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Motion deblurring with temporally coded illumination in an LED array microscope

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Motion blur, which results from time-averaging an image over the camera's exposure time, is a common problem in microscopy of moving samples. Here, we demonstrate linear motion deblurring using temporally coded illumination in an LED array microscope. By illuminating moving objects with a well-designed temporal coded sequence that varies during each single camera exposure, the resulting motion blur is invertible and can be computationally removed. This scheme is implemented in an existing LED array microscope, providing benefits of being grayscale, fast, and adaptive, which leads to high-quality deblur performance and a flexible implementation with no moving parts. The proposed method is demonstrated experimentally for fast moving targets in a microfluidic environment.

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Computational imaging involves the joint design of optical systems and post-processing algorithms for new imaging capabilities, such as 3D and digital refocusing [1,2]. In the recently introduced LED array microscope, the illumination unit of a commercial microscope is replaced by a programmable LED array, creating a powerful computational imaging platform. Spatially coding the illumination has lead to a variety of techniques, including digital refocusing [2], real-time multicontrast [3], 3D phase imaging [4,5], and resolution beyond the objective's diffraction limit via Fourier Ptychography [6,7]. All of these capabilities use the same hardware but different illumination pattern schemes. While previous work all involves illumination coding in the *spatial domain*, here we demonstrate illumination coding in the *temporal domain*, without any hardware changes. The LEDs are modulated on timescales much faster than the exposure time of the camera, creating structured motion blur for fast moving objects. This temporally coded illumination enables robust computational removal of motion blur for objects moving at constant velocity.

Motion blur occurs when objects move across the field of view during the camera exposure time. This is a common problem in microscopy, where high magnification instruments can incur significant blur, even from small movements. Using shorter exposure times reduces motion blur, at the cost of reduced signal-to-noise ratio (SNR). Even when SNR is sufficient, the camera's maximum frame rate may limit the speed of samples that can be imaged clearly. In this Letter, we remove motion blur for samples that are moving in a single direction at high speed. The method enables increased flow speed for imaging with high-throughput micro-fluidic channels.

When the sample moves at a constant velocity, we can describe motion blur using a convolution operation. Given source intensity variation $I(t)$ during one exposure, the point spread function (PSF) for motion blur can be written as $p(x) = \text{Velocity} \times I(t)$. Without temporal coding, the exposure duration defines a box filter, which destroys important high-frequency spatial details of the image and thus makes motion deblur an ill-posed problem. By "fluttering" the camera's shutter open and closed during the chosen exposure time, the resulting filter can be broadband, and the deblur problem becomes well-posed [8,9]. This coded exposure method has been recently adapted to flash imaging [10], fluorescence microscopy [11], and illumination coding [12]. Here, we apply the same strategy for illumination coding in our LED array microscope, whose LEDs are already capable of modulation at speeds much faster than the camera exposure time. Compared with previous implementations, ours has two advantages. First, it can achieve grayscale (nonbinary) illumination sequences, which leads to improved deblur performance. Second, as mentioned in [13], optimal coded sequences are velocity-dependent, and our system offers flexibility for changing the codes without hardware modifications.

Our microscope setup is shown in Fig. 1. An LED array is placed in the source plane, replacing the original illumination unit of a commercial microscope. The LEDs can be controlled to vary the illumination in the desired temporal code over a single exposure. In this way, when the sample moves with linear, shift-invariant motion, the illumination sequence defines a PSF for the blurring (see Fig. 2). As in previous work, we first model the coded illuminated image, $B(x)$, as a convolution between the sharp latent image that we wish to estimate, $X(x)$, and the time-coded PSF:

$$B(x) = p(x) * X(x) + \eta(x), \tag{1}$$

where $\eta(x)$ represents noise. In Fourier domain, this can be written as

$$\hat{B}(\omega) = \hat{p}(\omega)\hat{X}(\omega) + \hat{\eta}(\omega), \tag{2}$$

and so the deblurred result is

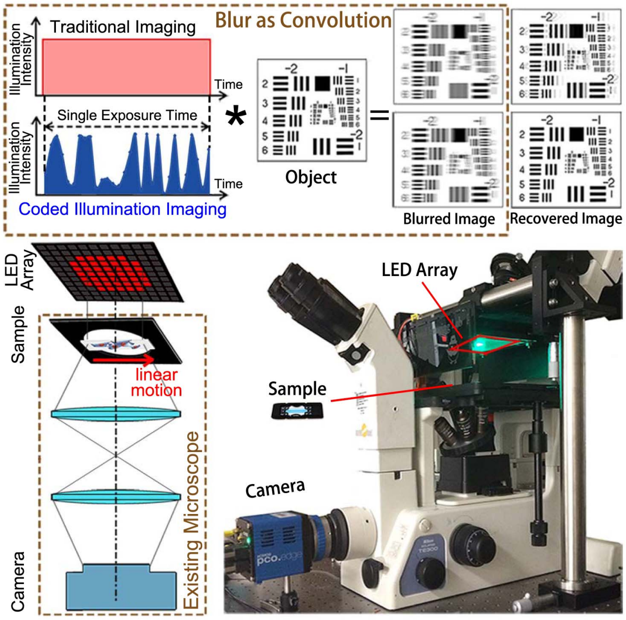


Fig. 1. Setup of our LED array microscope and overview of the temporal illumination coding strategy for motion deblur.

