

## Discriminative Learning of Iteration-wise Priors for Blind Deconvolution *Supplementary Materials*

The supplementary includes two parts: First, to show the power of  $p < 0$ , we visualize the intermediate gradient maps of our method, and also provide variants of our method to verify its robustness. Then we provide more deblurring results of real blurry images.

### 1. Power of $p < 0$

We first show the intermediate gradient maps with  $p$  ranged in  $[-1, 0.2]$ . As shown in Figure S1, at beginning, GST with  $p < 0$  magnified the salient gradients, significantly facilitating coarse kernel estimation, and then the gradually added gradient details refine the kernel. Moreover, Figure S2 provides the varying PSNR and SSIM w.r.t. iterations, from which one can see that with the rapid kernel estimation at first a few iterations, both PSNR and SSIM are improved.

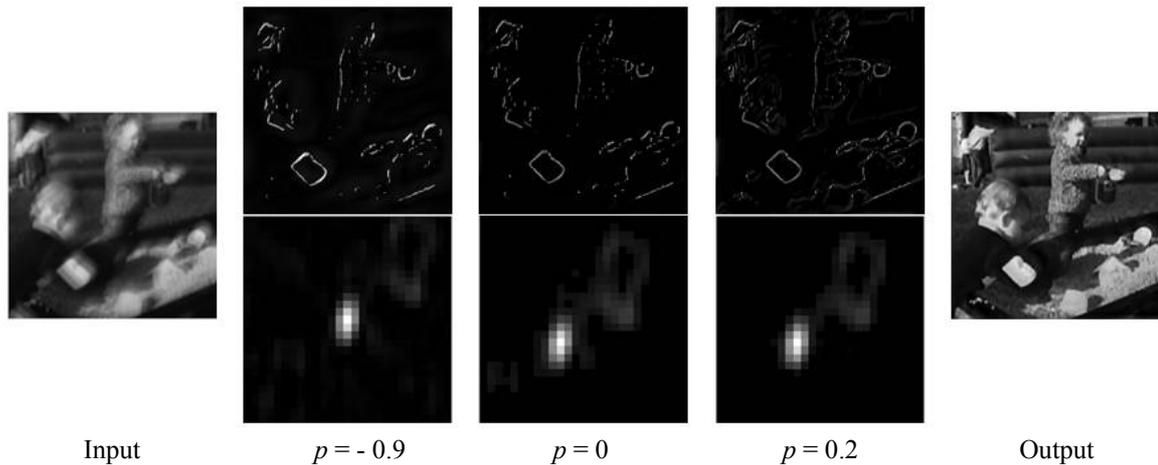


Figure S1: Illustration of intermediate kernel estimation with learned  $p$  values. The above row provides the gradient maps and the bottom row shows the corresponding estimated kernels.

Then we provide a variant of our method with  $p$  searched in  $[0, 0.2]$  on Levin et al.'s dataset. The three quantitative indicators, i.e., mean PSNR, mean SSIM and mean Error Ratio, are presented in Table S1, which validates that  $p < 0$  contributes more to kernel estimation compared to that only with positive  $p$  values. The 32 estimated blur kernels of variants of our method are demonstrated in Figure S3 and Figure S4, and apparently the blur kernels obtained with  $p$  searched in  $[-1, 0.2]$  are more similar to ground truth of kernels shown in Figure S6, and succeed in all the 32 cases, while the variant with only positive  $p$  values failed on some cases and suffer from visible artifacts or noises. In the manuscript, the increasing ratio of  $\alpha$  was set as 1.1, and to verify its robustness, we tested  $\rho$  as 1.2 and also  $p$  value was searched in  $[-1, 0.2]$ . Table S1 shows that our method is robust, and Figure S5 provides the estimated blur kernels, which is also

a little inferior to Figure S4 in details.

