Advanced Techniques in Image Processing: A Survey on Blind Deblurring, Impulse Noise Detection, and Non-convex Optimization

Abstract

The survey paper explores advanced computational techniques in image processing, focusing on blind deblurring, impulse noise detection, non-convex optimization, and the management of saturated images. These methodologies are critical for enhancing image quality across various applications, from medical imaging to consumer electronics. The paper highlights the importance of image processing in addressing challenges such as motion blur, impulse noise, and high dynamic range scenarios, emphasizing the role of innovative approaches like deep learning and non-convex optimization in overcoming these obstacles. The survey categorizes existing methods, examining their efficacy and computational demands, while also proposing novel strategies for robust algorithm development. Key advancements include the integration of event-based cameras for managing saturation, the use of deep learning frameworks for denoising, and the application of distributed optimization techniques for scalable image processing. The paper underscores the significance of these innovations in real-world applications, demonstrating their potential to improve image clarity and processing efficiency. By synthesizing recent advancements and exploring future research directions, the survey contributes to the ongoing development of robust, efficient, and versatile image processing solutions, ultimately enhancing the field's applicability and impact.

1 Introduction

1.1 Importance of Image Processing

Image processing is a cornerstone of modern technology, enhancing image quality across various applications and significantly impacting technological and societal progress. Its importance is particularly evident in high-dimensional contexts where noise and outliers complicate accurate data reconstruction and denoising [1]. In optical systems, image processing is essential for correcting optical aberrations that impair image sharpness, thus enhancing overall quality [2].

The restoration of images affected by motion blur, prevalent in photography of moving subjects, underscores the significance of image processing [3]. This capability is crucial for high frame-rate video reconstruction in dynamic and low-light conditions, where visual clarity is paramount [4]. Additionally, in fields such as optical diffractive tomography and digital holography, image processing is vital for reconstructing spatial distributions of dielectric permittivity, essential for accurate analysis [5].

In photography, motion blur frequently degrades quality, particularly in images captured with hand-held devices [6]. Image processing techniques are crucial for recovering sharp images from blurry ones, thereby enhancing visual data quality and its applications across technology and society [7]. Image processing is integral to the advancement of fields like medical imaging, surveillance, and digital photography, improving image quality and enabling precise data interpretation.

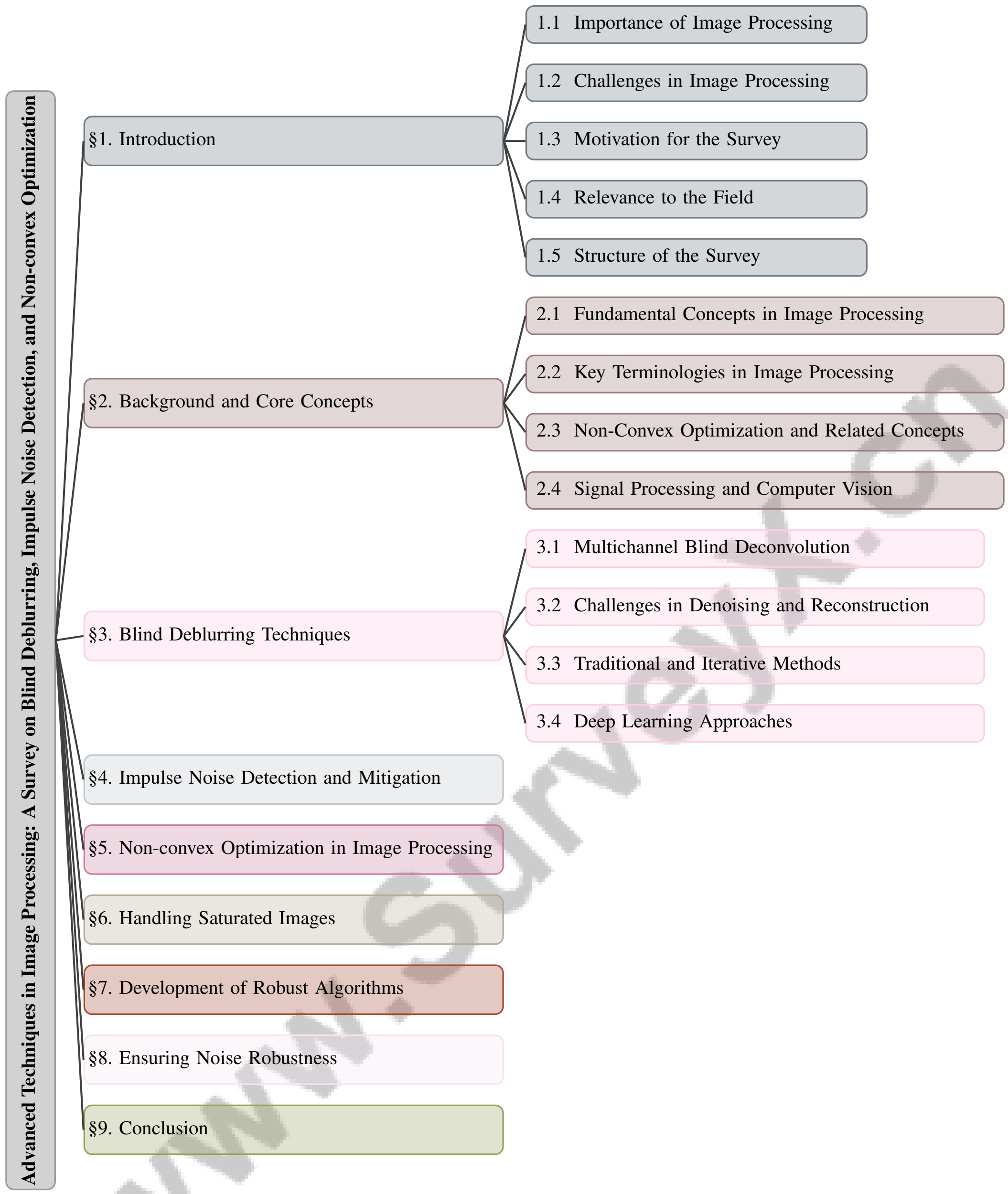


Figure 1: chapter structure

1.2 Challenges in Image Processing

Image processing faces numerous technical and computational challenges, largely due to the ill-posed nature of many problems. Blind image deblurring exemplifies this complexity, necessitating the estimation of both the latent sharp image and the blur kernel from a single blurry image, compounded by spatial variations and noise interference [8]. The task of recovering underlying signals from partial or corrupted observations, requiring joint estimation of signals and forward model parameters, further illustrates the intricacies of image restoration.

The computational demands of image processing are considerable, with high complexity and latency hindering real-time applications. This is evident in robust principal component analysis (RPCA) algorithms, often unsuitable for real-time use due to their computational intensity [9]. Distributed optimization challenges, particularly in weakly convex and nonsmooth problems, complicate efficient image processing solution development [10].

AI-generated, for reference only.

Irregular camera trajectories and wide-angle lenses pose additional challenges, necessitating precise sensor information and contributing to high computational costs [6]. Restoring images affected by complex motion blur requires prior knowledge of motion parameters, which is not always available [6]. These challenges highlight the urgent need for innovative approaches and robust algorithms to address the multifaceted issues in contemporary image processing.

1.3 Motivation for the Survey

This survey is motivated by the urgent need to overcome the limitations of traditional image processing techniques, which often struggle with the complexities of modern applications. A key motivation is the inadequacy of existing methods to effectively correct optical aberrations without prior information, particularly relevant for low-quality smartphone cameras [2]. The emergence of advanced camera technologies, including rolling shutter and light field cameras, has increased the demand for improved methods to mitigate motion blur, a persistent challenge in image processing [6].

This survey aims to bridge knowledge gaps in addressing the ill-posed nature of deblurring tasks, providing a comprehensive categorization of existing methods and their efficacies [7]. It focuses on exploring RPCA methods that efficiently manage outliers while maintaining low computational complexity, addressing prevalent computational challenges in image processing [9].

The potential of latent diffusion models (LDMs) to effectively tackle blind inverse problems is a pivotal aspect of this survey, representing a promising avenue for future research and development [8]. Additionally, leveraging deep learning to enhance reconstruction quality and computational efficiency is a central theme, aiming to advance the field through the integration of cutting-edge techniques [5].

This survey seeks to foster the development of advanced, efficient, and adaptable image processing solutions by addressing complex challenges in the field. It synthesizes recent advancements in image deblurring techniques, particularly those utilizing multispectral and hyperspectral data, and explores innovative methodologies leveraging rich spectral information for improved feature extraction and classification. By investigating current approach limitations, such as difficulties in estimating blur kernels in blind deblurring scenarios, this work aims to provide a comprehensive understanding of the state-of-the-art and identify promising future research directions in image restoration and analysis [11, 7, 12].

