Deep Edge-Aware Filters

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Why Edge-Aware Filters

- A fundamental operator in image processing

Image abstraction (Xu et al. SIGGRAPH Asia 2011)

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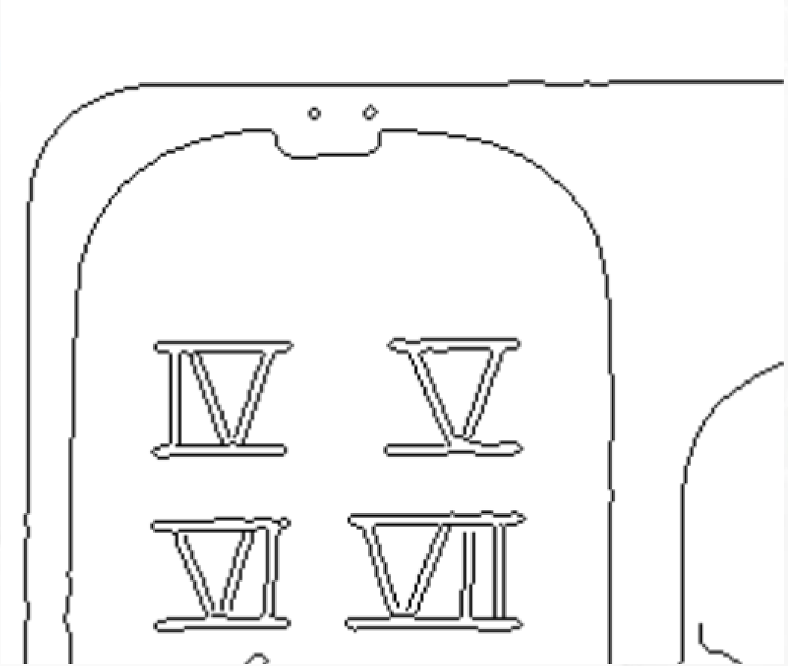
- A fundamental operator in image processing



Edge extraction (Xu et al. SIGGRAPH Asia 2011)

Why Edge-Aware Filters

- A fundamental operator in image processing

Detail enhancement (Xu et al. SIGGRAPH Asia 2011)

Why Edge-Aware Filters

- A fundamental operator in image processing

Tone mapping (Xu et al. SIGGRAPH Asia 2011)

Filter Acceleration Efforts

- More than a decade effort in accelerating bilateral filter

- Proposed (Tomasi & Manduchi, 1998)

(direct implementation very slow, several minutes per megapixel)

- Piecewise-linear approximation in the intensity domain and sub-sampling in the spatial domain (Durand & Dorsey, 2002)

- Signal processing interpretation, linear filtering in high dimensional space, more accurate approximation (Paris & Durand, 2006)

- A very fast median filter, adapted to perform bilateral filtering (Weiss 2006)

(1 second per megapixel, still not real time)

- Bilateral Grid, new data structure, extension to high dimensional filtering. GPU enabled (Chen et al. 2007)

- O(1) time algorithms (Porikli. 2008, Yang et al. 2009 2010)

(real time for HD videos)

Filter Acceleration Efforts

- There are many more edge-aware filters
  - L0 smoothing, local laplacian, relative total variation, rolling guidance, region covariance, etc.
- New methods emerge every year
- Acceleration techniques for one filter, hard to be applied to others
- No previous work to unify the acceleration of edge-aware filters