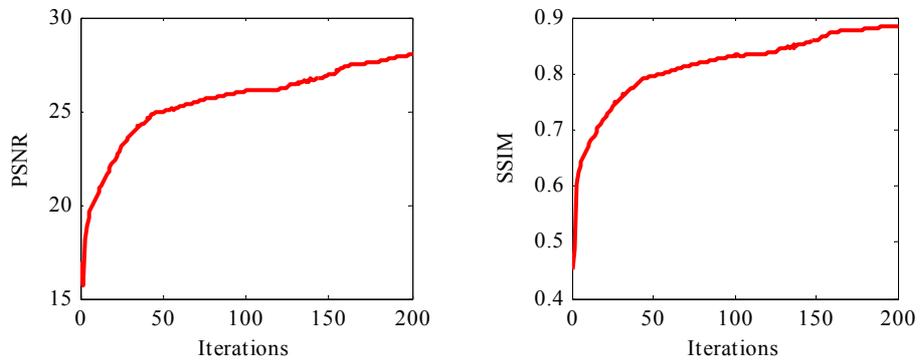


Figure S2: Varying PSNR and SSIM w.r.t. iterations

Table S1: Comparison of variants of our method with different  $p$  settings

	PSNR	SSIM	Error Ratio
Ours ( $[0, 0.2], \rho=1.1$ )	29.51	0.8877	1.4132
Ours ( $[-1, 0.2], \rho=1.1$ )	30.33	0.9192	1.2537
Ours ( $[-1, 0.2], \rho=1.2$ )	29.96	0.9180	1.2623

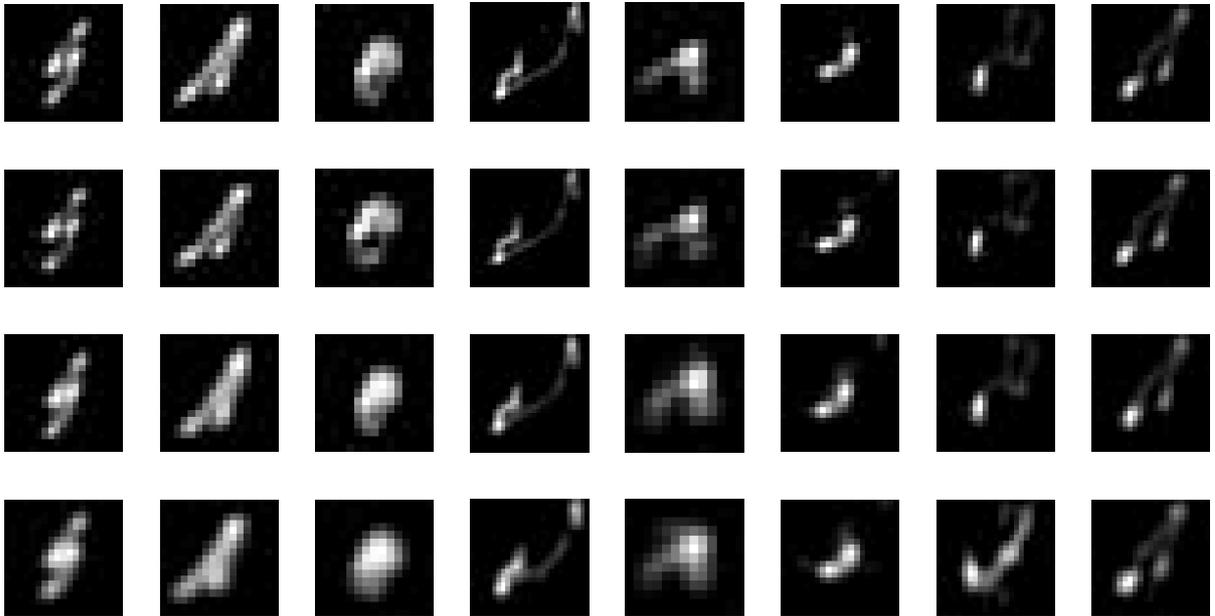


Figure S3: 32 estimated kernels by our method ( $[0, 0.2], \rho=1.1$ )

