Estimation and Removal of Motion Blur by Capturing Two Images with Different Exposures

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Abstract:

Deblurring refers to restoring digital photographs or videos that have been degraded by optical blurring such as motion blur. Motion blur typically occurs due to the long exposure time relative to the amount of motion of the object or the camera. A simple reduction in the exposure time does not produce desirable images since it results in high noise (i.e., low signal-to-noise ratio). Short exposure images on the other hand have the advantage of much less blur while the long exposure images have the advantage of much less image noise. In this paper, we describe an approach to deblur the long exposure image with additional information from the short exposure image. Our method i) captures two images of the same scene with different exposures, ii) estimates the blur kernel of the long exposure image from the images and iii) uses the estimated kernel to deblur the long exposure image while regularizing on the short exposure image. The goal is to combine the merits of the long and short exposure images and produce a high quality image with low noise and little motion blur. We show experimental results that illustrate the accuracy of the blur kernel estimation and the effectiveness of our deblurring method.

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ESTIMATION AND REMOVAL OF MOTION BLUR BY CAPTURING TWO IMAGES WITH DIFFERENT EXPOSURES

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Deblurring refers to restoring digital photographs or videos that have been degraded by optical blurring such as motion blur. Motion blur typically occurs due to the long exposure time relative to the amount of motion of the object or the camera. A simple reduction in the exposure time does not produce desirable images since it results in high noise (i.e., low signal-to-noise ratio). Short exposure images on the other hand have the advantage of much less blur while the long exposure images have the advantage of much less image noise. In this paper, we describe an approach to deblur the long exposure image with additional information from the short exposure image. Our method i) captures two images of the same scene with different exposures, ii) estimates the blur kernel of the long exposure image from the images and iii) uses the estimated kernel to deblur the long exposure image while regularizing on the short exposure image. The goal is to combine the merits of the long and short exposure images and produce a high quality image with low noise and little motion blur. We show experimental results that illustrate the accuracy of the blur kernel estimation and the effectiveness of our deblurring method.

1. Introduction

Many image/video capture devices do not have enough sensitivity to take high quality pictures especially in low light situations such as indoors or at night. For example, the user may want to take photos in a museum or some performance where they need to take pictures without the flash on. The most commonly used adjustment to control the amount of light received by the capture device is the exposure time. By exposing the pixels for a longer period of time, the pixels can collect more light leading to higher signal integrity (and lower noise) [1]. However, the drawback is that any movement in the camera or object significantly blurs the image. In many low light situations, the camera typically automatically sets the exposure time very long (e.g. several seconds) and often captures blurry photos. This occurs because the user cannot hold the camera steady enough during the capture time (i.e. exposure time). Thus, there is a practical limit on the length of the exposure time unless the camera is mounted on a tripod. This problem is further exacerbated when capturing an image with a telephoto lens. It is very difficult for a user to capture an image at a high zoom because small hand movements result in large movements in the image plane.

Deblurring refers to restoring digital photographs or videos that have been degraded by optical blurring that includes motion blur or out-of-focus blur. The quality of the image is degraded where the high frequency details of the scene are lost. In some cases, motion blur occurs when the object in the scene moves during the capture. In this scenario, the object appears blurry while other parts of the scene appear sharp. There are other cases when the scene (including the object-of-interest) is stationary but the camera moves due to the hand-shake of the user holding the camera. In these circumstances, all parts of the captured photograph are blurry due to the motion blur.

Deblurring an image corrupted by blur has been researched by many researchers [2~13]. However, most deblurring methods require the knowledge of the blur kernel, which is often unknown in the applications of digital photography. Blind deconvolution aims at solving the deblurring problem without any prior knowledge of the blur kernel [7~13]. It implicitly or explicitly estimates the blur kernel from the blurry image and uses the estimated blur kernel to deblur the blurry image. Although blind deconvolution has shown success in applications such as astronomy, solving the blind deconvolution problem reliably for consumer digital photography has been extremely difficult.

