Image Deblurring Using Blind Deconvolution

Vikram Panda, Akshay Patil, Arvind Rathod, Prof. Shyamal Virnodkar
Department of Computer Engineering
K.J. Somaiya Institute of Engineering and Information Technology,
Ayurvihar Complex, Everard Nagar, Sion, Mumbai-400022
Maharashtra, India
Email :{ vikram.panda, akshay.lp, arvind.r, shyamal} @somaiya.edu

Abstract-In this project, we propose a novel blind image restoration method based on the PSF of the image. It involves alternate iteration of point spread function (PSF) estimation and deconvolution. [1]Using this method, we can obtain clear images from blurred images without increasing noise and ringing. Experimental results show that our proposed method improves picture quality by removing various types of noise present in the image.

Index Terms - PSF, Blind Deconvolution, Weight.

1. INTRODUCTION

The recent proliferation of digital cameras and cell phones with built-in cameras has contributed to the growing popularity of photography .Photographs suffer from undesirable quality degradation due to various factors such as camera shake and loss of focus. Therefore, image restoration is necessary to enhance the quality of deteriorated images.

Motion blur occurs when a camera or the objects being captured move during its sensor exposure time. Motion blur can be reduced by decreasing the exposure time. However, low-contrast images are obtained in dark conditions because it is impossible for a sensor to detect sufficient light.Therefore, a flash is used for illumination; however, the output images are flat and lack shadows. Moreover, methods for increasing the sensor sensitivity also magnify image noise.

Digital cameras with optical image stabilizers have been introduced to overcome the problems described above. However, such devices are complex and expensive. In addition, image stabilizers are employed to prevent motion blur; hence, previously captured blurred images cannot be restored. Blurred images can be restored via image processing. However, in practice, image processing entails drawbacks such as the inclusion of ringing artifacts or enhancing image noise in restored images[1].

2. REVIEW OF LITERATURE

Image blur due to camera shake is a common problem in consumer-level photography. It arises when a long exposure is required and the camera is not held still. As the camera moves, the image formation process integrates a stream of photographs of the scene taken from slightly different viewpoints. Removing blur due to camera shake is currently a very active area of research. Given only a single photograph, this blur removal is known as blind deconvolution, i.e., simultaneously recovering both the blur kernel and the deblurred, latent image. Commonly, it is assumed that the blur kernel is spatially invariant, reducing the set of camera motions that may be modeled.

Software-based methods use image priors and kernel priors to constrain an optimization for the blur kernel and the latent image. Fergus et al. [6] recover a blur kernel by using a natural image prior on image gradients in a variation Bayes framework. Shan et al. [2] incorporate spatial parameters to enforce natural image statistics using a local ringing suppression step. Jia et al. [3] use transparency maps to get cues for object motion to recover blur kernels by performing blind deconvolution on the alpha matte, with a prior on the alpha-matte. Joshi et al. [3] predict a sharp image that is consistent with an observed blurred image. Levin et al. [7] give a nice overview of several of these existing deblurring techniques. Common to all of them is that they assume spatial invariance for the blur. Levin et al. show that spatial invariance is often violated, as it is only valid in limited cases of camera motion.

2.1 Motion Blur Model-

Let l be the latent image of a constant depth scene and b be the recorded blurred image. The blurred image can be written as a convolution of the latent image with a kernel k and the addition of some noise n. The convolution model does not account for variations in depth and view-dependent illumination changes and we do not handle them here

$$b = k \otimes l + n \qquad (1)$$

For simplicity, we assume Gaussian noise,

$$n \sim \mathrm{N}(0, \sigma^2)$$

This convolution model can also be written as a matrix-vector product:

$$B = KL + N \qquad (2)$$

where L, B, and N denote the column-vector forms of l, b, and n respectively. K is an image filtering matrix that applies the convolution each row of K is the blur kernel placed at each pixel location and unraveled into a row vector. For this reason, we also refer to K as the blur matrix. With spatially invariant blur each row has the same values that are just shifted in location. This matrix-vector form becomes particularly useful for formulating spatially varying blur as each row contains a different blur kernel for each pixel, as we will discuss in the next section [1].

3. PROBLEM STATEMENT

Image blur due to a minor movement in the position of the camera is a common problem in consumer level photography. It arises when the consumer wants to take the snap of any object which is kept at a very far distance and the camera is not held still.Also most of the deblurring techniques use natural image priors which may not apply to all local areas in an image thus leading to unreliable blur in the deblurred result. This application encompasses various Image processing techniques like Deblurring and Image restoration to obtain high quality image with less processing time.

4. PROPOSED SYSTEM

4.1 Read image -

In this step the system reads a clear image.

