Fast Image Processing with Fully-Convolutional Networks

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Introduction

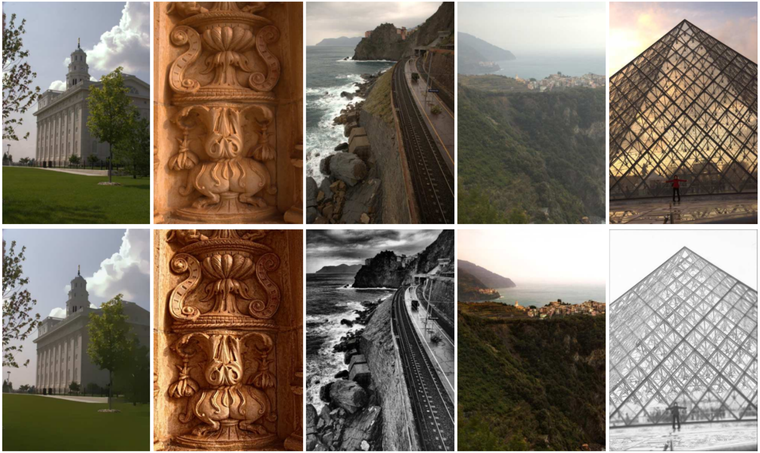
Background

- The computational demands and running times of existing operators vary greatly.
- One general approach to accelerating a broad range of image processing operators is well-known: downsample the image, execute the operator at low resolution, and upsample. This can limit the accuracy of the approximation.

What we do

Unlike the downsampling approach, the method operates on full resolution images, is trained end-to-end to maximize accuracy, and does not require running the original operator at all.

Introduction



L_0 smoothing | Multiscale tone | Photographic style | Nonlocal dehazing | Pencil drawing

Algorithms

Context aggregation networks(CAN)

$$\mathbf{L}_i^s = \Phi\left(\Psi^s\left(b_i^s + \sum_j \mathbf{L}_j^{s-1} *_{r_s} \mathbf{K}_{i,j}^s\right)\right) \tag{1}$$

$$\left(\mathbf{L}_j^{s-1} *_{r_s} \mathbf{K}_{i,j}^s\right)(\mathbf{x}) = \sum_{\mathbf{a}+r_s\mathbf{b}=\mathbf{x}} \mathbf{L}_j^{s-1}(\mathbf{a})\mathbf{K}_{i,j}^s(\mathbf{b}) \tag{2}$$

$$\Psi^s(x) = \lambda_s x + \mu_s BN(x) \tag{3}$$

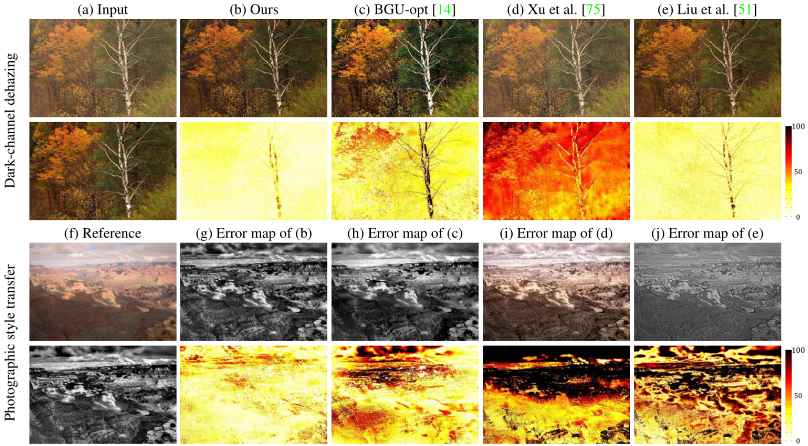
Algorithms

Image-space regression loss

$$\ell(\mathcal{K}, \mathcal{B}) = \sum_i \frac{1}{N_i} \left\| \hat{f}(\mathbf{I}_i; \mathcal{K}, \mathcal{B}) - f(\mathbf{I}_i) \right\|^2 \tag{4}$$

Experiments

Qualitative results on images from the MIT-Adobe test set



Further

Ongoing Optimization

- Parameterized operators.
- One network to represent them all.
- Video processing.

References

- Qifeng Chen, Jia Xu, Vladlen Koltun *Fast Image Processing with Fully-Convolutional Networks*