AN ITERATIVE METHOD FOR IMAGE RESTORATION USING ROBUST MOTION BLUR KERNEL ESTIMATION

Abstract

Most of the time, when people take a picture in their day-to-day lives, they get motion blur. Non-linear motion is a common type of blur that can seriously affect this image's contents. The image restoration result depends heavily on the precise estimation of the degradation Point Spread Function (PSF) model. Blind motion deblurring depends heavily on the precise estimation of the kernel. For kernel estimation, numerous previous methods relied on image regularization to recover the observed image's strong edges. However, if recovered strong edges are not accurately reconstructed, the estimated kernel will degrade in images with a lot of small-scale edges. Therefore, this analysis presents an Iterative Method for Image Restoration using Robust Motion Blur Kernel Estimation. We improve the kernel's continuity through the use of a kernel prior, its understanding that the continuous camera motion trajectories during the acquired images have a major impact on the blur kernel supports. The variable exponent regularizer was utilized to increase kernel flexibility while concentrating on the diversity of various PSF types. The best motion blur kernel can be using this method, and it also maintains a high level of image deblurring with low MSE and high SSIM. The implementation of this method in reducing processing times is supported by experimental results.

Keywords: Image deblurring, Image Restoration, Blur Kernel Estimation, regularizer, Point Spread Function (PSF).

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I. INTRODUCTION

In our day-to-day lives, motion blur images frequently appear on handheld or vehicle-mounted cameras [1]. One of the most noticeable causes of photo degrading is motion blur. The performance of various sensing applications, such as object detection, tracking, and disaster monitoring, could be harmed by blurry images, which can significantly lower the quality of remote sensing images. Complex optical systems like free surface design [2] can enhance image quality but are expensive. Manufacturers of photographic equipment have proposed a number of anti-shock theories to prevent motion blur caused by camera shake. These theories include optical, electronic, and mechanical anti-shake technologies. There are restrictions regardless of the anti-shake technology utilized. As a result, excessive shock cannot prevent image blurring [3].

Depending on whether we are familiar with the blur kernel k, the two types of image deconvolution are blind and non-blind. While it is assumed that k is common in non-blind deconvolution, the issue of estimating the sharp image remains to be resolved [4]. A sharp image can be quickly and effectively recovered using traditional techniques like Richardson-Lucy(RL) deconvolution, Wiener filtering, and inverse filtering. However, noise has a significant impact on these methods, and they need the most information possible to support The results will also include a significant amount of ringing artifacts near strong edges. Therefore, non-blind deconvolution techniques are generally inappropriate for single image deblur [5]. In many practical situations, whether utilizing hand-held cameras or cameras placed on moving bodies, camera shaking is difficult to totally remove. Therefore, reducing its effects computationally is suitable. On the basis of the observed, blurred, blind deblurring makes an attempt to recover the blurring kernels and the latent image from an incorrectly displayed image.

$$\min_{x,k} ||y - k * x||_2^2 + \lambda\phi(x) + \rho(k) \ldots\ldots (1)$$

Where the blur kernel, latent sharp image, and blurred image are represented by the letters y, x, and k, respectively. Comparisons will be made between the latent image deterioration $k * x$, the blurred image y, and the likelihood $||y - k * x||_2^2$ enforces agreement. The blur kernel prior is represented by $\rho(k)$ and the image prior by $\phi(x)$.

When utilizing faster exposures, camera motion can be reduced, this might also result in other issues including sensor noise or a smaller depth of field than required. However, these are difficult to transport. Reduce camera shake through the utilization of a tripod or other specialist hardware. Conventional hand-held cameras are used to take the majority of consumer photographs. Digital photography would benefit significantly from a way to get remove of motion blur from an image that has been captured. Picture deblurring issue is challenging in numerous aspects fundamentally because of the under-constraint nature of the issue. This is so that the blurred images can be addressed for through a number of different image-blur combinations. The original image and the blur kernel simply indicate that there are more unknowns than measurements.

As a result, the natural image and blur kernels are further restricted by current deblurring methods [6]. Estimating the blur kernel is the first step toward solving the deblurring problem. The simple and significant explanation provided by the kernel is more accurate. It strongly resembles a connected and continuous trajectory since the motion blur kernel is a function of the continuous camera shaking trajectory during the exposure. Consequently, the kernel's continuity is a crucial property.

