (RMSE) values and parallelism implementation to reduce latency, ensuring faster processing and better noise reduction results[22]. Novel approaches like the wavelet matrix data structure have enabled constant complexity median filtering, particularly beneficial for high dynamic range images, outperforming traditional methods in terms of speed and accuracy. These advancements underscore the continued relevance and evolution of median filtering as a crucial technique in noise reduction for digital images and signals[23].

3. Advanced Mathematical Models

3.1. Hybrid Denoising Model Combining Modified ID and PM Models

The hybrid image denoising model presented by N. Wang et al. (2018) offers an innovative solution by combining the modified isotropic diffusion (ID) model and the modified Perona-Malik (PM) model. This approach effectively addresses the shortcomings of each individual model while enhancing their strengths. The core innovation lies in the use of a control function based on patch similarity modulus, which directs the diffusion process along the tangential direction of image edges. This strategic guidance allows for the efficient preservation of edges, textures, thin lines, weak edges, and fine details, while simultaneously reducing noise and minimizing aliasing effects. The modified ID model's second-order directional derivative focuses on smoothing flat regions without compromising edge information. Simultaneously, the modified PM model utilizes the patch similarity modulus as a structure indicator, aiding in the differentiation between significant image features and noise. This hybridization of methodologies results in a model that significantly outperforms conventional partial differential equation (PDE) models in both edge preservation and noise reduction. The model's efficacy is demonstrated through extensive computer experiments on synthetic and natural images, where it consistently shows superior performance in maintaining image details and reducing noise. The adaptiveness of the control function ensures that the model applies the most suitable diffusion process for different parts of the image, thereby enhancing overall image quality. The DLHPDE (Directional Laplacian Hybrid Partial Differential Equation) algorithm, as depicted in the flow chart from the paper, exemplifies the integration of the patch similarity modulus and the second-order directional derivative. This integration is crucial for achieving effective image denoising, showcasing the model's ability to preserve fine details and reduce unwanted noise comprehensively[24].

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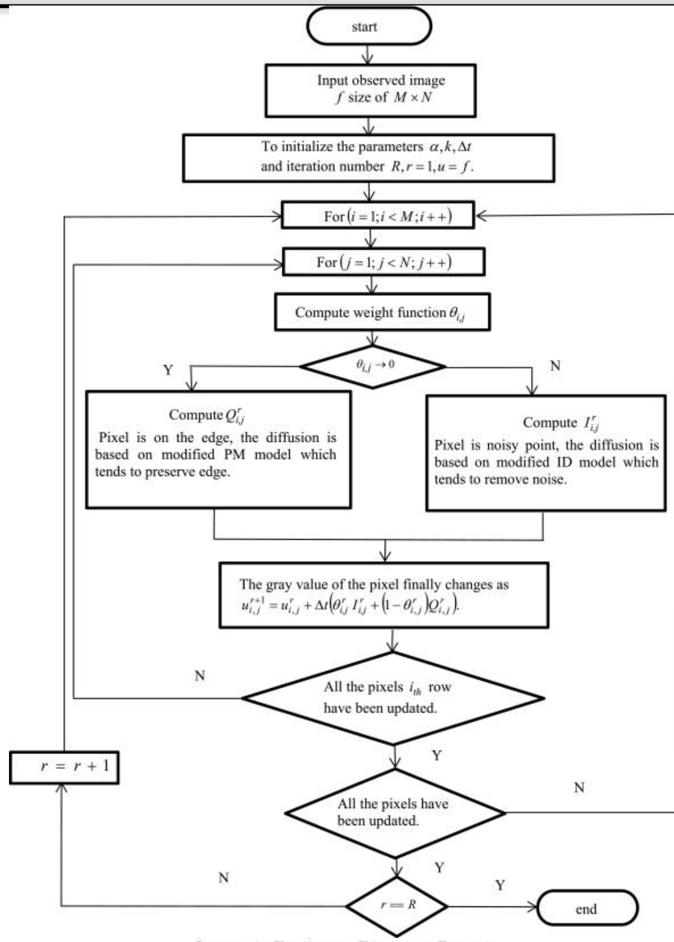

Fig:1 Flow Chart of Proposed DLHPDE Algorithm[24]

4.2. A Novel Fixed Pattern Noise Reduction Algorithm in CMOS Detector for LEO Satellite Application

M. Fiuzy et al. (2016) presents a novel fixed pattern noise (FPN) reduction algorithm for CMOS detectors used in LEO satellite applications, which I find highly innovative and practical. The algorithm addresses the critical issue of FPN, a major source of image quality degradation in star tracker cameras essential for precise satellite attitude determination. By averaging the variations in pixel output values and adapting them to an ideal image, the proposed method effectively reduces noise while maintaining high processing speeds. The implementation on an ARM processor showcases its efficiency, achieving FPN removal in under 5 milliseconds, and outperforming conventional filters like Wiener, median, and averaging filters. The results demonstrate the algorithm's potential to significantly enhance the accuracy of star tracker images, which is crucial for satellite operations[25].

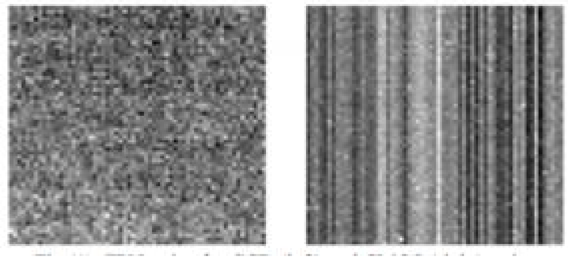

Fig: 2 FPN Noise for CCD (lift) and CMOS (right) noise[25]

4.3. Rician Noise Removal Model Based on Energy Function Minimization

Bo Chen et al. (2018) introduces a novel algorithm to address the persistent issue of Rician noise in Magnetic Resonance Imaging (MRI). This noise, inherent to the MRI process, degrades image quality, blurs organizational boundaries, and complicates medical diagnosis. The authors propose an advanced model based on energy function minimization, which enhances the Total Variation (TV) term from classical models to better preserve image edges while avoiding the creation of false edges. The model's effectiveness is confirmed through theoretical validation and practical implementation, showing superior performance in retaining structural details and improving the Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) compared to traditional models. The experimental results validate the model's capability to maintain edge details and significantly reduce noise, demonstrating its potential to improve MRI image analysis[26].