A Unified Framework - Benefits

- Optimize for one get ALL

- Ideal for hardware implementation

- Beyond, more to come

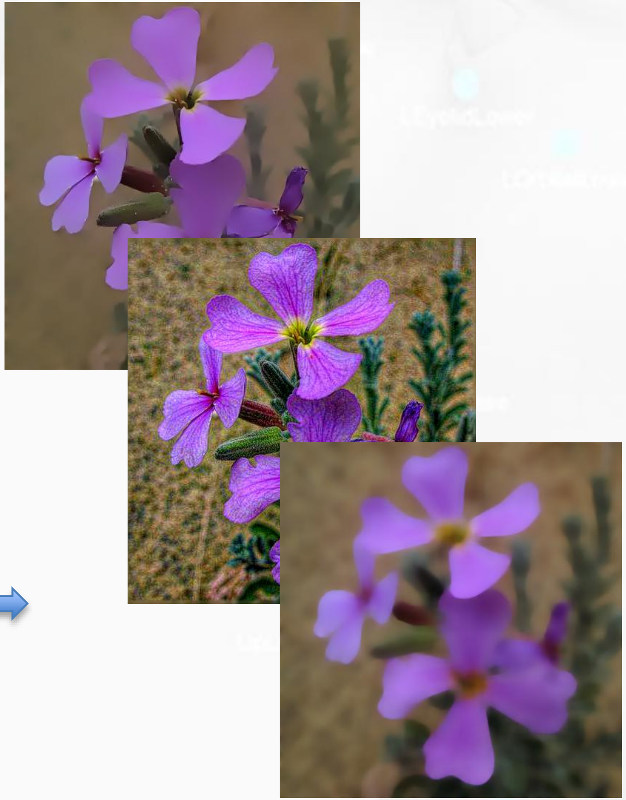
Problem Statement

Original approach to image filtering

Design a nonlinear filtering operator

Problem Statement

Our approach to image filtering



Learn any nonlinear edge-aware filtering operator from data using a unified learning framework

