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Review of Restoration of Spatially Varying Blur Image From A Single Image

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Abstract : Restoration of spatially varying blur images is a critical challenge in the field of image processing and computer vision. Unlike uniform blur, spatially varying blur arises from non-uniform motion, depth variations, or lens aberrations, making its restoration a highly complex task. This review explores various techniques and methodologies for restoring images affected by spatially varying blur using a single input image. The paper delves into the mathematical modeling of spatially varying blur, covering topics such as point spread functions (PSF), kernel estimation, and optimization-based restoration methods. Additionally, it examines the integration of deep learning and artificial intelligence techniques for addressing this problem, emphasizing their potential for improved accuracy and efficiency. The review highlights the limitations, advantages, and applicability of these techniques in real-world scenarios such as photography, medical imaging, and remote sensing.

***Index Terms* – Restoration, Spatially, Blur, Image PSF.**

I. INTRODUCTION

Images play a pivotal role in various fields, ranging from photography and surveillance to medical imaging and scientific research. However, the quality of images is often degraded by various types of blur, which can significantly impact their interpretability and utility. Among the various forms of blur, spatially varying blur poses a particularly intricate challenge due to its non-uniform nature. Unlike uniform blur, which affects the entire image in a consistent manner, spatially varying blur changes across the image, arising from complex phenomena such as camera shake, depth variation, object motion, and optical distortions. This non-uniformity adds a layer of complexity to the restoration process, requiring advanced techniques for effective recovery.

The restoration of spatially varying blur from a single image has garnered substantial attention from researchers in recent years. This problem is highly relevant in scenarios where acquiring multiple images or additional hardware assistance is impractical. Single-image restoration techniques rely on extracting and analyzing inherent information within the degraded image to reverse the effects of blur. Over the years, researchers have developed various mathematical models and computational algorithms to address this problem, each with its unique assumptions, advantages, and limitations.

The process of restoring spatially varying blur involves two key stages: blur modeling and image reconstruction. Blur modeling focuses on estimating the point spread function (PSF) or blur kernel that characterizes the blurring effect. This step is particularly challenging for spatially varying blur, as the PSF changes across different regions of the image. Traditional methods rely on approximations and assumptions to simplify this task, but these approaches often struggle with accuracy and generalizability. Recent advancements in machine learning, particularly deep learning, have introduced data-driven techniques that can model complex, non-linear blur patterns with remarkable precision.

Image reconstruction, on the other hand, involves using the estimated blur model to recover the latent sharp image. This stage typically employs optimization techniques, regularization methods, or learning-based frameworks to balance fidelity to the original image and suppression of artifacts. Modern approaches integrate prior knowledge, such as natural image statistics, to further enhance the restoration quality. However, challenges such as noise amplification, computational cost, and overfitting remain significant obstacles in achieving optimal results.

This review aims to provide a comprehensive overview of the state-of-the-art techniques for restoring spatially varying blur from a single image. It covers a broad spectrum of methods, from classical deconvolution and optimization-based approaches to cutting-edge machine learning and deep learning frameworks. By critically analyzing the strengths and limitations of these techniques, the review seeks to identify key gaps in the current research and propose potential directions for future work. Furthermore, it explores the practical applications of spatially varying blur restoration in fields such as photography, medical imaging, autonomous driving, and satellite imaging, underscoring its importance in both academic research and real-world scenarios.

II. BACKGROUND

H. M. Aharon, et.al. (2006 IEEE) studied and proposed initial population consists of chromosomes represented in binary encoding. Perform an iteration and for different values of optimizing parameter (e.g. sigma in case of Gaussian blur, theta in case of motion blur etc); find the restored image through inverse/Wiener filtering in the spectral domain and calculate its spectral kurtosis (i.e. the fitness function) for different population samples. Generate the child population for the next iteration by evolving from the parents on the basis of the fitness function in subsequent iterations (generations), through mutations and crossover. Repeat the process again till the algorithm converges for the deblurring measure. The blur angles from 180 to 360 are similar to blur angles 0 to 180 and can be estimated using the 11-bit chromosome. The radius of out-of-focus PSF was approximated by 8-bit chromosomes in the range of 0 to 31 pixels. It was noted empirically that out-of- focus blur with radius above 23 pixels causes severe blurring and a lot of information is lost. The parameters (variance, angle and radius) were approximated to the precision of 0.125. In all cases, the population size was set to 100, while up to 3 bits of the chromosomes were randomly mutated every iteration.