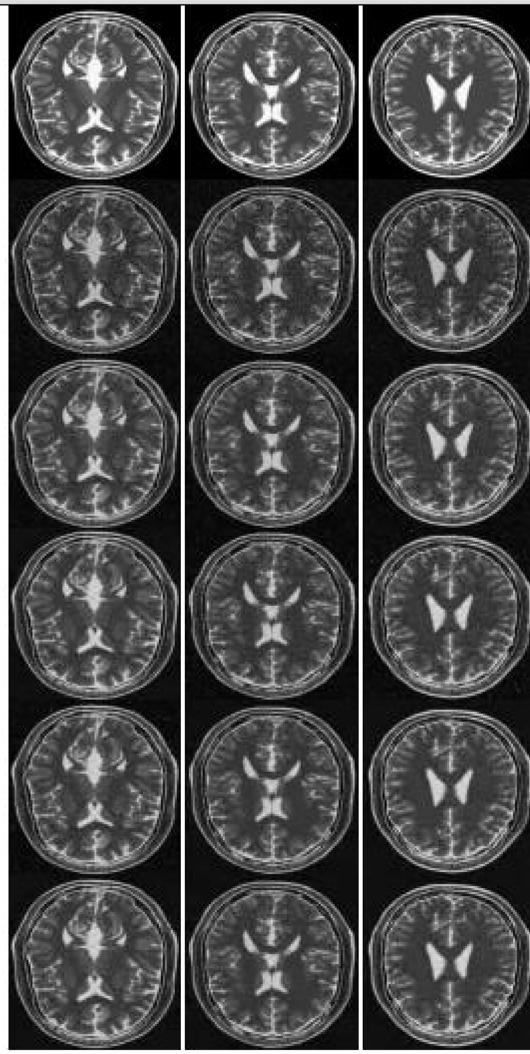

Fig: 3 Experimental Results for different slices of MRI image [26]

4.4. Application of Convolutional Neural Networks for Parallel Multi-Scale Feature Extraction in Noise Image Denoising

Yiming Li et al. (2024) propose a new image denoising model that utilizes Convolutional Neural Networks (CNNs) for parallel multi-scale feature extraction to address the challenges posed by noisy images. This innovative model combines channel attention mechanisms and adaptive dense connected residual blocks to enhance denoising performance. The proposed network structure, termed PMSF-CNN, integrates these components to process feature information at different scales simultaneously, improving the capture of image details and texture information. The model achieves high denoising accuracy and efficiency, reaching a stable state after just 121 and 86 iterations on the training and test sets, respectively. Notably, it achieves a denoising accuracy of up to 0.96 and processes images in as little as 0.09 seconds. This approach significantly outperforms traditional methods and other advanced models, making it highly suitable for applications requiring real-time image processing[27].

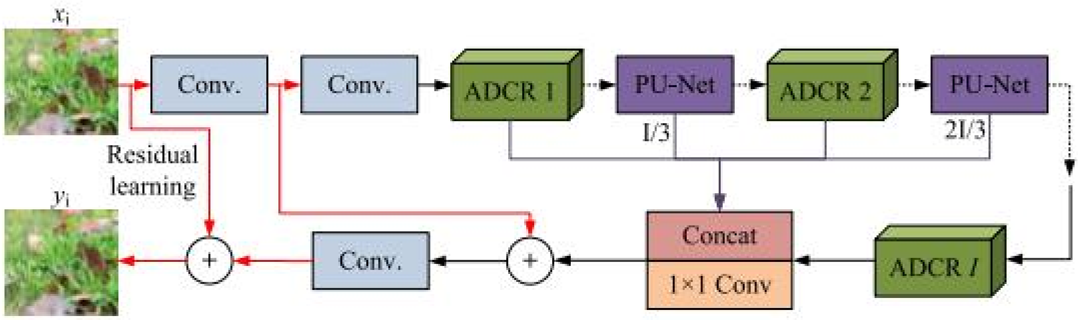

Fig: 4 Structure of the PMSF-CNN [27]

4.5. Deep Generalized Learning Model for PET Image Reconstruction

Qiyang Zhang et al. (2024) introduces an innovative approach to PET image reconstruction using a deep generalized learning model. This model integrates deep learning (DL) with the alternating direction method of multipliers (ADMM)-based iterative optimization to address the challenges of low-count PET imaging, which is known for its ill-posed nature. By deeply incorporating neural networks to handle fidelity operators and generalizing the regularization term, this method improves the quality of PET images and recovers fine structures that are often degraded in other DL-based models. The proposed framework demonstrates superior performance in both qualitative and quantitative assessments on simulated and real datasets, outperforming traditional and existing DL methods. This hybrid approach effectively balances noise suppression and detail preservation, providing high-quality PET images essential for accurate diagnosis and clinical applications[28].

