Kernel Modeling Super-Resolution on Real Low-Resolution Images

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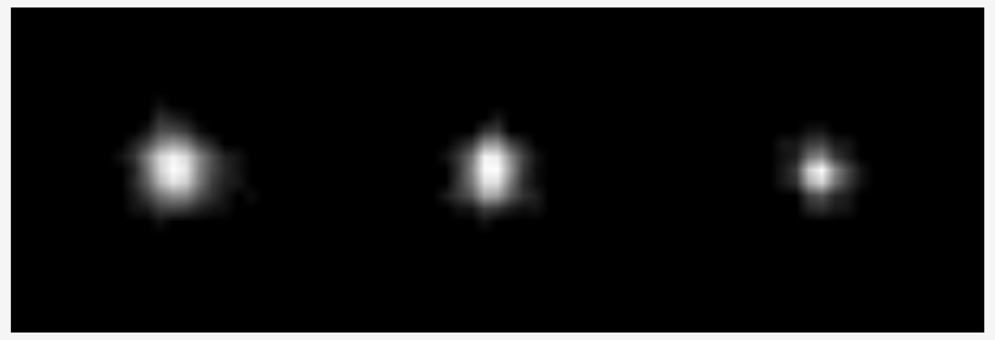
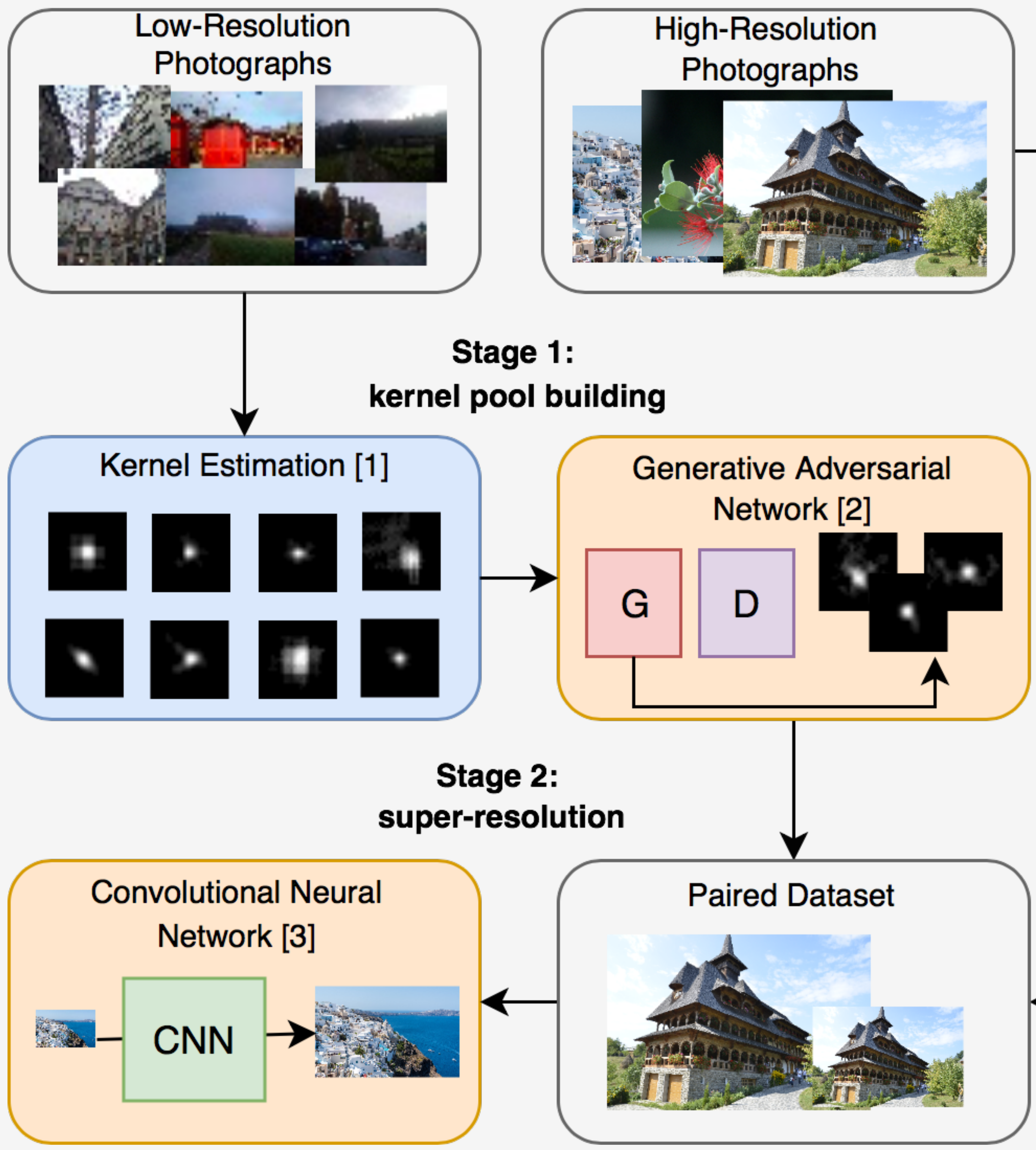
The performance of CNN based SR is limited on real photographs as the bicubic blur-kernel assumed in these networks deviate from real camera-blur.