Due to the limitations of deblurring an image without a complete knowledge of the blur kernel, we have decided to focus our attention on a system where we capture two or more images. We use the fact that short exposure images have a low signal-to-noise ratio (i.e., noisy) but are sharp and that long exposure images have high signal-to-noise-ratio (i.e., clean) but are blurry. This can be seen in Figure 1. The left image is contrast-enhanced short exposure image and the right image is long exposure image. Since deblurring solutions based on a single frame do not produce reliable results, we attempt to solve the deblurring problem by capturing an additional short exposure image which maintains the sharpness.

The problem of deblurring an image given a second image with a different exposure is summarized as follows. Given a blurry, low-noise, long exposure image and an additional sharp but noisy short exposure image, how can we obtain a sharp and clean image? We approach the problem by de-blurring the blurry/low-noise image while regularizing against the sharp/noisy image. We attempt to combine the merits of the long and short exposure images and produce a high quality image with low noise and little motion blur.

A previously described approach [14] also combined a short exposure image and a long exposure image to remove motion blur. The key idea in this paper is to detect if there was any motion for each pixel and use short exposure values for pixels if motion is detected and long exposure values for pixels with no motion. Note that this approach is a passive approach, which just decides whether to use a long exposure or short exposure based on motion detection. Thus, if there were movement for all the pixels, then this method merely chooses the short exposure image. Our approach, on the other hand, is an active one and can intelligently combine the two images.

Since our work was filed as a patent in 2004, there have been recent publications on a similar idea [15~16]. Unlike [14], these methods "actively" attempt to remove blur. In [15], the problem is formulated as a MAP estimation problem with edge-preserving image prior. In [16], the blur kernel is estimated and is used to perform gain-controlled residual deconvolution and ringing artifact reduction. However, both methods are very compute intensive and require many iterations.

The paper is organized as follows. In the next section, we describe our method of i) capturing two images with different exposures, ii) estimating blur kernel from the two images and iii) deblurring the blurry image using the images and the estimate blur kernel. We then show experimental results in Section 3 both with simulated and real scenes.

2. Our Method

The block diagram of the operation of the method is shown in Figure 2. The two exposure images are first captured using a CCD or CMOS image sensor. Then, the blur kernel is derived from the two differently exposed images and the long exposure image can be deblurred to obtain a sharp image with low noise. The details of each part are given in the following subsections.

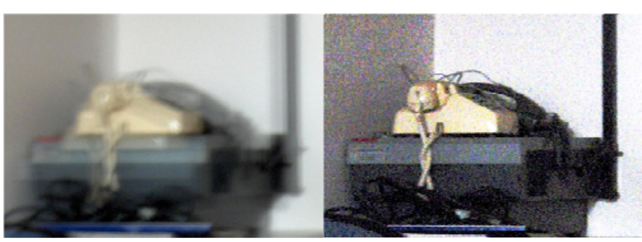

Figure 1: An example of long exposure (left) and short exposure image

2.1. Capturing two images

A digital camera can be used to capture a long exposure image and a short exposure image closely spaced apart in time. Most cameras have a burst mode where the time offsets between the frames are short. Note that the order of the two images does not seem to matter based on our experiments. It is also possible to capture the two images overlapping in time by using an image sensor with a non-destructive readout capability (such as CMOS image sensors) or multiple sensors. Note that it is beneficial to have a very short time offset between the two captures, but is not essential. Optionally, the motion between the short and long exposure images can be estimated and compensated by registering the images prior to performing the blur estimation and deblurring.

After performing the motion registration, the two images need to be normalized by the exposure ratio between them such that the two images have similar range of pixel intensity values. Let iS be the normalized short-exposure image,

$$iS = I + nS$$

where I is the ideal (sharp/low-noise) image that we would like to obtain and nS is the noise in the short exposure image. We are assuming that the exposure time for the short exposure image is short enough such that the blur kernel for the short exposure image is negligible (i.e. close to a delta function) and that the image is corrupted only by noise. Also, let iL be the long exposure image,

$$iL = I*h + nL$$

where h is the blur kernel, * denotes 2D convolution and nL is the noise in the long exposure image. Note that iS and iL are observed, but nS, nL, h and I are unknown. In an ideal world where we have no blur (h=δ, when the blur kernel is just a delta function) and no noise (nL=nS=0), the difference between the long and short exposure images is zero (i.e., iL=iS).