Learning in The Color Domain

Learning a mapping function in the color domain

Min $\|\mathcal{F}_{\mathbf{W}}(I) - \mathcal{L}(I)\|^2$

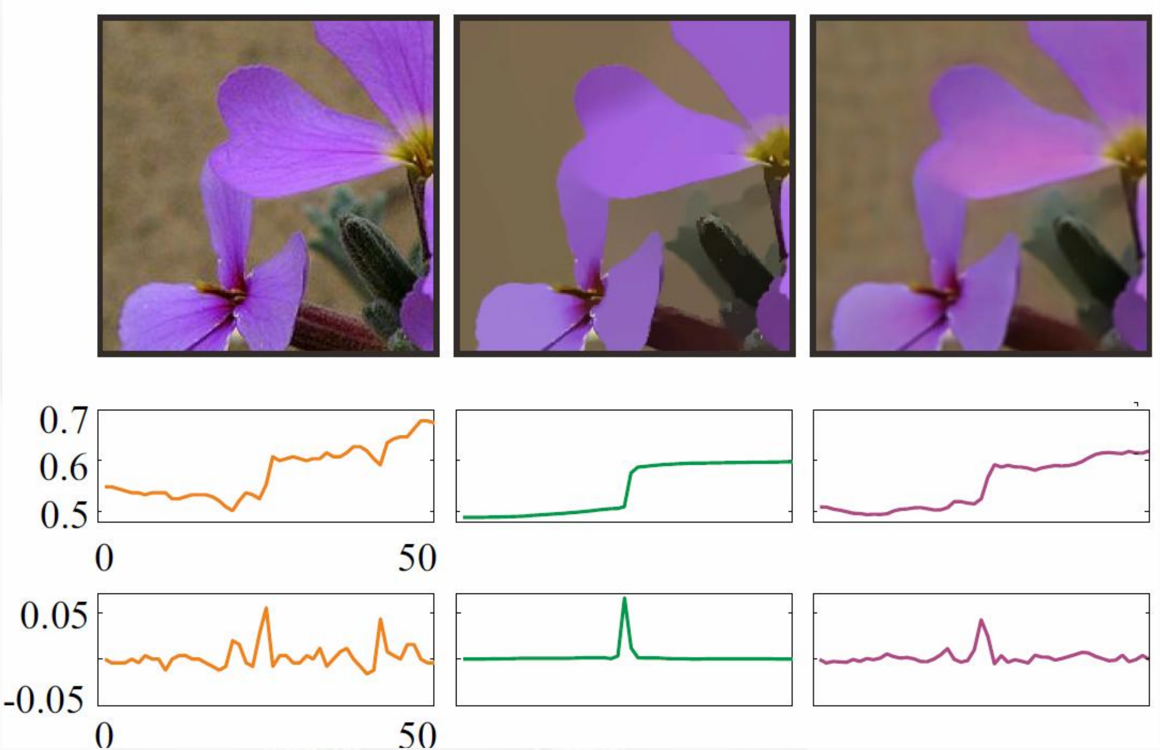
Input image

Learned color domain filter, more blur and contain unwanted details

Target L0 smoothing effect (Xu et al. 2011)

Learning in The Color Domain

- Reason



Quantitatively, MSE in the color domain is pretty small. But in the gradient domain it is relatively big.

Do edge-aware filters by optimizing edges?

Our Approach

We define our objective function on ∇I instead of I.

$$\text{Min} \quad \|\mathcal{F}_{\mathbf{W}}(I) - \mathcal{L}(I)\|^2$$

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

Gradient of I_i

Gradient of $\mathcal{L}(I_i)$

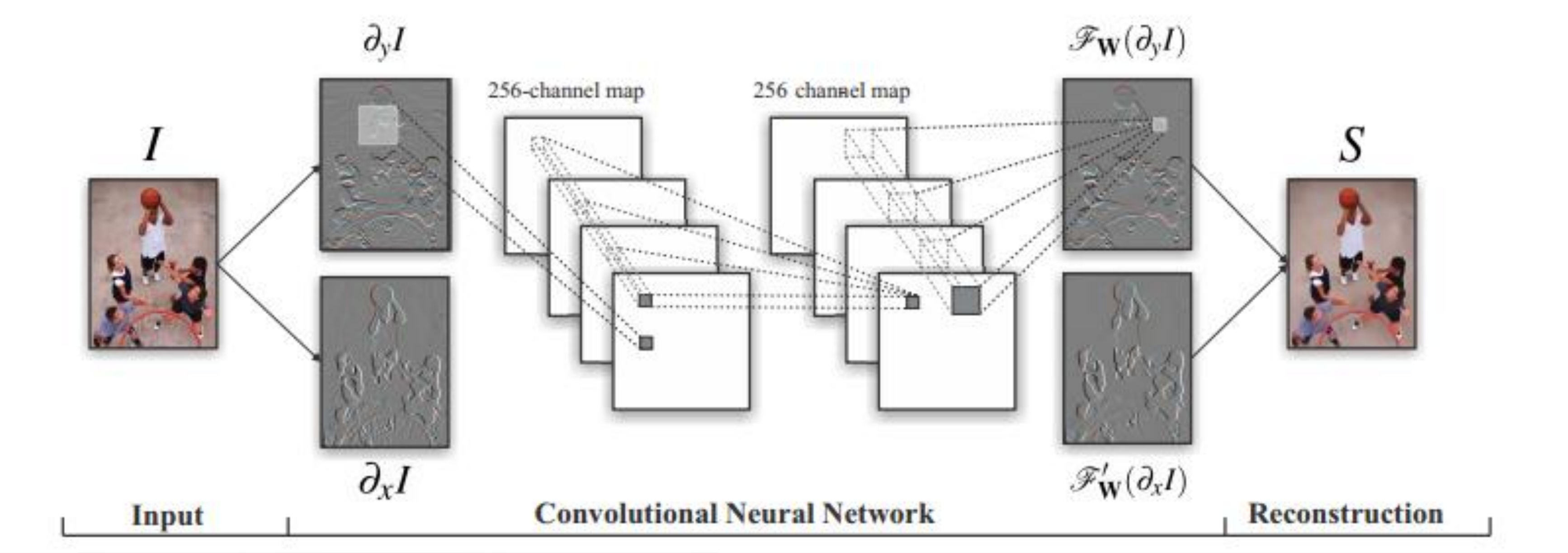
Data Collection

- 1000 natural images scraped from Flickr
- Randomly sample 1 million image patches
- Use the target filter to generate 1 million filtered patches
- Generate the gradient map pairs from patches
  - Only vertical gradient is used in the training
  - Horizontal gradient map is rotated 90 degrees to go through the same network and rotate back in testing