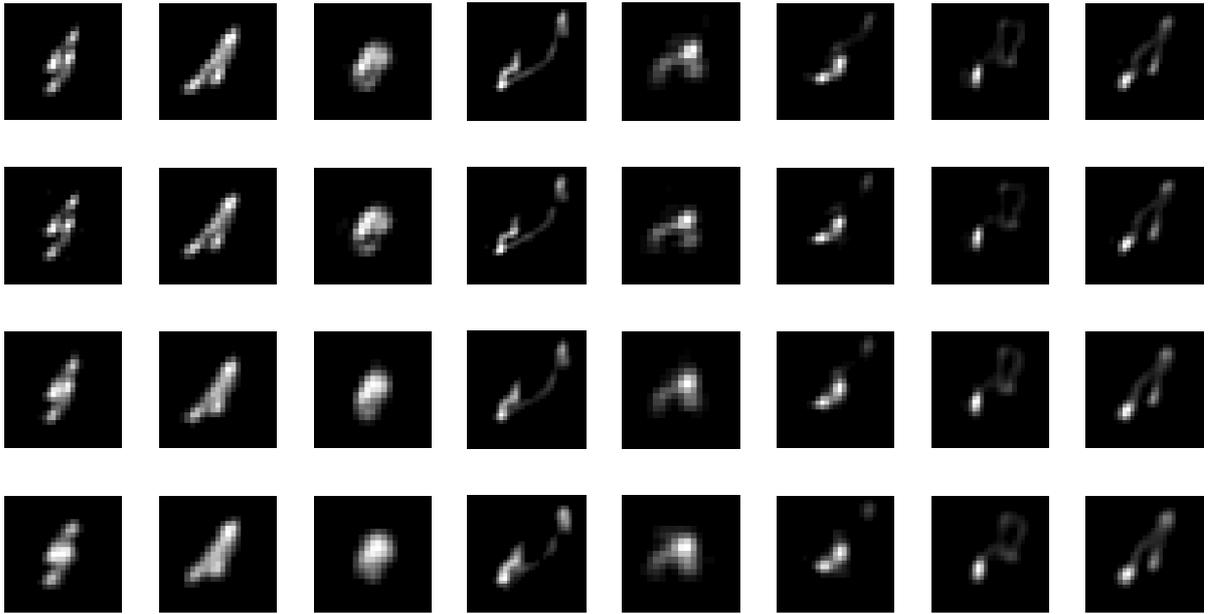


Figure S4: 32 estimated kernels by our method  $([-1, 0.2], \rho=1.1)$

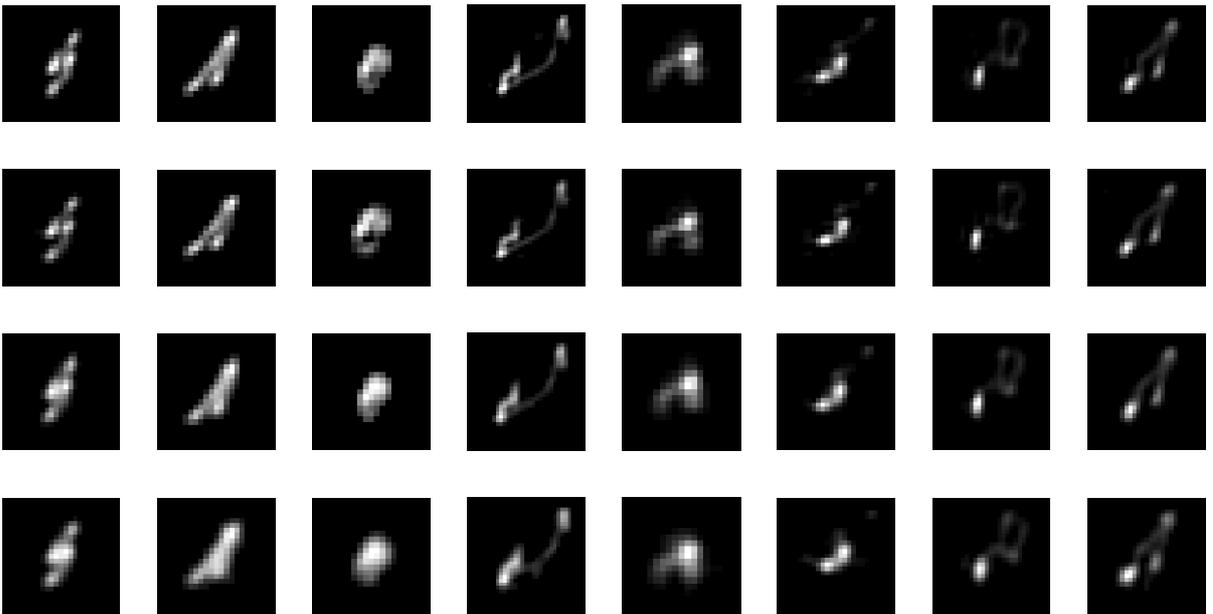


Figure S5: 32 estimated kernels by our method  $([-1, 0.2], \rho=1.2)$