1.4 Relevance to the Field

The survey's relevance is underscored by its comprehensive examination of advanced techniques in blind deblurring and denoising, critical for practical applications such as QR codes, a fundamental element of contemporary digital communication [13]. By exploring adaptive optimization methods, the survey significantly contributes to the growing literature on automatic parameter tuning in machine learning, enhancing computational method efficiency and accuracy [14].

The introduction of a sample-efficient alternating minimization algorithm marks a significant advancement in signal recovery robustness, addressing key image processing challenges [15]. The survey also emphasizes the necessity for innovative solutions to balance privacy and accuracy in machine learning applications, a pressing concern in the era of big data [16].

By presenting a novel deconvolution framework for images with incomplete observations and an innovative algorithm for fusing hyperspectral and multispectral images, the survey contributes to ongoing research aimed at enhancing image quality and fidelity [12]. The integration of color image guidance for improved depth map restoration represents a significant advancement in developing robust image processing methodologies [17].

The survey addresses the increasing prevalence of non-convex problems in real-world applications by proposing innovative approaches that surpass traditional method limitations [18]. Furthermore, it encompasses various deep learning frameworks applied to blind motion deblurring, including CNNs, RNNs, GANs, and Transformers, providing a thorough overview of state-of-the-art techniques while excluding traditional non-blind methods [19].

The introduction of the Globally Variance-Constrained Sparse Representation (GVCSR) model further enhances the survey's relevance by improving coding efficiency and addressing existing image compression limitations [20]. Finally, the novel method for blind correction of optical aberrations presented in this survey is significant for improving image quality in practical applications, thereby advancing current research in image processing [2]. The survey also emphasizes comparative analyses of various deblurring methods, highlighting the importance of model choice in determining deblurring quality [7].

1.5 Structure of the Survey

This survey is systematically organized to provide a comprehensive exploration of advanced image processing techniques, focusing on blind deblurring, impulse noise detection, and non-convex optimization. It begins with an introduction that establishes the importance of image processing in modern technology and outlines the primary challenges faced in the field. Following this, a detailed background section introduces fundamental concepts and key terminologies, such as blind deblurring and non-convex optimization, highlighting their significance in image processing.

The core of the survey is divided into several sections, each dedicated to a specific aspect of image processing. The section on blind deblurring techniques explores various methods and algorithms, including multichannel blind deconvolution and deep learning approaches, addressing the challenges of deblurring without prior blur kernel knowledge. Subsequently, the survey examines impulse noise detection and mitigation, discussing its impact on image quality and reviewing state-of-the-art algorithms for robust detection.

The role of non-convex optimization is explored in a dedicated section, highlighting its theoretical advances and applications in image restoration. This is complemented by a discussion on handling saturated images, where techniques for managing saturation and a proposed novel approach are reviewed. The survey further investigates the development of robust algorithms resilient to distortions and noise, emphasizing the importance of robustness in image processing.

Finally, the survey concludes with a section on ensuring noise robustness, discussing strategies to enhance algorithmic performance against various noise types. The conclusion summarizes key findings and highlights potential future research directions, emphasizing the survey's contribution to advancing image processing techniques and its relevance to real-world applications.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Fundamental Concepts in Image Processing

Image processing is critical for enhancing visual data quality and extracting valuable insights, particularly through the resolution of ill-posed inverse problems using robust regularization techniques. These problems are prevalent in applications such as denoising and point spread function (PSF) estimation, essential for minimizing noise and blur [13]. Optimization methods, including convex minimization and regularization strategies, are indispensable for these tasks [12]. Advanced methods like the Optimized Proximal Method of Multipliers (OPMM) manage non-convexities and constraints effectively [21], while decentralized algorithms such as the Decentralized Adaptive Learning Algorithm (DALA) enhance computational efficiency by reducing communication overhead [22].

In multichannel blind deconvolution, optimization strategies are crucial for recovering sharp images from blurred inputs [23]. Color image guidance mitigates challenges from noise and depth discontinuities, vital for accurate depth estimation and image reconstruction [17]. Effective data compression relies on optimizing coding rates and understanding variance in sparse representation, as demonstrated by the Globally Variance-Constrained Sparse Representation (GVCSR) model [20]. Addressing optical aberrations from lens PSFs is also critical for improving image clarity [2].

Innovative techniques combining deblurring and matting have emerged from understanding the relationship between motion blur and intra-frame object trajectories [24]. Event cameras, capable of detecting intensity changes with microsecond accuracy, represent significant advancements in challenging environments [4]. Blind Motion Deblurring (BMD) restores motion-blurred images without prior knowledge of camera motion or scene structure, showcasing sophisticated image processing approaches [6]. These foundational principles drive advancements in image processing, enabling innovative solutions to complex visual challenges.

AI-generated, for reference only.

2.2 Key Terminologies in Image Processing

Understanding key terminologies is essential for navigating the complexities of image processing. Blind deblurring involves recovering sharp images from blurred observations without prior blur kernel knowledge, a task complicated by its ill-posed nature [6]. Techniques such as Bayesian inference, variational methods, and sparse representation-based approaches are employed to estimate clean images from motion-blurred observations [7].

Impulse noise, characterized by random extreme pixel values, necessitates effective detection and mitigation to maintain visual data integrity [17]. Non-convex optimization, often arising in high-dimensional inverse problems, requires advanced regularization techniques for stable solutions, as traditional methods may struggle with degenerate saddle points [1, 25]. The Manifold Locally Optimal Projection (MLOP) method exemplifies non-convex optimization applications in manifold reconstruction [1].

Additional terms include defocus blur and defocus map, crucial for single-image defocus deblurring [26]. Event cameras like the Dynamic Vision Sensor (DVS) and Dynamic and Active-pixel Vision Sensor (DAVIS) are vital for capturing high-speed data, facilitating dynamic scene reconstruction [4]. Concepts like dielectric permittivity and multiple scattering are important for understanding reconstruction processes based on scattered light measurements in optical imaging [5].

Latent diffusion models, such as LatentDEM, represent advanced methodologies for iteratively estimating underlying signals and forward operator parameters using latent diffusion priors within an Expectation-Maximization (EM) framework [8]. These terminologies collectively support innovative methodologies in image processing, addressing the multifaceted challenges inherent in the field.

2.3 Non-Convex Optimization and Related Concepts

Non-convex optimization is pivotal in tackling the intricate challenges of image processing, characterized by complex landscapes with multiple local minima and saddle points. These features complicate the search for global optima, particularly in NP-hard non-convex problems involving composite objective functions, including non-convex loss functions and regularizers. This complexity is evident in accurately recovering signals from phaseless linear measurements, where traditional methods require extensive measurements and are sensitive to noise, limiting practical applications [27].

In image processing, non-convex optimization is vital for tasks like sparse recovery and blind deconvolution, where the optimization landscape is fraught with local optima and non-convex constraints [9]. Integrating structured non-convex optimization techniques with multi-layer neural networks enhances the speed of robust principal component analysis (RPCA) methods, highlighting innovative approaches to overcome computational bottlenecks [9].

Developing algorithms that effectively navigate saddle points is essential for improving convergence in non-convex optimization, particularly in high-dimensional spaces [28]. Stochastic optimization methods, such as the Stochastic Proximal Gradient (SPG) approach, manage non-convex optimization with non-smooth regularizers, providing a framework for achieving convergence from initial solutions to global optima [29].

In distributed settings, the Distributed Projected Subgradient Method (DPSM) offers a robust solution for minimizing weakly convex functions across a network of agents, with theoretical guarantees of convergence in weakly convex environments [10]. This is particularly relevant in applications requiring efficient coordination among multiple agents to achieve optimal solutions.

Non-convex optimization plays a critical role in advancing image processing techniques by providing a framework for tackling complex non-linear and ill-posed problems. This approach incorporates structural constraints, such as sparsity and low rank, essential for modeling high-dimensional data and training non-linear models like deep neural networks. Despite the computational difficulties posed by non-convex problems, including the risk of converging to spurious local minima, recent theoretical advancements and practical algorithms have shown effectiveness in applications like robust matrix completion and neural network learning. Consequently, non-convex optimization enhances image processing algorithms' modeling capabilities and facilitates the development of explainable systems that meet safety and privacy demands in machine learning applications [30, 31, 32, 33]. Developing robust algorithms to navigate this complex landscape is essential for driving innovation and achieving accurate solutions in image processing.

2.4 Signal Processing and Computer Vision

The intersection of signal processing and computer vision is crucial for advancing image processing capabilities, enabling the extraction and analysis of meaningful information from visual data. Signal processing techniques are integral to enhancing and restoring images, addressing noise reduction, feature extraction, and reconstruction. These foundational algorithms enhance computer vision systems' performance [34].

