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A Review of Computational Methods for Image Restoration and Noise Reduction Using Reference Images

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Abstract

Digital imaging systems play a vital role in numerous application domains, including consumer photography, biomedical imaging, remote sensing, aerial surveillance, and astronomical observation. Despite continuous advancements in imaging hardware and software, the visual data acquired by these systems often suffer from degradation caused by spatially non-uniform blur. This blur may arise due to several factors, such as lens imperfections, atmospheric turbulence, sensor limitations, motion between the camera and the scene, and various post-processing operations. The presence of such degradation significantly affects image interpretability and overall visual quality, making accurate blur estimation a crucial and challenging research problem. Both global and local blur estimation are essential for effectively addressing spatially varying blur and restoring image fidelity. Reliable blur estimation not only enables improved image restoration but also provides meaningful information about the underlying scene structure. For instance, blur characteristics can be exploited to infer depth cues, object boundaries, and regions of visual saliency. Motivated by these considerations, this study investigates a transformation-based image restoration framework to mitigate blur-related degradation. Transformation-driven techniques have been shown in prior studies to effectively preserve fine structural details while suppressing noise and unwanted artifacts. Building upon these insights, the proposed approach leverages transformation-domain analysis to enhance edge information, recover lost textures, and improve overall restoration performance. Experimental analysis demonstrates that the method effectively handles spatially varying blur and produces visually improved results, highlighting its potential for advanced imaging applications.

Keywords: Algorithms, digital, fine features, imaging systems, restoration, visual quality

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INTRODUCTION

Human communication relies on multiple modes to convey information effectively. In direct, face-to-face interactions, both spoken language and nonverbal cues, such as gestures, posture, and facial expressions, play a significant role. Verbal communication primarily depends on spoken words, whereas nonverbal communication conveys meaning without language. When communication must occur beyond the immediate physical presence, unique challenges related to time and distance arise. Traditional oral methods, such as folk tales and songs transmitted verbally across generations, exemplified early attempts at long-distance and long-term communication. However, repeated retelling often leads to variations in expression and content, resulting in partial loss or distortion of information [1–5].

Technologies such as telephones and video conferencing platforms enable communication across geographical distances, but they do not inherently preserve information over time. Written representation has proven to be more effective for communication that transcends both time and space. Early civilizations employed pictographs, visual representations resembling real-world objects, to record and transmit information. These images were painted on cave walls or engraved on stone surfaces using natural pigments. Although the precise intentions behind many of these symbols remain unclear, they continue to provide valuable insights into the cultural and historical contexts of their eras. The development of printing technology, particularly the invention of the printing press in the fifteenth century, marked a transformative milestone by enabling the fast, accurate, and large-scale reproduction of written material. This innovation is widely regarded as one of the most influential technological revolutions of the second millennium.

The ability to preserve information in physical form reinforces the notion that visual evidence is often more convincing than verbal descriptions alone, as reflected in the common saying “seeing is believing.” This preference for visual representation has naturally led to the development of imaging devices capable of capturing real-world scenes by recording reflected or projected light [6–10].

The conceptual foundation of modern photography can be traced back to the pinhole camera principle, which was independently described by Mo Di in ancient China and Aristotle in ancient Greece during the fifth and fourth centuries BCE. The camera obscura, a practical implementation of this principle, consists of a dark enclosure with a small aperture through which light enters and forms an inverted image of the external scene on the internal surface.

In recent decades, rapid advancements in imaging technology have resulted in an exponential increase in the amount of image data acquired from sources such as handheld cameras, smartphones, satellites, closed-circuit television (CCTV) systems, and aerial imaging platforms. Despite these advancements, captured images frequently suffer from quality degradation owing to limitations in the imaging process. Therefore, the recorded image is often a distorted or degraded representation of the original scene. Common sources of degradation include lens defocus, optical aberrations in digital cameras, and atmospheric disturbances in satellite and aerial imaging. In particular, images captured using handheld devices, especially by non-professional users, are highly susceptible to motion blur caused by camera shaking or improper focusing. Figure 1 shows representative examples of degraded images.