After rearranging some terms, the relationship between iS and iL can be represented as

$$iL = iS*h + (nL-nS*h) \qquad (1)$$

,where (nL -nS*h) is the aggregate of the noise terms. It is worthwhile to point out that even though we do not know specific values of the noise (nS and nL) at each pixel, it is possible to obtain the statistical properties (e.g. standard-deviation profiles) of them via image analysis or by examining the sensor specifications and capture parameters.

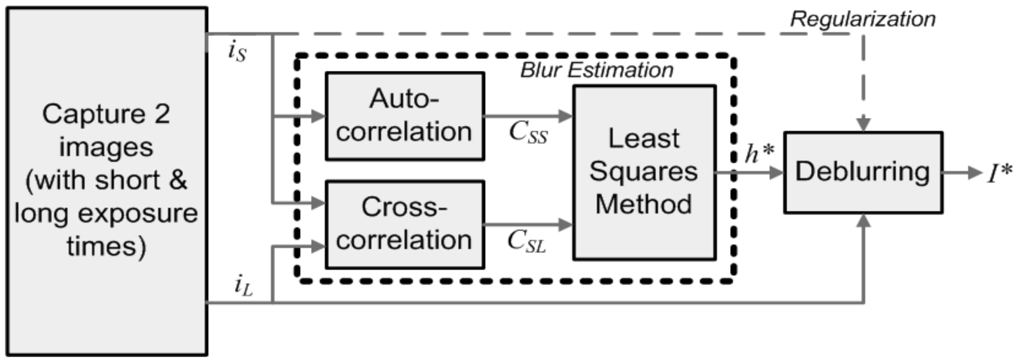

Figure 2: Block diagram of our method.

2.2. Estimating the blur kernel

Since we know *iS* and *iL* in Equation (1), it may be possible to estimate the blur kernel (*h*) if we can account for noise appropriately. The key is to find a method that is robust to the high noise in the image.

One way to derive the motion blur kernel is to first calculate the Fourier transform of the two images and then to take the ratio of them. In the following equation, $F\{\}$ is the Fourier transform operation and $F^{-1}\{\}$ is the inverse Fourier transform. The blur kernel *h* can be calculated as

$$h = F^{-1}\left\{\frac{F\{iL\}}{F\{iS\}}\right\}. \qquad (2)$$

This method is very sensitive to the noise present in *iS* and *iL*. It can be improved by using the Wiener method but from our experience, the results are not desirable.

Another method is to model Equation (1) as a linear system and solve it with a least squares method or regularized least squares method [16]. This method yields more accurate results than the Fourier Transform method above but is compute intensive and sensitive to noise.

To overcome the high sensitivity to noise and computational complexity, we developed a method to derive the blur kernel from the auto-correlation and cross correlation between the two images instead of trying to derive the blur kernel from the images directly. Note that robustness to noise is critical since the short-exposure image generally have low SNR due to lack of photons captured. Correlations are much less sensitive to noise because they are computed by multiplying the signal with a shifted version of the signal and averaging it. The auto-correlation of image $x(i,j)$ is defined as (assuming wide-sense stationarity)

$$C_{XX}(a,b) = \sum_i \sum_j x(i,j)x(i-a,i-b).$$

The cross-correlation between signal $x(i,j)$ and $y(i,j)$ is defined as

$$C_{YX}(a,b) = \sum_i \sum_j y(i,j)x(i-a,i-b).$$

If *y* is obtained by convolving x with z (i.e., $y=z*x$), then the relation between the cross-correlation of *y* and *x* and the auto-correlation of *x* are the same as the relation between *y* and *x*. In other words, $C_{YX} = z * C_{XX}$. When we apply this to the problem of blur estimation, we conclude that the correlations are blurred the same way as the signal itself. From Equation (1) and the properties of auto and cross-correlations, the relationship between the auto-correlation (C_{SS}) of the short-exposure image (*iS*) and the cross-correlation (C_{SL}) between long exposure (*iL*) and short exposure images can be summarized as

