IMAGE DEBLURRING USING MAPS OF HIGHLIGHTS

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ABSTRACT

In deblurring an image, we seek to recover the original sharp image. However, without knowledge of the blurring process, we cannot expect to recover the image perfectly. We propose a deblurring method of a single-image where the blur kernel is directly estimated from highlight spots or streaks with high intensity value. These highlighted points can be represented by specular reflection of light that may appear in the eye, on a shiny surface, or in small light sources present in the image. In this work, we detect automatically these highlighted points in a blurred image. Therefore, creating a map of highlight, which is used as a guide to extract automatically a single highlight from the blurred image. Due to its unique nature, it is demosntrated that the highlighted points are a good estimation of the blur kernel and a sharp image is restored using these kernel. The experimental results show the performance of this method in comparison to several other deblurring methods.

***Index Terms*—** Image Restoration, Image Deblurring, Blind Deconvolution, Highlight Points.

1. INTRODUCTION

Digital images often exhibit blur, which may be a result from an abrupt movement of the photographer, insufficient lighting (slow shutter speed), use of a small aperture (shallow depth of field) or a wrong setup of the lens focus. Recovering a sharp image from the blurred one is a difficult task.

Real-world blur is complex and usually contains high frequency components. For example, blur caused by shaking the camera may contain convoluted paths. However, in most works motion is assumed to be linear. Similarly, while focal blur is often modeled as a simple circular disk or a low frequency Fourier component, in practice the shape of the blur kernel is elaborate and may contain sharp edges. Therefore, to successfully deblur an image, knowledge of the blur process is required.

In non-blind deconvolution, the blur kernel is assumed to be known or it is computed elsewhere; the only task remaining is to estimate the unblurred latent image [1]. Blind deconvolution allows recovery of a sharp image from a single blurred image and the blur kernel is unknown. Some techniques make the problem more tractable by leveraging additional input, such as multiple images [2] and other methods take advantage of specialized hardware [3].

Other techniques operate on a single image and require no additional hardware. Shan et al. [4] use sparse priors and the multi-scale framework for their results. Xu and Jia [5] proposed an efficient and high-quality kernel estimation method based on the spatial prior and the Iterative Support Detection (ISD) kernel refinement, and employed a deconvolution process solved with a new variable substitution scheme to robustly suppress noise. Tai and Lin [6] propose a technique for jointly denoising and deblurring. Many of these kernel estimation methods rely on a large number of parameters, which require a long computation time. Hua and Low [7] used light streaks information for motion debluring. The user need to interactively select an region in the blurred image in which there is a noticeable light streak point. However, if the choosen light point is not appropriate, the method performs poorly.

In this work, we propose a simple *blind estimation* scheme for blurred images which contain highlight information - specular reflections of light or small source of light. Highlights are detected automatically, and from a map of these detected highlights, one of it is extracted automatically from the blurred image in order to calculate a blur kernel for the restoration process. We demonstrate how to recover complex blur kernels, and use the deconvolution method to restore the resulting sharp image.

2. BLUR ESTIMATION FROM HIGHLIGHTS POINTS

Highlight of an image are defined by specular reflection or small sources of light in a image. Specular reflection is a surface phenomenon in which light rays incident on the surface are reflected such that the angle of reflection equals the angle of incidence. Light energy due to specular reflection and small source of light are usually concentrated in a compact lobe, causing strong highlight (bright region) to appear in the image. Specular highlights may naturally appear in reflections from shiny objects (e.g., water, metal, glass, etc). Small light sources may vary from illuminated decorations of Christmas trees to light poles of a city, for example, depending on the distance between the photograph and the light source. Figure 1 presents two examples of highlights in blurred images.

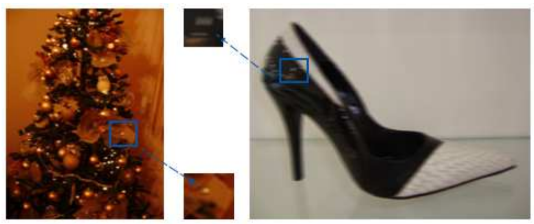

Fig. 1. Highlights represented by spots of small sources of light (Left). Highlight points represented by streaks of specular reflections of light.(Right).

We propose a scheme for estimating complex blur kernels in images which contain highlights. The highlights points, once identified and extracted, can effectively be used to estimate the degradation process. In equation 1, the blurred signal B_s, on the left, was created by convolving the sharp signal S_s and the blur kernel k_b, on the right. We assume that the sharp signal contains a highlight, the peak k_s:

$$B_s = S_s \otimes k_b \quad (1)$$

Given the blurred signal, assume that it is possible to find a signal separation that satisfies:

$$B_s = I_b \otimes k_s \quad (2)$$

where I_b is the blurred scene without the highlight point k_s.