Network Architecture

Reason to use convolutional neural networks (CNN)

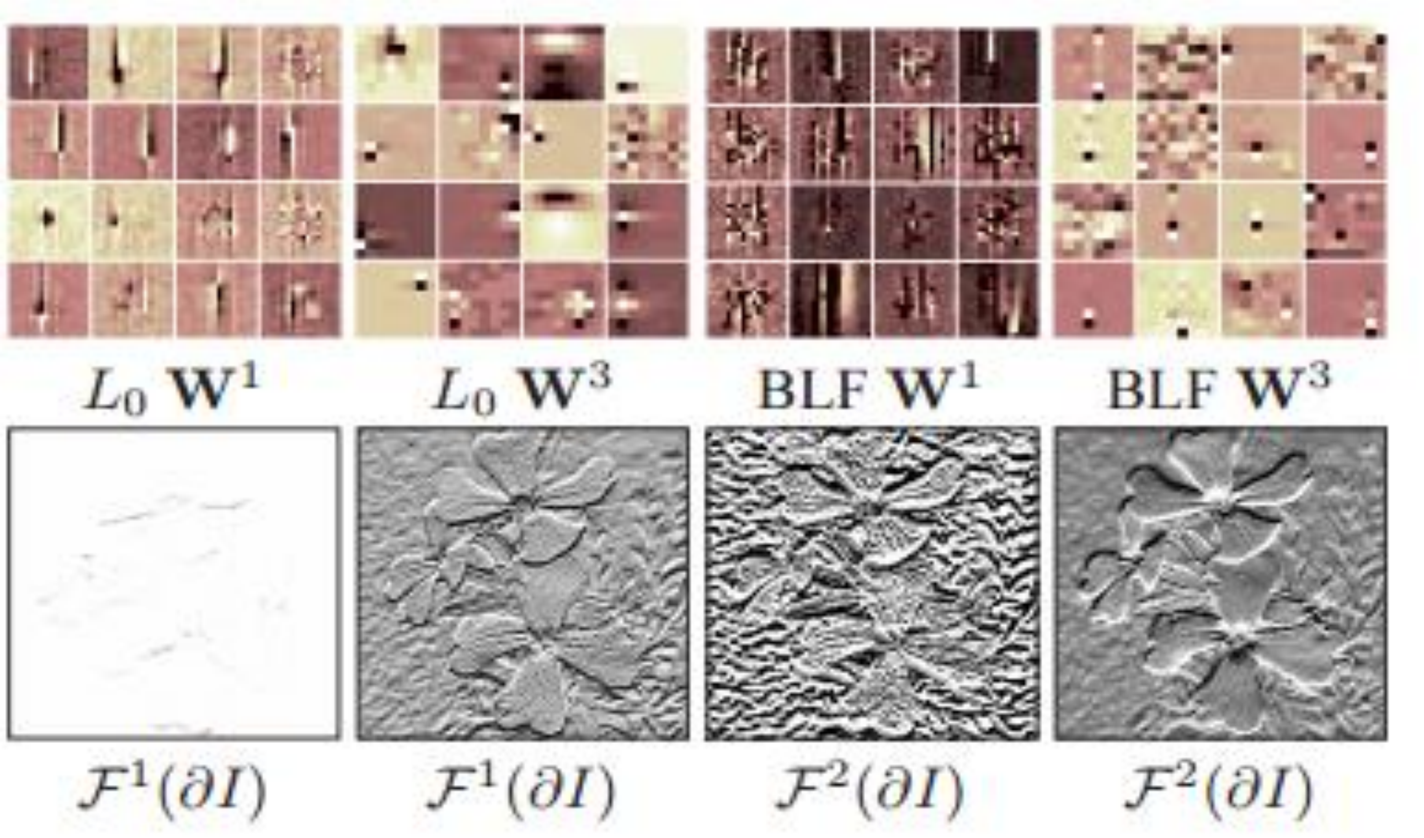
1. Existing filter acceleration methods use high dimension Gaussian convolution. Indicates edge-aware operators can be done using convolutions
2. Weight sharing property, network applies to large images