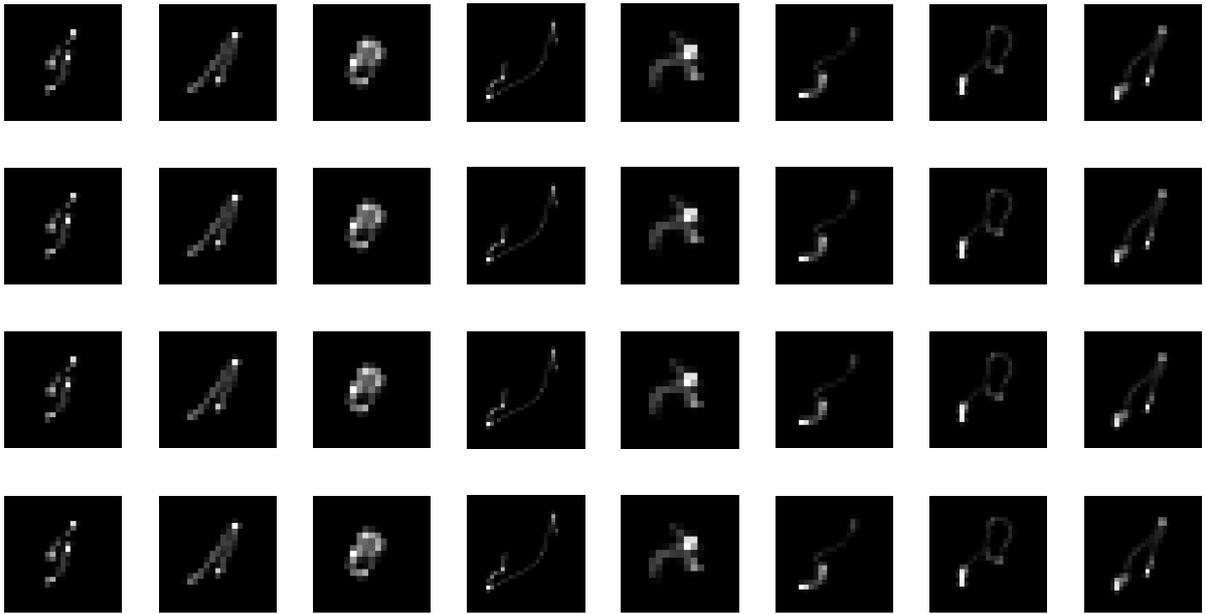


Figure S6: Ground truth of 32 kernels

## 2. More deblurring results for real blurry images

The kernel sizes for the first 7 images are set as  $51 \times 51$ , and  $95 \times 95$  is set for the 8<sup>th</sup> image.