The PSF would be piecewise constant and sparse if aircraft motion is the primary cause. In reality, degradation is caused by all three factors, and the PSF is a combination of the three forms. As a result, using a simple prior will not produce satisfactory outcomes [7]. On the other hand, the majority of current blind restoration techniques, restrict algorithm flexibility by requiring a hard decision on the PSF structure, often of the Gaussian type, by including simple priors into the algorithms. As a result, the issue of encouraging map sparsity exceeded the issue of encouraging kernel continuity. A kernel continuity prior is present in the final model is provided. The nonlinear and nonlinear cost function is minimized using a proposed approximate solver that converges quickly.

The remainder of the analysis is structured as follows: Section II reviews the relevant literature. The described Image Restoration utilizing Robust Motion Blur Kernel Estimation is described in Section III. The test results are displayed in Section IV. In this Section V presents the paper to a conclusion.

II. LITERATURE SURVEY

X. Tao, X. Shen, H. Gao, J. Wang, and J. Jia, et al. [8] Recurrent modules can be integrated into Convolutional Neutral Network (CNN)-based deblurring systems by using a novel Scale-Recurrent Network (SRN), which might also make it harder to train as many parameters as possible.

O. Kupyn, D. Mishkin, M. Mykhailych, V. Budzan, and J. Matas, et al. [9] create conditional Generative adversarial networks (GANs) net and content loss-based end-to-end learning approach for motion deblurring. Image deconvolution can be avoided and irregularly blurred images can be managed with success using end-to-end deep learning-based deblurring techniques. Considering that the completeness of the training dataset is necessary for deep learning to perform blind image deblurring, further training data pairs are still required. Xianqiu Xu, Hongqing Liu, Yong Li, Yi Zhou, et. al. [10] describes a novel approach to estimating blur kernels using each RGB (Red, Green, Blue) channel sequentially rather than the grey domain in order to obtain more precise blur kernels for picture reconstruction. The extraction of the clear image from the blurry image is the objective of image deblurring. The digital camera's color image frequently has a different blur effect for each color channel. The numerical results show that, the proposed approach can perform better than other existing methods.

Hui Yu Huang, Wei Chang Tsai, et. al. [11] proposes a fast blur-kernel estimation-based, effective method for quickly selecting the best kernels from a set of kernels for blurred image restoration. The recursive method is frequently used in advanced motion blur evaluation techniques to determine the motion blur kernels. However, it takes a lot of time. They utilize a normalized sparsity measure and an iterative phase retrieval approach to effectively identify the best kernels and perform deblurring while reducing the computational time. According to the findings of the experiments, this method is capable of effectively reducing execution time, while providing a high level of image deblurring quality, to provide the best motion blur kernel. Dong-bok Lee, Bo-Young Heo, Byung Cheol Song, et. al. [12] uses high-resolution information from adjacent unblurred frames to create a video deblurring algorithm. Bidirectional motion compensation is used to create two motion-compensated predictors for a blurred frame from its neighboring unblurred frames. Finally, between the predictors and the blurred image, an accurate blur kernel is generated, from the blurred frame itself which is difficult to separate. In order to decrease the essential ringing artifacts induced by conventional deconvolution, a residual deconvolution is then used. For the deblurred frame, both blur kernel estimation and deconvolution operations are used frequently. According to the findings of the experiments, compared to the most recent algorithms, the suggested algorithm results in sharper details and images with less artifacts.

L. Sun, J. Wang, S. Cho, and J. Hays, et al. [13] Use a previous patch to explore a new edge-based approach for kernel estimation from an image. They evaluate a "trusted" subset of latent images by forcing a fix earlier explicitly custom-made towards displaying the presence of picture edges and corner primitives. The performance of blind deblurring is significantly improved by patch-based priors in contrast to pixels-based priors. However, In order to learn a prior from patches or extract useful edges from a set of patches, more computations are needed. M. Dobeša, L. Cachalab, T. Furstc, et al. [14] proposed a solution for blurry images caused by linear motion. The blurred kernel length is calculated by projecting the target function, and the blurred kernel angle is calculated by the authors using Fourier spectral features dappling Radon projection.