In computer vision, integrating signal processing methodologies fosters robust algorithms capable of interpreting complex scenes and recognizing patterns. For instance, combining signal processing techniques with advanced optimization algorithms addresses the challenge of avoiding saddle points in high-dimensional optimization tasks, improving convergence rates and stability in computer vision models [34]. This synergy is crucial for applications like object detection and image segmentation, where precise feature extraction and classification are essential.

Signal processing also transforms raw image data into formats more suitable for analysis by computer vision algorithms. Techniques such as wavelet transforms and Fourier analysis decompose images into their frequency components, facilitating the identification of salient features while mitigating noise interference. This is particularly beneficial in analyzing multispectral and hyperspectral images, which contain richer spectral information than traditional RGB images. Enhanced feature extraction and classification capabilities improve the accuracy of historical document analysis, especially in the presence of camera-induced noise and blur. Advanced preprocessing methods, such as low-rank projection and PSF estimation, further optimize the deblurring process, enhancing image quality across spectral bands [11, 7, 35]. This preprocessing step is critical for improving the accuracy and efficiency of subsequent computer vision tasks, such as recognition and tracking.

The convergence of signal processing and computer vision has led to significant advancements in innovative imaging modalities like hyperspectral (HS) and multispectral (MS) imaging. These modalities capture data across multiple wavelengths, providing spatial and spectral information that extends beyond the visible range. This rich spectral data enhances feature extraction, classification, and recognition capabilities, improving complex image analysis, including historical documents. However, challenges like camera-induced noise and blur necessitate sophisticated preprocessing techniques, including novel blind deblurring methods leveraging HS images' low-rank properties. These advancements are crucial for achieving high-quality outputs in various applications, particularly under challenging conditions [11, 7]. Advanced imaging techniques rely on signal processing algorithms to manage the vast data generated, enabling detailed spectral information extraction that enhances computer vision capabilities.

The integration of signal processing and computer vision is essential for advancing image processing, providing theoretical and practical frameworks for developing sophisticated image analysis techniques. Ongoing collaboration among computer vision, machine learning, and advanced imaging techniques significantly enhances innovation in image processing. This interdisciplinary effort leads to developing more accurate, efficient, and robust solutions, particularly in analyzing multispectral and hyperspectral images. By leveraging the rich spectral information in these images, researchers improve feature extraction and classification processes, crucial for historical document analysis. Additionally, novel blind deblurring methods address challenges like camera-induced noise and blur, facilitating clearer image extraction for further analysis and advancing image restoration in complex environments [11, 7].

3 Blind Deblurring Techniques

Blind deblurring techniques are pivotal in image processing, facilitating the restoration of sharp images from blurred inputs. This section delves into various methodologies, highlighting significant advancements in the field. Table 1 offers a detailed classification of blind deblurring techniques, elucidating the methods and features across different categories such as multichannel blind deconvolution and deep learning approaches. Additionally, Table 2 offers a comprehensive comparison of blind deblurring techniques, highlighting distinct methodologies and their respective innovations and challenges. As illustrated in **??**, the hierarchical categorization of blind deblurring techniques encompasses multichannel blind deconvolution, which enhances image quality by utilizing information from multiple channels to address varying blur conditions. The figure further delineates challenges in

AI-generated, for reference only.

Category	Feature	Method
Multichannel Blind Deconvolution	Progressive Refinement Techniques	MSLS[36]
Challenges in Denoising and Reconstruction	Optimization Challenges	NIDF[37], EBD[38], LUD-SO(d)[39], INFWIDE[40], MGSTNet[41], SPKE[42], INRPCA[43], POIKE[44], DUBLID[45]
Traditional and Iterative Methods	Iterative Enhancement Techniques Complex Optimization Challenges	SNUBD[46], DDDP[47], DRLD[48], LDM[8] EDI[4]
Deep Learning Approaches	Motion and Spatial Techniques Direct Learning Approaches Feature Adjustment Methods Architecture and Framework Modifications	BMD[6], DDSD[49], SPAC[3] DGF[50], DD[51] SFTN-DD[26] DFD[52], RGTV[53]

Table 1: This table provides a comprehensive overview of various blind deblurring techniques categorized into multichannel blind deconvolution, challenges in denoising and reconstruction, traditional and iterative methods, and deep learning approaches. Each category is associated with specific features and methodologies, highlighting the diverse strategies employed to enhance image restoration processes. The table serves as a reference for understanding the current landscape of blind deblurring advancements, showcasing the integration of traditional methods with modern deep learning techniques.

denoising and reconstruction, as well as traditional and iterative methods, alongside emerging deep learning approaches, each accompanied by their respective techniques, applications, and innovations.

3.1 Multichannel Blind Deconvolution

Multichannel blind deconvolution is crucial for recovering sharp images from blurred observations by leveraging information across multiple channels, especially in scenarios with spatially variant blur. Techniques like using a coarse image as a latent structure prior progressively restore sharp images from coarse to fine scales on a blurry image pyramid [36]. The Multiscale Generalized Shrinkage Threshold Network (MGSTNet) advances this domain by iteratively updating blurring kernels and images through shrinkage thresholds [41].

Innovative methods such as Phase-only Image Based Kernel Estimation (POIKE) exploit phase information for robust kernel estimation, less sensitive to noise [44]. The Data-Driven Discriminative Prior (DDDP) method enhances deblurring accuracy using a binary classifier to learn an image prior distinguishing between clear and blurred images [47]. Deep Unrolling for Blind Deblurring (DUBLID) integrates traditional optimization techniques with neural networks, learning key parameters from training images [45]. The Spatiotemporal Phase Aperture Coding (SPAC) method captures motion dynamics by varying the PSF based on color during exposure, effective in motion blur scenarios [3].

The BMD method tailors models for specific devices, ensuring effective deblurring across various photographic conditions [6]. Multichannel blind deconvolution represents significant advancement by leveraging rich spectral information from multispectral and hyperspectral images, enhancing feature extraction and classification for applications like historical document restoration [11, 7, 35]. These techniques enhance precision and reliability in image restoration.

3.2 Challenges in Denoising and Reconstruction

Challenges in denoising and reconstructing images stem from the ill-posed nature of blind deconvolution, requiring estimation of both the blur kernel and latent image from degraded observations [41]. Non-convex optimization complicates this process, necessitating effective initialization to avoid local minima [44]. Residual noise post-denoising leads to artifacts degrading image quality [37].

As illustrated in Figure 2, the hierarchical challenges in image denoising and reconstruction are depicted, emphasizing the ill-posed nature of blind deconvolution alongside the impact of noise and artifacts, as well as the limitations of current methodologies. Accurate blur kernel estimation under high noise conditions is challenging, often resulting in oversmoothing and errors [38]. Low-light scenarios exacerbate these issues due to non-linear saturation effects and complex noise distributions [40]. Additionally, the inability to identify outliers a priori distorts estimates, as fitting models to data with outliers can lead to inaccurate reconstructions [42].

Traditional methods struggle with outliers, where conventional least squares and convex relaxation techniques may underperform [39]. Existing RPCA methods face performance degradation with increasing subspaces due to row-coherence issues [43]. Deep algorithm unrolling integrates regularization within the optimization framework, enhancing the ability to handle the ill-posedness of blind deconvolution tasks [45]. Despite advancements, challenges in accurately reconstructing images while mitigating noise persist, underscoring the need for ongoing research.

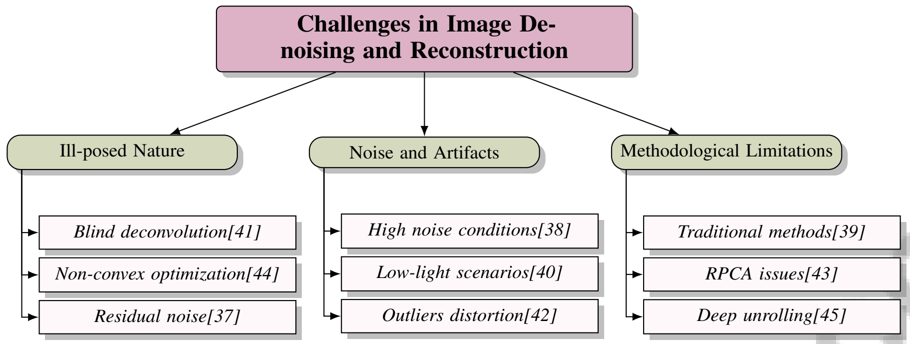


Figure 2: This figure illustrates the hierarchical challenges in image denoising and reconstruction, highlighting the ill-posed nature of blind deconvolution, the impact of noise and artifacts, and the limitations of current methodologies.

3.3 Traditional and Iterative Methods

Traditional and iterative methods have long been foundational in blind deblurring, providing structured frameworks for refining both blur kernels and latent images. These methods rely on iterative estimates to enhance precision, especially when initial estimates are error-prone. A significant challenge is their dependence on known blur kernel assumptions, which can lead to artifacts and inaccuracies [46]. High computational costs and difficulties in managing irregular camera trajectories further underscore the need for innovative solutions [6].