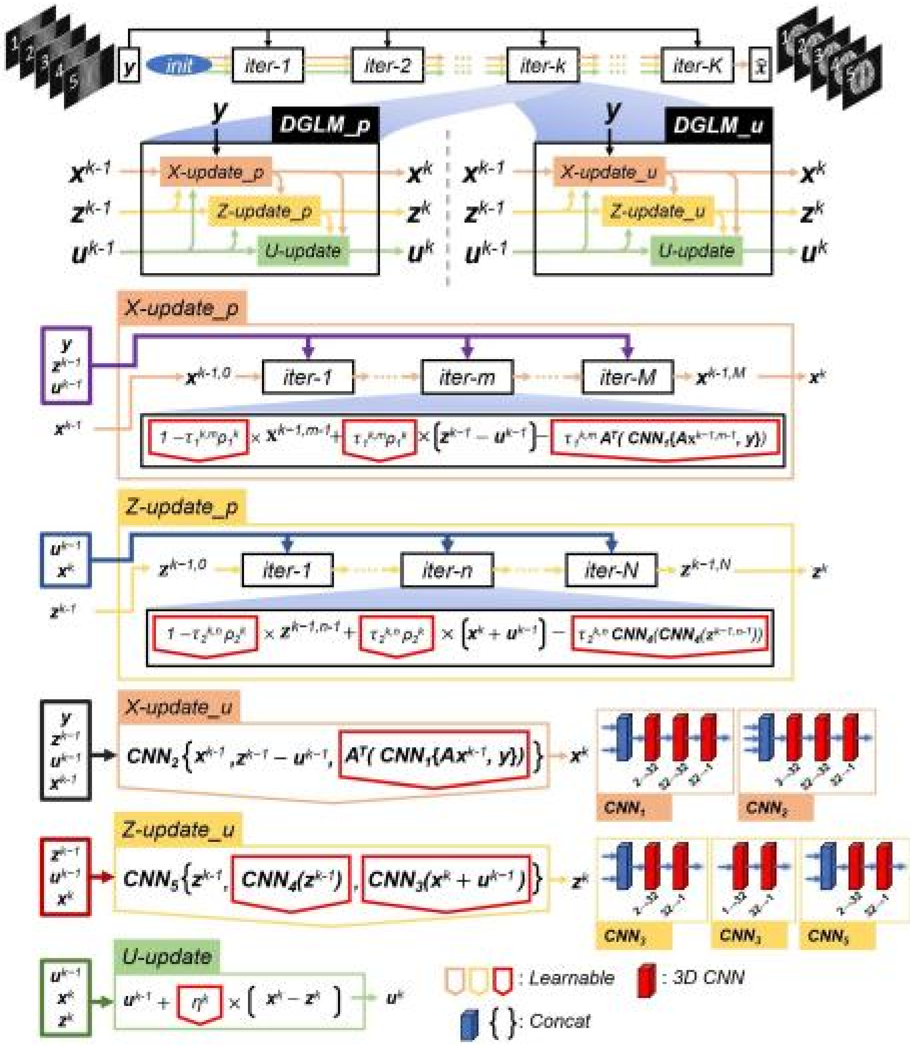

Fig: 5 Architectures of the DGLM _p and DGLM_u network [28]

4.6. Denoising Methods for Retinal Fundus Images

Ahmad Fadzil M. Hani et al. (2014) presents an in-depth study on various denoising techniques to enhance the signal-to-noise ratio (SNR) of retinal fundus images, which are crucial for the accurate analysis of retinal vasculature. The research identifies the Time Domain Constraint Estimator (TDCE) as the most effective method in improving the peak SNR (PSNR) of these images. The TDCE method is compared with other denoising techniques like Least Square Estimator (LSE), Wiener filter, Minimum Variance Estimator (MVE), and Stationary Wavelet Transform (SWT), demonstrating superior performance in preserving image details and maintaining contrast. The study uses the FINDeRS database consisting of 175 images across various stages of diabetic retinopathy to validate the effectiveness of these techniques. The results show that TDCE significantly enhances the PSNR, providing better noise reduction while preserving essential image features necessary for diagnosing retinal diseases[29].

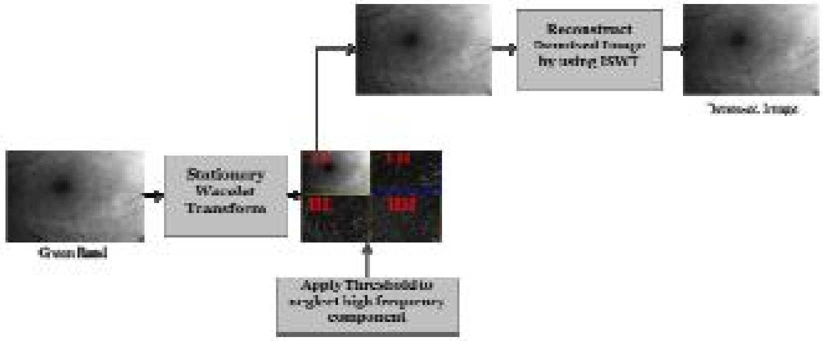

Fig: 6 Noise reduction in retinal fundus images[29]

4.7. Double-Factor-Regularized Low-Rank Tensor Factorization Model for Hyperspectral Image Noise Removal

Yu-Bang Zheng et al. (2020) presents an advanced model for mixed noise removal in hyperspectral images (HSI) using a double-factor-regularized low-rank tensor factorization (LRTF-DFR) approach. This model effectively addresses the limitations of previous methods that often neglect the common characteristics among different spectral bands and the spectral continuity of HSIs. The LRTF-DFR model utilizes low-rank tensor factorization to capture the spectral global low rankness, introduces a weighted group sparsity constraint on the spatial difference images (SpatDIs) of the spatial factor to enhance group sparsity, and imposes a continuity constraint on the spectral factor to maintain spectral continuity. The model is solved using a proximal alternating minimization-based algorithm, demonstrating superior performance in mixed noise removal, spatial image recovery, and spectral signatures preservation. Extensive experiments on simulated and real HSIs confirm that the proposed method outperforms state-of-the-art methods in both qualitative and quantitative metrics[30].