$$\hat{X}^*(\omega) = \hat{X}(\omega) + \frac{\hat{\eta}(\omega)}{\hat{p}(\omega)}, \tag{3}$$

where $\hat{X}^*(\omega)$ is the Fourier transform of the deblurred image. From Eq. (3), we see that if the PSF contains zeros in Fourier space, the deconvolution becomes unstable and noise is amplified. For stable deblurring, we should choose a PSF (coded pattern) that maximizes the minimum of its Fourier transform magnitude.

Alternatively, we can also describe the problem in matrix form, where X denotes the target image and B the blurred measurement (Fig. 2). The blur model becomes

$$\boldsymbol{B} = \boldsymbol{A}\boldsymbol{X} + \eta. \tag{4}$$

$\boldsymbol{A}$ is a circulant matrix where each column vector is the blur PSF padded with zeros. The invertibility of this problem is determined by the condition number (ratio of the largest to the smallest singular value) of $\boldsymbol{A}$. With an ideal coded pattern $p(x)$ that makes the corresponding condition number small enough, the deblurred result is given using a least square estimation [8]:

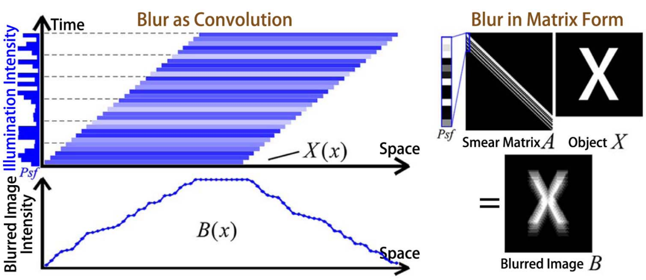


Fig. 2. Motion blur model for a sample moving at constant speed in the x direction, with time-coded illumination.

$$\boldsymbol{X}^* = \boldsymbol{A}^{\dagger}\boldsymbol{B}, \tag{5}$$

where $\boldsymbol{A}^{\dagger} = (\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}$ is the pseudo-inverse of $\boldsymbol{A}$.

Our proposed system has an advantage in achieving optimal coded patterns, since it can provide 8-bit grayscale illumination for nearly continuous illumination in time. Previous work all used hardware that was limited to binary patterns, so the codes were optimized through a randomized binary search. Here, we exploit the additional degrees of freedom provided by the illumination grayscale in order to achieve better motion deblurring. To do so, we formulate the problem of finding a temporal code as the following optimization:

$$\begin{aligned} \underset{p}{\text{minimize}} \quad & \kappa(\boldsymbol{A}) \\ \text{subject to} \quad & \Sigma p \geq \gamma, \quad 1 \geq p \geq 0. \end{aligned} \tag{6}$$

$\kappa(\boldsymbol{A})$ denotes the condition number of $\boldsymbol{A}$, and γ imposes a user-chosen threshold representing the light throughput requirement. Since there is an inherent tradeoff between image quality, blur level, and light throughput, γ should not be either too large or too small for deblurring. In practice, we set γ to be half the length of p. Then we solve this nonconvex optimization problem using nonlinear or intelligent optimization algorithms (e.g., Matlab toolbox fmincon and ga). One example of our optimized illumination pattern is shown in Fig. 3 for a pattern length of 30 time steps. In comparison with previous binary patterns and the traditional box pattern, we can see that our pattern corresponds to a blurring matrix with smaller condition number (ours 12.9, binary 17.3, traditional 231) and has a larger minimum of its own Fourier transform, which all indicate a better deblur performance according to Eqs. (3) and (5).

