BLIND IMAGE DEBLURRING USING ITERATIVE MAXIMUM A POSTERIORI ESTIMATION

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ABSTRACT

This paper presents a blind image deblurring algorithm based on iterative Maximum A Posteriori (MAP) estimation, designed to recover a sharp image from a blurred observation without prior knowledge of the blur kernel. We model the observed blurred image as a convolution of a sharp latent image with a blur kernel, plus noise. The algorithm alternates between estimating the latent image and the blur kernel through an iterative energy minimization framework. Experimental results demonstrate the algorithm's ability to produce high-quality deblurred images by exploiting image decomposition, gradient thresholding, and multi-scale refinement.

***Index Terms*—** Blind deblurring, maximum a posteriori estimation, iterative optimization, image restoration, multi-scale approach

1. INTRODUCTION

Motion blur is a common issue encountered in image capture due to camera shake or object motion, and restoring sharpness in such blurred images presents a challenging task. To address this problem of single image blind deblurring, where both the blur kernel and the original sharp image are unknown advanced Digital signal processing techniques shall be harnessed. Traditional methods such as Iterative Blind Deconvolution, Gradient-Based Methods, Ensemble Learning and Regularization etc often rely on iterative algorithms that alternately estimate the blur kernel and the latent image. However, these methods may be unstable, especially in the presence of small image gradients, which can lead to artifacts and inaccurate restoration. We propose a novel approach that integrates image decomposition into the deblurring. The blurred image is decomposed into two components: the cartoon part (which captures large-scale structures and edges) and the texture part (which contains fine details and noise). By focusing on the cartoon component for deblurring, this method enhances the algorithm's stability and robustness, as it avoids the amplification of noise and ringing artifacts that typically arise from texture. This decomposition-based technique ensures more reliable kernel estimation, especially in the initial iterations when errors are more likely. We apply a Maximum A Posteriori (MAP[SSK15] framework to optimize the blur kernel and sharp image estimates, leveraging the decomposed cartoon image to guide the deblurring process. Our method demonstrates improved performance on both synthetic and real-world images, outperform- ing several state-of-the-art algorithms in terms of accuracy and robustness.

2. PROBLEM FORMULATION

In our model, the blurred image B is formulated as:

$$B = I * k + n \tag{1}$$

where I is the latent sharp image, k is the blur kernel, n represents additive noise, and $*$ denotes convolution. We employ a MAP approach[CL09] to jointly estimate I and k, defined by the posterior probability:

$$p(I, k|B) \propto p(B|I, k)p(I)p(k) \tag{2}$$

where $p(B|I, k)$ is the likelihood, and $p(I)$ and $p(k)$ are priors on the latent image and kernel, respectively. We assume Gaussian noise, leading to a Gaussian likelihood, and model the priors using a Laplacian distribution for the image gradients and an exponential prior for the kernel.

3. PROPOSED ALGORITHM

The MAP estimation problem is transformed into an energy minimization[Xu+12] problem:

$$\min_{I,k} E(I, k) = \|I * k - B\|_2^2 + \lambda_1 \|\nabla I\|_1 + \lambda_2 \|k\|_1 \tag{3}$$

where λ_1 and λ_2 are regularization parameters controlling the image smoothness and kernel sparsity. The algorithm iteratively updates I and k as follows:

3.1. Latent Image Estimation

In each iteration, given the current kernel estimate, we solve for the latent image I by minimizing:

$$I = \arg\min_I \|B - I * k\|_2^2 + \lambda_1 \|\nabla I - \nabla I_{\text{car, thr}}\|_2^2 \tag{4}$$

where $I_{\text{car, thr}}$ is the cartoon component of the image after thresholding the gradients, allowing the algorithm to ignore small gradients and focus on strong edges.

3.2. Kernel Estimation

The kernel k is updated by minimizing:

$$k = \arg\min_{k} \|\nabla B - \nabla I_{\text{car, thr}} * k\|_2^2 + \lambda_2 \|k\|_1 \tag{5}$$

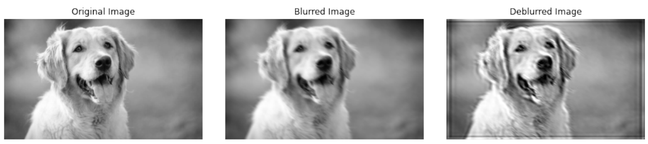
The sparsity prior on k encourages the kernel to represent camera motion by suppressing noise and irrelevant values.

3.3. Multi-scale Optimization

To enhance robustness, a multi-scale approach is employed. The blurred image is downsampled, and the algorithm performs kernel estimation at each scale from coarse to fine. This allows for a more stable solution, especially in the presence of larger blurs.

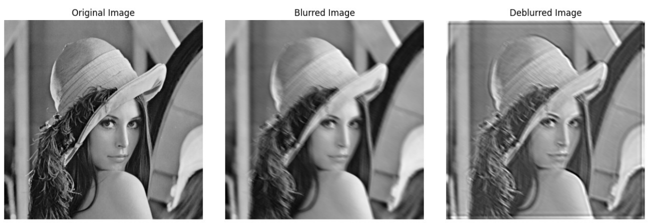
4. EXPERIMENTAL RESULTS

Experiments were conducted on images with varying types of motion blur. The algorithm was implemented in Python, using libraries like OpenCV and SciPy for image processing. Key parameters, including λ_1, λ_2, and kernel size, were tuned to optimize performance across different images.Below Figure shows sample results, demonstrating that the deblurred images retain sharp edges and fine details.



(a) Original Image (b) Blurred Image (c) Deblurred Image

Fig. 1. Comparison of the original, blurred, and deblurred images using the proposed method.



(a) Original Image (b) Blurred Image (c) Deblurred Image

Fig. 2. Comparison of the original, blurred, and deblurred images using the proposed method.

5. CONCLUSION

This paper presented an iterative MAP-based approach for blind deblurring.we successfully implemented the single-image blind deblurring algorithm using image decomposition. The algorithm addresses motion blur by iteratively estimating the blur kernel and restoring the sharp image, with a novel focus on decomposing the image into cartoon and texture components.

This decomposition aids in isolating essential image gradients, thus enhancing kernel estimation and reducing artifacts. Our tests on two images demonstrated the algorithm's effectiveness in restoring clarity with fewer artifacts than traditional methods, confirming the robustness and accuracy of the decomposition-based approach. This implementation gives the potential of image decomposition in improving deblurring results, particularly for real-world images affected by camera shake. Future work may explore adaptive parameter tuning and real-time deblurring applications.

6. REFERENCES

References

[CL09] Sunghyun Cho and Seungyong Lee. "Fast motion deblurring". In: *ACM Trans. Graph.* 28.5 (Dec. 2009), pp. 1–8. ISSN: 0730-0301. DOI: 10.1145/1618452.1618491. URL: https://doi.org/10.1145/1618452.1618491.

[Xu+12] Yuquan Xu et al. "Single image blind deblurring with image decomposition". In: Mar. 2012, pp. 929–932. ISBN: 978-1-4673-0045-2. DOI: 10.1109/ICASSP.2012.6288037.

[SSK15] Filip Sroubek, Vaclav Smidl, and Jan Kotera. "Understanding image priors in blind deconvolution". In: *2014 IEEE International Conference on Image Processing, ICIP 2014* (Jan. 2015), pp. 4492–4496. DOI: 10.1109/ICIP.2014.7025911.