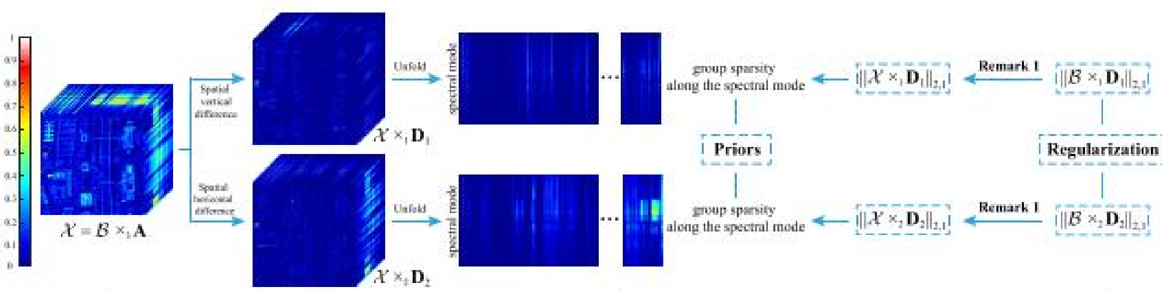

Fig: 7 Illustration of the proposed LRTF-DFR model [30]

4.8. Least Square Approach Using Wavelet Filters for Hyperspectral Image Denoising

Vishnu S. Dev et al. (2017) explores an efficient method for denoising hyperspectral images (HSI) that combines the least square approach with wavelet filters. The authors address the inherent noise issues in hyperspectral datasets, which consist of hundreds of spectral bands, making denoising both a challenging and computationally intensive task. Their proposed method leverages the least square denoising technique enhanced by various wavelet filters, including Haar, Daubechies, Coiflets, and Symlets, to achieve better noise reduction while preserving essential image details. The results demonstrate that this approach significantly improves the Signal-to-Noise Ratio (SNR) with reduced computational time compared to traditional methods like Total

Variation Denoising (TVD) and Legendre-Fenchel Transform (LFT). For instance, the method achieved notable improvements in SNR for the Pavia Centre and Pavia University datasets, with db1 filter yielding the highest SNR among the tested wavelet filters. The findings highlight the potential of the least square approach with wavelet filters as a superior denoising technique for HSIs, ensuring enhanced image quality and efficient processing time[31].

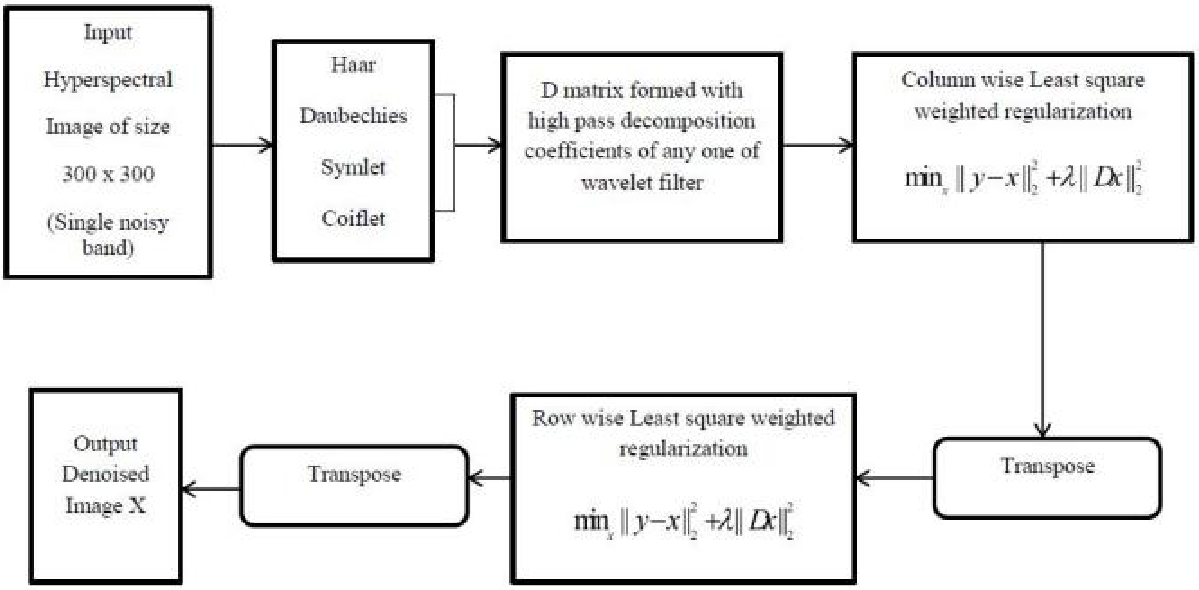

Fig: 8 Block diagrams of proposed system[31]

4.9. Hyperspectral Image Denoising Using Factor Group Sparsity-Regularized Nonconvex Low-Rank Approximation

In the paper by Yong Chen et al. (2022), the authors present an advanced method for denoising hyperspectral images (HSIs) that integrates factor group sparsity-regularized nonconvex low-rank approximation (FGSLR). This model addresses the limitations of previous HSI denoising techniques by incorporating a low-rank factorization approach combined with factor group sparsity regularization, effectively capturing the spectral correlation while preserving spatial information. The FGSLR model is SVD-free and robust to rank selection, providing a tighter rank approximation compared to the nuclear norm. Additionally, the model incorporates total variation (TV) regularization to enhance spatial detail preservation. The FGSLR method is implemented using a proximal alternating minimization algorithm, demonstrating significant improvements in noise reduction and detail preservation over existing low-rank approximation methods in both simulated and real HSI datasets. The model's robustness and efficiency are validated through extensive experimental results, highlighting its superiority in handling mixed noise in HSIs[32].

