Camera Intrinsic Blur Kernel Estimation: A Reliable Framework

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Blur most often occurs on out of focus objects or due to camera motion. While these kinds of blur can be prevented by adequate photography skills, there is a permanent intrinsic blur caused by the optics of image formation e.g. lens aberration and light diffraction. Image deconvolution can reduce this intrinsic blur if the lens PSF is precisely known. There is a requirement to measure the blur function by analyzing the captured images. Such a PSF estimation is an ill-posed problem that can be approached by blind and non-blind methods. This problem is even more challenging for mobile devices since they have very small sensor area that typically creates a large amount of noise.

In this paper, we introduce a method motivated by non-blind techniques (e.g. [2, 3]) to measure the intrinsic camera blur. We build a reliable hardware setup that unlike existing non-blind techniques omits homography and radial distortion estimation for the camera-scene alignment. Hence, potential errors of the geometric alignment between the captured pattern and the original one are greatly reduced. This setup also provides pixel to pixel intensity correspondence between the captured pattern and the sharp pattern. Hence, there is no need for tone curve estimation or complicated radiometric correction between the two images. We use Bernoulli (0.5) noise patterns to estimate the PSF. Unlike the method proposed in [1], we introduce a non-negativity constraint and take into account the frequency and energy specifications of the Bernoulli noise pattern directly in the functional of the PSF estimation. Also, the proposed alignment allows us to utilize multiple PSF estimation targets (i.e. Bernoulli noise patterns) in the PSF estimation function to significantly reduce the effect of noise. As a result of our main contributions i.e. simplified and accurate alignment, employing spectral information of the kernel as a prior, and using multiple targets, we achieve an accurate PSF estimation which is greatly robust against noise. This becomes an appropriate scheme to measure lens blur of mobile devices that suffer from a large amount of noise caused by their small sensors.

Denoting the sharp correspondence of the observed image b by u, the imaging can be modeled as:

$$b = S(u * k) + n. \tag{1}$$

where k is a PSF that represents lens aberrations, S is the sensor's sampling function, and n denotes additive Gaussian noise. The sharp image can be generated by a function of perspective projection h, radial distortion d, and vignetting v; $u = v\Big(d\big(h(i)\big)\Big)$. Our approach to measure lens blur includes two main steps; camera-scene alignment, and PSF estimation.

We use four different patterns in the alignment step; a 0.5 expectation Bernoulli noise pattern as the scene pattern, a checkerboard with a large number of checker patterns as the calibration guide, and a black and a white image as intensity references. A high resolution screen is used to display these patterns sequentially so that no relative motion between them and between the camera and the scene is induced during the imaging. The corners found in the picture of the checkerboard are used to find the correspondence between the camera grid and the scene. These points are used in a bilinear interpolation scheme to transform the synthetic noise pattern into the camera grid space. Next, the pictures of the black and the white images are used to adjust the intensity of the transformed synthetic noise pattern. The resulting warped and color adjusted sharp noise pattern u is then employed in our PSF estimation procedure.

Considering model (1), the lens PSF k is estimated by generating a linear system to solve a least squares problem with smoothness and sparsity constraints for the kernel. In addition, since the spectrum of the Bernoulli pattern is uniform and contains all frequency components, we employ its spectral density function (SDF) to derive a prior for the PSF. The Bernoulli noise pattern has a homogeneous SDF i.e. $|\mathcal{F}(i)|^2$ where $\mathcal{F}(.)$ denotes the Fourier transform. Hence, in an ideal noise-free image acquisition, the SDF of the captured image b is $|\mathcal{F}(i)|^2|\mathcal{F}(k)|^2$. Therefore, the SDF of the ideal blur kernel $\acute{k}$ is expected to be

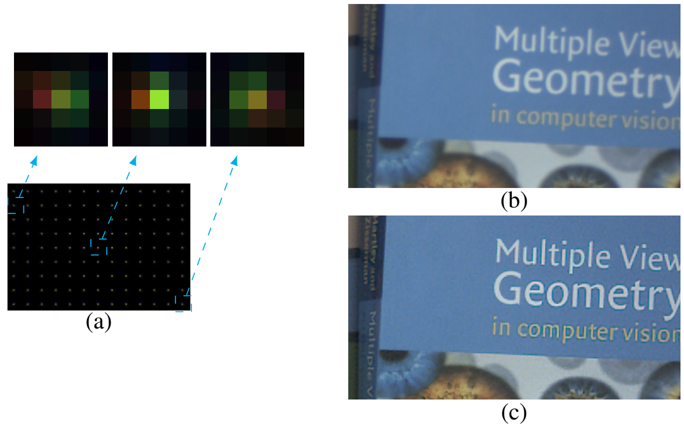

Figure 1: (a) Our PSF estimation result for Blackberry mobile phone camera. (b) Image captured using Blackberry mobile phone camera. (c) Enhanced image using our measured PSFs (a) and deconvolution.

$$|\mathcal{F}(\acute{k})|^2 = \frac{\mathcal{F}(b)\overline{\mathcal{F}(b)}}{\mathcal{F}(u)\overline{\mathcal{F}(u)}}, \tag{2}$$

We propose to solve the following function to estimate the PSF:

$$\begin{aligned} \underset{\mathbf{k}}{\text{minimize}}\, E(\mathbf{k}) =& ||\hat{\mathbf{u}}\mathbf{k} - \hat{\mathbf{b}}||^2 + \lambda||\mathbf{k}||^2 + \mu||\nabla\mathbf{k}||^2 \\ &+ \gamma|||\mathcal{F}(\mathbf{k})| - |\mathcal{F}(\acute{\mathbf{k}})|||^2, \text{ s.t. } \mathbf{k} \geqslant 0 \end{aligned} \tag{3}$$

where the first term is the data fitting term, the second term is the kernel sparsity, the third terms is the kernel smoothness constraints, and the last term is the constraint of the SDF of the PSF.

There is more flexibility to provide a large number of feature points in the calibration pattern and to guide the alignment more precisely using a high-resolution screen to display the patterns. Also, our proposed method benefits from multiple Bernoulli patterns in generating the linear system and solving Eq. (3). Fig. 1 demonstrate how the measured lens PSFs are used to significantly enhance the quality of the images captured by the cameras. Our experimental results show that our method is robust against noise, and therefore suitable for mobile devices. Our technique achieves better performance than the existing non-blind PSF estimation approaches.

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This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.