

Supporting Information

Zheng et al. 10.1073/pnas.1110681108

SI Text

Supplementary Note 1. In this note, we briefly describe the general pixel superresolution model and solution. Detailed description can be found in ref. S1–S4.

We denote the N measured low-resolution images by $Y_k (k = 1, 2, \dots, N)$. These images are used to reconstruct a single improved high resolution image, denoted as X . The images are all represented by lexicographically ordered column vectors. The low-resolution image can be modeled by the following equation

$$Y_k = DHF_k X + V_k \quad (k = 1, 2, \dots, N).$$

The matrix F_k stands for the subpixel shift operation for the image X . The matrix H is the pixel transfer function of the image sensor. The matrix D stands for the decimation operation, representing the reduction of the number of observed pixels in the measured images. V_k represents Gaussian additive measurement noise with zeros mean and auto-correlation matrix $W_k = E\{V_k V_k^T\}$.

1. Hardie R, et al. (1997) Joint MAP registration and high-resolution image estimation using asequence of undersampled images. *IEEE Trans Image Process* 6:1621–1633.
2. Elad M, Hel-Or Y (2001) A fast super-resolution reconstruction algorithm for pure-translational motion and common space-invariant blur. *IEEE Trans Image Process* 10:1187–1193.

The maximum-likelihood estimation of X can be described as following expression

$$\hat{X} = \text{ArgMin} \left\{ \sum_{k=1}^N (Y_k - DHF_k X)^T W_k^{-1} (Y_k - DHF_k X) \right\}.$$

And the closed-form solution for \hat{X} is shown to be

$$\hat{X} = H^{-1} R^{-1} P$$

where, $R = \sum_{k=1}^N F_k^T D^T D F_k$, $P = \sum_{k=1}^N F_k^T D^T Y_k$.

It can be proved that R is a diagonal matrix and the computation complexity of this approach is $O(n * \log(n))$, where n is the number of pixels.

For readers interested in building their own ePetri, a free Matlab-based superresolution software package can be downloaded at ref. S5. For a similar ePetri platform like ours, the default setup of ref. S5 can be used to get a reasonably good result.

3. Farsiu S, et al. (2004) Fast and robust multiframe super resolution. *IEEE Trans Image Process* 13:1327–1344.
4. Farsiu S, et al. (2006) Multiframe demosaicing and super-resolution of color images. *IEEE Trans Image Process* 15:141–159.
5. Farsiu, et al. (2004) MDSP Resolution Enhancement Software, <http://users.soe.ucsc.edu/~milanfar/software/superresolution.html>.

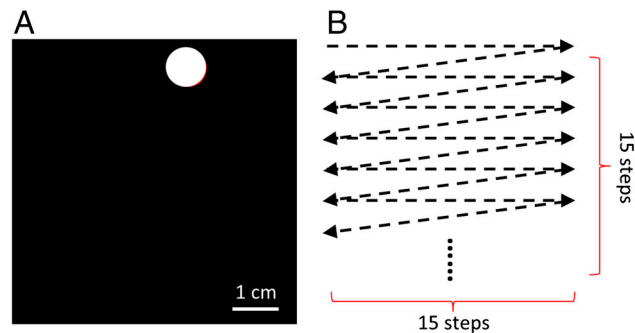
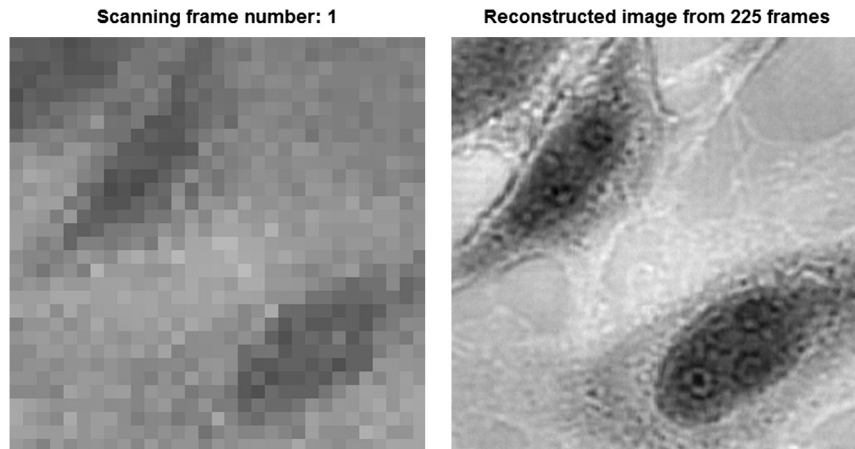
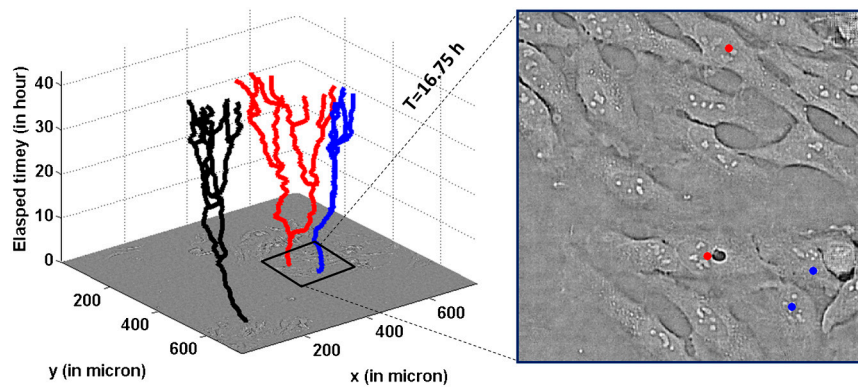


Fig. S1. (A) The scanning pattern on the smartphone screen, with 640×640 pixel size. (B) We use 15×15 steps for illumination. When the bright spot moves away from the center of smartphone screen, the readout from the image sensor chip will decrease because of the large incident angle; therefore, in our setup, the bright spot size linearly increases when it moves away from the center of the screen.



Movie S2. Acquired low-resolution image (2.2- μm pixel size) sequence for HeLa cell sample and the reconstructed high resolution image. Data corresponds to Fig. 6B.

[Movie S2 \(MOV\)](#)



Movie S3. Time-lapse cell culture imaging and cell tracking. The defocus effect in some of the images in the video is due to the cell detaching from the sensor surface when cell division occurs. The quality of images may be degraded in video due to the compression.

[Movie S3 \(MOV\)](#)