Handling Moving Objects and Over-Exposed Regions in Non-Blind Multi-Image Deconvolution

Sung Hee Park Marc Levoy
Stanford University
shpark7@stanford.edu levoy@cs.stanford.edu

1. Introduction

In our CVPR paper "Gyro-based Multi-Image Deconvolution for Removing Handshake Blur" [4], we proposed a multi-image deblurring system that uses gyroscope data for camera motion estimation. Although our method effectively removes handshake blur in static regions, moving objects and over-exposed regions are not handled properly. These regions are considered as *outliers* because they do not follow our image formation model. Moving objects may suffer from excessive blur caused by the object motion occurred during the entire capture time. In addition, pixel values in highlights may be clipped due to limited dynamic range of image sensor, and often cause artifacts after deconvolution.

Patch-based denoising method merges similar image patches to effectively reduce noise [2][3]. When multiple images are available, these methods reduce noise in a reference image using image patches from all available images. One advantage of this type of denoiser is that outliers are handled better than with multi-image deconvolution. That is, although moving objects remain as blurry as in the reference image, the amount of motion blur is less than when multi-image deconvolution is used. In addition, while over-exposed regions may also contain some blur, they will not suffer from noticeable artifacts.

In this technical report, we propose an additional image blending step that follows non-blind multi-image deconvolution. Our goal is not to handle outliers in a physically based method. Instead, we hide possible deconvolution artifacts. First, we detect outliers in the image obtained from multi-image deconvolution. Then, the pixel values around outliers are blended with the result of patch-based denoising. As a result, the blended image contains sharp details in static regions, while moving objects and over-exposed regions are expressed naturally without excessive blur.

2. Combining the Results of Multi-Image Deconvolution and Multi-Image Denoising

Our blended image $\tilde{X}$ is obtained by combining the result of deconvolution $\tilde{X}_{dc}$ and the denoised image $\tilde{X}_{dn}$ as follows:

$$\tilde{X} = W\tilde{X}_{dn} + (1 - W)\tilde{X}_{dc} \tag{1}$$

where W is the blend weight. Outliers are assigned with higher weights to make the blended image rely less on $\tilde{X}_{dc}$.

2.1. Detecting Outliers in Multi-Image Deconvolution

We estimate the weight W by finding the maximum residual error obtained by pair-wise comparisons. First, we select a reference image $Y_{i_{ref}}$, which is the sharpest among input images. Then, the residual error between $Y_{i_{ref}}$ and other input images Y_i is evaluated to quantify how these images deviate from the convolution blur model. A map of residual error W_{err} is defined as

$$W_{err} = \max_{i \neq i_{ref}, c \in C} \|K_i^T \otimes K_{i_{ref}}^T \otimes (K_i \otimes Y_{i_{ref}}^c - K_{i_{ref}} \otimes Y_i^c)\|^2 \tag{2}$$

