Leveraging histogram equalization for expert photo enhancement

Luca Cavalli
Gianpaolo Di Pietro

Motivations and Objectives

- Photo enhancement is a widespread need
- High quality enhancements are traditionally **handcrafted** by professionals

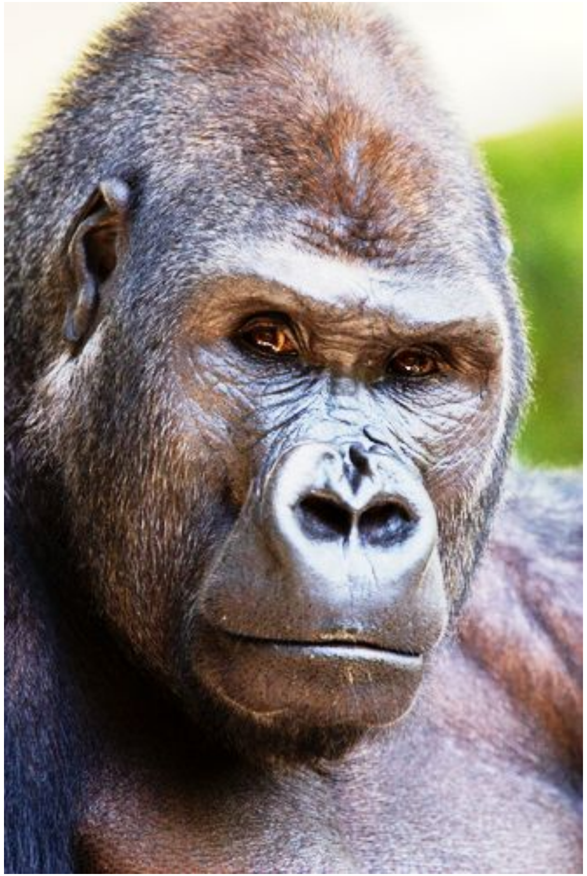
Motivations and Objectives

- Photo enhancement is a widespread need
- High quality enhancements are traditionally **handcrafted** by professionals

- Learning expert photo enhancement is a very complex problem
- Histogram equalization is very simple and provides rough enhancement

Original

Expert enhanced



Histogram equalization

Motivations and Objectives

- Photo enhancement is a widespread need
- High quality enhancements are traditionally **handcrafted** by professionals

- Learning expert photo enhancement is a very complex problem
- Histogram equalization is very simple and provides rough enhancement

- **Research** techniques to effectively learn histogram equalization
- **Transfer** these techniques to expert photo enhancement

State of the Art

- *Kaufman et al.* (2012): hand crafted transformations on detected semantic regions
- *Yan et al.* (2016): learned transformations on detected semantic regions with hand crafted features
- *Kinoshita et al.* (2019): learned enhancement from synthesized samples generated from high dynamic range images, uses U-Net

Problem formulation

- Photo enhancement can be framed as a pixel-wise function depending on local and global features:

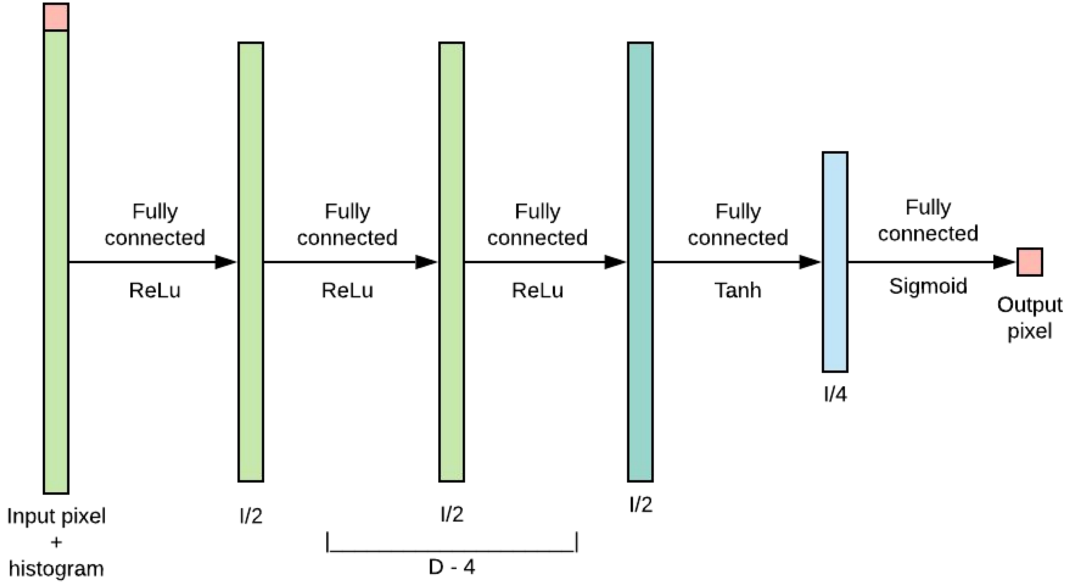
$$Q^i = \mathcal{F}_{pw}(\mathcal{P}^i, \mathcal{L}(\mathcal{N}_i(\mathcal{P})), \mathcal{G}(\mathcal{P}))$$