The integration of deep learning with traditional iterative methods has led to substantial advancements, such as using CNNs for PSF estimation and image deblurring [3]. The Event-based Double Integral (EDI) model reconstructs sharp videos from a single blurry frame through non-convex optimization, demonstrating the potential of combining traditional methods with modern optimization techniques [4].

Optimizing deblurring with learned image priors, particularly involving non-linear CNNs, presents challenges in achieving effective deblurring [47]. Traditional methods often favor blurry images with low-frequency content, complicating sharpness restoration [53]. Innovative approaches like the LatentDEM model leverage iterative processes of image recovery and forward operator estimation, using latent diffusion models (LDMs) [8].

The JIED method integrates event data with blurry images to iteratively reconstruct high-quality images and denoised events, addressing traditional deblurring limitations. Using a learnable latent map for modeling saturated pixels allows more accurate representation and effective deblurring, particularly in low-light conditions [48]. Traditional and iterative methods are pivotal in advancing blind deblurring, addressing challenges posed by various types of blur, such as camera shake and defocus. Recent developments focus on leveraging advanced image properties, including rich spectral information in hyperspectral images, to enhance feature extraction and classification accuracy. These methods have evolved to tackle spatially variant blur kernels through frameworks like Bayesian inference, variational methods, and sparse representation, significantly improving image restoration quality in diverse and challenging conditions [11, 7, 35]. By iteratively refining estimates and integrating deep learning advancements, these methods continue to enhance the precision and reliability of image restoration processes.

3.4 Deep Learning Approaches

Deep learning models have revolutionized blind deblurring by utilizing neural networks to map blurred images directly to sharp ones, eliminating the need for explicit blur kernel estimation. GANs have played a crucial role in this area, offering a framework that restores sharp images from blurred inputs without kernel estimation, thereby simplifying the deblurring process [50]. The application of deep generative filter frameworks exemplifies this innovation, streamlining the deblurring task through end-to-end learning.

A notable challenge in deploying deep learning models for deblurring is balancing network size with receptive field, which can hinder the training of larger networks [54]. The Deep Face Deblurring (DFD) method addresses this by employing a modified ResNet to enhance face images, effectively managing alignment issues that often arise in face deblurring [52]. Similarly, one-step methods utilizing CNNs aim to efficiently restore sharp face images, highlighting the importance of network architecture in overcoming traditional deblurring challenges [51].

Integrating optical flow with spatially variant RNNs has proven effective in dynamic scene deblurring, adaptively handling spatial variations within images to improve blur removal [49]. This approach illustrates the potential of combining traditional motion estimation techniques with deep learning to enhance deblurring outcomes. Additionally, the Spatial Feature Transform Network for Defocus Deblurring (SFTN-DD) utilizes a defocus map as conditional guidance, dynamically adjusting features from input blurry images to enhance the deblurring of defocused regions [26].

The method proposed by Elmalem et al. showcases significant improvements in motion deblurring performance by effectively utilizing encoded motion information captured during image acquisition, demonstrating the potential of integrating domain-specific knowledge into deep learning models [3]. The use of a reweighted graph total variation (RGTV) prior facilitates better kernel estimation and image restoration, promoting a bi-modal edge weight distribution [53].

Future research may explore integrating deep learning techniques to enhance the adaptability and performance of BMD methods in dynamic environments, further advancing the capabilities of these models [6]. By focusing on improving dataset diversity, robustness, and exploring novel priors, the field can continue to provide versatile solutions to the complex challenges of blind deblurring.

Feature	Multichannel Blind Deconvolution	Challenges in Denoising and Reconstruction	Traditional and Iterative Methods
Core Technique	Multi-channel Analysis	Kernel Estimation	Iterative Estimation
Key Innovation	Latent Structure Prior	Deep Algorithm Unrolling	Deep Learning Integration
Primary Challenge	Spatially Variant Blur	Ill-posed Nature	High Computational Cost

Table 2: This table provides a comparative analysis of various blind deblurring techniques, detailing the core techniques, key innovations, and primary challenges associated with each method. It encompasses multichannel blind deconvolution, challenges in denoising and reconstruction, and traditional and iterative methods, offering insights into their unique approaches and limitations.

4 Impulse Noise Detection and Mitigation

Impulse noise poses a significant challenge in image processing, characterized by sporadic disturbances that introduce extreme pixel values, potentially degrading image quality. This is particularly critical in applications such as medical imaging and the restoration of historical documents. Understanding how impulse noise affects image quality is imperative for developing effective detection and mitigation strategies.

4.1 Impact of Impulse Noise on Image Quality

Impulse noise degrades image quality by introducing random extreme pixel values, complicating scenarios where clean images for training denoising methods are scarce. This noise impairs the readability of QR codes and necessitates robust detection methods for accurate data retrieval [55, 13]. In historical document restoration, impulse noise, combined with blur, requires specialized preprocessing techniques to preserve original content integrity [11]. The accurate estimation of the camera's point-spread function further complicates noise mitigation [56].

As illustrated in Figure 3, the hierarchical impact of impulse noise on image quality is categorized, highlighting the degradation effects, challenges in noise mitigation, and advanced strategies for addressing impulse noise across various imaging scenarios. Impulse noise affects image features like textures and edges, especially when combined with other noise types such as multiplicative noise or speckle [57]. This degradation complicates data analysis and interpretation, as artifacts like motion blur and pixel saturation hinder assessments in applications like endoscopy videos [58]. Errors in blur kernel estimation during non-blind deconvolution exacerbate these challenges [51]. Advanced techniques, such as Laplacian filtering, are crucial for improved edge preservation and computational efficiency in managing impulse noise.

Sophisticated detection and mitigation strategies are needed to address impulse noise's significant impact on image quality, particularly in scenarios involving blur from camera movement or out-of-focus effects. Techniques like self-paced kernel estimation, which identify reliable inlier pixels for accurate kernel estimation, effectively address both feature and label noise within a unified learning framework [59, 42].

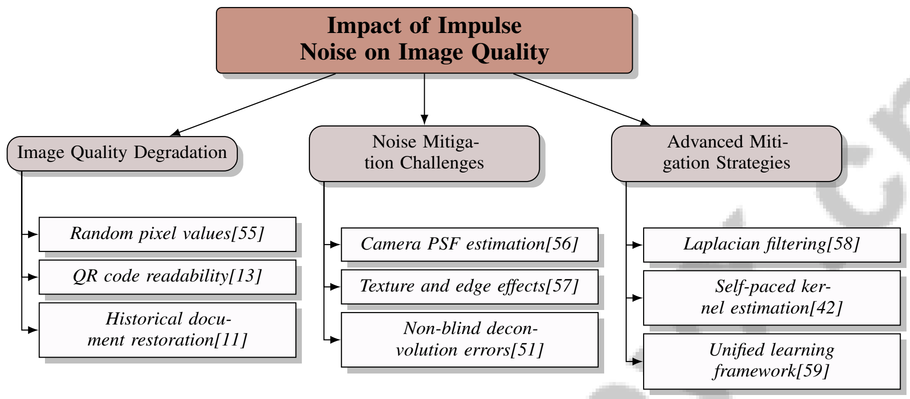


Figure 3: This figure illustrates the hierarchical impact of impulse noise on image quality, categorizing the degradation effects, challenges in noise mitigation, and advanced strategies for addressing impulse noise in various imaging scenarios.

4.2 Robust Detection Methods

Robust detection methods are essential for identifying and mitigating impulse noise, which significantly impacts image quality. Recent advancements include partially linear denoisers trained exclusively on noisy images, addressing clean training data scarcity [55]. The Fields of Experts (FoE) model integrated with non-convex optimization algorithms enhances noise reduction, particularly for speckle noise [57]. A Bayesian framework with learned priors significantly improves impulse noise detection and mitigation [60].

The Sliding Frank-Wolfe algorithm enhances accuracy in spike recovery without a discretized grid, accommodating various imaging modalities [61]. Block sparse recovery methods improve detection by managing redundant and non-redundant blocks, enhancing recovery performance across diverse datasets [62]. In event-based imaging, using image gradients for event denoising effectively mitigates noise in dynamic scenes [63]. Frameworks for endoscopic video analysis have successfully detected and restored multiple artifacts, significantly improving quantitative and visual quality [58].

The integration of advanced detection methods demonstrates significant progress in addressing impulse noise, particularly through innovative approaches like "Feature and Label Recovery" (FLR) that reconstruct both feature and label matrices. Recent advancements in blind image deblurring, focusing on identifying reliable inliers for kernel estimation, further enhance image quality across diverse applications [59, 42].

4.3 State-of-the-Art Algorithms

State-of-the-art algorithms for impulse noise detection and mitigation have advanced through integrating deep learning frameworks and innovative computational strategies. A notable approach employs a multi-scale, single-stage convolutional neural network (CNN) for impulse noise detection, combined with generative adversarial networks (GANs) for restoration [58]. This fusion enhances the ability to accurately identify and mitigate impulse noise in complex imaging scenarios.