Given the optimized pattern, we then apply it in our LED array microscope hardware to generate coded illumination within each single camera exposure. Images with modulated motion blur are captured for fast moving objects. After identifying the area of interest in our image, we run a PSF estimation to decide the actual blur length and direction using the "motion from blur" algorithm [9], which is realized using a motion blur constraint [14]. Thus, the direction and speed of the sample need not be known, as long as it is consistent across the entire image. Finally, with the estimated PSF, after necessary

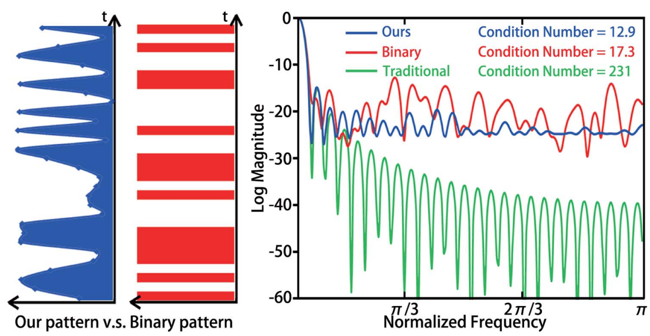


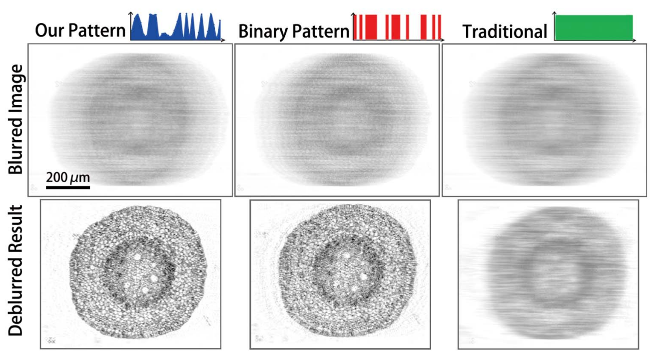
Fig. 3. Left: Our optimized illumination pattern versus flutter shutter binary pattern with a length of 30 time steps. Right: The Fourier transform (DFT) and the corresponding condition number of different patterns.

imaging preprocessing (e.g., rotation, scaling), we do the least-square estimation as in Eq. (5) to solve for the final blur-removed result.

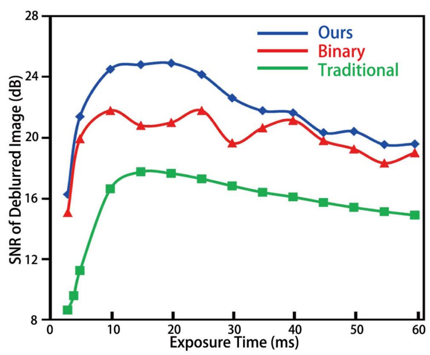
To verify our proposed method, we capture a sequence of images containing a target object (zea root c.s.) that moves linearly with a sub-pixel velocity. We treat the stationary image as the "ground truth" test object and synthesize blurred images using different blur patterns for comparison. In Fig. 4(a), the targets in the first two images are blurred with our grayscale illumination pattern and the binary flutter shutter pattern. Taking these as input, we deblur each using our proposed algorithm. For comparison, the blurred image of the same target with the traditional box exposure is shown and deblurred using the well-known Richardson–Lucy (RL) algorithm. Both codes are successful at restoring fine details in the deblurred image, but our grayscale code produces higher image quality and fewer artifacts than the binary pattern.

Furthermore, to evaluate performance in the case of different camera exposure times, we synthesize blurred images having different exposure length, with consideration of camera noise. The noise level for different exposure times is estimated from captured images under the same camera settings. The grayscale and binary illumination patterns are optimized individually for each exposure time using our proposed method and [8]. After conducting motion deblurring, we calculate the signal-to-noise ratio (SNR) of their corresponding deblurred results ($\mathrm{SNR}_{\mathrm{dB}} = 10\log_{10}[\frac{A^2_{\mathrm{target}}}{A^2_{\mathrm{error}}}]$) and plot it in Fig. 4(b). The results show that motion blur can be removed by the coded exposure technique, and our grayscale coded illumination approach has better performance. When the camera exposure time is short, we capture less-blurred images, but they are corrupted by heavy noise. As the exposure time goes up, image noise is reduced, and the deblurring performance improves. However, when the exposure time increases too far, motion blur destroys more and more image details, so the quality of the deblurred image reduces. Thus, there is clearly a tradeoff between exposure time and image quality, even with computational deblurring.

Our LED array microscope (shown in Fig. 1) uses an inverted Nikon TE300 microscope (Melville, New York) with the illumination unit replaced by a custom-built LED array at 70 mm above the sample. The LEDs are controlled by an ARM-based microcontroller



(a)



(b)

Fig. 4. (a) Synthesized experiment comparing deblur performance for our coded grayscale illumination method, binary flutter shutter method, and traditionally captured image. (b) Deblur performance for different lengths of exposure and different methods.