Jiaya Jia et al. (2007 IEEE) proposed in their paper “Single Image Motion Deblurring Using Transparency”, they separate the image deblurring into filter estimation and image deconvolution processes, and propose a novel algorithm to estimate the motion blur filter from a perspective of alpha values. The scheme highly depends on ideal restoration filter (no noise amplification and ringing during deblurring). At present, a functional form of the PSF is assumed which is a limited form model of real PSFs. The real images deblurred using the proposed scheme here had an almost uniform shape which could be estimated by PSFs with functional form as given in. These real blurred images were assumed to be noise free but manual adjustment of the NSR (Noise-to-Signal Ratio) parameter d was still needed for the restoration filter. For an image with N elements or MxM dimensions, the FFT algorithm by Cooley and Tukey reduces the number of computations from N 2 (or M 4) to N log2 N [130]. A single iteration for calculating the spatial kurtosis measure takes about twice the time as compared to the spectral kurtosis measure. However, the MATLAB ‘s Wiener filter implementation also has other severe overheads losing per iteration efficiency.

The average percentage efficiency in computation time per iteration for the FFT-iFFT cycle is 44 percent and for the MATLAB ‘s Wiener filter based deblurring it is 8 percent. The execution time depicted for the Wiener filter show deblurring schemes for both measures takes almost the same time per iteration. The spectral kurtosis with a low overhead deblurring filter will have low execution time especially when deblurring large size images or when multiple parameters need to be estimated. This is very important, especially when the deblurring is done online where the resources are very limited.

Yu-Wing Tai et al. (2009 Information Processing Society of Japan) The blur angles from 180 to 360 are similar to blur angles 0 to 180 and can be estimated using the 11- bit chromosome. The radius of out-of-focus PSF was approximated by 8-bit chromosomes in the range of 0 to 31 pixels. It was noted empirically that out-of-focus blur with radius above 23 pixels causes severe blurring and a lot of information is lost. The parameters (variance, angle and radius) were approximated to the precision of 0.125. In all cases, the population size was set to 100, while up to 3 bits of the chromosomes were randomly mutated every iteration. 3.6.2. Restoration of Gaussian Blurred Images The 2-D Gaussian PSF for PSF pixel coordinates (m,n) is given by, MATLAB based BID scheme is second in order of deblurred image quality however this scheme requires an initial PSF estimation and cannot be regarded as totally blind. The graph result developed by the author depicts a non-Gaussian behaviour in the early stages of blurring (up to 0.5 PSF variance) before the image starts to become more Gaussian as a result of further blurring. This is due to the finite PSF matrix which for small variances (usually from 0.1 up to .9) has unnecessary zero elements that during convolution result in smaller values than the expected average value. This in turn affects the image statistics.

R. Amiri, et.al. (2009, IEEE) Spectral kurtosis is also independent of the statistical nature of an image. The absolute value of spectral kurtosis is maximised at or in the near vicinity of the true values of PSF parameters. To search for this optimum point, initially a gradient based search algorithm was used which was later replaced by GA. Results for the artificial and real blurred images using both search algorithms shows that spectral kurtosis serves as a suitable alternative to the spatial kurtosis measure. The spectral kurtosis measure is able to estimate blurring parameter values for the parametric Gaussian, motion and out-of-focus blur. The IQMs used for computing the deblurred image quality shows that the quality of blurred images improves using the estimated PSFs. The spectral kurtosis measure was investigated for parametric blurs only. Deblurring was performed on noise free images in the artificial blurring case and with inherent image noise in the real blurred case. The spectral kurtosis is computationally efficient with the deblurring speed almost doubled for the FFT-iFFT cycle for images larger than 256 x 256 pixels. However, the overall improvement in computational speed was marred by the MATLAB based implementation of Wiener filter employed in the proposed BID scheme.