Fig: 9 Denoising results of simulated WDC dataset under Case 5[32]

4.10. MR Image Denoising and Super-Resolution Using Regularized Reverse Diffusion

In the paper by Hyungjin Chung et al. (2023), the authors propose an innovative denoising method for MR images utilizing a regularized reverse diffusion model. This model is designed to address the shortcomings of traditional deep learning-based denoising approaches, which often rely on minimum mean squared error (MMSE) estimates that can produce blurred outputs. The proposed method employs score-based reverse diffusion sampling, trained on coronal knee scans, to effectively denoise images, even when applied to out-of-distribution data such as in vivo liver MRI scans contaminated with complex noise. Additionally, the method enhances image resolution using the same network, achieving state-of-the-art performance. The model allows for flexible denoising and quantifies uncertainty, which is crucial for clinical applications where diagnostic accuracy is paramount. Extensive experiments demonstrate that this method not only surpasses traditional and other advanced denoising techniques in preserving fine details but also improves the structural similarity index and peak signal-to-noise ratio[33].

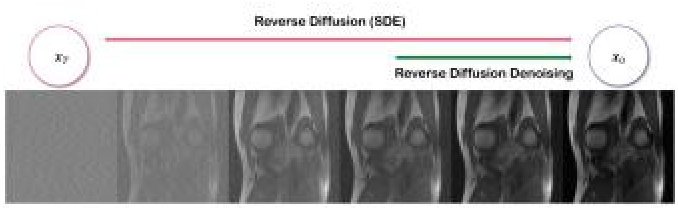

Fig: 10 Overview of the proposed reverse diffusion denoising scheme [33]

4.11. OCT Image Denoising Based on Asymmetric Normal Laplace Mixture Model

Sahar Jorjandi et al. (2019), the authors propose a novel approach to denoising Optical Coherence Tomography (OCT) images using the Asymmetric Normal Laplace Mixture Model (ANLMM). This model is developed to address the speckle noise prevalent in OCT images, which hampers the accurate interpretation of retinal structures. The method involves statistically modeling the intensity distribution of retinal layers using the ANL distribution, which effectively captures the heavy tail and asymmetry of the data. By applying a Gaussianization Transform (GT) to convert the ANL distribution to a normal distribution and subsequently utilizing a Spatially Constrained Gaussian Mixture Model (SC-GMM), the proposed denoising algorithm significantly improves the Contrast-to-Noise Ratio (CNR) of OCT images. The effectiveness of the ANLMM-GT-SCGMM method is validated through extensive experiments, demonstrating superior performance in noise reduction compared to other methods[34].

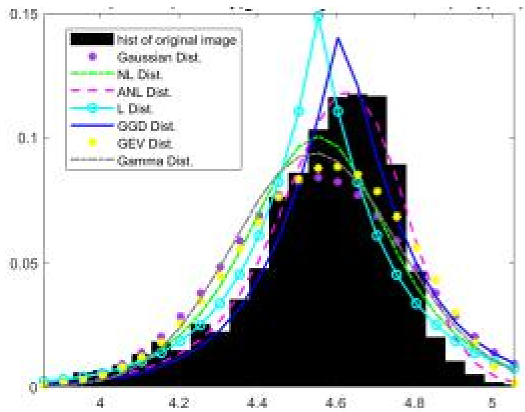

Fig:11 Comparison of goodness of fit for various distribution to the histogram of the GCL layer [34]

4.12. Carbon Emission Calculation Model for Electromagnetic Vibration Noise Reduction in Power Systems

Chao Fan et al. (2023), the authors investigate the effectiveness of electromagnetic vibration noise reduction equipment in power systems and establish a comprehensive carbon emission calculation model. This study is centered on reducing the electromagnetic vibration noise of power transformers, a significant noise source in substations. The authors propose an active noise reduction hardware system and develop a main control algorithm program to implement various unit functions modularly. The carbon emission model is constructed based on the PAS2050, GHGP protocol, and ISO14067 standards. The methodology involves transient electromagnetic analysis, mechanical vibration calculation, and sound field simulation using the indirect boundary element method. The model's accuracy and efficiency are validated through comparisons between simulated results and experimental data, highlighting its potential for improving transformer design and operational stability. The research demonstrates that the proposed model can significantly reduce noise and carbon emissions, contributing to a greener and quieter power system environment[35].

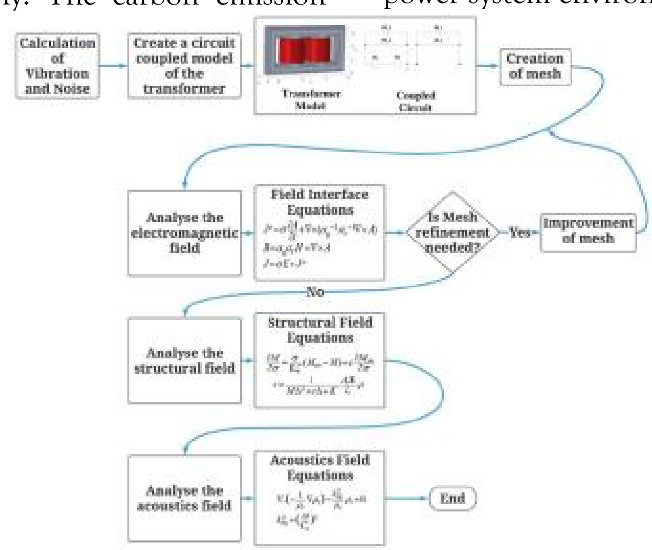

Fig: 12 Procedure flow of electromagnetic vibration noise calculation [35]