$$C_{SL} = C_{SS} * h. \qquad (3)$$

Here, we assumed that the noise terms *nS* and *nL* have zero mean and are uncorrelated to the image signals *iS* and *iL*. An example of the auto-correlation and cross-correlation is shown in Figure 3. As expected, the auto-correlation of the short exposure image is significantly sharper than the cross-correlation between the long and short exposure images. It is worthwhile to point out that the correlations are much more robust to noise than actual images as can be expected from Figure 3.

Our method makes use of Equation (3) and estimates the blur kernel by first computing the auto correlation C_{SS} of *iS* and the cross correlation C_{SL} between *iS* and *iL*. Once the correlations (C_{SL} and C_{SS}) have been computed, they can be rasterized and reformatted into a vector and matrix form such that Equation (3) can be represented as a linear matrix multiplication.

$$\mathbf{c}_{SL} = \mathbf{C}_{SS}\,\mathbf{h} \qquad (4)$$

,where $\mathbf{c}_{SL}$ and $\mathbf{h}$ are the rasterized vector forms of the cross-correlation (C_{SL}) and the blur kernel (*h*) and $\mathbf{C}_{SS}$ is the matrix whose rows are shifted versions of the auto-correlation (C_{SS}) such that the matrix multiplication Equation (4) correctly represents the convolution operation in Equation (3). We estimate the blur kernel by solving Equation (4) with a least-squares method.

$$\mathbf{h}^* = (\mathbf{C}_{SS}^{T}\mathbf{C}_{SS})^{-1}\mathbf{C}_{SS}^{T}\mathbf{c}_{SL}$$

Note that the spatial support for the auto and cross-

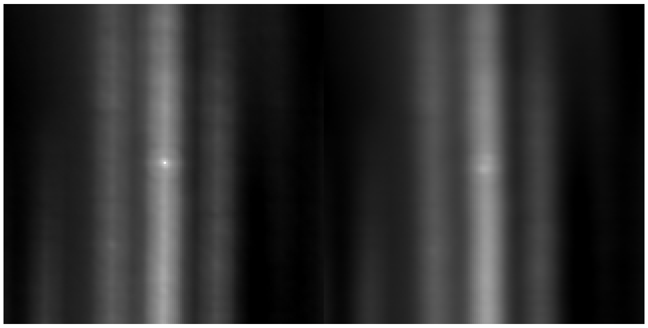

Figure 3: An example of the auto-correlation of the short exposure image (left) and cross-correlation between the long and short exposure images (right) for real images

correlations and hence the size of $\mathbf{C}_{SS}$ and $\mathbf{c}_{SL}$ is much smaller than that of the captured images. As can be seen from Figure 3, the correlations decay very quickly and can be represented with a much smaller vectors and matrices than the images themselves. Thus, estimating the blur kernel using the correlations is not only robust to noise but also computationally efficient.

2.3. Deblurring with an additional image

Since we have estimated the blur kernel using the two images, we may use conventional methods that assume a known blur kernel and a blurred image. Many of these methods perform some variant of inverse filtering with some regularization or additional *prior* assumptions. Note that the key difference in our problem setting is the availability of the short exposure image which is noisy but sharp.