A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, et al. [15] In order to eliminate harmful structures, deblurring procedures have proposed numerous natural image priors, during the process of several iterations gradually increase resolution while attempting to approximate the latent image.

III. IMAGE RESTORATION USING ROBUST MOTION BLUR KERNEL ESTIMATION

The framework of An Iterative Method for Image Restoration using Robust Motion Blur Kernel Estimation is represented in below Fig. 1.

Real and synthesis image sequences are both included in the input data. One moving object can be seen in each of the sets images, multiple moving objects, and blurred images caused by camera shake. The first step is to divide the initial image into its component parts using the K-means clustering algorithm. An algorithm called K-means clustering divides the objects into K clusters by reducing their distance from the centroid point. Consequently, K can be chosen randomly or manually.

Before inpainting (filling in the missing areas of an image with the appropriate values), a preprocessing step is added to increase the contrast. Curvature can be captured with greater precision when contrast is greater and gradient values are larger. As a result, an inverse correction is used to restore the original contrast after inpainting is finished. It implements the standard Gamma Correction procedure.

The continuity map M. (k) is made more sparse by applying the L0 norm. Considering the proposed previous as a given, the cost function is:

$$\min_{x,k} ||y - k * x||_2^2 + \lambda\phi(x) + \gamma||k||_2 + \alpha||M(k)||_0 \ldots\ldots(2)$$

In terms of various weights are λ, γ and α. Alternately, they fix x while updating the blur kernel k to reduce (2):

$$\min_{k} ||y - k * x||_2^2 + \gamma||k||_2 + \alpha||M(k)||_0 \ldots\ldots(3)$$

and 'x' is the picture while k is fixed:

$$\min_{x} ||y - k * x||_2^2 + \lambda\phi(x) \ldots\ldots(4)$$

Estimating a blur kernel consists of two steps in described framework: the evaluation of both the intermediate images and the intermediate kernels. It is created the intermediate kernel and image, making use of the most recent x and k in each subsequent iteration of the alternative optimization.

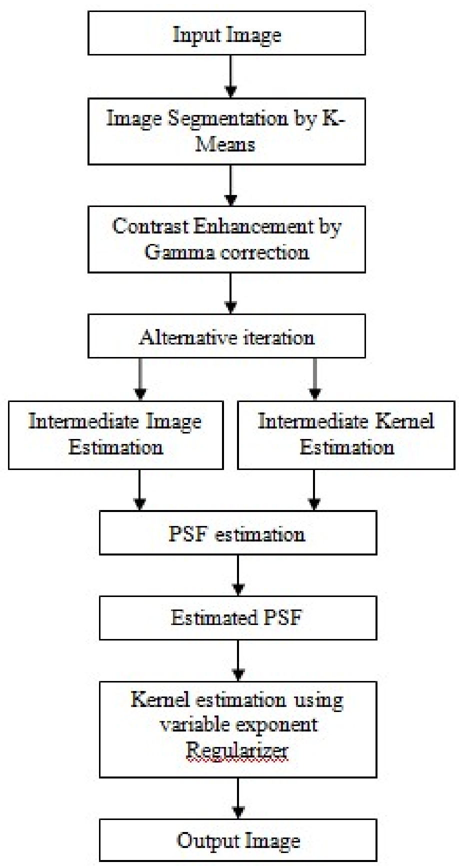


Figure 1: Framework of Image Restoration Using Robust Motion Blur Kernel Estimation

1. **Intermediate Blur kernel estimation:** The non-linear function M(•) and the non-convex function L0 together make it difficult to estimate k using (3). Through integrating auxiliary variables u with regard to M (k), they solve the L0 regularized term using the half quadratic splitting. Then modify the cost function as follows:

$$\min_{k} ||y - k * x||_2^2 + \gamma||k||_2 + \beta||M(k) - u||_2 + \alpha||u||_0 \ldots\ldots (5)$$

where the penalty variable was 'β'. The answer to the query (5) is quite similar to answer (3) when close to infinity is 'β'. By alternatively resolving the two subproblems listed below, they minimize (5): While fixing u, and 'k' is the estimating

$$\min_{k} ||y - k * x||_2^2 + \gamma||k||_2 + \beta||M(k) - u||_2 \ldots\ldots (6)$$

and fixing k while 'u' is estimating:

$$\min_{u} \beta||M(k) - u||_2 + \alpha||u||_0 \ldots\ldots (7)$$

When estimating u, the solution to problem (7) transforms into an element-wise minimization problem, which is very easy to solve because they can compute M(k) directly when k is fixed. Using M(•), a noisy kernel is first moved to continuity map 'u'. Secondly, the noise in the map 'u' is discovered because of the updating 'u'. Thirdly, when reducing noise to zero in k, they may transfer u back to the blur kernel k = $M^T(u)$.