In addition to blurring, noise may be introduced during image acquisition or recording owing to sensor limitations, environmental conditions, or measurement inaccuracies. Noise can also emerge during the restoration process when the applied filtering techniques fail to accurately estimate the original image data, which is commonly referred to as deblurring noise. Furthermore, artifacts such as ringing may appear in the restored images because of imperfect blur modeling. Ringing effects typically occur when restoration filters assume periodicity in the image frequency domain, leading to the attenuation of high-frequency components near the image boundaries [11–20].

Modern cameras are equipped with advanced image stabilization and automatic focusing mechanisms to mitigate the issues arising from camera motion and inaccurate focus. In addition, improvements such as high-speed shutter systems, enhanced sensor sensitivity, and built-in anti-shake technologies have significantly reduced image degradation caused by unintentional movement during image capture.

Optical image stabilization mechanisms typically operate by dynamically adjusting the image sensor or specific optical components to compensate for unintended camera movements. Automatic focusing systems determine the optimal focus position using one or more sensors that analyze incoming light measurements and subsequently drive an electromechanical assembly to regulate the lens configuration. Designing such systems is technically challenging because they aim to suppress motion-induced blur without amplifying image noise. Consequently, these solutions often lead to increased device complexity, production costs, weight, and power consumption. Despite the advances introduced by the digital camera industry, blur caused by hand-induced camera motion can only be mitigated to a certain extent using these techniques. To further address image degradation at the acquisition stage, alternative hardware-based approaches have been proposed, including coded aperture designs, coded exposure strategies, and multi-camera frameworks for effectively estimating the point spread function (PSF) effectively [21–25].

The origins of image restoration research can be traced to the early 1960s, particularly in the context of nonlinear filtering applied to convolved and noisy images. Image restoration seeks to recover the original scene by exploiting prior knowledge of the degradation process that affects the observed data. Early and significant contributions to this domain were driven by the need to enhance astronomical imagery, which continues to attract considerable research interest. Over time, restoration techniques have expanded into diverse application areas, such as computer vision, remote sensing, and medical imaging, with growing relevance in forensic and law-enforcement investigations. In particular, methods based on blind image deconvolution (BID) have demonstrated effectiveness across a broad spectrum of signal and image types, including biomedical scans, satellites, and aerial imagery, handheld camera photographs and videos, seismic and audio signals, industrial tomography data, and astronomical observations [26–36].

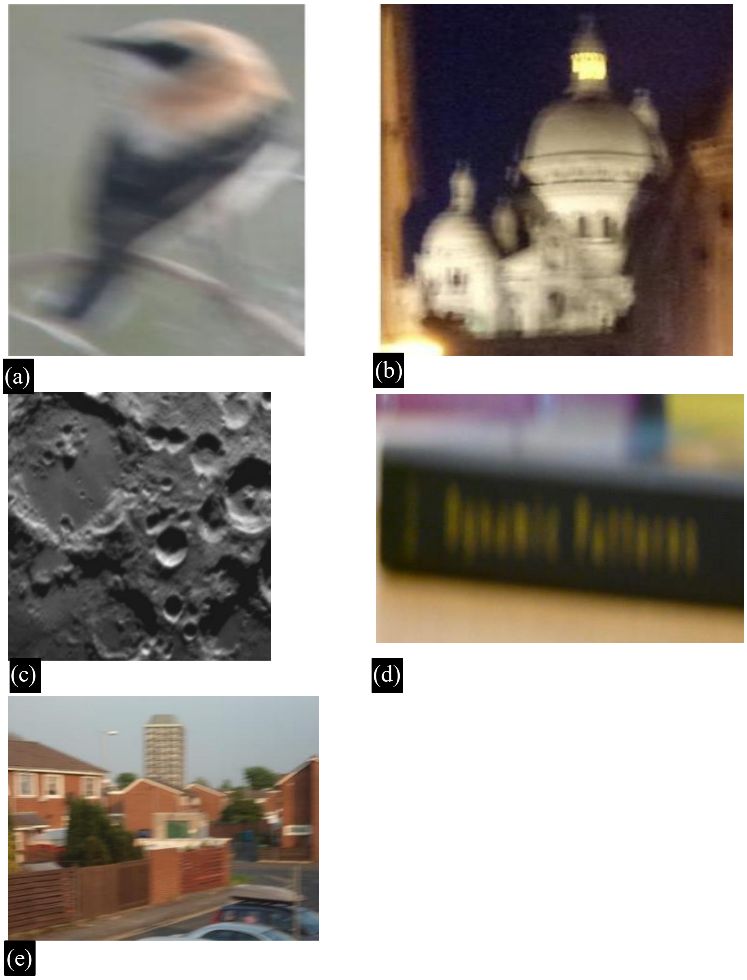

Figure 1. (a–e) Examples of real-life blurred images.