4.2 Simulate a blur-

Simulate a real-life image that could be blurred (e.g., due to camera motion or lack of focus). The Gaussian filter then represents a point-spread function i.e. PSF.

4.3 Restore the blurred image using PSFs of various sizes -

To illustrate the importance of knowing the size of the true PSF, each time the PSF reconstruction starts from a uniform array--an array of ones.

The first restoration uses an undersized array, UNDERPSF, for an initial guess of the PSF. The size of the UNDERPSF array is 4 pixels shorter in each dimension than the true PSF.

The second restoration uses an array of ones, OVERPSF, for an initial PSF that is 4 pixels longer in each dimension than the true PSF.

The third restoration uses an array of ones, INITPSF, for an initial PSF that is exactly of the same size as the true PSF.

4.4 Analyzing the restored PSF-

All three restorations also produce a PSF. The following pictures show how the analysis of the reconstructed PSF might help in guessing the right size for the initial PSF. In the true PSF, a Gaussian filter, the maximum values are at the center (white) and diminish at the borders (black).

The PSF reconstructed in the first restoration, obviously does not fit into the constrained size. It has a strong signal variation at the borders. The corresponding image does not show any improved clarity vs. the blurred image.

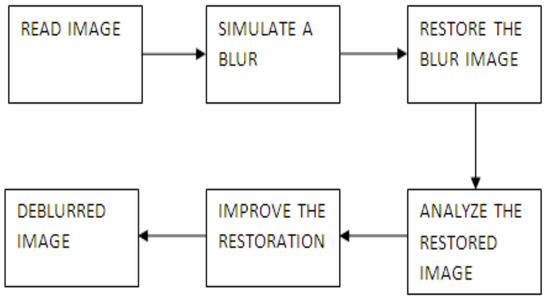

Fig. 1. Block Diagram of Proposed System

The PSF reconstructed in the second restoration, becomes very smooth at the edges. This implies that the restoration can handle a PSF of a smaller size. The corresponding image shows some deblurring but it is strongly corrupted by the ringing.

Finally, the PSF reconstructed in the third restoration, is somewhat intermediate between first and second restoration. The array of third restoration resembles the true PSF very well. The corresponding image shows significant improvement; however it is still corrupted by the ringing.

4.5 Improving the restoration-

The ringing in the image of third restoration occurs along the areas of sharp intensity contrast in the image and along the image borders. This step shows how to reduce the ringing effect by specifying a weighting function. Finally the deblurred image is obtained.

5. CONCLUSION

In this system, we proposed an algorithm for the effective restoration of blurred images using various PSF of the image.Clear images can be constructed with considerably less noise and less ringing effect. In this system we will implement one more algorithm to show that the proposed system is good as compared to existing algorithm.

ACKNOWLEDGEMENT

We would like to convey our sincere thanks to the many people who guided us throughout the course of this project. In addition, we would like to express our sincere thanks to Prof. Shyamal Virnodkar for her immense guidance, encouragement, co-operation and suggestions given to us at progressing stages of the project. Finally we would like to thanks our Head of Department Prof.Dr.Sunita Patil and all teaching, non-teaching staff of the college and friends for their moral support rendered during the course of the project work and for their direct and indirect involvement in the completion of our project work, which made our endeavor fruitful.

REFERENCES

[1] Kyosuke Ohkoshi, Masanao Sawada, Tomio Goto, Satoshi Hirano, and Masaru Sakurai: ―Blind Image Restoration Based on Total Variation Regularization and Shock Filter for Blurred Images, ICCE, 2014.
[2] Q. Shan, et al.: ―High-quality motion deblurring from a single image, ACM Transactions on Graphics (SIGGRAPH), Vol.27, No.3, Aug. 2008.
[3] N. Joshi, et al.: ―Personal photo enhancement using example images, ACM Transactions on Graphics (SIGGRAPH), Vol.29, No.2, Mar. 2010.
[4] S. J. Osher and L. I. Rudin: ―Feature-oriented image enhancement using shock filter, SIAM Journal on Numerical Analysis, Vol.27, No.4, pp.919 – 940, Aug. 1990.
[5] A. Chambolle: ―An algorithm for total variation minimization and applications, J. mathematical Imaging and Vision, Vol.20, No.1, pp.89 – 97, 2004.
[6] D.Krishnan and R.Fergus: "Fast image deconvolution using hyperlaplacian prior", In Advances in Neural Information Processing Systems, Vol. 22, pp. 1033-1041, Dec. 2009.
[7] Levin, A., Weiss, Y., Durand, F.: Understanding and evaluating blind deconvolution algorithms. In: Proceedings of IEEE CVPR ’09. (2009).