4.13. Multi-Scale Convolutional Sparse Coding for Image Denoising

Jingyi Xu et al. (2022), the authors revisit convolutional sparse coding (CSC) for image denoising from a multi-scale perspective, addressing the limitations of traditional CSC methods in handling noisy images. They propose a multi-scale CSC model, which is unrolled into a learnable network termed MCSCNet. This network leverages multi-scale convolutional filters to mimic the human visual system's perception, effectively capturing image details at various scales. The proposed MCSCNet significantly improves denoising performance, achieving an average PSNR improvement of 0.32 dB over the state-of-the-art CSC-based methods and performing on par with many deep learning-based approaches, while maintaining fewer network parameters and lower computational complexity. The experimental results validate the model's effectiveness, highlighting its potential in advancing CSC-based image denoising techniques[36].

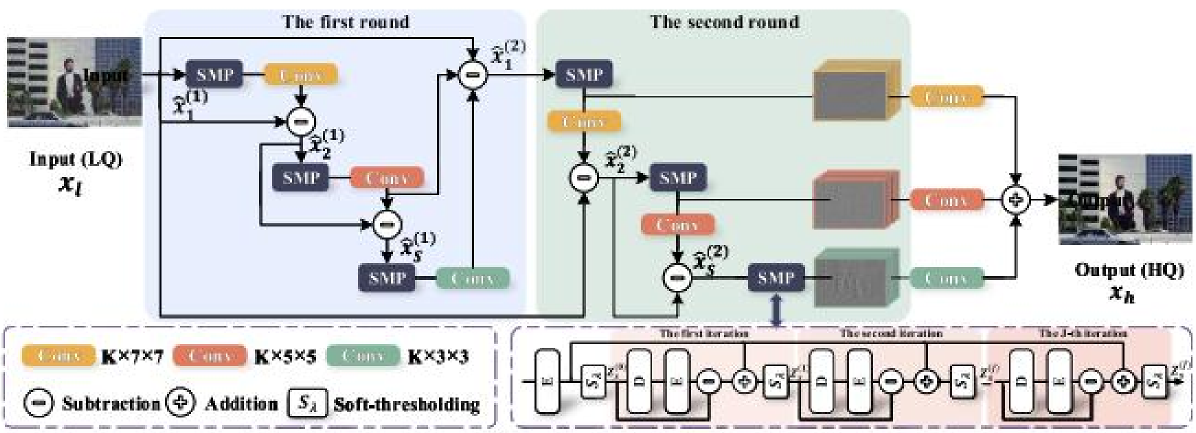

Fig: 13 The network architecture of the proposed MCSCNet [36]

4.14. Speckle Reduction and Restoration of Synthetic Aperture Radar Data with an Adoptive Markov Random Field Model

M. MahdianPari et al. (2012), the authors present an innovative speckle reduction technique for Synthetic Aperture Radar (SAR) data using an adoptive Markov Random Field (MRF) model. This method combines advanced statistical distribution with spatial contextual information, integrating a K-distribution for the SAR data statistics and a Gauss-MRF model for the spatial context. The technique involves a weighted summation of pixel-wise and contextual models, which effectively preserves edge information and improves the signal-to-noise ratio (SNR) of the despeckled data. The proposed method is tested on high-resolution X-band TerraSAR-X data, demonstrating superior performance in preserving edges and enhancing image quality compared to traditional speckle reduction methods like Lee and Kuan filters. This approach not only reduces noise but also maintains important image features, making it highly suitable for applications in SAR data analysis[37].

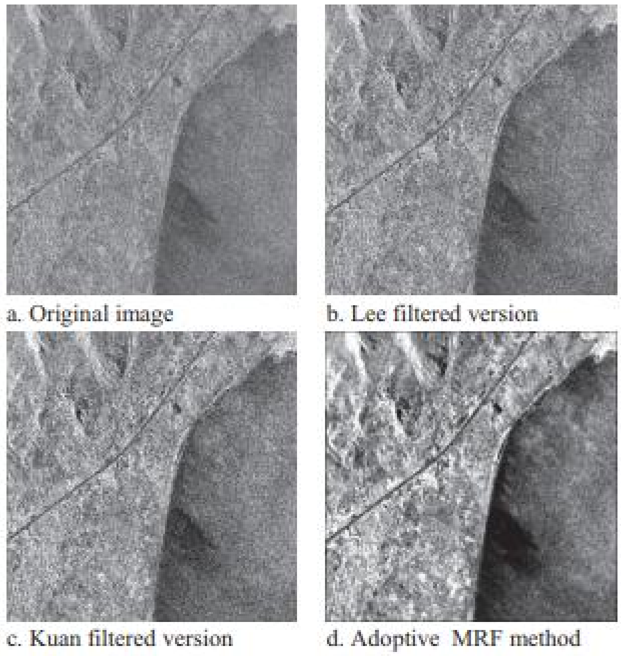

Fig: 14 Restoration of the TerraSAR-X SAR image covering a region of VAN (Turkey) [37]

4.15. Weighting Wiener and Total Variation for Image Denoising

Yun Liu et al. (2016), the authors propose an innovative image denoising method that optimally combines Wiener filtering with Total Variation (TV) denoising. This hybrid approach leverages the strengths of both techniques: Wiener filtering excels at preserving image structures and edges, while TV denoising is effective at reducing noise. The challenge of balancing these complementary strengths is addressed by introducing a weighting parameter that adjusts the influence of each method according to the noise level in the image. Through extensive experimentation, the authors determine the optimal weights for different noise levels, achieving significant improvements in denoising performance. The results show that this combined approach maintains edge structures while effectively suppressing noise, outperforming the individual methods. This is validated through experiments on various images and quantitative assessments using metrics like FSIM and PSNR[38].