Our objective is to develop a simple method that is not compute intensive and does not require many iterations. We propose to deblur the long exposure image while fully exploiting the estimated blur kernel and the additional information from the short exposure image. One way to achieve this is to regularize the deblurring process with the short exposure image. The deblurring problem is posed as a 2nd order minimization problem which tries to find the deblurred image that does not deviate too much from the short exposure image. Thus, the deblurred image is obtained by solving

$$\hat{I} = \arg\min_{j} \left\{ \| iL - h * j \|^2 + \lambda \| iS - j \|^2 \right\}.$$

A closed form solution exists for this minimization problem and can be represented as

$$\hat{I} = F^{-1}\left\{ \frac{F\{h\}^* F\{iL\} + \lambda F\{iS\}}{F\{h\}^* F\{h\} + \lambda} \right\}$$

where * represent complex conjugate and $F\{\}$ represents the Fourier transform. For higher performance (albeit with higher computational complexity), a more sophisticated method (e.g., a non-linear or iterative methods) than the regularized least-squares solution may be extended to exploit the short exposure image and achieve high quality. It is worthwhile to point out that the short exposure image may be denoised or pre-smoothed, in order to minimize the effect of the high noise in the short exposure image. This optional step prior to the deblurring process significantly improves the image quality of the resulting image at the expense of some additional computational complexity. Note that it is also possible to regularize the deblurring process such that the gradient of the deblurred image does not deviate from the gradient of the short exposure image.

3. Experimental Results

In this section, we show experimental results for estimation of the blur kernel and deblurring. In the first subsection, we show experimental results by starting with an ideal image and simulating blur and noise. In the second subsection, we show results by actually capturing two images with short and long exposure time and applying our method.

3.1. Simulated scenes

In order to investigate the effectiveness of our blur kernel estimation and deblurring method, we simulated the capture of short and long exposure images. By simulating

Figure 4: An example of simulated long exposure image (top) and short exposure image (bottom)

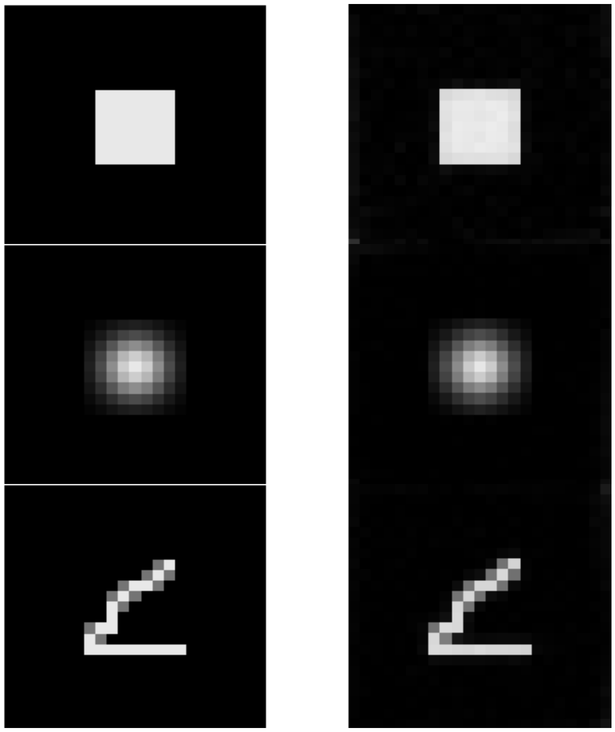

Figure 5: Examples of simulated blur kernels (left) and estimated blur kernels using our method (right)

the blurring process, the ground truth of the blur kernel is known such that we can measure the accuracy of our method and assess the quality of the output image. We obtained the short exposure image by adding Gaussian noise (e.g., with standard deviation of 20) to an ideal image with intensity range of 0 to 255. The long exposure image is obtained by blurring the ideal image with a known blur kernel and adding Gaussian noise with a smaller standard deviation of 1. An example of short and long exposure image is shown in Figure 4. As described earlier, short exposure image is sharp but noisy and long exposure image is blurry but has low noise. We simulated various types of blur kernels and some examples of them can be found in Figure 5. From top to bottom are box kernel, Gaussian kernel and some arbitrary curved line kernel.

