Deep Stacked Hierarchical Multi-Patch Network for Image Deblurring (Supplementary Material)

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1. Outputs of Stacked Network

Below we present the intermediate outputs of our Stack-VMPHN. Figure 1 shows that the performance is optimized level by level, which is consistent with the behaviour of Stack-DMPHN. We also provide more instances for Stack-DMPHN to demonstrate its process in Figure 2.

Figure 1. The outputs for different sub-models of Stack(3)-VMHPN. From left to right are the outputs of $\mathbf{M}_1$ to $\mathbf{M}_3$.

Figure 2. The outputs for different sub-models of Stack(3)-DMHPN. From left to right are the outputs of $\mathbf{M}_1$ to $\mathbf{M}_3$.

2. Extension to Saliency Detection

We perform saliency detection with our proposed model to investigate the generalization ability on different tasks. Our proposed model is evaluated on the MSRA-B dataset. This dataset consists of 3000 images for training and 2000 images for testing. Note that all current deep methods of saliency detection highly depend on VGG or ResNet pre-trained on ImageNet and these methods often will not converge without pre-training on ImageNet. By contrast, our network can be easily trained from scratch. It outperforms all conventional methods and it is real-time. We evaluated single VMPHN for quantitative analysis. To make our network compatible with the saliency detection task, the output channel is modified to 1 for gray image generation, and the residual connection between input and output at level 1 is disabled in VMPHN. Figure 3 and Table 1 show our results.

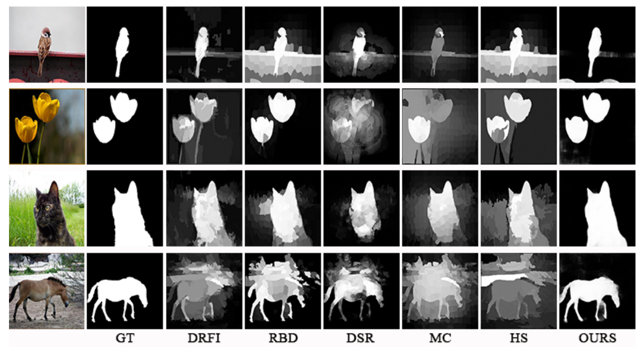

Figure 3. Instances of saliency detection on the MSRA-B dataset.

Table 1. Quantitative analysis of saliency detection on MSRA-B. For F_β, higher scores are better. For MAE, lower scores are better.

Model	[2]	[4]	[3]	[1]	[5]	OURS
F_β	.728	.751	.723	.717	.713	**.768**
MAE	.123	.117	.121	.144	.161	**.107**

References

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