- Histogram equalization is a simplified instance of this framework

- Designed architectures should excel at histogram equalization, and be open towards the general problem

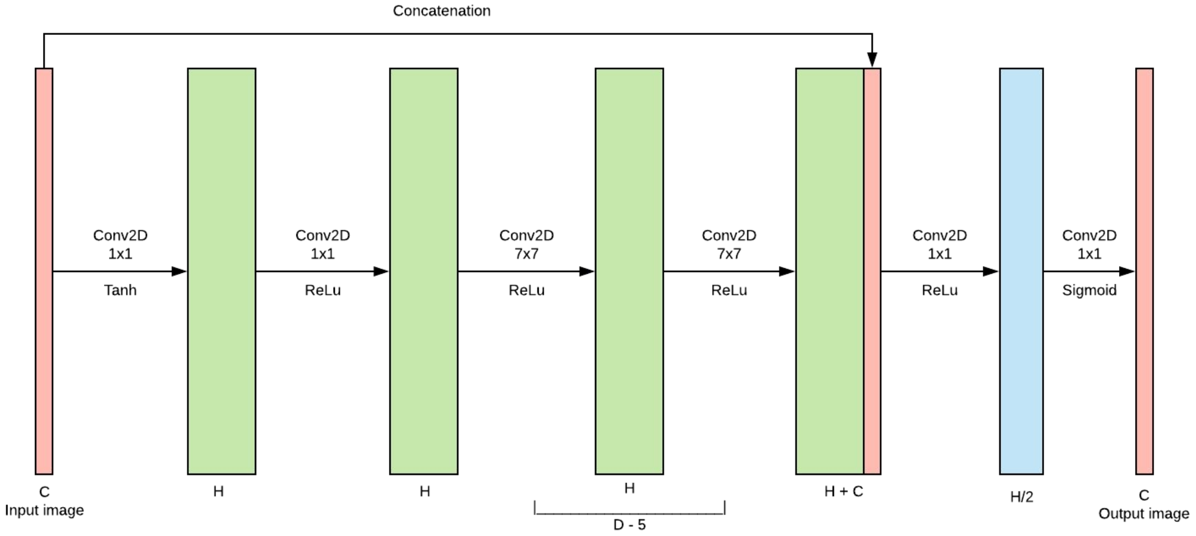
Pixel-wise mapper

- Use the histogram as a feature and just learn the pixel-wise function
- The complexity of the function depends on the size of the input histogram