GANs, particularly impactful during the restoration phase, excel in generating high-quality images by learning underlying data distributions, effectively eliminating noise artifacts introduced during

AI-generated, for reference only.

detection. Recent developments include edge-enhanced networks that use a "coarse-to-fine" approach to guide deblurring with sharp edge information and hierarchical content loss functions to improve performance. GANs can also function in unsupervised settings, utilizing structured denoisers trained solely on noisy images, achieving impressive results without clean reference images [64, 65, 55, 66].

Multi-scale CNNs enhance feature capture across various resolutions, establishing a comprehensive detection framework. This approach addresses hybrid noise challenges—comprising both feature and label noise—and improves image deblurring robustness by enabling the sequential identification of reliable inlier pixels for better kernel estimation. By leveraging adaptive matrix norms and advanced optimization methods, such as the non-convex Alternating Direction Method of Multipliers (ADMM), multi-scale CNNs facilitate superior performance in real-world scenarios, ultimately enhancing image quality and model generalization [59, 67, 42].

The integration of advanced algorithms into a cohesive framework marks significant progress in impulse noise detection and mitigation, offering robust solutions for enhancing image quality across diverse applications. This framework leverages structured denoisers that operate effectively with only noisy images, circumventing the need for costly clean datasets. By employing a cascaded architecture that combines denoising and deblurring processes, the system demonstrates improved resilience against residual noise, leading to superior performance in restoring clarity and detail in images affected by various degradations [37, 55, 35, 42]. The combination of CNNs and GANs provides a flexible and effective solution for the challenges posed by impulse noise in modern image processing.

4.4 Challenges in Impulse Noise Mitigation

Mitigating impulse noise presents several challenges, primarily due to the complexities of accurately detecting and removing noise while preserving critical image features such as small textures and edges. A significant difficulty arises from the established pessimistic worst-case complexities for non-convex functions, which often do not reflect practical performance in real-world applications [68]. This discrepancy underscores the need for sophisticated algorithms capable of effectively managing the non-convex nature of impulse noise problems.

The reliance on generative models in deconvolution methods presents another challenge, as these models may not adequately capture the complexities of certain image classes, limiting their effectiveness in impulse noise mitigation [69]. Developing more adaptable models that can handle a broader range of image complexities is essential.

Furthermore, robust detection methods must preserve small textures and edges during the deblurring process. Designing algorithms that accurately detect and mitigate noise without compromising fine image details requires a delicate balance between noise suppression and detail preservation, which is often challenging for conventional techniques [70]. Additionally, methods like FLR face limitations due to their reliance on linearity assumptions, which can restrict performance in capturing complex, non-linear relationships in certain datasets [59].

These multifaceted challenges necessitate advanced detection techniques, adaptable generative models, and algorithms that effectively preserve image details while managing the complexities of non-convex optimization. Addressing these issues is crucial for advancing image processing, particularly in applications involving multispectral and hyperspectral images, where integrating rich spectral information can significantly enhance feature extraction and classification accuracy. Effective solutions must overcome challenges such as camera-induced noise and blur, which can degrade image quality and hinder analysis. By tackling these complexities, we can improve impulse noise mitigation strategies, ultimately enhancing performance in image restoration and analysis tasks [35, 12, 11, 59, 42].

5 Non-convex Optimization in Image Processing

Non-convex optimization in image processing necessitates an in-depth examination of both theoretical advancements and their practical implementations. This section addresses key theoretical developments that form the foundation of methodologies in image restoration and enhancement, offering insights into their broader implications.

5.1 Theoretical Advances

Recent advancements in non-convex optimization have significantly enriched image processing by introducing frameworks to tackle its inherent complexities. Concepts such as H()-convexity and H()-smoothness have redefined traditional convexity and smoothness paradigms, facilitating robust optimization techniques suited for non-convex challenges [29]. The Distributed Projected Subgradient Method (DPSM) enhances distributed optimization in weakly convex settings, bridging theoretical gaps of earlier methods [10]. The Stochastic Fast Newton (SFN) method has improved the handling of saddle points in high-dimensional non-convex landscapes, expediting convergence rates [28], which is beneficial for applications requiring rapid convergence to high-quality solutions.

Integrating robust low-rank representations into optimization frameworks accelerates computational speed, making these methods viable for real-time applications while maintaining performance across diverse tasks [9]. These theoretical insights are crucial for managing large-scale data and complex image processing challenges, particularly in hyperspectral and multispectral imagery, where leveraging spectral and spatial information enhances feature extraction and classification. Innovative blind deblurring techniques tailored for document images address issues such as camera-induced noise and blur, offering potential improvements in image quality across spectral bands [11, 7]. Continued refinement of these methodologies is essential for navigating the complexities of non-convex optimization landscapes, advancing the field of image processing.

5.2 Applications in Image Processing

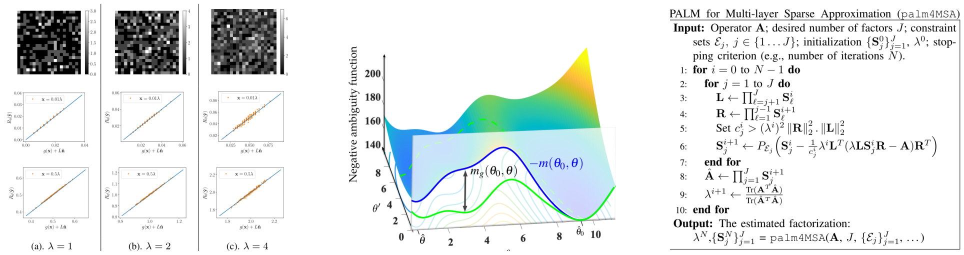
Non-convex optimization is pivotal in image processing, particularly in restoration and enhancement tasks that address ill-posed inverse problems. The RGTV prior exemplifies its utility, demonstrating superior performance in enhancing image sharpness and addressing blind image deblurring, achieving reconstruction quality comparable to state-of-the-art methods [53]. This underscores the effectiveness of non-convex optimization in refining image processing tasks through advanced priors.

The LatentDEM framework illustrates the application of non-convex optimization in blind inversion problems by employing latent diffusion models (LDMs) for enhanced prior modeling and efficient computation [8], highlighting the importance of integrating powerful priors with optimization strategies for improved restoration outcomes. The SFN method's proficiency in high-dimensional non-convex landscapes enhances convergence rates, benefiting applications that require swift access to high-quality solutions, as shown in multilayer perceptron experiments on down-sampled datasets [28].

In image restoration, non-convex optimization techniques support real-time processing and high detection accuracy, critical for robust solutions. Frameworks capable of restoring multiple artifact types within a single system exemplify this advancement [29]. Ongoing refinement of stagewise learning frameworks promises enhanced theoretical convergence and empirical performance, reinforcing the role of non-convex optimization in image processing.

Furthermore, non-convex optimization advances image processing technologies by providing sophisticated solutions for complex tasks such as restoration and enhancement. Techniques like robust matrix completion and non-convex principal component analysis enable accurate recovery of low-rank structures from noisy data, improving performance in applications like classification and denoising. These methods not only enhance result quality but also offer theoretical convergence guarantees, addressing challenges posed by traditional convex approaches in high-dimensional scenarios [43, 30, 71, 33]. By leveraging advanced optimization strategies, researchers can develop more effective methodologies for image restoration, propelling the field forward.

As depicted in Figure 4, non-convex optimization is crucial in enhancing the quality and efficiency of various image processing applications. The first image showcases a comparative analysis of different regularization methods in linear regression, highlighting their capability to improve data interpretation and prediction accuracy by managing overfitting and noise. The second image examines the negative ambiguity function, offering insights into information loss during signal compression or quantization, key for optimizing data storage and transmission. The third image illustrates the Palm algorithm for multi-layer sparse approximation (palm4MSA), a technique for approximating operators with sparse matrices, boosting computational efficiency and accuracy in multi-layered data structures. Collectively, these examples highlight the transformative potential of non-convex



(a) Comparison of the performance of different regularization methods in the context of a linear regression problem[55]

(b) The Negative Ambiguity Function[72]

(c) Palm for Multi-layer Sparse Approximation (palm4MSA)[73]

Figure 4: Examples of Applications in Image Processing

optimization techniques in advancing image processing methodologies, pushing the boundaries of digital analysis and manipulation of visual data [55, 72, 73].

6 Handling Saturated Images

6.1 Challenges of Saturated Images

Image saturation poses significant challenges in processing by impairing dynamic range and detail retention in overexposed areas. When pixel values exceed the sensor's threshold, highlights are clipped, leading to a loss of brightness nuances, a problem exacerbated in high-dynamic-range (HDR) scenes [8]. Saturation complicates deblurring as traditional algorithms assume a linear relationship between captured images and the actual scene, which is disrupted by saturation, leading to inaccurate blur kernel estimations [7]. This non-linearity necessitates advanced modeling techniques [3].