Fig: 15 Image Denoising with different methods [38]

5. Optimization Techniques for Image Denoising and Noise Reduction

Image denoising and noise reduction are crucial in enhancing image quality and facilitating accurate interpretation in various applications, including medical imaging and machine vision. Several advanced optimization techniques have been developed to tackle different types of noise while preserving essential image details. These techniques include both traditional methods and deep learning-based approaches[39].

5.1. Traditional Optimization Techniques

5.1.1. Linear Filtering

Linear filters, such as Gaussian filters, are commonly used for their simplicity and effectiveness in reducing Gaussian noise. Gaussian filters smooth the image by averaging pixel values with weights determined by a Gaussian function. However, this method often results in the blurring of edges and loss of fine details[40].

5.1.2. Non-Linear Filtering

Non-linear filters, like median filters, are effective in handling impulse noise (e.g., salt-and-pepper noise). The median filter replaces each pixel's value with the median of neighboring pixel values, which helps in preserving edges while removing noise. Despite its effectiveness in certain scenarios, it may not perform well with other noise types, such as Gaussian noise[41] .

5.1.3. Wavelet Thresholding

Wavelet-based denoising techniques decompose the image into different frequency components and apply thresholding to remove noise. The choice of wavelet basis and threshold function significantly impacts the denoising performance. Methods like soft and hard thresholding are commonly used, with soft thresholding being more effective in preserving image features while reducing noise[42].

5.2. Deep Learning-Based Optimization Techniques

Deep learning has revolutionized image denoising, offering superior performance by learning complex patterns from data.

5.2.1. Autoencoders

Autoencoders are neural networks designed to learn a compressed representation of input data. They consist of an encoder, which compresses the input, and a decoder, which reconstructs the image. Convolutional autoencoders (CAEs) are particularly effective for image denoising, capturing spatial hierarchies in the data. In medical imaging, CAEs have shown substantial improvements in denoising performance, making them valuable for applications like MRI image enhancement[43].

5.2.2. Deep Convolutional Neural Networks (CNNs)

CNNs are widely used for their ability to automatically learn features from images. In image denoising, CNNs can be trained to distinguish between noise and important image details. Techniques like DnCNN utilize CNNs to predict the noise component, which is then subtracted from the noisy image to obtain a clean image. This approach has proven effective in various denoising tasks[44].

5.2.3. Sparse Representation and Dictionary Learning

Sparse representation involves representing images as a sparse combination of basic elements from a learned dictionary. Methods like the K-SVD algorithm iteratively update the dictionary and sparse codes to minimize reconstruction error. Recent advancements integrate deep learning with sparse coding, enhancing the ability to capture complex structures and textures in images. Hybrid methods combining deep dictionary learning with elastic thresholding have shown promising results in reducing noise while preserving crucial details[5].

5.2.4. Unsupervised Learning Approaches

Unsupervised learning techniques, such as Generative Adversarial Networks (GANs) and variational autoencoders (VAEs), have been employed for image denoising. These methods do not require paired noisy and clean images for training, making them suitable for scenarios with limited labeled data. GAN-based denoising methods, for example, use a generator to produce denoised images and a discriminator to distinguish between real and generated images, iteratively improving the denoising quality[45].

Optimization techniques for image denoising have evolved significantly, with deep learning methods offering substantial improvements over traditional techniques. By leveraging the power of neural networks and sparse representation, modern denoising methods achieve higher accuracy and better preservation of image details. The choice of technique depends on the specific application and the nature of the noise, with hybrid and deep learning-based approaches providing versatile and robust solutions for various denoising challenges[46].

Machine Learning and Deep Learning

The fields of machine learning (ML) and deep learning (DL) have made substantial contributions to image processing, particularly in the area of denoising. Both approaches offer unique methodologies for reducing noise in images, with deep learning providing notable advancements over traditional techniques[47].

6.1. Traditional Machine Learning Approaches

Traditional ML methods for image denoising include non-local means (NLM), bilateral filtering, and wavelet transforms. These methods rely on the statistical properties of the image to filter out noise. For example, NLM uses image redundancy to denoise by averaging similar patches across the image . However, these techniques often struggle to preserve fine details and may not perform well under complex noise conditions[48].

6.2. Deep Learning Approaches

Deep learning, a subset of machine learning, utilizes neural networks with multiple layers to learn representations directly from data. This approach has shown superior performance in image denoising tasks compared to traditional methods[49].

6.3. Convolutional Neural Networks (CNNs)

CNNs are particularly effective for image-related tasks due to their ability to capture spatial hierarchies in images. In denoising applications, CNNs can differentiate noise from the useful signal by learning from extensive datasets of noisy and clean image pairs. Models such as DnCNN leverage deep residual learning and batch normalization to achieve high denoising performance[50]

6.4. Autoencoders

Autoencoders are another popular deep learning architecture used for image denoising. They consist of an encoder that compresses the image into a lower-dimensional latent space and a decoder that reconstructs the image from this representation. Variants such as variational autoencoders (VAEs) and convolutional autoencoders (CAEs) have shown promising results in removing noise while preserving essential image details. Comparative studies between traditional and deep learning-based methods highlight the effectiveness of deep learning in denoising. For instance, a study comparing traditional filters and deep learning methods found that CNNs and autoencoders significantly outperformed traditional filters like Gaussian and median filters in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) . Another study demonstrated that deep learning methods maintained higher image detail and achieved better noise reduction under various noise conditions[51].