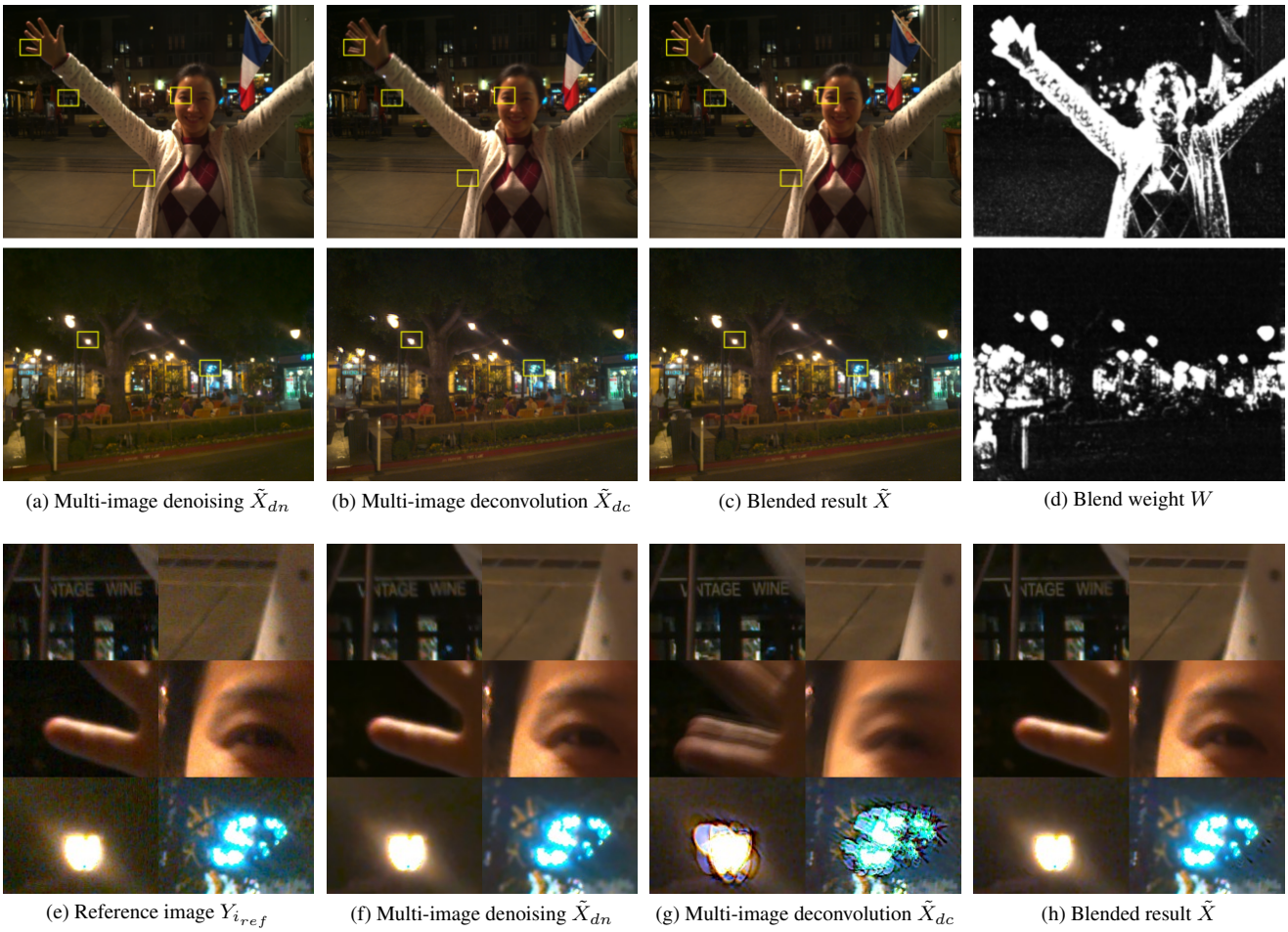
where $C = \{R, G, B\}$ represents color channels, K_i is the blur kernel for Y_i and $\otimes$ represents the 2D convolution operator. Last, the blend weight is obtained as $W = \min(1, \beta W_{err})$ where β is a positive scaling factor that tunes the blending.

2.2. Patch-Based Multi-Image Denoising

First, all input images are globally aligned with $Y_{i_{ref}}$ by means of the affine transform. Then, the non-local means method [2] implemented with the permutohedral lattice [1] is applied to n aligned images to obtain the denoised image $\tilde{X}_{dn}$. The position vector in Gaussian filtering has six principal component analysis (PCA) dimensions for the space of image patches, in addition to two spatial dimensions. A patch size of 13×13 pixels is used.

3. Results

Figure 1 shows examples obtained from our image blending operation. A burst of eight images is captured at 5M-pixel resolution, while gyroscope data is recorded at the same time to measure the camera motion. Eight images are



(a) Multi-image denoising $\tilde{X}_{dn}$ (b) Multi-image deconvolution $\tilde{X}_{dc}$ (c) Blended result $\tilde{X}$ (d) Blend weight W

(e) Reference image $Y_{i_{ref}}$ (f) Multi-image denoising $\tilde{X}_{dn}$ (g) Multi-image deconvolution $\tilde{X}_{dc}$ (h) Blended result $\tilde{X}$

Figure 1: Output images after combining the results of multi-image deconvolution and patch-based multi-image denoising. Eight images are captured from a single burst at 5M-pixel resolution, while gyroscope data is recorded at the same time. (a) A reference image is denoised by a patch-based method. (b) Our multi-image deconvolution is applied. Then, (a) and (b) are blended to obtain the final output images shown in (c). Close-ups, shown as yellow boxes in (a)-(c), are shown in (e)-(h). Note that the reference images in (e) are noisy and contain some amount of blur, while noise is reduced in (f). The deconvolved images in (g) recovered sharp details in static regions (top row), but moving objects suffer from motion blur (middle row) and highlights caused artifacts (bottom row). The blended results in (h) effectively hide artifacts in (g) while preserving sharpness in the background. Also note that outliers, i.e., moving objects and over-exposed regions, are well detected with our method as shown in (d).

jointly deconvolved to obtain $\tilde{X}_{dc}$. Although the deconvolution recovered sharp details well in static regions, moving objects are quite blurry and over-exposed regions suffer from objectionable artifacts. These outliers are blended with the denoised result $\tilde{X}_{dn}$. The blended output contains only the better parts from two images and shows minimum artifacts. Figure 1d shows that outliers, a person moved during the capture and bright street lights, have high weights in the weight maps to hide deconvolution artifacts. This image blending operation makes multi-image deconvolution more robust to handle real-world photographic situations.

References

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