In optical imaging and digital holography, saturation impedes precise phase retrieval, affecting spatial distribution accuracy and image fidelity, crucial in scientific and medical imaging [5]. Event-based cameras, which rely on intensity changes to capture dynamic scenes, also suffer from saturation, leading to erroneous event generation and complicating data processing [4]. Addressing these issues requires innovative algorithms to effectively manage saturation effects, enhancing image restoration and data interpretation across various applications.

6.2 Techniques for Managing Saturation

Managing saturation is crucial in image processing, especially in HDR scenarios where scene dynamic range surpasses sensor capabilities. Advanced tone mapping algorithms compress the dynamic range of HDR images while preserving visual details and minimizing saturation artifacts through non-linear transformations [7]. Exposure fusion combines multiple exposures of the same scene to create a single image capturing details in shadows and highlights, mitigating saturation by leveraging various exposure levels [4].

Integrating event-based cameras with traditional imaging systems shows promise in deblurring saturated images by capturing intensity changes with high temporal resolution, aiding in reconstructing saturated regions [3]. Machine learning, particularly deep learning frameworks, offers powerful tools for managing saturation by training models on datasets of saturated and non-saturated images, effectively correcting saturation artifacts [8].

Advancements in managing saturation and blur are vital for high-quality image restoration and accurate data interpretation, especially in complex scenarios like historical document analysis and medical imaging. Techniques such as tone mapping, exposure fusion, event-based imaging, and machine learning enhance visual quality and fidelity [7, 55, 11, 48, 58].

6.3 Proposed Approach for Saturation Handling

The proposed approach integrates advanced imaging techniques with machine learning frameworks to address saturation challenges, enhancing image quality and fidelity. It combines traditional and contemporary strategies, leveraging hyperspectral image spectral information and addressing issues like camera-induced noise and blur through preprocessing techniques such as blind deblurring and Weber's Law-based regularization for edge preservation [11, 70].

A critical element is the use of event-based cameras, capturing intensity changes with microsecond precision, aiding in reconstructing details in saturated regions [4]. Deep learning models, trained on datasets of varying saturation levels, recognize and correct saturation artifacts, effective across different scenarios [8]. The approach also employs advanced tone mapping and exposure fusion techniques to compress HDR image dynamic range while preserving visual details and mitigating saturation [7, 3].

This innovative method establishes a robust framework for managing saturation, enhancing high-quality visual data restoration under challenging conditions. By employing techniques such as blind hyperspectral image deblurring and data-driven models, it addresses issues like noise and blur while improving feature extraction and classification accuracy. Generative adversarial networks facilitate artifact detection and restoration, ensuring higher fidelity of visual data across applications, including historical document analysis and medical imaging [11, 58, 16, 48]. Combining event-based imaging, deep learning, tone mapping, and exposure fusion, this method offers a robust solution for managing saturated images, advancing image processing applications.

7 Development of Robust Algorithms

Developing robust algorithms for image processing requires strategies that enhance resilience against noise and distortions. This involves utilizing advanced regularization techniques, robust low-rank representations, and higher-order Markov Random Fields (MRFs), which collectively improve algorithm performance in deep learning and non-convex optimization contexts. Adaptive algorithms, which optimize training efficiency without prior parameter knowledge, significantly enhance deep neural network training. Additionally, innovative multiplicative update rules and momentum-based methods accelerate training and strengthen model robustness against diverse optimization challenges, thereby advancing machine learning systems and enriching their theoretical foundations [14, 67, 33, 74].

7.1 Algorithmic Strategies for Robustness

Robust algorithm development is crucial in image processing to withstand various noise and distortion types. Advanced regularization techniques are vital for managing noise and blurring complexities, enhancing algorithmic efficiency [13]. Robust low-rank representations enable real-time performance with minimal latency, effectively handling outliers that obscure critical information [9]. Incorporating higher-order MRFs into variational frameworks enhances robustness, particularly in despeckling applications where rapid noise reduction is essential [57]. By integrating these sophisticated strategies, algorithms can better manage noise and distortions, improving their applicability and performance in real-world scenarios [43, 9, 59, 33].

7.2 Optimization Techniques for Robust Performance

Optimization techniques are pivotal for ensuring robust image processing algorithm performance amid noise and distortions. Adaptive optimization methods, which dynamically adjust parameters, are essential for managing complex image processing tasks [14]. Non-convex optimization methods effectively navigate complex landscapes, especially suited for high-dimensional data and ill-posed problems [29]. Advanced regularization strategies further enhance stability and accuracy in image restoration tasks [9]. Distributed optimization frameworks, like the Distributed Projected Subgradient Method (DPSM), efficiently manage weakly convex functions in large-scale applications [10]. Stochastic optimization techniques, such as the Stochastic Fast Newton (SFN) method, provide rapid convergence to high-quality solutions, improving convergence rates [28]. These strategies ensure robust algorithm performance, effectively mitigating noise and distortion challenges. Techniques like blind deblurring for hyperspectral images enhance feature extraction, while frameworks like Feature and Label Recovery (FLR) address hybrid noise by reconstructing feature and label matrices. Novel regularization methods, such as Weber's Law Regularization, focus on preserving critical image edges during deblurring, contributing to overall image analysis quality and reliability [12, 11, 59, 33, 70].

7.3 Real-Time Processing and Scalability

Real-time processing and scalability are crucial in developing image processing algorithms due to the growing demand for high-speed, efficient solutions. The computational complexity of tasks like blind deblurring and noise mitigation poses significant challenges, often involving large-scale optimization problems requiring substantial resources [9]. Efficient algorithmic strategies are essential to address these challenges. Robust low-rank representations facilitate real-time performance by reducing data dimensionality, enabling faster processing while maintaining high accuracy [9]. Distributed optimization frameworks, like DPSM, offer scalable solutions for large-scale tasks by coordinating computations across multiple agents [10]. Adaptive optimization techniques enhance scalability by dynamically adjusting parameters, ensuring consistent performance across varying datasets [14]. These solutions, including advanced blind deblurring techniques for hyperspectral images and comprehensive reviews of deblurring methods, enable the creation of robust, scalable algorithms that effectively address complex imaging conditions, meeting contemporary application demands [11, 7, 12].

8 Ensuring Noise Robustness

8.1 Handling Noise and Distortions

Addressing noise and distortions in image processing is crucial, especially when ground truth images are unavailable for training conventional supervised models. The reliance on clean images limits traditional denoising techniques [55]. Innovative unsupervised learning methods have emerged, enabling the training of denoisers using only noisy images by exploiting their inherent structure and statistical properties. Partially linear denoisers exemplify this approach, modeling noise distribution and image features directly from noisy data, thus providing robust denoising solutions applicable in real-world scenarios [55].

Advanced regularization techniques play a vital role in mitigating noise and distortions, particularly in ill-posed inverse problems. These techniques enhance the recovery of latent images and blur kernels in applications like blind image deblurring, improving feature extraction accuracy in multispectral and hyperspectral imagery by addressing camera-induced noise and blur. Methods such as inexact Krylov techniques and Weber's Law-based regularization offer computational savings and improved image quality, facilitating accurate analysis across various domains [11, 70, 12, 75]. By incorporating prior knowledge about natural image structures, these methods enhance denoising algorithm stability and accuracy, preserving fine details and edges while effectively suppressing noise.

The integration of unsupervised learning and advanced regularization techniques establishes a robust framework for noise management in image processing. These approaches enable the development of advanced denoising algorithms that operate effectively without ground truth data. By leveraging structured denoisers trained solely on noisy images and utilizing joint learning techniques for denoising and deblurring, these methods significantly enhance image restoration outcomes. They address challenges posed by hybrid noise in real-world scenarios, thereby expanding the applicability of image processing across various contexts, including blind deblurring and robust machine learning under noisy conditions [37, 59, 55].

8.2 Techniques for Enhancing Noise Robustness

Enhancing noise robustness is essential for high-quality image restoration, especially in environments lacking clean reference images. Partially linear denoisers facilitate image restoration without requiring clean counterparts by leveraging the inherent structure within noisy images, effectively addressing the limitations of traditional supervised methods [55]. Stagewise learning algorithms further enhance noise robustness by incrementally refining the learning process, improving generalization, reducing testing errors, and outperforming traditional approaches [76].

Incorporating advanced techniques such as hybrid noise recovery, low-rank approximation, and joint learning frameworks significantly bolsters algorithmic resilience to noise. These methods address both feature and label noise prevalent in real-world scenarios, ensuring robust performance even under high noise levels and limited clean reference images. Frameworks like "Feature and Label Recovery" and cascaded networks for denoising and deblurring contribute to improved feature extraction and blur kernel estimation, leading to superior outcomes in document analysis and image restoration tasks [11, 37, 59]. These advancements are crucial for expanding the applicability of image processing solutions across diverse real-world scenarios.