Training Details

- Stochastic gradient descent works well, AdaGrad works slightly better
- Tanh and ReLU both work well, convergence speed similar
- Went through the data 10 times
- No dropout was used

What Does The Network Do?



Improvement

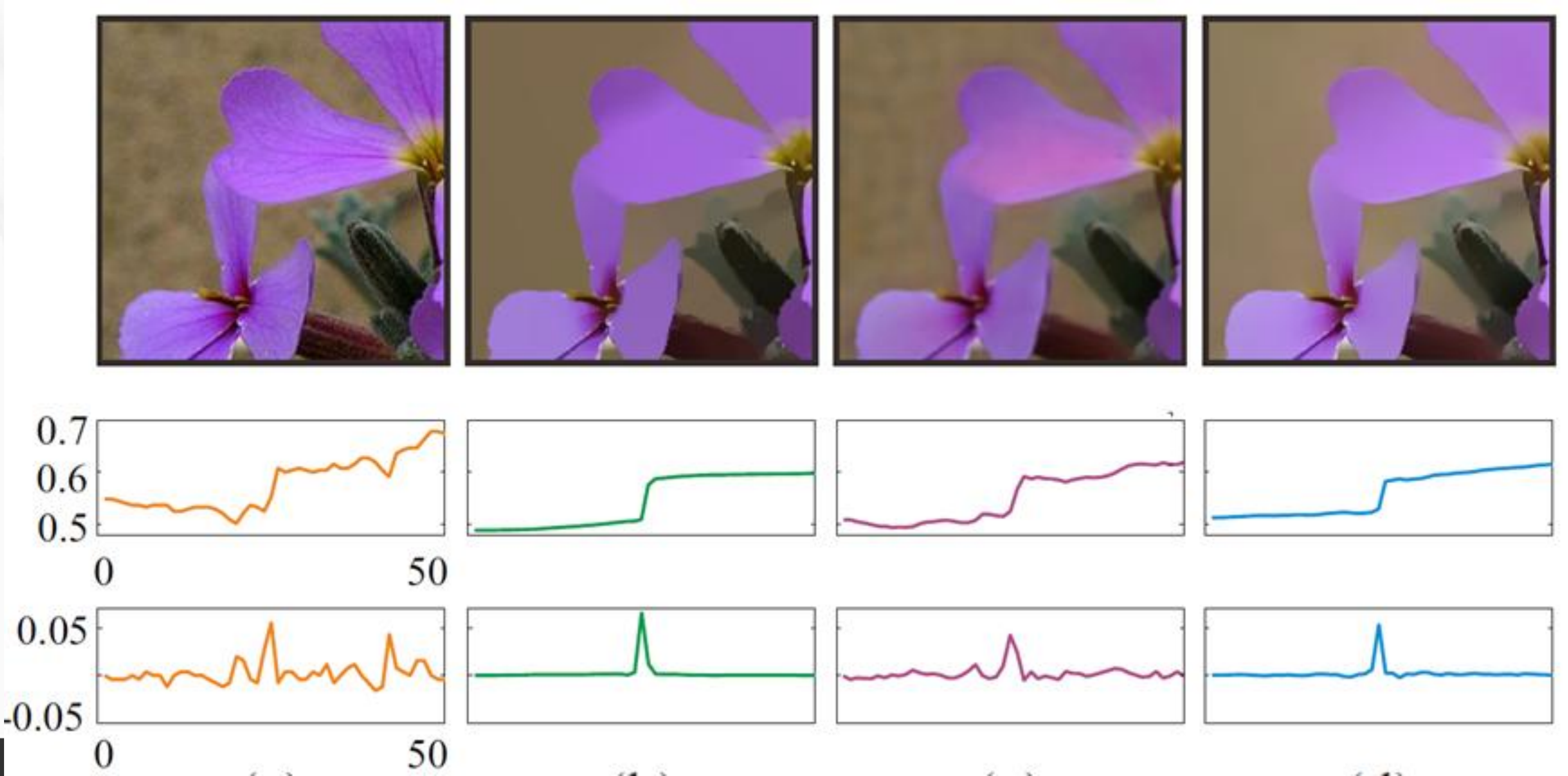


Image Reconstruction

Image Reconstruction

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