From the simulated short and long exposure images, we estimated the blur kernel and applied our deblurring method. Figure 5 shows the comparison between the simulated blur kernel and the estimated blur kernel. It can be seen that the estimate of the blur kernel is very accurate. This is important as most deblurring methods are very sensitive to the blur kernel estimates.

We compared the results of our method with that of blind deconvolution (implemented as “deconvblind” function in MATLAB) method and Wiener deblurring method (implemented as “deconvwnr” function in

Figure 6: (Top left) Our deblur method, (Top right) Wiener method, (Bottom left) Long exposure image, and (Bottom right) blind deconvolution (deconvblind) in MATLAB

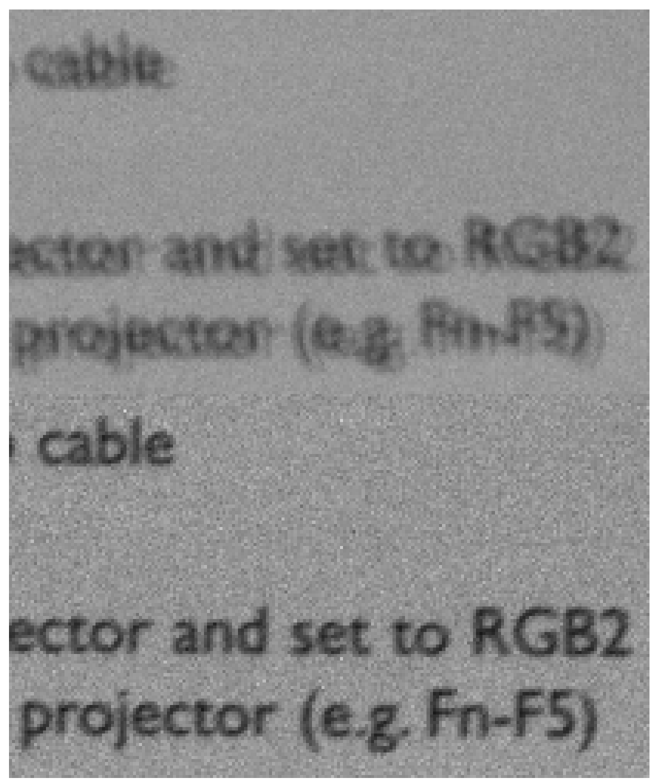

Figure 7: From top to bottom: Long exposure image and short exposure image,

MATLAB). For the Wiener deblurring method, we used the estimated blur kernel from our method. The input images were the images shown in Figure 4. For all the deblurring methods, we performed edge tapering in order to reduce the effect of ringing at the border of the image. Figure 6 shows the deblurred images using various methods. Note in Figure 6 that the result of our method is visually the best and that it is much less noisy than the short exposure image and much less blurry than the long exposure image. Also, note that the result of Wiener deblurring method has more ringing than that of our method. The result with our method was obtained by regularizing on the short exposure image pre-smoothed with a 3x3 Gaussian kernel (sigma=1). Lambda was chosen to be 0.01, which is typically a good choice for most images and noise levels.

Since we know the ground truth ideal image, we can compute the sum-of-squared-error between the ideal image and the input or deblurred images. Note that the error for our method is by far the smallest even though our method is not compute intensive and simple.

Blur Type	Gaussian	Box	Linear
Long Exp	14.54	19.5	25.37
Short Exp	9.76	9.77	9.76
Our Method	**5.28**	**3.72**	**3.05**
Wiener method	7.03	5.67	4.66
Blind-deconv	35.28	19.56	23.81

Table 1: Sum-of-squared-error (x 10^6) for various blur and image types.

3.2. Real-world scenes

Our method was also tested on real data captured with a digital camera. The image was captured in the burst mode of the digital camera with the raw capture setting. The long and short exposure image is shown in Figure 7. Note again that the long exposure image is blurry while the short exposure image is noisy.