8.3 Algorithmic Innovations and Their Impact

Recent algorithmic innovations have significantly enhanced noise robustness in image processing, addressing diverse noise types and improving the fidelity of restored images. The Deep Mean-Shift Priors (DMSP) framework integrates learned priors into a Bayesian framework for superior noise suppression and image restoration, utilizing deep learning to model complex noise distributions [60]. The Sliding Frank-Wolfe algorithm offers an efficient method for spike recovery without a discretized grid, enhancing noise robustness by accurately recovering sparse signals amidst substantial noise [61].

In unsupervised learning, partially linear denoisers enable effective noise removal without clean training data by utilizing the statistical properties of noisy images to learn robust noise suppression models [55]. Robust low-rank representations facilitate real-time performance with minimal latency, addressing computational challenges associated with large-scale data processing by effectively managing outliers and noise [9].

Advancements in algorithmic techniques have notably improved noise robustness, particularly in addressing hybrid noise, which includes both feature and label noise. Innovations such as the "Feature and Label Recovery" (FLR) framework reconstruct feature and label matrices to enhance model performance, while self-paced kernel estimation methods effectively identify reliable inlier pixels for blind image deblurring. New multiplicative update rules accelerate deep learning training and enhance model robustness, collectively improving image quality and broadening the functional capabilities of image processing systems across diverse applications, from historical document analysis to real-time photography [11, 59, 67, 42]. Continued exploration and integration of advanced algorithmic strategies will further enhance noise robustness and drive future advancements in the field.

9 Conclusion

9.1 Future Directions and Open Challenges

Advancements in image processing continue to open new research avenues that address existing limitations and foster innovative methodologies. A key area of focus is optimizing Blind Motion Deblurring (BMD) techniques for real-time applications, especially in scenarios involving extreme motion. Enhancing the computational efficiency and robustness of these algorithms is crucial for managing high-velocity motion blurs effectively. Another persistent challenge is the optimal modeling of various blur types, which remains a complex aspect of deblurring techniques. Future research should integrate advancements in hardware, such as improved sensor technologies, to enhance the effectiveness of deblurring algorithms. Additionally, exploring the application of Distributed Projected Subgradient Method (DPSM) in directed networks and extending it to non-convex constraints could provide valuable insights into distributed optimization within image processing.

The exploration of Latent Diffusion Expectation Maximization (LatentDEM) models presents another promising research direction. By integrating LatentDEM with various loss functions, researchers can enhance its performance in 3D inference from 2D diffusion models, potentially transforming approaches to complex image reconstruction tasks. Furthermore, improving model robustness to distribution shifts and investigating complex geometric transformations could significantly enhance the adaptability and generalization of image processing algorithms. In non-convex optimization, future research is likely to focus on scaling Stochastic Fast Newton (SFN) methods for high-dimensional problems while further analyzing the theoretical properties of critical points in neural network training. These efforts aim to enhance the scalability and efficiency of optimization techniques, thereby advancing image processing capabilities. By pursuing these research directions and overcoming identified challenges, the field of image processing can continue to deliver sophisticated and effective solutions across various applications, fostering innovation and expanding its influence across multiple domains.

9.2 Real-World Applications and Performance Evaluation

Benchmark	Size	Domain	Task Format	Metric

Table 3: This table provides a comprehensive overview of representative benchmarks used in evaluating advanced image processing techniques. It details the size, domain, task format, and performance metric associated with each benchmark, offering insights into their applicability for real-world scenarios.

Deploying advanced image processing techniques in real-world scenarios is crucial for enhancing the quality and interpretability of visual data across diverse fields. In medical imaging, integrating robust deblurring and denoising algorithms is vital for improving diagnostic accuracy, as image clarity significantly impacts clinical outcomes. Techniques utilizing deep learning frameworks for blind deblurring have shown promise in reconstructing high-quality images from motion-blurred medical scans, facilitating more accurate diagnoses. In surveillance, the ability to detect and mitigate impulse noise is essential for preserving the integrity of visual data captured in challenging environments. Developing robust detection methods enhances the reliability of surveillance systems by maintaining fine detail even under noisy conditions. These advancements contribute to more effective monitoring and analysis, especially in security applications where image quality is critical.

Moreover, applying non-convex optimization techniques in image restoration has proven instrumental in addressing the complexities associated with real-time video processing. Implementing distributed optimization frameworks enables efficient handling of large-scale video data, ensuring high-quality visual outputs despite the computational demands of real-time processing. In consumer electronics, integrating image processing techniques in smartphone cameras has significantly enhanced user experience by improving image clarity and reducing artifacts from motion blur and noise. Advanced algorithms empower smartphones to capture high-quality images across various lighting conditions, broadening their usability and appeal. Evaluating the performance of these techniques in real-world applications underscores their effectiveness in enhancing image quality and processing efficiency. Table 3 presents a detailed summary of representative benchmarks that are instrumental in assessing the performance of image processing techniques across various domains. By continuously refining methodologies and exploring new applications, the field of image processing can further extend its impact across diverse sectors, driving innovation and improving the accessibility and reliability of visual data.

References

[1] Shira Faigenbaum-Golovin and David Levin. Manifold reconstruction and denoising from scattered data in high dimension via a generalization of l_1-median, 2022.

[2] Thomas Eboli, Jean-Michel Morel, and Gabriele Facciolo. Fast two-step blind optical aberration correction, 2022.

[3] Shay Elmalem, Raja Giryes, and Emanuel Marom. Motion deblurring using spatiotemporal phase aperture coding, 2020.

[4] Liyuan Pan, Cedric Scheerlinck, Xin Yu, Richard Hartley, Miaomiao Liu, and Yuchao Dai. Bringing a blurry frame alive at high frame-rate with an event camera, 2018.

[5] Yu Sun and Ulugbek S. Kamilov. Stability of scattering decoder for nonlinear diffractive imaging, 2018.

[6] MAHESH MOHAN MR and Om Nama Sivaya. *Motion Deblurring Methodologies: Going Beyond Conventional Cameras*. PhD thesis, INDIAN INSTITUTE OF TECHNOLOGY MADRAS, 2021.

[7] Ruxin Wang and Dacheng Tao. Recent progress in image deblurring, 2014.

[8] Weimin Bai, Siyi Chen, Wenzheng Chen, and He Sun. Blind inversion using latent diffusion priors, 2024.

[9] Pablo Sprechmann, Alex M. Bronstein, and Guillermo Sapiro. Learning robust low-rank representations, 2012.

[10] Shixiang Chen, Alfredo Garcia, and Shahin Shahrampour. On distributed non-convex optimization: Projected subgradient method for weakly convex problems in networks, 2021.

[11] M. Ljubenovic, P. Guzzonato, G. Franceschin, and A. Traviglia. Blind deblurring of hyperspectral document images, 2023.

[12] Miguel Antunes Dias Alfaiate Simoes. *On some aspects of inverse problems in image processing*. PhD thesis, Université Grenoble Alpes; Instituto superior técnico (Lisbonne), 2017.

[13] Yves van Gennip, Prashant Athavale, Jérôme Gilles, and Rustum Choksi. A regularization approach to blind deblurring and denoising of qr barcodes, 2017.

[14] Zhenxun Zhuang. Adaptive strategies in non-convex optimization, 2023.

[15] Adarsh Barik, Anand Krishna, and Vincent Y. F. Tan. A sample efficient alternating minimization-based algorithm for robust phase retrieval, 2024.

[16] Nassir Mohammad and Alexander Balinsky. Colorization of natural images via l1 optimization, 2009.

[17] Wei Liu, Yun Gu, Chunhua Shen, Xiaogang Chen, Qiang Wu, and Jie Yang. Data driven robust image guided depth map restoration, 2015.

[18] Felipe Lara and Cristian Vega. Delayed feedback in online non-convex optimization: A non-stationary approach with applications, 2025.

[19] Yawen Xiang, Heng Zhou, Chengyang Li, Fangwei Sun, Zhongbo Li, and Yongqiang Xie. Deep learning in motion deblurring: current status, benchmarks and future prospects, 2024.

[20] Xiang Zhang, Jiarui Sun, Siwei Ma, Zhouchen Lin, Jian Zhang, Shiqi Wang, and Wen Gao. Globally variance-constrained sparse representation and its application in image set coding, 2018.

[21] Liwei Zhang, Haoyang Liu, and Xiantao Xiao. Regrets of proximal method of multipliers for online non-convex optimization with long term constraints, 2022.

[22] Mauricio Delbracio, Ignacio Garcia-Dorado, Sungjoon Choi, Damien Kelly, and Peyman Milanfar. Polyblur: Removing mild blur by polynomial reblurring, 2021.