#1 image



Blurry input



Xu & Jia

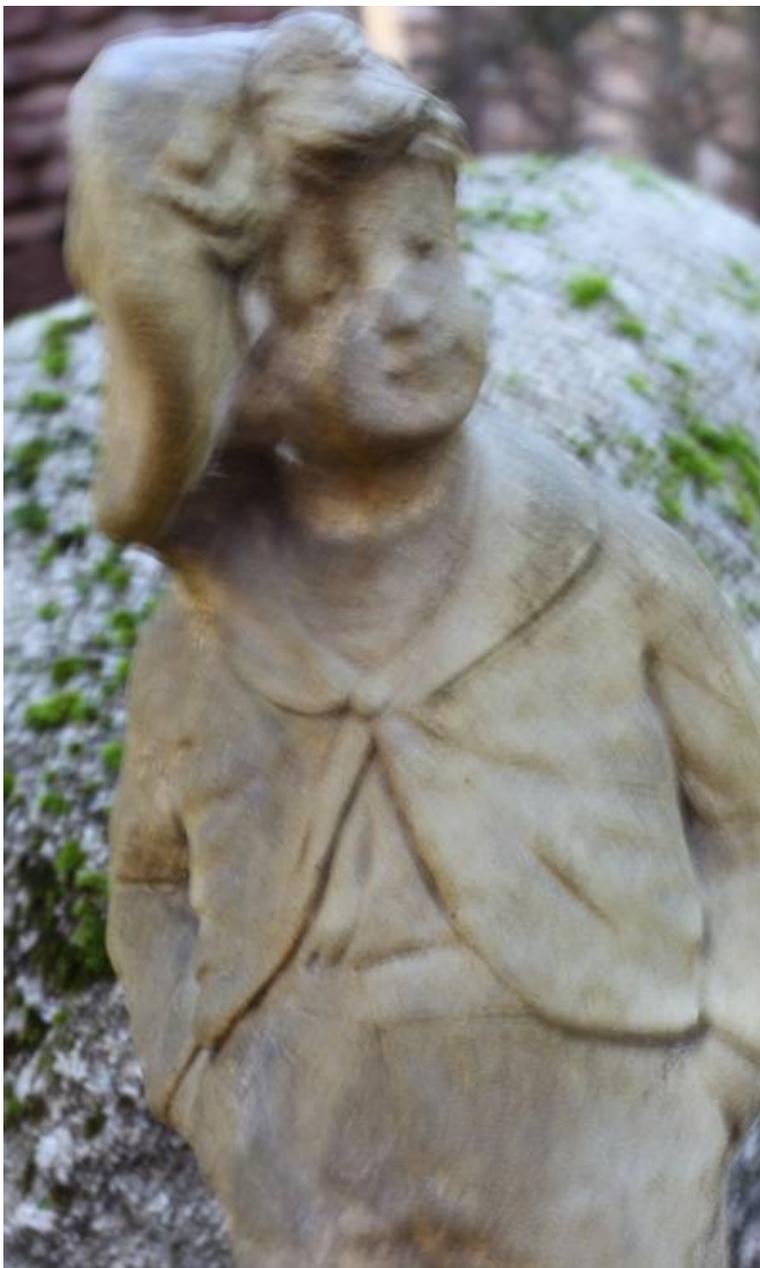


Sun et al.

