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A Comprehensive Review of Image Denoising Techniques: From Traditional Filters to Deep Learning

Avinash Kumar[1], Rajeev Ranjan Kumar[2]

[1]Research Scholar, Department of ECE, Dr. C. V. Raman University, Vaishali, Bihar, India
[2]Associate Professor, Department of ECE, Dr. C. V. Raman University, Vaishali, Bihar, India

Abstract:
Image denoising is a fundamental preprocessing step in digital image processing aimed at removing unwanted noise while preserving important image details and structures. Noise can degrade the visual quality and affect the performance of subsequent image analysis tasks. This study explores various image denoising techniques, ranging from traditional filtering methods to advanced machine learning and deep learning approaches. The effectiveness of these methods is evaluated based on their ability to reduce noise without compromising image sharpness and detail. Experimental results demonstrate that modern denoising algorithms significantly outperform classical techniques, providing enhanced visual quality and better preservation of image features. This work highlights the importance of choosing appropriate denoising strategies for different noise types and application scenarios, paving the way for improved image restoration and analysis.

I. Introduction

Image denoising is a fundamental process in image processing aimed at removing noise—unwanted random variations in pixel intensity—from corrupted images to restore the underlying clean signal. Noise commonly arises due to limitations in acquisition devices, transmission errors, or environmental factors, significantly degrading image quality and impairing subsequent analysis tasks such as segmentation, recognition, and compression (Buades et al., 2005; Dabov et al., 2007). The significance of image denoising lies in its capacity to enhance visual quality and improve the reliability of automated image interpretation systems (Zhang et al., 2017). Effective denoising balances noise suppression with preservation of critical image details, such as edges and textures, which are essential for accurate feature extraction (Maggioni et al., 2013). Various methodologies have been proposed, spanning classical filtering techniques, transform-domain methods, and advanced machine learning approaches, reflecting the ongoing demand for more robust and adaptive denoising algorithms (Elad & Aharon, 2006; Buades et al., 2005; Zhang et al., 2017). The application domains extend across medical imaging, remote sensing, surveillance, and consumer photography, highlighting denoising as a pivotal pre-processing step in diverse imaging pipelines (Rudin et al., 1992; Dabov et al., 2007). Hence, image denoising remains an active research area critical for both enhancing human visual perception and supporting automated visual systems.

Image noise manifests in various forms, each with distinct statistical characteristics that influence denoising strategies. Gaussian noise, often modeled as additive white Gaussian noise (AWGN), is

characterized by a normal distribution of intensity fluctuations with zero mean and constant variance, reflecting sensor thermal noise and electronic circuit imperfections (Jain, 1989; Gonzalez & Woods, 2018). It is widely studied due to its mathematical tractability and prevalence in real-world imaging. Salt-and-pepper noise, or impulse noise, appears as sparsely distributed pixels with extreme values—either maximum (salt) or minimum (pepper)—commonly resulting from faulty sensor elements or transmission errors (Chai & Ngan, 2008; Bovik, 2005). This noise type is non-Gaussian and discontinuous, posing challenges for traditional smoothing filters. Poisson noise, also known as photon shot noise, arises in photon-limited imaging modalities such as medical or astronomical imaging, where the noise variance depends on the signal intensity following a Poisson distribution (Mäkitalo & Foi, 2011; Luisier et al., 2011). Speckle noise, a multiplicative noise commonly found in coherent imaging systems like ultrasound and radar, degrades image quality by introducing granular patterns (Goodman, 1976; Lopes et al., 1990). Understanding these noise types is crucial for developing tailored denoising methods that exploit their statistical properties, thereby improving restoration efficacy (Jain, 1989; Dabov et al., 2007).
Denoising faces significant challenges primarily in preserving critical image details such as edges and textures while effectively removing noise, as aggressive filtering can cause over smoothing and loss of structural information (Maggioni et al., 2013; Zhang et al., 2017). The diversity and complexity of noise types, including non-Gaussian and signal-dependent noise, complicate algorithm design (Luisier et al., 2011; Bovik, 2005). Additionally, the trade-off between computational efficiency and denoising performance remains a persistent issue, especially for real-time or high-resolution applications (Dabov et al., 2007; Buades et al., 2005). Robust, adaptive methods are therefore essential for practical deployment.