[23] Kiryung Lee, Ning Tian, and Justin Romberg. Fast and guaranteed blind multichannel deconvolution under a bilinear system model, 2017.

[24] Jan Kotera, Denys Rozumnyi, Filip Šroubek, and Jiří Matas. Intra-frame object tracking by deblatting, 2019.

[25] Anima Anandkumar and Rong Ge. Efficient approaches for escaping higher order saddle points in non-convex optimization, 2016.

[26] Qian Ye, Masanori Suganuma, and Takayuki Okatani. Single-image defocus deblurring by integration of defocus map prediction tracing the inverse problem computation, 2022.

[27] Junjie Ma, Ji Xu, and Arian Maleki. Approximate message passing for amplitude based optimization, 2018.

[28] Yann Dauphin, Razvan Pascanu, Caglar Gulcehre, Kyunghyun Cho, Surya Ganguli, and Yoshua Bengio. Identifying and attacking the saddle point problem in high-dimensional non-convex optimization, 2014.

[29] Binchuan Qi, Wei Gong, and Li Li. Extended convexity and smoothness and their applications in deep learning, 2025.

[30] Prateek Jain and Purushottam Kar. Non-convex optimization for machine learning, 2017.

[31] Marina Danilova, Pavel Dvurechensky, Alexander Gasnikov, Eduard Gorbunov, Sergey Guminov, Dmitry Kamzolov, and Innokentiy Shibaev. Recent theoretical advances in non-convex optimization, 2021.

[32] Peter Ochs, Jalal Fadili, and Thomas Brox. Non-smooth non-convex bregman minimization: Unification and new algorithms, 2018.

[33] Shuai Zhang. Non-convex optimizations for machine learning with theoretical guarantee: Robust matrix completion and neural network learning, 2023.

[34] Lampros Flokas, Emmanouil-Vasileios Vlatakis-Gkaragkounis, and Georgios Piliouras. Efficiently avoiding saddle points with zero order methods: No gradients required, 2019.

[35] Zhengrong Xue. Blind image deblurring: a review, 2022.

[36] Yuanchao Bai, Huizhu Jia, Ming Jiang, Xianming Liu, Xiaodong Xie, and Wen Gao. Single image blind deblurring using multi-scale latent structure prior, 2019.

[37] Si Miao and Yongxin Zhu. Handling noise in image deblurring via joint learning, 2020.

[38] Jérémy Anger, Mauricio Delbracio, and Gabriele Facciolo. Efficient blind deblurring under high noise levels, 2019.

[39] Cindy Orozco Bohorquez, Yuehaw Khoo, and Lexing Ying. Maximizing robustness of point-set registration by leveraging non-convexity, 2020.

[40] Zhihong Zhang, Yuxiao Cheng, Jinli Suo, Liheng Bian, and Qionghai Dai. Infwide: Image and feature space wiener deconvolution network for non-blind image deblurring in low-light conditions, 2023.

[41] Yujie Feng, Yin Yang, Xiaohong Fan, Zhengpeng Zhang, and Jianping Zhang. A multi-scale generalized shrinkage threshold network for image blind deblurring in remote sensing, 2024.

[42] This iccv paper is the open acce.

[43] Niannan Xue, Jiankang Deng, Yannis Panagakis, and Stefanos Zafeiriou. Informed non-convex robust principal component analysis with features, 2017.

[44] Liyuan Pan, Richard Hartley, Miaomiao Liu, and Yuchao Dai. Phase-only image based kernel estimation for single-image blind deblurring, 2019.

[45] Yuelong Li, Mohammad Tofighi, Junyi Geng, Vishal Monga, and Yonina C. Eldar. Deep algorithm unrolling for blind image deblurring, 2019.

[46] Xiangfei Kong and Lin Yang. Microscopic muscle image enhancement, 2016.

[47] Lerenhan Li, Jinshan Pan, Wei-Sheng Lai, Changxin Gao, Nong Sang, and Ming-Hsuan Yang. Learning a discriminative prior for blind image deblurring, 2018.

[48] Liang Chen, Jiawei Zhang, Zhenhua Li, Yunxuan Wei, Faming Fang, Jimmy Ren, and Jinshan Pan. Deep richardson-lucy deconvolution for low-light image deblurring, 2023.

[49] Jiawei Zhang, Jinshan Pan, Daoye Wang, Shangchen Zhou, Xing Wei, Furong Zhao, Jianbo Liu, and Jimmy Ren. Deep dynamic scene deblurring from optical flow, 2023.

[50] Sainandan Ramakrishnan, Shubham Pachori. Aalok Gangopadhyay, and Shanmuganathan Raman. Deep generative filter for motion deblurring, 2017.

[51] Lingxiao Wang, Yali Li, and Shengjin Wang. Deepdeblur: Fast one-step blurry face images restoration, 2017.

[52] Grigorios G. Chrysos and Stefanos Zafeiriou. Deep face deblurring, 2017.

[53] Yuanchao Bai, Gene Cheung, Xianming Liu, and Wen Gao. Blind image deblurring via reweighted graph total variation, 2017.

[54] Siddhant Sahu, Manoj Kumar Lenka, and Pankaj Kumar Sa. Blind deblurring using deep learning: A survey, 2019.

[55] Rihuan Ke and Carola-Bibiane Schönlieb. Unsupervised image restoration using partially linear denoisers, 2021.

[56] Thomas Eboli, Jian Sun, and Jean Ponce. Learning to jointly deblur, demosaick and denoise raw images, 2021.

[57] Yunjin Chen, Wensen Feng, René Ranftl, Hong Qiao, and Thomas Pock. A higher-order mrf based variational model for multiplicative noise reduction, 2014.

[58] Sharib Ali, Felix Zhou, Adam Bailey, Barbara Braden, James East, Xin Lu, and Jens Rittscher. A deep learning framework for quality assessment and restoration in video endoscopy, 2019.

[59] Yang Wei, Shuo Chen, Shanshan Ye, Bo Han, and Chen Gong. Robust learning under hybrid noise, 2024.

[60] Siavash Arjomand Bigdeli, Meiguang Jin, Paolo Favaro, and Matthias Zwicker. Deep mean-shift priors for image restoration, 2017.

[61] Quentin Denoyelle, Vincent Duval, Gabriel Peyré, and Emmanuel Soubies. The sliding frank-wolfe algorithm and its application to super-resolution microscopy, 2018.

[62] Ehsan Elhamifar and Rene Vidal. Block-sparse recovery via convex optimization, 2012.

[63] Pei Zhang, Haosen Liu, Zhou Ge, Chutian Wang, and Edmund Y. Lam. Neuromorphic imaging with joint image deblurring and event denoising, 2024.

[64] Shuai Zheng, Zhenfeng Zhu, Jian Cheng, Yandong Guo, and Yao Zhao. Edge heuristic gan for non-uniform blind deblurring, 2019.

[65] Manoj Kumar Lenka, Anubha Pandey, and Anurag Mittal. Blind deblurring using gans, 2019.

[66] Junde Wu, Xiaoguang Di, Jiehao Huang, and Yu Zhang. Integrating neural networks into the blind deblurring framework to compete with the end-to-end learning-based methods, 2019.

[67] Manos Kirtas, Nikolaos Passalis, and Anastasios Tefas. Multiplicative update rules for accelerating deep learning training and increasing robustness, 2023.

[68] Jikai Jin. On the convergence of first order methods for quasar-convex optimization, 2020.

[69] Muhammad Asim, Fahad Shamshad, and Ali Ahmed. Blind image deconvolution using deep generative priors, 2019.

[70] Malik Najmus Saqib, Hussain Dawood, Ahmed Alghamdi, and Hassan Dawood. Weber's law-based regularization for blind image deblurring. *Engineering, Technology & Applied Science Research*, 14(1):12937–12943, 2024.

[71] Laming Chen and Yuantao Gu. The convergence guarantees of a non-convex approach for sparse recovery, 2014.

[72] Joel W. LeBlanc, Brian J. Thelen, and Alfred O. Hero. Testing that a local optimum of the likelihood is globally optimum using reparameterized embeddings, 2020.

[73] Luc Le Magoarou and Rémi Gribonval. Flexible multi-layer sparse approximations of matrices and applications, 2016.

[74] Cristian Daniel Alecsa. A theoretical and empirical study of new adaptive algorithms with additional momentum steps and shifted updates for stochastic non-convex optimization, 2024.

[75] Silvia Gazzola and Malena Sabaté Landman. Regularization by inexact krylov methods with applications to blind deblurring, 2021.

[76] Zaiyi Chen, Zhuoning Yuan, Jinfeng Yi, Bowen Zhou, Enhong Chen, and Tianbao Yang. Universal stagewise learning for non-convex problems with convergence on averaged solutions, 2019.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.

AI-generated, for reference only.