bicubic blur-kernel



examples of real camera blur-kernel

To improve the generalization capability of SR networks, we present a kernel modeling super-resolution network (KMSR) that incorporates blur-kernel modeling in the training.



Our proposed KMSR consists of two stages:
1) a pool of realistic blur-kernels extracted from photographs and augmented with a generative adversarial network;
2) a super-resolution network with HR and corresponding LR images constructed with the generated kernels.

Experimental setting

We use the DPED [4] dataset to extract realistic blur-kernels and the DIV2K [5] dataset as HR images.

Gaussian and realistic kernels

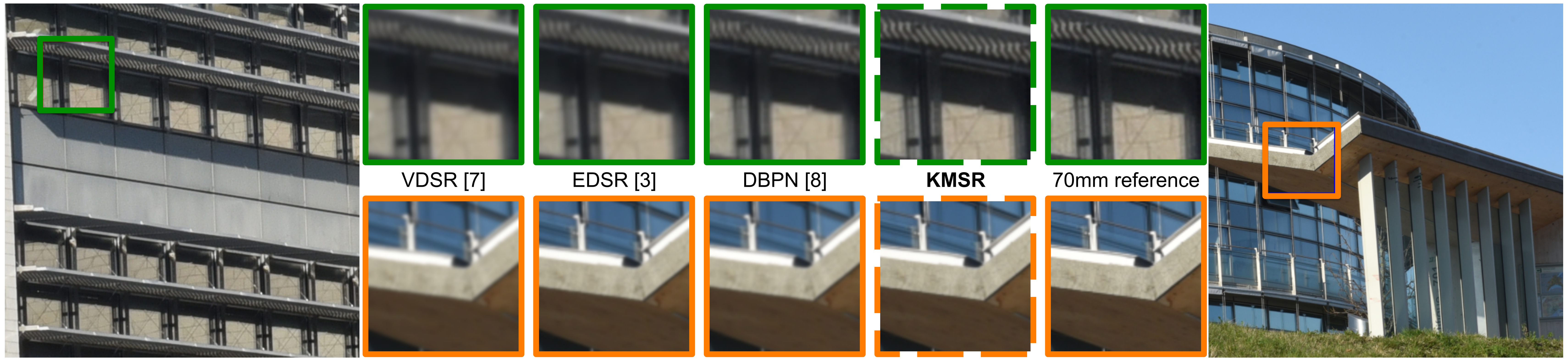
We conduct x2 SR experiments on 4 synthetic LR datasets that are generated using different Gaussian kernels ($g_{1.25}$, $g_{1.5}$ and $g_{1.7}$) and realistic blur-kernels estimated from DPED. KMSR successfully reconstructs the detailed textures and edges in the HR images and produces better outputs.