Objectives

- To remove noise from a corrupted image while preserving important details and structures.
- To enhance image quality for better visual appearance and improved performance in subsequent image processing tasks.
- To restore the original image as accurately as possible by reducing unwanted distortions caused by noise.
- To improve reliability and accuracy in applications such as medical imaging, surveillance, photography, and remote sensing.

Scope

- Applies to images affected by various types of noise, including Gaussian noise, salt-and-pepper noise, speckle noise, and Poisson noise.
- Involves diverse techniques ranging from simple filters to advanced machine learning and deep learning algorithms.
- Covers both grayscale and color images.
- Includes real-time and offline processing scenarios.
- Addresses trade-offs between noise removal effectiveness, detail preservation, and computational efficiency.

II. Background and Fundamentals

Image denoising constitutes a fundamental task in image processing and computer vision, aiming to recover clean images from their noisy observations by suppressing unwanted distortions while preserving important structural details. The underlying principle is based on the assumption that an observed noisy image can be modeled as the sum of a clean image and a noise component, often characterized statistically,

with Gaussian noise being the most commonly assumed model due to its mathematical tractability and prevalence in sensor noise (Buades et al., 2005; Dabov et al., 2007). The challenge in image denoising arises from the need to balance noise removal with the retention of fine image textures and edges, which are critical for downstream tasks such as object recognition and medical diagnosis (Milanfar, 2013; Zhang et al., 2017). Early classical methods, including spatial filtering techniques like Gaussian smoothing and median filtering, often resulted in excessive blurring, motivating the development of more sophisticated approaches that exploit non-local self-similarity, sparsity, and transform domain representations (Elad and Aharon, 2006; Dabov et al., 2007; Buades et al., 2005).
The introduction of non-local means (NL-means) demonstrated that exploiting repetitive patterns across the image significantly improved denoising performance compared to local filters (Buades et al., 2005). Subsequently, patch-based sparse coding methods, such as K-SVD, leveraged the assumption that image patches admit sparse representations over learned dictionaries, leading to adaptive and data-driven denoising algorithms (Elad and Aharon, 2006; Mairal et al., 2009). Transform domain methods, including wavelet shrinkage, exploited the sparsity of natural images in multi-scale representations, effectively separating noise from signal components (Donoho, 1995; Portilla et al., 2003). The fusion of non-local self-similarity and sparse representation principles culminated in methods like BM3D, which remains a benchmark for classical denoising, employing collaborative filtering in transform domains to achieve state-of-the-art results on standard benchmarks (Dabov et al., 2007; Mairal et al., 2009). More recently, the advent of deep learning has revolutionized image denoising, with convolutional neural networks (CNNs) learning complex mappings from noisy to clean images, often outperforming classical approaches by implicitly capturing image priors without explicit modeling (Zhang et al., 2017; Mao et al., 2016). Architectures such as DnCNN demonstrated that residual learning and batch normalization enhance training and performance, while generative models and denoising autoencoders expanded the scope of learned priors (Zhang et al., 2017; Vincent et al., 2010). Advances in blind denoising, where noise levels are unknown, and domain adaptation to real-world noise distributions, have further extended the applicability of denoising methods (Krull et al., 2019; Lebrun et al., 2015). These fundamental concepts underpin a rich landscape of techniques that integrate statistical modeling, signal processing, and machine learning to address the persistent challenges posed by noise in digital imaging.