LITERATURE REVIEW

A detailed literature review was conducted to understand the factors that encourage or restrict the adoption of image processing and restoration techniques, as well as the conditions that lead to successful image enhancement outcomes. Literature reviews play a vital role in research, as they help identify existing knowledge, reveal research gaps, and provide a strong theoretical base for further study.

Zhou et al. [37]. Ancient murals represent precious cultural heritage and pose enduring challenges in the domain of preservation. Conventional restoration techniques often handle texture and structural elements independently, resulting in mismatches between fine local details and the broader structural coherence. Such separate processing falls short of addressing the intricate requirements for effectively restoring both texture and structure in ancient mural images. To overcome these limitations, this paper introduces MIR-SGPR, a collaborative encoder–decoder framework designed to simultaneously restore texture and structural characteristics of damaged mural images. The generator employs an encoder to capture shallow-level texture details and deep-level structural information, while the spatial geometric awareness (SGA) module enables accurate modeling of the spatial positions and directional properties of deteriorated regions. To mitigate the conflict between fine-grained local details and global semantic understanding, we propose the progressive contextual refinement (PCR) network. This module iteratively refines multi-scale features and seamlessly fuses texture and structural cues, thereby strengthening the joint representation of local and global elements. Additionally, the mask reverse-focus mechanism (MRF) is introduced, which utilizes mask guidance to suppress irrelevant features from intact regions, markedly boosting both restoration efficiency and precision. Finally, the output generated is refined through a combination of global and local discriminators. Extensive experiments show that the proposed method surpasses current state-of-the-art techniques across various quantitative metrics. The restored images demonstrate enhanced visual harmony, faithful reproduction of details, and superior structural reconstruction, offering a robust and practical approach for the digital safeguarding of ancient murals.

Patil and Wagh (2013) [27] presented a study that incorporated rotational blur constraints and evaluated the approach under two deblurring scenarios. In the first case, the method was applied to restore a single blurred image, whereas in the second case, information from a noisy pair of blurred images was combined with a single blurred image to estimate the corresponding PSF. In addition to algorithm-based approaches, several hardware-assisted blind image deblurring techniques have been proposed for digital cameras. Coded aperture methods use a patterned mask at the lens aperture to alter the frequency characteristics of the defocused blur, making blur estimation and removal easier. These techniques require minimal modification of conventional camera systems and support portable imaging, although they rely heavily on scene depth information and are generally limited to shift-variant blind deconvolution.

Several camera hardware designs have also been developed to estimate the scene depth using defocus cues, which can be alternatively interpreted as methods for estimating out-of-focus blur PSFs. Modified multi-pinhole camera systems have been used to estimate depth by analyzing different image textures and combining them in a depth-dependent way. In addition, coded exposure techniques were applied to reduce motion blur by controlling the shutter opening and closing during exposure. This strategy helps preserve high-frequency image details and is particularly useful when no prior information regarding blur or noise is available.

Cohen et al. (2013) [28], in their work on image restoration using Ising theory and automatic noise estimation, discussed the limitations of independent component analysis (ICA) for BID. Although ICA provides a statistical framework for exploiting signal independence, its effectiveness is restricted by the limited number of available observations, which is a fundamental requirement for blind source separation problems. ICA assumes that the number of observations equals the number of underlying sources, that the observations are mutually independent, and that only one source follows a Gaussian distribution.

In image degradation processes, the observed image is formed by the convolution of neighboring pixels according to the PSF, resulting in a unique observation. To meet the multichannel requirements of ICA, alternative representations must be generated using specialized techniques. Recent studies have proposed redefining a blurred image as a multichannel signal, enabling the application of ICA-based restoration techniques. Although these approaches offer feasible solutions, they are limited by unresolved independence assumptions, small blur kernel support, and limited noise-handling capability. In practical scenarios, the independence assumption may not always be valid. To overcome these issues, dependent component analysis (DCA) was introduced, which relaxes the strict independence condition of ICA. However, this method is not fully blind, as it requires an initial estimate of the blur kernel, indicating that blind deconvolution remains an open research area [27].