6.5. Applications in Medical Imaging

Deep learning has been particularly transformative in medical imaging applications. Techniques like MRI and CT scans benefit significantly from advanced denoising methods. For example, convolutional autoencoders have been effectively used to denoise MRI images, leading to clearer and more accurate diagnostic images. These improvements are crucial for accurate diagnosis and treatment planning, highlighting the importance of advanced denoising techniques in the medical field. While traditional machine learning methods have provided valuable tools for image denoising, deep learning approaches, especially those involving CNNs and autoencoders, offer substantial improvements. These advancements are particularly critical in fields like medical imaging, where the quality and accuracy of images are paramount[52].

Challenges and Future Directions

Despite significant advancements in image denoising and noise reduction techniques, several challenges persist that impede the attainment of optimal results. Addressing these challenges is crucial for improving the efficacy of denoising algorithms and ensuring high-quality image reconstruction across various applications[51].

7.1. Challenges

7.1.1. Complex Noise Patterns

Traditional denoising techniques often struggle with complex noise patterns such as mixed noise (e.g., Gaussian, Rician, and speckle noise) commonly encountered in medical imaging. For instance, MRI and CT scans are particularly prone to such noise, complicating the denoising process and potentially leading to loss of critical diagnostic information[53].

7.1.2. Edge Preservation

One of the major challenges in image denoising is preserving edges and fine details while removing noise. Many traditional methods tend to blur edges, which are essential for accurately interpreting and analyzing images, particularly in medical and remote sensing applications [54].

7.1.3. Computational Complexity

Advanced denoising techniques, including those based on deep learning, often require substantial computational resources for training and inference. This high computational cost can be a barrier to the practical deployment of these methods, especially in resource-constrained environments[55].

7.1.4. Generalization Across Datasets

Denoising models trained on specific datasets may not generalize well to other datasets with different noise characteristics. This variability poses a challenge in developing robust denoising algorithms that perform consistently across various imaging conditions and applications[56].

7.1.5. Interpretability and Transparency

Deep learning models, despite their superior performance, often operate as "black boxes," making it difficult to interpret their decision-making processes. This lack of transparency can hinder their acceptance in critical applications like medical imaging, where understanding the rationale behind decisions is paramount[57].

7.2. Future Directions

7.2.1. Hybrid Approaches

Future research should focus on developing hybrid approaches that combine the strengths of traditional and deep learning-based methods. For instance, integrating wavelet thresholding with deep learning models could leverage the advantages of both frequency domain processing and data-driven learning for more effective denoising[58].

7.2.2. Adaptive and Real-Time Denoising

There is a growing need for adaptive denoising techniques that can dynamically adjust to different noise levels and types in real-time. Such methods would be particularly beneficial in applications like autonomous driving and real-time medical imaging, where immediate and accurate noise reduction is critical[59].

7.2.3. Transfer Learning and Domain Adaptation

Implementing transfer learning and domain adaptation techniques can enhance the generalizability of denoising models across different datasets and imaging modalities. By fine-tuning pre-trained models on new datasets, it is possible to achieve robust performance without extensive retraining from scratch[60].

7.2.4. Explainable AI (XAI) in Denoising

Incorporating explainable AI techniques into denoising models can help in understanding and interpreting the models' outputs. This would increase the transparency of the denoising process and build trust among users, particularly in sensitive fields like healthcare[60].

7.2.5. Advanced Optimization Techniques

Employing advanced optimization techniques, such as evolutionary algorithms and swarm intelligence, can further refine denoising algorithms. These methods can optimize hyperparameters and network architectures more effectively, leading to better performance and efficiency[61].

7.2.6. Quantum Computing for Denoising

Exploring the potential of quantum computing in image denoising could open new frontiers in processing speed and efficiency. Quantum algorithms can handle large-scale computations more effectively, potentially revolutionizing the field of image denoising . The field of image denoising and noise reduction continues to evolve, driven by advancements in both traditional methods and modern deep learning techniques. Addressing the existing challenges and exploring future directions, such as hybrid approaches, adaptive denoising, transfer learning, and explainable AI, will be crucial in achieving superior image quality and enhancing the applicability of denoising algorithms across various domains[62].

Conclusion

In the domain of applied mathematics, the integration with image denoising and noise reduction has achieved significant advancements, largely due to the incorporation of sophisticated mathematical principles such as optimization, statistical inference, and deep learning methodologies. This convergence has led to marked improvements in image quality across a range of applications, demonstrating the efficacy of these innovative approaches in addressing complex noise challenges. The application of optimization techniques has refined algorithms for noise reduction, allowing for more precise and efficient denoising processes. Statistical inference methods have enhanced the understanding of noise characteristics and the development of robust models that can better differentiate between signal and noise. Moreover, the advent of deep learning has revolutionized the field by leveraging neural network architectures to learn intricate patterns and improve denoising performance beyond traditional methods. The continuous exploration and application of these mathematical concepts are expanding the capabilities of noise reduction and image enhancement. This ongoing research is not only advancing current methodologies but also fostering interdisciplinary collaborations, driving forward new techniques and applications. The dynamic nature of this field suggests a trajectory of continuous innovation and breakthroughs, with promising developments anticipated in the coming years. As researchers continue to delve into and refine these methodologies, the potential for further advancements remains substantial. The synergy between applied mathematics and image processing technologies promises to yield even greater improvements in image quality and noise reduction, marking a bright future for this area of study.

Acknowledgement

We would like to express our sincere gratitude to the College of Mathematical Sciences and Geomathematics Key Laboratory of Sichuan Province, Chengdu University of Technology, China, for providing the necessary facilities and support for this research.

Conflict of Interest

The authors declare no competing financial, personal, or professional interests that could influence the findings or interpretations of this research.

Author Contributions

Faria Mirza; Conceptualization, methodology, literature review, manuscript drafting, and revision. **Jun Feng;** Validation, supervision, critical analysis, and manuscript refinement.

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