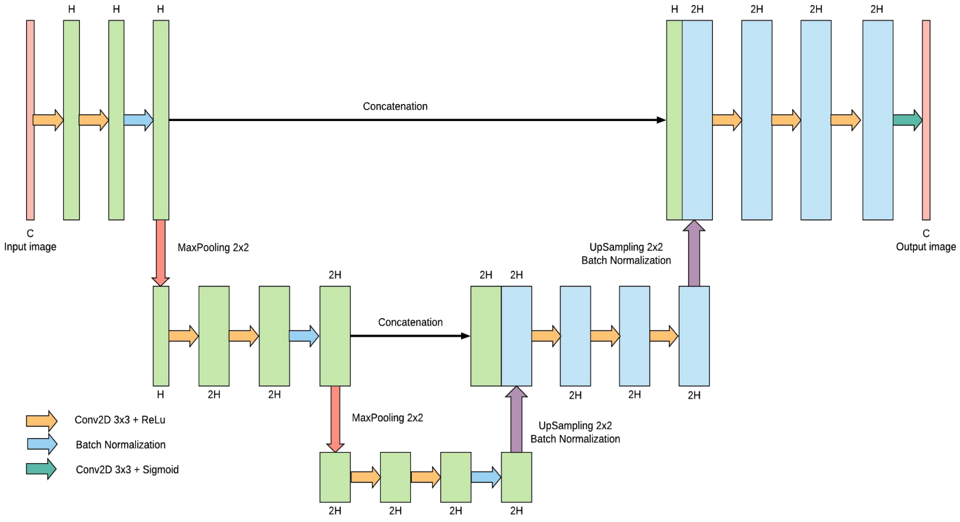
Histogram CNN

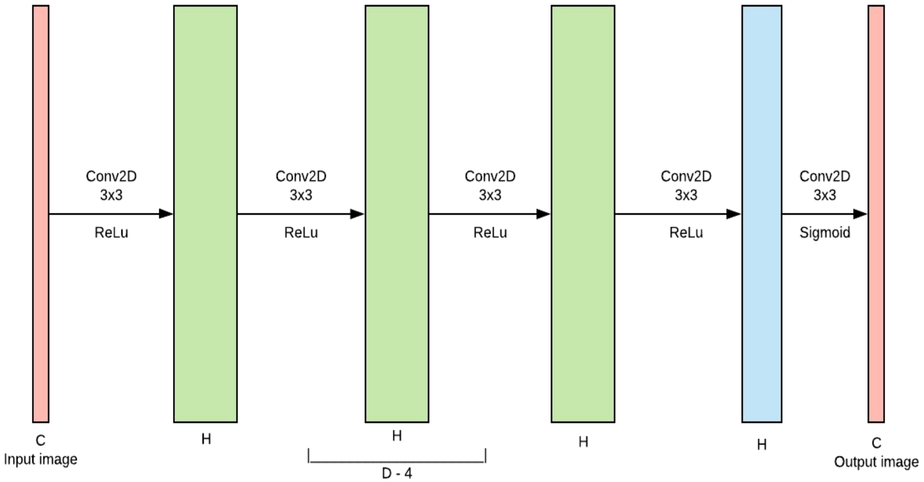
- Classify pixels independently to build pixel-sized local histograms
- Merge smaller local histograms into larger local histograms
- Remap each pixel independently according to collected local histograms



Comparative architectures

- Compare performances with classical architectures
- Plain CNN and U-Net have been chosen





Histogram Equalization experimental results

- Training and validation on cifar10 dataset in grayscale
- Ground truth generated algorithmically

Architecture	$\mathcal{H}$	$\mathcal{D}$	Parameters	MSE
Pixel-wise FC	64	10	10k	1.45e-2
Histogram CNN	128	12	6.4M	**1.6e-3**
Histogram CNN	32	12	400k	4.1e-3
Plain CNN	128	10	1.2M	1.1e-2

Qualitative assessment

a
b
c
d
e

a: Original
b: Ground Truth

c: Histogram CNN
d: Plain CNN

e: Pixel-wise FC

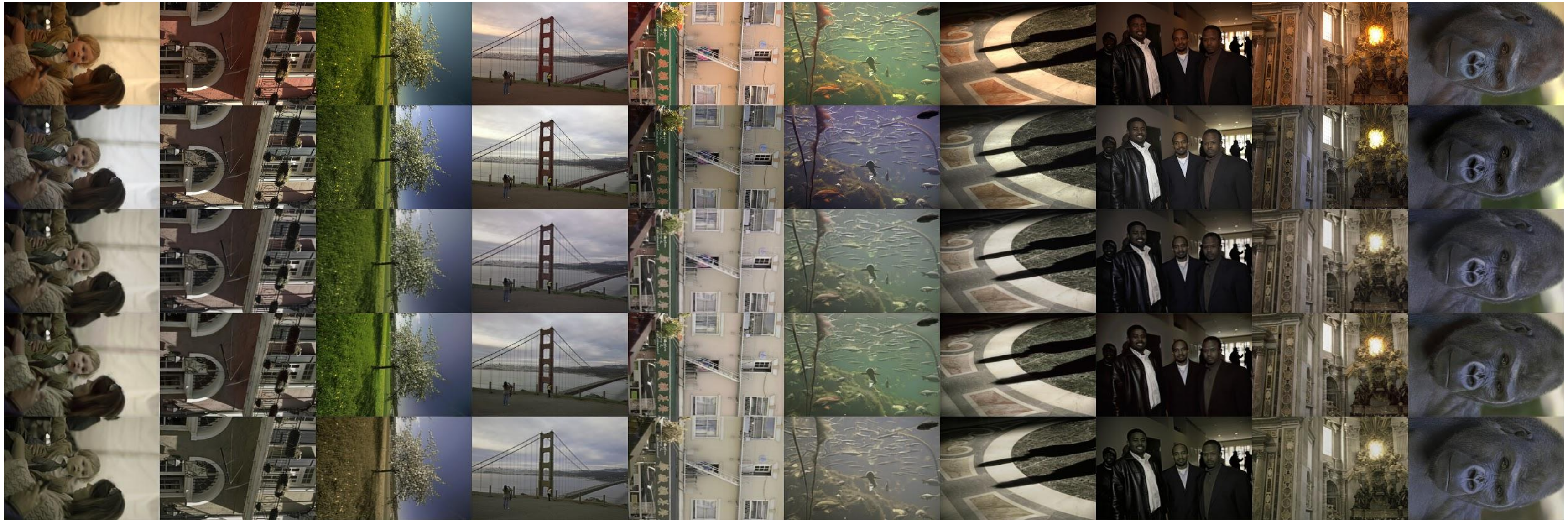
Expert photo enhancement experimental results

- Training and validation on MIT FiveK dataset with fixed size 500x332
- Ground truth taken from ExpertB

Architecture	$\mathcal{H}$	$\mathcal{D}$	Parameters	MSE
Histogram CNN	64	7	611k	**9.5e-3**
Plain CNN	128	10	1.2M	1.0e-2
U-Net	256	11	5.3M	9.7e-3

Qualitative assessment

a
b
c
d
e



a: Original
b: Ground Truth
c: Histogram CNN
d: Plain CNN
e: U-Net

Original **Expert enhanced** **Ours**