Burger and Harmeling (2011) MATLAB based BID scheme is second in order of deblurred image quality however this scheme requires an initial PSF estimation and cannot be regarded as totally blind. Deblurring Results for Real Blurred Images The proposed deblurring scheme has also been tested on several real images. The two blurring cases studied here include motion blur, a typical problem faced by amateur photographers, as well as atmospheric turbulence blur, a typical degradation in remote sensing. In the first case of motion deblurring, a video was captured by a low-quality camera. A blurred image frame was designed, shows an approximate vertical motion blur with the small numbers at the bottom becoming almost unreadable. The blurred image also contains certain amounts of noise due to poor lighting which is one of the most difficult issues in deblurring. Parameters were approximated by using a Wiener filter as the base for calculating both spatial and spectral non-Gaussianity values. Different restoration algorithms were compared for restoration quality. the restoration results of different filters such as regularized, Wiener and Richardson- Lucy.

III. CHALLENGES

1. Blur Modeling and Estimation

- **Complexity of Spatial Variation**: Spatially varying blur arises from dynamic sources such as motion, depth variations, or lens aberrations, making the blur inconsistent across the image. Accurately modeling these variations is highly challenging.

- **Point Spread Function (PSF) Estimation**: The PSF, which represents the blur kernel, changes across different regions of the image. Estimating a spatially varying PSF for each region requires sophisticated algorithms and often involves high computational complexity.

- **Lack of Priors**: Effective blur estimation relies on prior knowledge about the blurring process or the image's characteristics. However, such priors may not always be available or accurate, leading to suboptimal results.

2. Single Image Constraint

- **Limited Information**: Unlike multi-image approaches, single-image restoration lacks temporal or stereoscopic data to aid in blur estimation, making the process heavily reliant on the degraded image alone.

- **Ambiguity in Reconstruction**: Without additional information, separating blur effects from inherent image content can be ambiguous, leading to inaccurate reconstructions.

3. Noise Amplification

- Restoration methods often amplify noise present in the blurred image, especially when attempting to recover high-frequency details. Balancing blur removal with noise suppression is a persistent challenge.

4. Computational Complexity

- **High Resource Requirements**: Advanced techniques, particularly those involving spatially adaptive PSF estimation and deep learning, often require substantial computational resources, making them less practical for real-time applications or resource-constrained environments.

- **Scalability**: Scaling algorithms to handle high-resolution images while maintaining efficiency and accuracy is a significant challenge.

5. Artifact Generation

- **Ring and Halo Artifacts**: Deconvolution-based methods often produce artifacts such as ringing and halos, especially near edges and sharp transitions, which degrade the visual quality of the restored image.

- **Over-smoothing**: Regularization techniques to suppress artifacts can result in over-smoothing, leading to loss of fine details and textures.

6. Lack of Generalizability

- **Variation in Blur Characteristics**: Methods trained or designed for specific types of blur may not generalize well to other scenarios, such as blur caused by irregular motion or multiple depth layers.

- **Dataset Dependency**: Deep learning models often depend heavily on training data, which may not fully capture the diversity of real-world blur scenarios.

IV. CONCLUSION

Restoring spatially varying blur from a single image is a complex yet vital task in image processing, with applications spanning photography, medical imaging, and autonomous systems. The challenges associated with accurately modeling non-uniform blur, mitigating noise amplification, and achieving artifact-free restoration highlight the intricacies of this problem. While traditional methods offer foundational approaches, advancements in deep learning and data-driven models have demonstrated significant potential for improved accuracy and efficiency. However, issues such as computational complexity, lack of generalizability, and the need for robust evaluation metrics remain areas for further exploration. By addressing these limitations, future research can pave the way for more effective and practical solutions, enhancing the quality and utility of restored images in diverse real-world scenarios.

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