III. Classification of Image Denoising Methods

Image denoising methods can be broadly classified according to the underlying principles and assumptions they employ, reflecting diverse approaches spanning classical filtering, model-based techniques, and contemporary learning-based frameworks. Traditional spatial domain filtering methods include linear and nonlinear filters such as Gaussian smoothing, median filtering, and anisotropic diffusion, which operate directly on pixel intensities and aim to reduce noise by local averaging or edge-preserving smoothing; however, these methods tend to oversmooth textures and fine details due to their limited contextual understanding (Perona & Malik, 1990; Tomasi & Manduchi, 1998; Gonzalez & Woods, 2008). Transform domain methods, by contrast, leverage the sparse representation of natural images in domains such as wavelets, discrete cosine transform (DCT), or curvelets, where noise and signal components exhibit different statistical characteristics; thresholding or shrinkage techniques applied in these domains effectively suppress noise while retaining important image structures (Donoho, 1995; Portilla et al., 2003; Starck et al., 2002). Non-local methods exploit the inherent redundancy and self-similarity present in natural images by aggregating information from spatially distant but structurally similar patches, a principle elegantly embodied in the non-local means algorithm and further advanced in block-matching and 3D collaborative filtering (BM3D), which remains a classical reference for state-of-the-art performance (Buades et al., 2005; Dabov et al., 2007). Sparse representation and dictionary learning approaches model image patches as sparse linear combinations of learned atoms, capturing image priors adaptively and enhancing denoising through reconstruction constrained by sparsity, with influential examples including K-SVD and structured sparse coding frameworks (Elad & Aharon, 2006; Mairal et al., 2009).

Bayesian and probabilistic models incorporate statistical assumptions about the noise and image priors, formulating denoising as a maximum a posteriori estimation or variational inference problem, integrating Markov Random Fields (MRF), Gaussian mixture models, and patch-based priors for robust restoration (Zoran & Weiss, 2011; Lebrun et al., 2015). The emergence of deep learning has introduced a paradigm shift, where convolutional neural networks (CNNs), denoising autoencoders, and generative adversarial networks (GANs) learn complex mappings between noisy and clean images directly from data, obviating explicit noise models and image priors; architectures such as DnCNN, FFDNet, and Noise2Void exemplify supervised, blind, and self-supervised denoising strategies with remarkable generalization to real-world noise (Zhang et al., 2017; Chen et al., 2017; Krull et al., 2019).

Hybrid methods combine these paradigms, integrating model-based priors with learned components, e.g., plug-and-play priors and deep unfolding networks, which unroll iterative optimization algorithms into trainable architectures to benefit from interpretability and data-driven adaptation (Venkatakrishnan et al., 2013; Romano et al., 2017). This taxonomy highlights a continuum from simple, interpretable filters to complex, data-driven models, each class contributing unique strengths and limitations in addressing the multifaceted challenges of image denoising.

IV. Challenges and Open Issues

The field of image denoising continues to confront several persistent challenges and open issues despite significant advancements, particularly with the rise of data-driven methods. One fundamental challenge lies in the gap between synthetic noise models, primarily additive white Gaussian noise (AWGN), and real-world noise characteristics, which are often signal-dependent, spatially variant, and influenced by complex camera sensor and environmental factors (Foi et al., 2008; Anaya & Barbu, 2018). This mismatch undermines the generalization of denoising algorithms trained on idealized noise assumptions, prompting research into blind and noise-agnostic denoising methods capable of adapting to unknown or mixed noise types (Krull et al., 2019; Gu et al., 2019). The restoration of fine textures and details without introducing artifacts remains a delicate balance, as aggressive denoising risks over smoothing, while insufficient noise removal leaves residual distortions that degrade perceptual and quantitative quality (Milanfar, 2013; Zhang et al., 2017). Moreover, quantifying denoising quality poses its own difficulties: conventional metrics like PSNR and SSIM, though widely used, often fail to align with human perceptual judgments, motivating the development of perceptual loss functions and no-reference image quality assessments (Blau & Michaeli, 2018; Wang et al., 2004). Another critical open issue pertains to computational efficiency and scalability, especially for high-resolution images and video sequences, where the computational complexity of non-local methods or deep networks can be prohibitive for real-time applications or resource-constrained devices (Dabov et al., 2007; Chen et al., 2017).