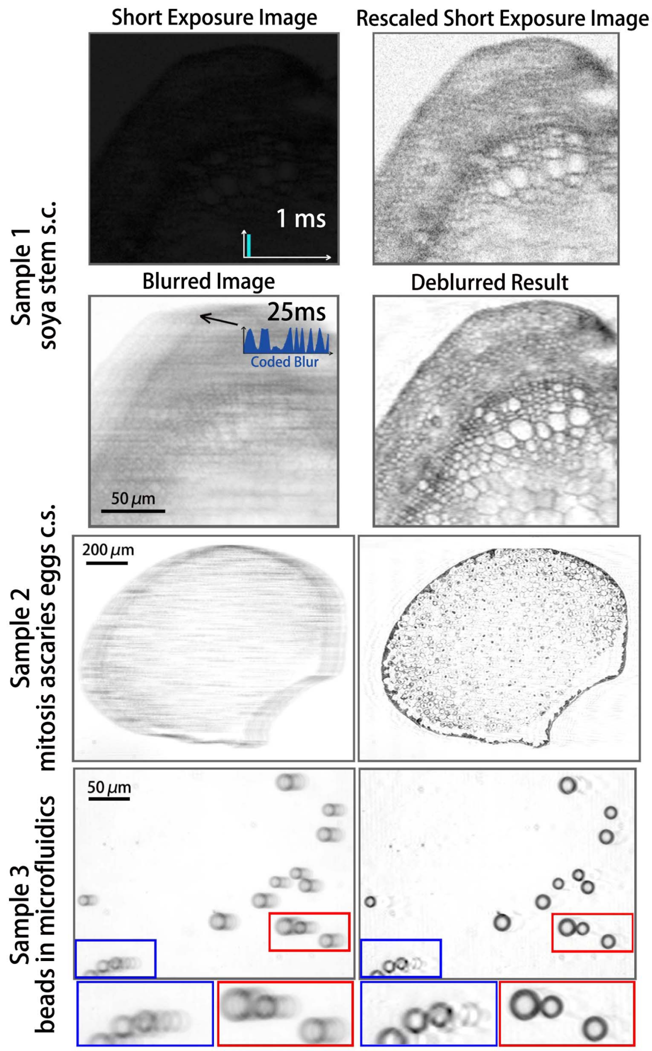


Fig. 5. Experimental results showing raw and deblurred images of three different samples: Samples 1 and 2 are moving on a motorized stage, while Sample 3 is beads traveling through a microfluidic channel. With a short exposure, the image is not blurred, but suffers noise corruption, whereas our coded exposure method retrieves an image that exhibits high SNR, without sacrificing image details due to blurring.

STM32F103C8T6, which has 8-bit grayscale. Images are captured with an sCMOS camera (PCO.edge 5.5) placed at the front port of the microscope. The camera works in external exposure control mode and is synchronized with the LED array by the same controller. The LED pattern transfer time is about 250 μs, achieving a maximum LED pattern changing speed of about 4 kHz. Thus, for coded illumination exposure using a pattern of length 30 time steps, capturing a single image takes about 10 ms, achieving a camera frame rate of nearly 50 Hz, with good SNR in each image. Note that the speed of the LED illumination could further be increased to nearly 1 MHz using optimized controller hardware, where necessary.

We first imaged samples moving on a motorized microscopy stage, as in a slide scanning device. Figure 5 shows both the raw and deblurred images of two samples (soya stem and mitosis ascaris egg c.s.) moving at approximately 30 mm per second from left to right with 10× magnification. The motion blur is modulated by the illumination pattern, as evident near sharp edges. Then, using our proposed algorithm, the image can be reconstructed with good fidelity. Detailed structure inside the sample, which would otherwise be lost, is now revealed. For comparison, images captured with a single short exposure (1 ms) and our coded illumination (25 ms) are compared, showing little motion blur but significant noise corruption. In this experiment, only the central 4×4 LEDs are used to trade off between the object blur length and camera exposure time. Note that the camera used in this experiment was an sCMOS sensor with 16-bit dynamic range and very good low- light performance. Therefore, short exposure is not a practical way to eliminate motion blur in this case, since the captured image suffers from low SNR.

Next, our method is applied experimentally to imaging of fast moving fluids (Fig. 5, bottom)—20 μm beads traveling through a microfluidic channel (Micronit Microfluidics FLC50.3). From the raw and deblurred images, we see that the motion blur is effectively removed, and intensity variations inside the beads can be clearly resolved. However, the blur of the beads in the blue region is not removed properly, since these beads are traveling at a different speed than the rest, which breaks our assumption of linear shift-invariant motion. To further deal with this kind of problem, we could do image segmentation first and then remove the motion blur for each bead individually.

In conclusion, we have presented an improved method for linear motion blur removal, using a programmable LED array to implement coded illumination. Beyond the microfluidic demonstration shown here, applications could include dynamic slide scanning for building a large field of view without stop-and-go scanning. Further, we hope to extend this technique to other methods that use the LED array platform, such as Fourier Ptychography, differential phase-contrast, and light-field imaging of fast moving objects.

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