2. **Intermediate image estimation:** By minimizing k, we can estimate x (4). The efficiency of the intermediate image estimation is significantly impacted by the image prior (x) that is selected. Deep neural networks have developed quickly, and some techniques currently integrate data-driven priors, which are acquired through the use of neural networks from training datasets. Whenever related to handcrafted priors, priors that are driven by data do not require the distribution of the latent image. Since, the training dataset could bias the data-driven prior. They choose on the framework $\phi(x) = ||\nabla x||_0$ for its performance and simplicity. The intermediate image's cost function is:

$$\min_{x} ||y - k * x||_2^2 + \lambda||\nabla x||_0 \ldots\ldots (8)$$

Estimating PSF is another major challenge in blind restoration. The actual PSFs for remote sensing typically consist of simple PSF types. Combining various characteristics of simple PSFs, composite PSFs have structures that are more adaptable. The shape of the PSF is typically less smooth than that of a pure Gaussian because it is typically made up of multiple simple PSFs. To estimate PSF, the described model makes use of the variable exponent regularizer R (K) k. The final deblurred image is created by deconvolution of the input image with the output kernel once the output kernel has been estimated.

IV. RESULT ANALYSIS

The 640-image deblurring dataset is used to assess the proposed prior outperforms the prior approach. They test the method with 640 blurred images from the Sun Dataset. The 640 images can be broken up into eight groups, with each group having the same blur kernel. By comparing average runtime, Structural Similarity Index (SSIM) and Mean Square Error (MSE), on Dataset, they also evaluate our strategy's effectiveness.

1. **Structural Similarity Index (SSIM):** The similarity measure between two signals is evaluated using the Structural Similarity Index (SSIM). The SSIM index is better for measuring the image's overall quality. As a result, they evaluate the overall image quality using the SSIM index, which is defined as

$$SSIM(i_1, i_2) = \frac{(2\mu_1\mu_2 + C_1)(2\sigma_{12} + C_2)}{(\mu_1^2 + \mu_2^2 + C_1)(\sigma_1^2 + \sigma_2^2 + C_2)} \dots (9)$$

The luminance of the two images are compared using the local means μ1,2 for image 1 and image 2. The contrast is compared using the standard deviations σ 21 and 2, respectively. The co-variance, σ 12 is used to compare the structure. Depending on the dynamic range, c1 and c2 remain constants. The SSIM value is between 0 and 1. If SSIM is 1, then the original image and the current images are similar.

2. **Mean Square Error (MSE):** The MSE refers the mean square error, which compares the original and compressed images. The inverse relationship between PSNR (Peak Signal to Noise Ratio) and MSE is that a lower value indicates less error.

$$MSE(i_1, i_2) = \frac{1}{NM} \sum_{x=1}^{M} \sum_{y=1}^{N} [i_1(x, y) - i_2(x, y)]^2 \dots (10)$$

Where M, N are the image's dimensions $i_2(x, y)$ is the reconstructed image, and $i_1(x, y)$ is the original image.

In terms of SSIM, MSE, and Average Runtime, the below table compares the Blur Kernel Estimation from Spectral Irregularities (BKE-SI), the Image Restoration using Robust Motion Blur Kernel Estimation (IR-RMBKE), and the Blur kernel estimation utilizing the Radon Transform (BKE-RT).

Table 1: Comparative Analysis Of Performance Parameters

Methods	SSIM	MSE	Average Runtime (ms)
IR-RMBKE	0.9	21	25
BKE-SI	0.5	35	42
BKE-RT	0.4	40	45

Below Fig. 2 shows the graphical representations of MSE and average time parameters for three models.