Consider the highlight extracted from the blurred image. Since the light energy of the highlight in the sharp image is assumed to be concentrated in a compact lobe, it can be approximated to an impulse $\delta_{(p,q)}$

$$\delta_{(p,q)}(x,y) = \begin{cases} \infty & \text{if } x = p \text{ and } y = q \\ 0 & \text{otherwise} \end{cases}$$

Therefore, the blurry signal can be approximated by a convolution of the blur kernel and a sum between S and δ.

$$B_s \approx [S_s + \delta_{(p,q)}] \otimes k_b \quad (3)$$

By substituting Equation 2 in Equation 3 we obtain:

$$I_b \otimes k_s \approx [S_s + \delta_{(p,q)}] \otimes k_b \quad (4)$$

Finally, we conclude that the blurry highlight is a convolution between an impulse and the blur kernel. Hence, the blurry highlight is the impulse response of the degradation process

$$k_s = \delta_{(p,q)} \otimes k_b = k_b \quad (5)$$

2.1. Blur Kernel Generation

The blur estimation requires a separation of the blurry highlight point from the rest of the image. We applied the alpha matting algorithm proposed by Levin et al. [8] to segment a highlight point from an image. The image I, which is assumed to be a composite of foreground image F and a background image B, is used as input. The color of a pixel $I(x,y)$ is defined to be a linear combination of foreground and background colors so that:

$$I(x,y) = \alpha_i \times F(x,y) + (1 - \alpha(x,y)) \times B(x,y) \quad (6)$$

where $\alpha(x,y)$ is the pixel foreground opacity.

In order to extract the highlight point, an automatic method to detect highlight points was implemented using the technique proposed by Ortiz and Torres [9] that propose to exploit the existing relations between (Intensity) M and S (Saturation) that permit the detection of brightness on a digital image, independently of the hue of the object in which the brightness exits. They use a bi-dimensional histogram where the number of pixels that have the values M and S are represented - the MS Diagram.

The binary image resulting from this detection is used as a map of highlights to choose the best highlight point within the blurry image to generate the kernel. For every white region of the map, a single foreground point (within the highlight) is obtained in the blurry image. Then, a window is automatically generated, surrounding the highlight point. The size of this window is large enough to completely contain the highlight area to be segmented by the alpha matting algorithm. In general, this size is between 2% and 4% of the total image size. The window contains the selected point, and its borders are assumed to be the background points (Figure 2).

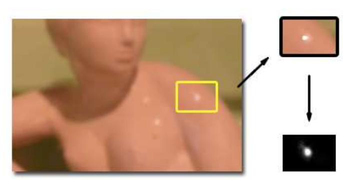

Fig. 2. For every white region of the highlight map, we generate a window containing a single highlight point, such that its borders are background points. We then extract the specular highlight usign alpha matting [8] to recover the blur kernel.

In our experiments, smaller specular highlights consistently produced better results. Therefore the larger point contain information irrelevant to the deblurring process, and causes artifacts in the image. The proposed kernel is chosen as the kernel that is used in the deconvolution process. This kernel is chosen from a simple blob analysis. Figure 3 illustrates a blurry image, its the map of highlights, its generated kernels using the alpha matting algorithm and the proposed kernel for the deconvolution process.

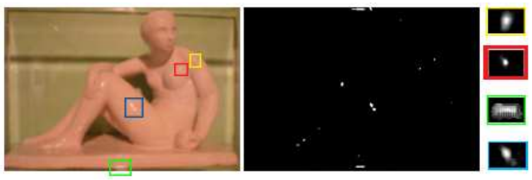

Fig. 3. Original blurred image (Left). Map resulting from the automatic detection of highlight points. (Middle). For obtains this result we set the max saturation of MS Diagram with value equal to MI/2.6, where MI is the max intensity value (see [9]).

2.2. Image Reconstruction

Given an estimate of the blur kernel from highlight information, several non-blind deconvolution methods [1, 4] were applied. However, when applied to real-world images, these methods tend to produce artifacts. Xu and Jia [5] produced the best results consistently. The method uses a fast TV-ℓ_1 deconvolution based on half-quadratic splitting [10, 11] to efficiently reject outliers and preserve structure.

