Matting and Depth Recovery of Thin Structures using a Focal Stack
Supplementary Material

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1. Calibrating Blur Kernel

In this section, we describe our method to calibrate the blur kernels for the light field refocused images. The optical blur kernel is assumed to be a separable filter kernel such that it can be written as a convolution of two 1D functions. In this case, the blurred image \( I \) can be written as:

\[
I = L * B(x, y) = L * f(x) * f(y),
\]

(1)

with \( B(x, y) = f(x) * f(y) \) because the blur kernel is separable. To estimate the 1D blur kernels \( f(x) \) and \( f(y) \), we use unidirectional binary patterns as described in [2]. In our experiment, we use vertical and horizontal strip binary patterns.

For a vertical pattern as shown in Figure 1, if the blur kernel is separable, the blurred image is only related to the blur kernel in the direction of \( x \)-axis:

\[
I = L * f(x)
\]

(2)

Then we can write this 1D-convolution into a matrix form:

\[
m = A_x b_x,
\]

(3)

where column vector \( m \) is the vectorized blurred image; the column vector \( b_x \) is the 1D blur kernel in the \( x \)-direction; each row of the matrix \( A_x \) is the un-blurred sharp image intensities in the surrounding range in \( x \)-direction for the corresponding pixel in \( m \).

During calibration, given the sharp image \( A_x \) and blurred image \( b_x \), the 1D blur kernel \( b_x \) is determined by:

\[
\begin{align*}
\min_{b_x} & \quad \| A_x b_x - m \|_2 + \lambda \| \nabla b_x \|_1 \\
\text{subject to} & \quad b_x \succeq 0,
\end{align*}
\]

(4)

with the second term in the energy function regularizing the shape of the blurring kernel. The optimization problem in Eq. 4 is convex and can be solved by a convex optimization solver. We use the CVX toolbox [1] in the implementation. The 1D blur kernel in the \( y \)-axis direction is optimized in the same way using a vertical binary pattern.

With the estimated 1D blur kernels \( f(x) \) and \( f(y) \), the blur kernel \( B(x, y) \) can be determined as:

\[
B(x, y) = f(x) * f(y).
\]

(5)

We repeat the above calibration with 26 focal settings for a set of 21 reference depths from 200 mm to 1000 mm equally spaced with 40 mm. The calibrated blur kernels of refocused image for a plane placed 680 mm from the light field camera are shown in Figure 2. Note that the shape of the blur kernel is not circularly symmetrical since the blur kernel for a refocused image from light field camera is related to both the main lens shape and the arrangement of the secondary lenslets array.

![Figure 1: The optical blur for a vertical binary edge pattern. The blur kernel is assumed to be separable, so the blurred image of the vertical pattern is independent from the blur kernel in the \( y \)-axis \( f(y) \).](image1)

![Figure 2: The calibrated blur kernels of refocused image for a plane placed 680 mm from the light field camera. (a)(b)The 1D blur kernels \( f(x) \) and \( f(y) \). (c)The blur kernels. The shapes of the blur kernels are not circularly symmetrical since the blur kernel for a refocused image from light field camera is related to both the main lens shape and the spatial arrangement of the secondary lenslets.](image2)
in the paper for estimating the depth, we assume the blur kernel changes smoothly w.r.t. the depth. So we can approximate the differential blur kernel as:

$$\frac{\partial B}{\partial d}(d_i) \approx \frac{B(d_i + \Delta d) - B(d_i)}{\Delta d} \quad (6)$$

2. More Results

We include more comparison results in Figure 3.

3. Limitations

As explained in the paper, our methods have several limitations. First, if the thin structures in the near field have similar color as the background, the occlusion matting estimation may fail because switching the occlusion matte values for the points in those regions will not introduce enough image intensity changes, as shown in Figure 4(a)(b).
Second, when the depth of the background is close to the depth of the thin occluder, the occlusion matte estimation tends to include the edges in the background as thin structures/occlusion boundaries, as shown in Figure 4(c).

References