The resulting image after it went through the blur kernel estimation and deblurring is shown in Figure 8. Note that the long exposure image has a "double" image where the weaker image and the stronger image are offset diagonally. This can be explained nicely with the estimated blur kernel shown in the figure. The estimated blur kernel in Figure 8 shows two distinct peaks whose relative positions are similar to the offset between the strong and weak images in the long exposure image. Note that the resulting image using our method has the best visual image quality and is less noisy than the short exposure image and sharper than the long exposure image.

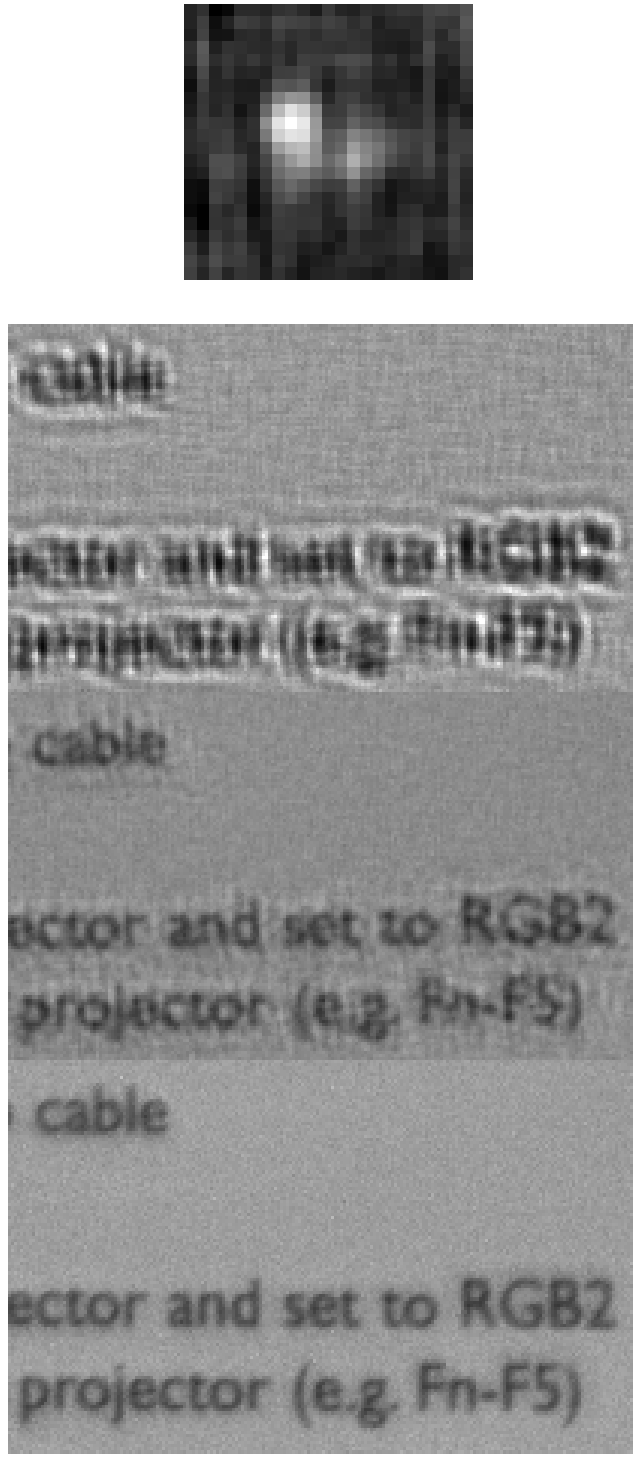

Figure 8: From top to bottom: i) Estimated blur kernel ii) Blind deconvolution method, iii) Wiener deblurring method and iv) deblurred output image with our method.

4. Summary and discussion

We described an approach to deblur the long exposure image with additional information from the short exposure image. The goal is to combine the merits of the long and short exposure images and produce a high quality image with low noise and little motion blur. Our method estimates the blur kernel by computing the auto and cross correlations of the images and uses the estimated kernel to deblur the long exposure image while regularizing on the short exposure image. The simulated and real experiments illustrate the high accuracy of the blur kernel estimation method and the effectiveness of our deblurring method.

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