3. RESULTS

The proposed approach is successful even when faced with complicated blur kernels (motion with streaks highlights and unfocus blur with spotted highlights from real photographs). In Figure 4 two examples of deblurring using the proposed approach are shown: the map of highlights and deblurred image with the highlight are chosen automatically. In the Christmas tree example, the image has a unfocus blur with spoted highlights and it is highly saturated. In the headphones example, the image has a medium motion blur with streaks highlights. The deblurring results shows a good visually plausible sharp deblurred result, with few ringing artifacts.

We tested the algorithm and compared them to two recent state-of-the-art methods [4, 5]. Figures 5 and 6 show the results of these two methods compared to the proposed method. In all examples, the parameters were tuned for the best result, using an identical kernel size. In Figure 5, the headphone of the latent image resulting from our method is sharper and has less ring artifacts that the image resulting from the methods proposed by [4] and [5]. Figure 6 shows a blurred image that

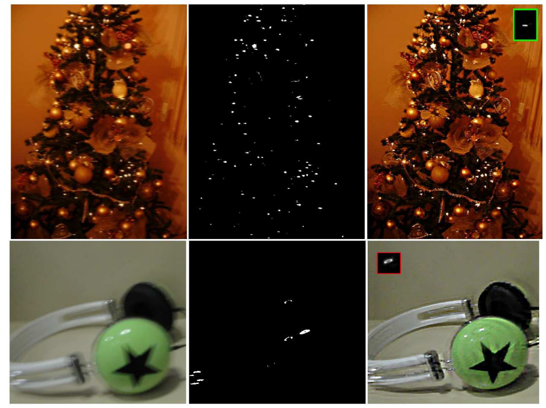

Fig. 4. Blurred images (Left). Map of highlights (Middle). The result of applying our algorithm with better highlight marked with a rectangle.

contains small details such as the number in the display of the alarm clock. The proposed method recovered these small details creating a final latent image with fewer ring artifacts than the methods proposed by [4] and [5].

We use the Structural SIMilarity (SSIM) index proposed by Wang et al. [12] to compare the quality of our results with the [4] and [5] results. The SSIM index is a method for measuring the similarity between two images and it can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. In this work, we compared the original blur image with the image resulting from different methods debluring. Since we have as reference image only a blurred image, we will assume that the sharped image resulting from each deblurring method is our "perfect image" used in the quality measure process. Then, the resulting sharped images is compared with the referential blurred image for measuring the similarity. The closer to 1 the SSIM index value resulting from the comparison, means that the quality of the resulting image deblurring process is better. Figures 5 and 6 shows the SSIM index for each different methods. As can be seen, our method have the best SSIM index value: 0.7309 to the headphone image result and 0.8915 to the alarm clock image result.

4. CONCLUSION

We proposed a novel method to restore blurry images which contain highlights. The proposed approach provides accurate estimates of complex blur kernels, which enables better and clear image restoration. The blur kernel is estimated using two steps: first using a binary map from the highlights automatic detection and second choosing automatically the cleaner highlight point that appears in the blurred image by using a simple blob analysis.

Our technique can successfully deblur most blurred im-

Fig. 5. From left to right: original blurred image, kernel estimation and deblurring from [4] (SSIM = 0.6417), kernel estimation and deblurring from [5](SSIM = 0.5747), our result (SSIM = 0.7309).

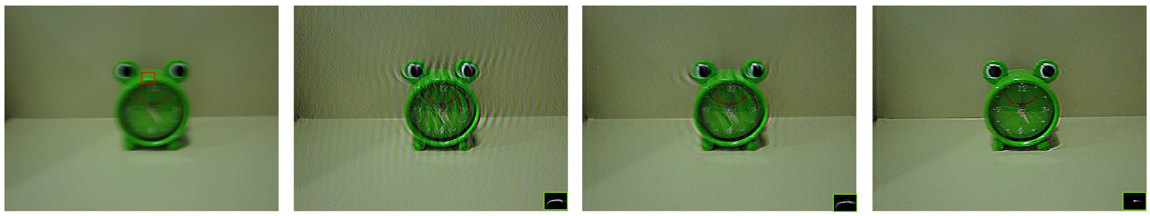

Fig. 6. From left to right: original blurred image, kernel estimation and deblurring from [4] (SSIM = 0.6696), kernel estimation and deblurring from [5] (SSIM = 0.7834), our result (SSIM = 0.8915).

ages (that contain highlight point). The kernel estimation approach is simple and intuitive, and does not require any parameters.

The approach, however, sometimes fails for blurred image that has large value of intensity because it generate incorrect maps of highlight. In these images the resulting estimated kernel is large, and may contain information irrelevant to the deconvolution process, leading to ringing artifacts.

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