Deep Edge-Aware Filters

Li Xu[1], Jimmy SJ. Ren[1], Qiong Yan[1], Renjie Liao[2], Jiaya Jia[2]

[1]SenseTime Group Limited [2]The Chinese University of Hong Kong

Code & More Results: http://lxu.me/projects/deepeaf/

Overview

There are many edge-aware filters varying in their construction forms and filtering properties. We made the attempt to learn a big and important family of edge-aware operators from data. Our method gives rise to a powerful tool to approximate various filters without knowing the original models and implementation details. Fast approximation for complex edge-aware filters and achieves up to 200x acceleration. Fast speed can also be achieved when creating new effects using spatially varying filter or filter combination.

E-A Filters, fundamental in Image Processing

Abstraction

Edge extraction

Detail enhancement

Tone mapping

A Decade Effort in Accelerating One Filter

- Bilateral filter proposed in 1998
- Bilateral Grid proposed in 2007

- Much more filters out there

- New filters proposed every year

- Conventional acceleration technique is not general, can't be applied to other filters

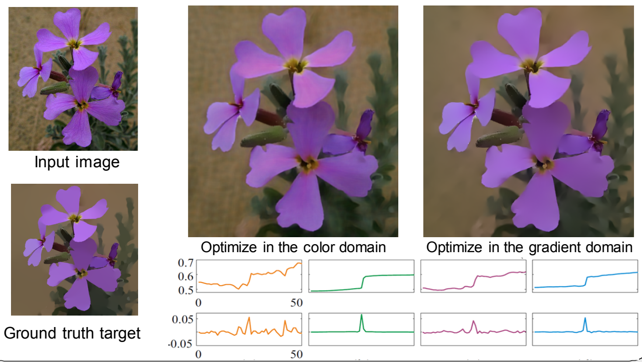
Benefits of Our Unified E-A Filter Framework

Optimize for one get ALL

Ideal for hardware

More sophisticated new effects (see results =>)

Optimize in Color VS. Gradient Domain



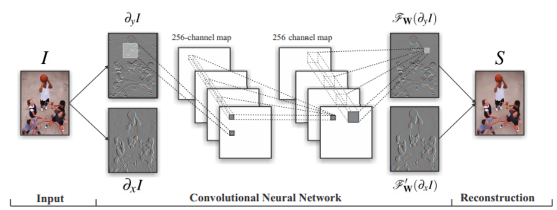
Input image

Ground truth target

Optimize in the color domain

Optimize in the gradient domain

Network Architecture



$$\text{Min} \quad \frac{1}{D}\sum_i \left\{\frac{1}{2}\|\mathcal{F}_W(\partial I_i) - \partial\mathcal{L}(I_i)\|^2 + \lambda\Phi(\mathcal{F}_W(\partial I_i))\right\}$$

Image Reconstruction from Gradients

Traditional approach: Solve a Possion equation

Direct integration may be problematic. The network output may not be integrable and causes color shift

Our approach: Solve

$$\|S - I\|^2 + \beta\left\{\|\partial_x S - \mathcal{F}_W(\partial_x I)\|^2 + \|\partial_y S - \mathcal{F}_W(\partial_y I)\|^2\right\}$$

New Effects Which Are Hard For Traditional Filters

Spatial variant filter

Filter Combo

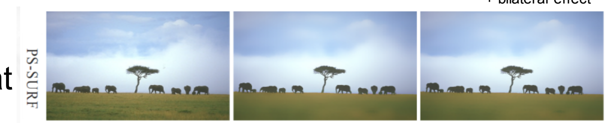
Input image

After L0 smooth

After bilateral filter

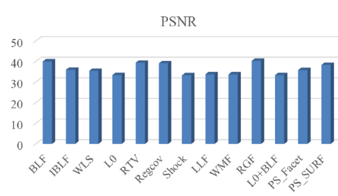
Our learned L0 + bilateral effect

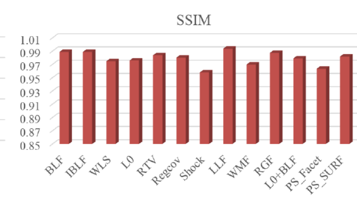
Filter copycat



Blindly learning Photoshop filters without knowing its implementation

Quantitative Evaluation





Average PSNRs and SSIMs of our approximation of various filtering techniques

Resolution	QVGA	VGA	720p	1080p	2k
BLF Grid	0.11	0.41	0.98	2.65	3.03
IBLF	0.46	1.41	3.18	8.36	12.03
WLS	0.71	3.25	9.42	28.65	33.73
L0	0.36	1.60	4.35	11.89	15.07
RTV	1.22	6.26	16.26	42.59	48.25
RegCov	59.05	229.68	577.82	1386.95	1571.91
Shock	0.45	3.19	8.48	23.88	26.93
LLF	207.93	849.78	2174.92	5381.36	6130.44
WMF	0.94	3.54	4.98	14.32	15.41
RGF	0.35	1.38	3.42	9.02	10.31
Ours	0.23	0.83	2.11	5.78	6.65

Running time for different resolution images on desktop PC (Intel i7 3.6GHz with 16GB RAM, Geforce GTX 780 Ti).