kernel	SRCNN	VDSR	EDSR	DBPN	KMSR
$g_{1.25}$	26.56	26.54	26.58	26.60	**27.94**
$g_{1.6}$	25.72	25.72	25.69	25.70	**27.63**
$g_{1.7}$	25.30	25.34	25.28	25.28	**27.15**
realistic	25.30	25.29	25.28	25.30	**27.52**

Quantitative results in terms of PSNR (dB)

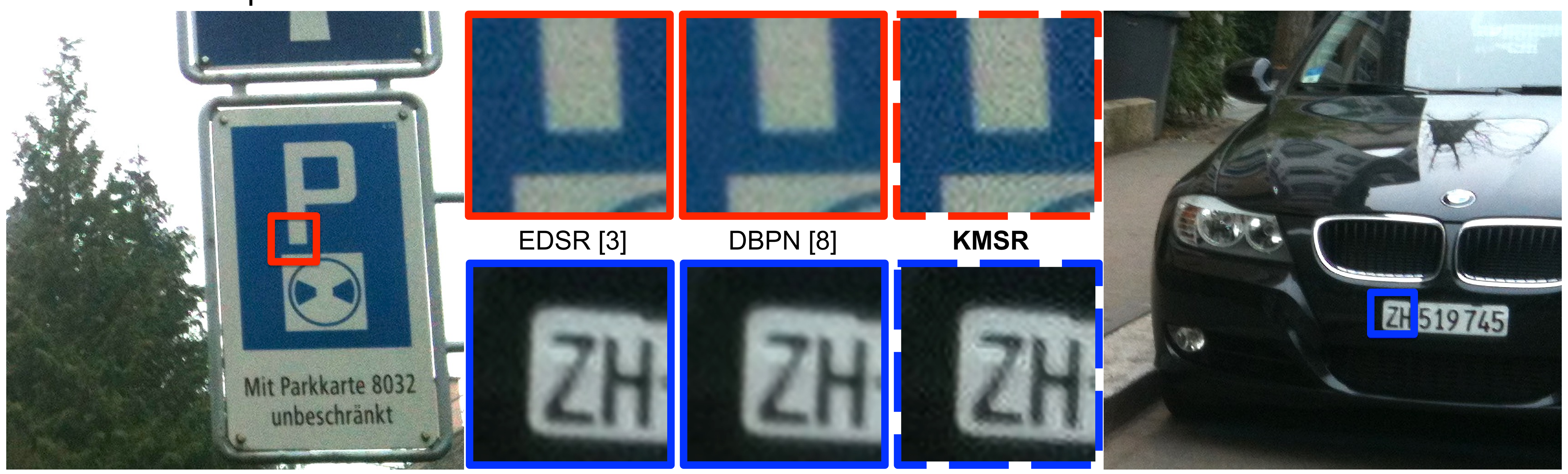
Zoom-in super-resolution

We build a zoom-in dataset by capturing photos with the same camera, with 35mm focal length (serving as LR input) and 70mm focal length (serving as reference output).



Real photographs

We validate our method with a psychovisual experiment on 35 users. For 44 out of 50 images, the results from KMSR are preferred over the other methods.



	EDSR	DBPN	KMSR
#preference	2/50	0/50	44/50
Raw votes	119	26	1605

#preference shows the number of SR results from the specific method that are chosen as "the clearest and sharpest image" by more than 50% of the participants.

References
[1] Pan et al. "Blind image deblurring using dark channel prior." *CVPR 2016.*
[2] Radford et al. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv:1511.06434.*
[3] Lim et al. "Enhanced deep residual networks for single image super-resolution." *CVPRW 2017.*
[4] Ignatov et al. "DSLR-quality photos on mobile devices with deep convolutional networks." *ICCV 2017.*
[5] Timofte et al. "NTIRE 2017 challenge on single image super-resolution: Methods and results." *CVPRW 2017.*
[6] Dong et al. "Image super-resolution using deep convolutional networks." *TPAMI 2016.*
[7] Kim et al. "Accurate image super-resolution using very deep convolutional networks." *CVPR 2016.*
[8] Haris et al. "Deep back-projection networks for super-resolution." *CVPR 2018.*