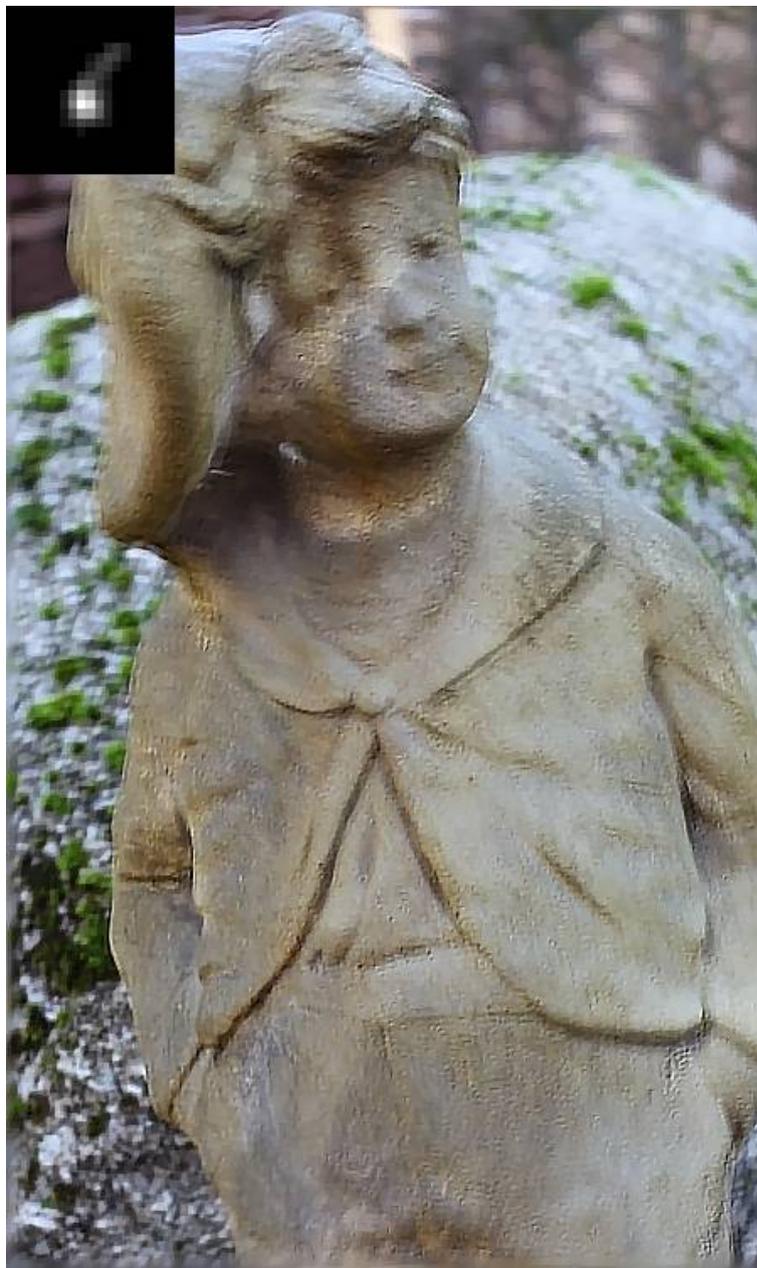


Ours

#2 image



Blurry input

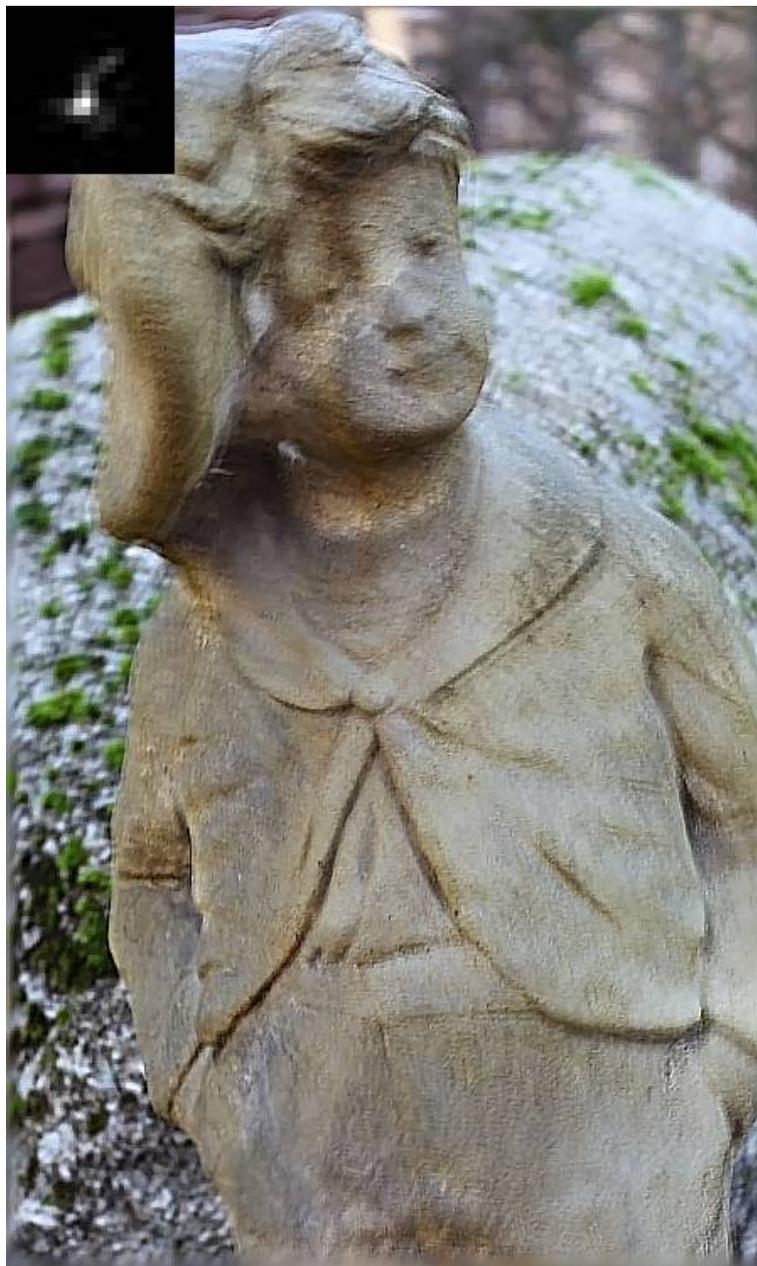


Xu & Jia

#2 image



Sun et al.



Ours

#3 image



Blurry input



Xu & Jia

#3 image



Sun et al.



Ours

#4 image



Blurry input



Xu & Jia



Sun et al.