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

Beyond Learning Existing Filters

- Learning filter combo and run in constant time


Input image


After L0 smooth


After bilateral filter


Our learned L0 + bilateral effect

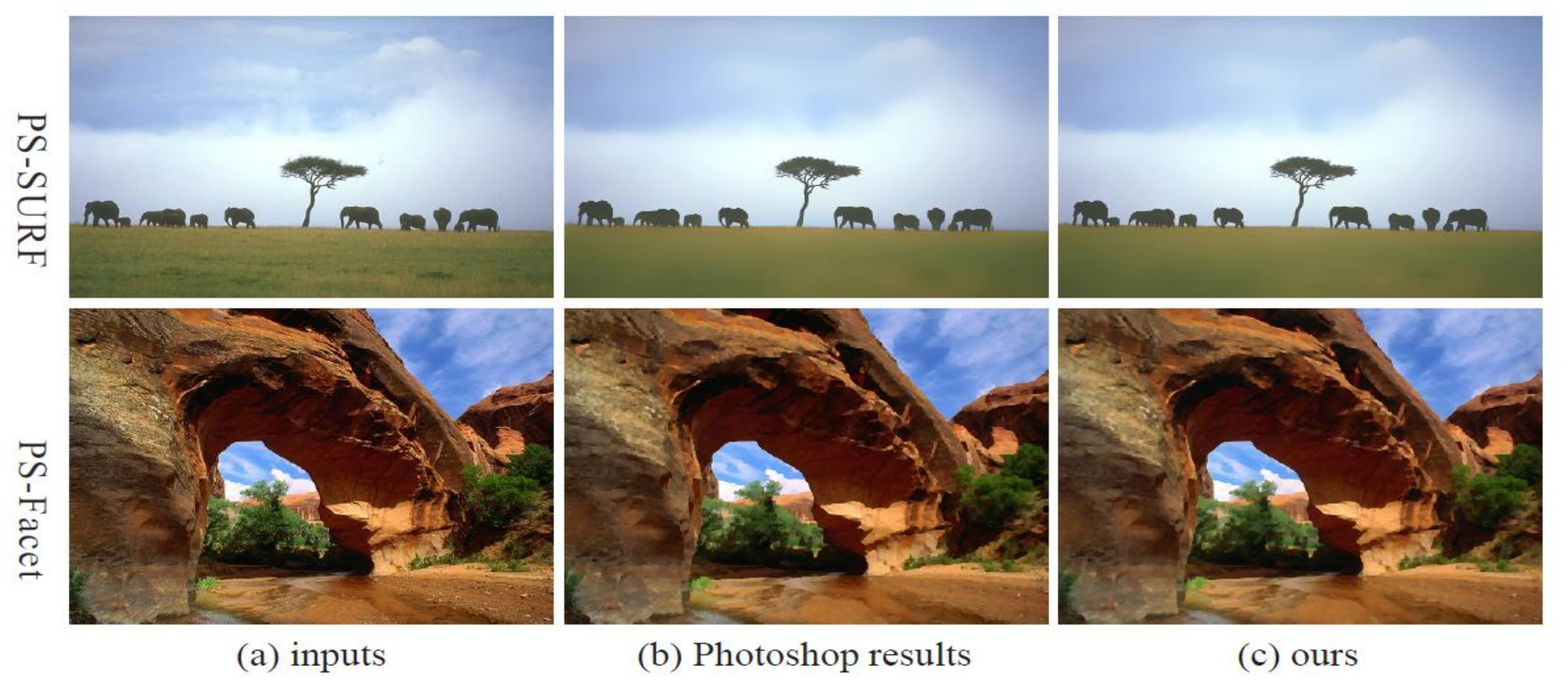
Very useful to remove highly contrast texture, conventional method is slow