Dang et al. (2013) [29] proposed a spatial non-Gaussianity-based blind image deblurring scheme aimed at restoring single-frame blurred images, where conventional ICA-based methods are less effective. Their approach is based on the observation that increased blur causes image distributions to become more Gaussian, as described by the central limit theorem (CLT). By maximizing non-Gaussianity measures, such as kurtosis or negentropy, the original image can be estimated more accurately.

This method combines Wiener filtering for deblurring and denoising with a genetic algorithm for optimization. Sandeep and Jacob (2013) [30] further extended this concept by using spatial kurtosis as a fitness function within a genetic algorithm framework. Their results showed that spatial kurtosis reaches extreme values near the true PSF parameters, indicating a closer restoration to the original image. However, spatial kurtosis is highly sensitive to ringing artifacts and noise that are introduced during deblurring. It was observed that applying a base-10 logarithmic transformation to the frequency-domain representation before calculating the spectral kurtosis produced a more distinct optimum and improved robustness against deblurring artifacts, resulting in better image restoration quality.

CONCLUSIONS

In conclusion, the findings are presented regarding the expected results of the case study in relation to the stated purpose and objectives.

Conclusions Associated with the Purpose and Objectives

In this study, a geometric transformation-based approach was employed to identify feature points from both the original image and its blurred counterpart. The extracted feature points were subsequently utilized to restore blurred images or images whose pixel coordinate values were altered owing to transformation effects or blur. In addition, a defocus sparse blur map was estimated from a single image using a bilateral filtering technique, which enabled the effective processing of color images and accurate estimation of defocus blur. The derived blur map was then used to recover the restored images. The performance evaluation of the proposed methods was carried out by computing the peak signal-to-noise ratio (PSNR) and mean squared error (MSE) values. Experimental observations indicate that the geometric transformation method is straightforward to implement, computationally efficient, and less complex than many conventional restoration algorithms.

Future Scope

Understanding the precise characteristics of image blur and its relationship with the original image is essential for effective image restoration. Traditional approaches based on cross-correlation and autocorrelation are often computationally intensive and difficult to apply to complex image data. To address this limitation, image segmentation techniques can be employed to better isolate the blurred regions and analyze their spatial behavior. Within the transformation-based restoration framework, the MSE can be further minimized by integrating advanced image enhancement methods to refine the restored output.

In this study, the Canny edge detection algorithm was used to identify prominent structural features. However, restoration performance can be further improved by exploring alternative edge detection methods, such as Sobel, Laplacian of Gaussian, and learning-based edge detectors. Adaptive thresholding strategies can also be introduced during the edge extraction process. Beyond conventional hard and soft thresholding, advanced thresholding techniques such as SureShrink and VisuShrink can be applied to achieve smoother edge transitions and improved noise suppression.

The current approach relies on a coherence labeling stage to align the detected boundaries with the nearest color edges in the original image, which generally correspond to true depth discontinuities. However, this assumption becomes less reliable in scenarios involving gradual blur variations or weak color contrasts at depth boundaries. Addressing these limitations presents an important research challenge and offers opportunities for further improvements.

Future Scope (2026 and Beyond)

Future work can focus on integrating deep-learning-based segmentation and edge detection models, such as convolutional neural networks (CNNs) and transformer-based architectures, to improve robustness in complex blur scenarios. Self-supervised and unsupervised learning frameworks can be explored to estimate blur maps without requiring ground truth data. Additionally, hybrid approaches that combine classical transformation-based methods with data-driven models may achieve superior restoration quality while maintaining computational efficiency.

Advancements in real-time image processing hardware and edge computing by 2026 are expected to enable the on-device implementation of adaptive blur estimation and restoration techniques for mobile cameras, surveillance systems, and autonomous platforms. Furthermore, incorporating depth sensors and multiview imaging can improve the blur-depth correlation, especially in scenes with gradual depth changes. Extending the proposed framework to video restoration, dynamic scenes, and low-light imaging is a promising direction for future research.

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