Ours

#5 image: Blurry input



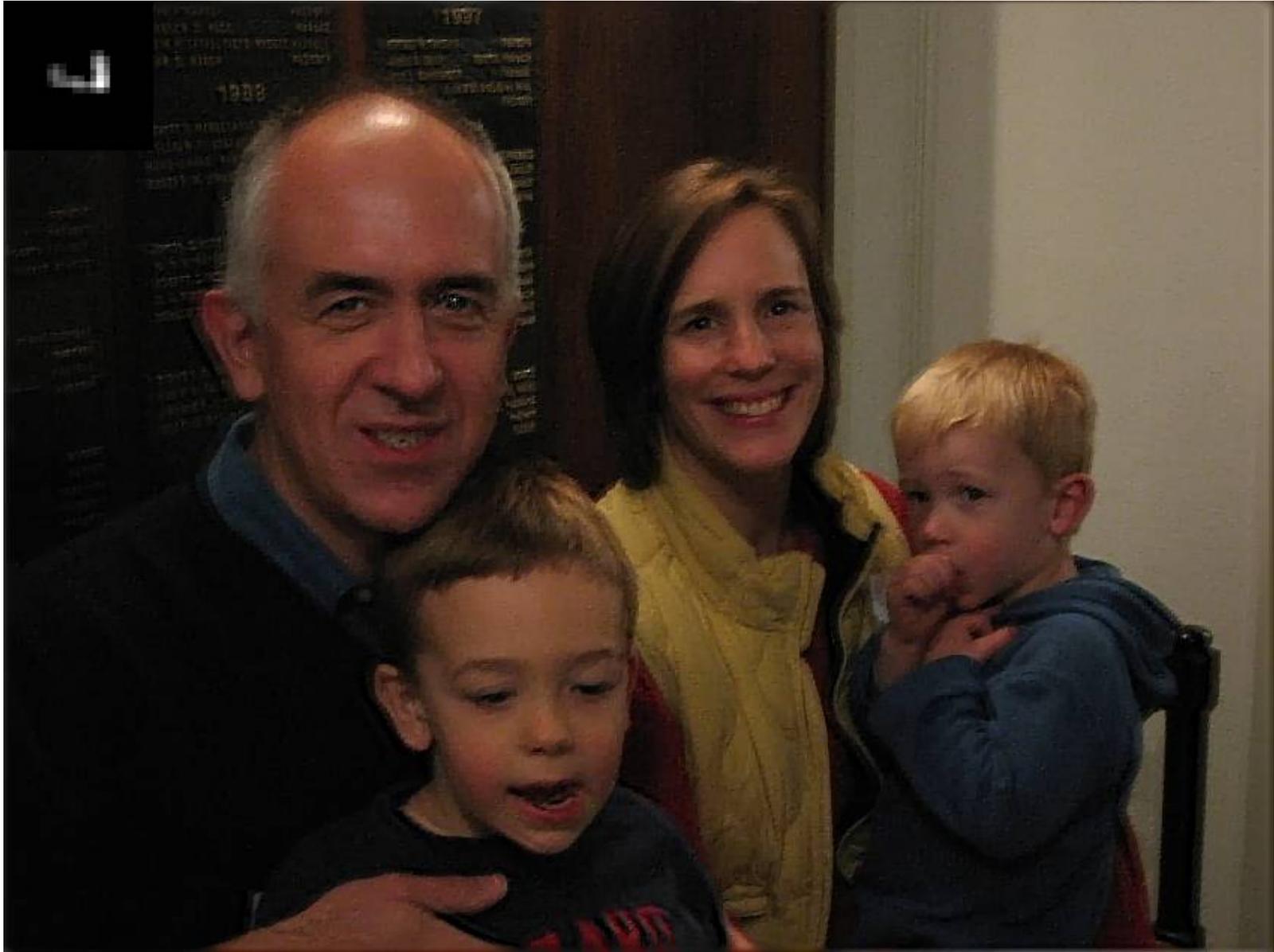
#5 image: Xu & Jia



#5 image: Sun et al.



#5 image: Ours



#6 image: Blurry input



#6 image: Xu & Jia



#6 image: Sun et al.



#6 image: Ours



#7 image: Blurry input



#7 image: Xu & Jia



#7 image: Sun et al.



#7 image: Ours



#8 image: Blurry input



#8 image: Xu & Jia



#8 image: Sun et al.



#8 image: Ours