Beyond Learning Existing Filters

- Spatial variant filter
  - Very hard to achieve by conventional global methods which rely on numerical solutions

Beyond Learning Existing Filters

- Learn Photoshop effects without knowing its implementation

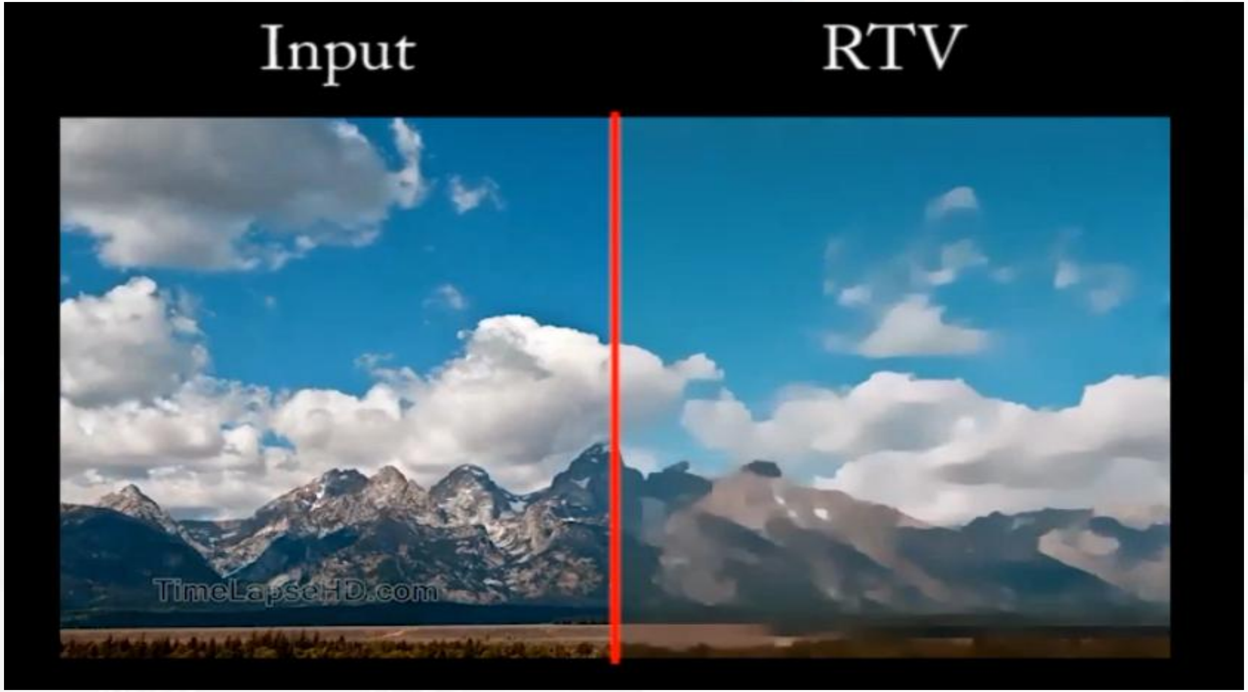


Contributions

- Unified and practical system for learning edge-aware filters with gradient-domain learning procedure and optimized image reconstruction
- Filter has linear complexity and run at a constant time, regardless original implementation
  - Up to 200X acceleration for several filters
- Various new effects can be created by combining or adapting original filters in our unified framework
  - Filter combo, filter copycat, spatial variant filter, etc.

More Results

- Demo Video



Thank You!