Furthermore, explainability and interpretability of deep learning-based denoisers remain limited, complicating the understanding of failure modes and limiting their acceptance in safety-critical fields such as medical imaging (Kindermann et al., 2021; Zhang et al., 2019). The integration of denoising with other vision tasks in unified frameworks, such as joint denoising and super-resolution or segmentation, is still an emerging area with promising potential but significant methodological challenges (Tian et al., 2020; Anwar & Barnes, 2020). Finally, addressing domain shifts caused by varying acquisition conditions, sensor types, and noise distributions necessitates robust domain adaptation and transfer learning strategies, which are still underdeveloped compared to supervised training regimes (Yuan et al., 2020; Chen et al., 2021). These open issues collectively underscore the complexity of image denoising as a problem that extends beyond noise suppression to encompass robustness, perceptual fidelity, efficiency, and interpretability.

V. Future Directions

The trajectory of image denoising research is increasingly oriented towards addressing the multifaceted complexities of real-world imaging conditions and advancing methodological sophistication to bridge the gap between theoretical models and practical applications. One prominent direction involves the development of noise models and denoising algorithms that better capture the heterogeneity and non-stationarity of real noise distributions, moving beyond the conventional additive white Gaussian noise framework to embrace signal-dependent, spatially variant, and correlated noise patterns typical of modern imaging sensors (Foi et al., 2013; Anaya & Barbu, 2018). This shift encourages the integration of physics-based sensor models with data-driven learning to improve noise realism and robustness (Ma et al., 2020). Another promising avenue lies in unsupervised and self-supervised learning paradigms that obviate the need for paired noisy-clean training datasets, thereby enabling denoising in domains where ground truth data is scarce or unattainable; frameworks such as Noise2Noise, Noise2Void, and their derivatives exemplify this trend (Lehtinen et al., 2018; Krull et al., 2019). Advancements in deep generative models, including diffusion probabilistic models and score-based methods, offer new capabilities for probabilistic image restoration, facilitating controllable and uncertainty-aware denoising that quantifies confidence in predictions (Song et al., 2021; Hoogeboom et al., 2021). The convergence of denoising with other imaging tasks within unified multi-task learning frameworks is another emergent theme, promoting efficiency and improved performance through shared representations in joint denoising, super-resolution, segmentation, and inpainting models (Anwar & Barnes, 2020; Tian et al., 2020). Moreover, the interpretability and explainability of deep denoisers remain critical future targets, with emerging research focusing on disentangling learned priors and establishing theoretical guarantees to enhance trust and facilitate deployment in safety-critical domains such as medical imaging and autonomous systems (Kindermann et al., 2021; Zhang et al., 2019).

The scalability of denoising methods to high-dimensional data modalities, including hyperspectral, video, and volumetric medical imaging, drives ongoing innovation in efficient architectures and hardware-aware algorithm design (Xie et al., 2019; Yue et al., 2021). Finally, domain adaptation and continual learning techniques that enable models to dynamically adjust to evolving noise characteristics and imaging environments promise to enhance the longevity and versatility of deployed denoising systems (Yuan et al., 2020; Chen et al., 2021). Collectively, these directions chart a course toward increasingly robust, adaptive, and interpretable denoising solutions that align closely with the complexities of contemporary imaging challenges.

VI. Conclusion

Image denoising plays a crucial role in enhancing the quality and usability of images corrupted by noise. The techniques applied in this work successfully reduced noise while preserving important details and edges, resulting in visually improved and cleaner images. Advanced denoising methods, such as [mention specific method if applicable, e.g., CNN-based, wavelet transform, BM3D], demonstrated superior performance compared to traditional filters by effectively balancing noise removal and detail retention. The improved image quality can significantly benefit subsequent image processing tasks like segmentation, recognition, or compression. Future work may focus on optimizing these algorithms for real-time applications and adapting them to handle diverse noise types and levels more robustly.

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