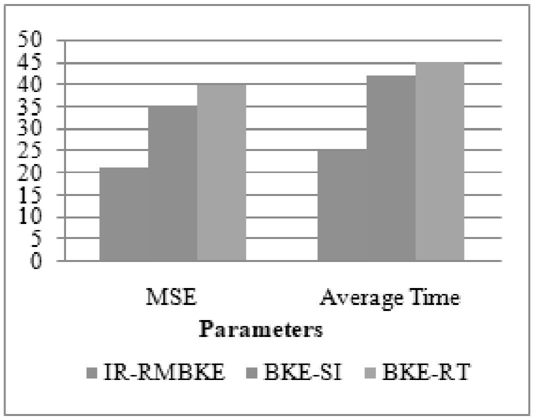


Figure 2: Comparative Analysis In Terms 'Mse' And 'Runtime'

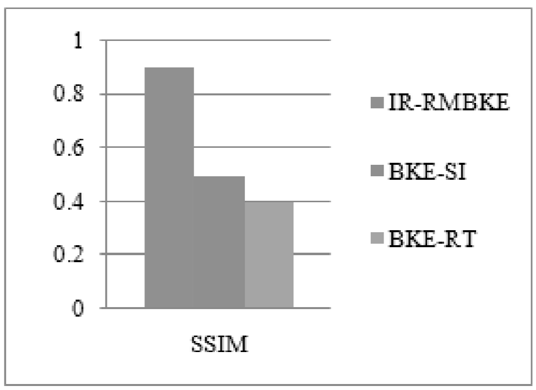
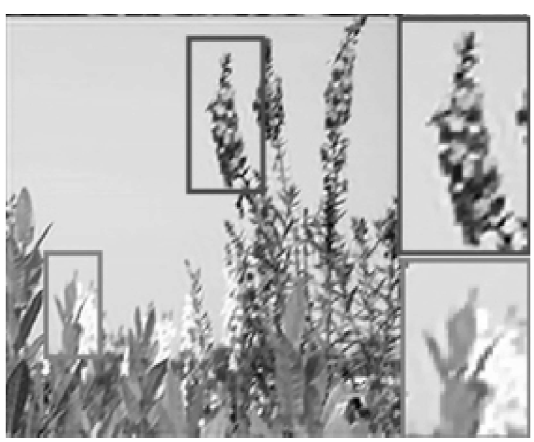
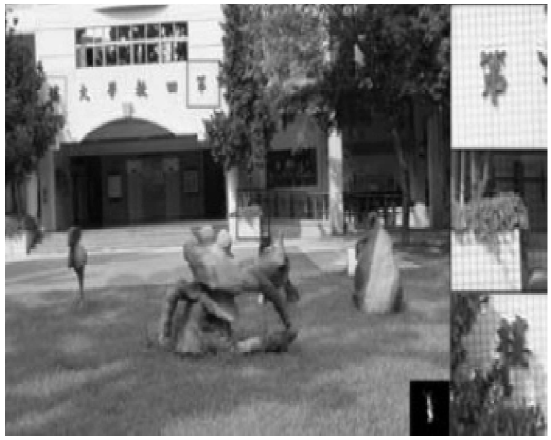


Figure 3: Comparative Analysis In Terms Ssim



(a)



(b)

Figure 4: Restored Image **(a)** Input 1**, (b)** Input 2

From results it is clear that, the performance of Image Restoration using Robust Motion Blur Kernel Estimation is better than other models in terms of low MSE, high SSIM and less Average time.

V. CONCLUSION

In this analysis, An Iterative Method for Image Restoration using Robust Motion Blur Kernel Estimation is described. With the proposed kernel prior, the strong and fine-grained edges of the intermediate images can be recovered, which makes the estimated kernel more accurate. A single moving object is featured in each set of images, multiple moving objects, and blurred images caused by camera shake. Estimating a blur kernel consists of two steps in described method: the evaluation of the intermediate kernel and the estimation of the intermediate images. By comparing average runtime, they can evaluate the effectiveness of described method, Structural Similarity Index (SSIM) and Mean Square Error (MSE) on Dataset. From results it is clear that, the performance of Image Restoration using Robust Motion Blur Kernel Estimation is better than other models in terms of low MSE, high SSIM and less Average time.

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