Deep-Learning-based Image Denoising in Ophthalmology
Guided Research Kick-Off

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Example Use-Case: Digital Window

Digital Window

What are we trying to do?

Idea

- Improve quality of retinal images by super-resolution & deblurring
- Should work in an intraoperative setting

Use cases

- Pre-processing for other computer vision algorithms
- Provide improved quality for digital zoom.

Constraints

- Real-time, as fast as possible
- Different levels of zoom
- Preserve anatomical structure (vessels, etc.)

State of the Art

General Super-Resolution

Many different super resolution approaches[1].

E.g. based on image statistics, self-similarity of images, learned patch-databases or **convolutional neural networks**.

CNNs fulfil **both** quality and speed constraints

Ophthalmology

Uses CNN-Upscaling[2]

Solid results, not optimised for intraoperative use-case

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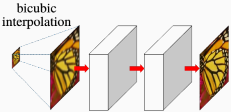
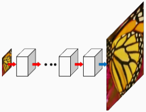
[1] K. Nasrollahi and T. B. Moeslund. 'Super-resolution: a comprehensive survey'. In: *Machine vision and applications* 25.6 (2014).

[2] D. Mahapatra, B. Bozorgtabar, S. Hewavitharanage and R. Garnavi. 'Image Super Resolution Using Generative Adversarial Networks and Local Saliency Maps for Retinal Image Analysis'. In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. 2017.

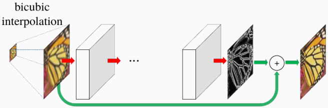
Some common CNN-Topologies[6]



SRCNN[3]



FSRCNN[4]



VDSR[5]

Red: Convolution

Blue: Transposed Convolution

Green: Summation

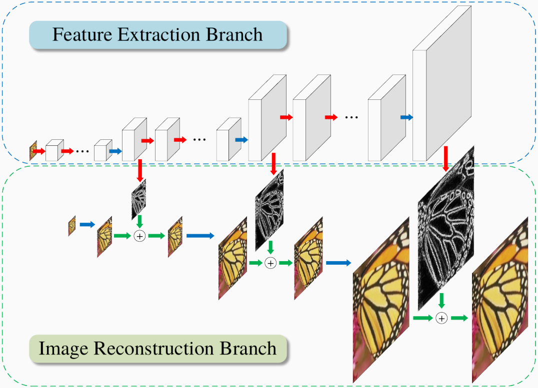
[3] C. Dong, C. C. Loy, K. He and X. Tang. 'Learning a deep convolutional network for image super-resolution'. In: *European Conference on Computer Vision*. 2014.

[4] C. Dong, C. C. Loy and X. Tang. 'Accelerating the super-resolution convolutional neural network'. In: *European Conference on Computer Vision*. 2016.

[5] J. Kim, J. Kwon Lee and K. Mu Lee. 'Accurate image super-resolution using very deep convolutional networks'. In: *IEEE Conference on Computer Vision and Pattern Recognition*. 2016.

[6] W.-S. Lai, J.-B. Huang, N. Ahuja and M.-H. Yang. 'Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution'. In: *IEEE Conference on Computer Vision and Pattern Recognition*. 2017.

Laplacian Network[7]



Laplacian pyramid network

1. Residual Learning
2. Progressive Reconstruction
3. Low-resolution filters
4. Non-SR-case: Add residual to HR-images

Red: 3×3 convolution, *blue*: transposed convolution, *green* summation

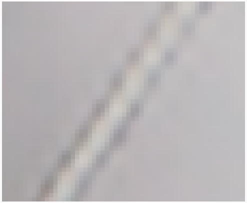
[7]W.-S. Lai, J.-B. Huang, N. Ahuja and M.-H. Yang. 'Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution'. In: *IEEE Conference on Computer Vision and Pattern Recognition*. 2017.

Robust (Charbonnier) Loss[8]

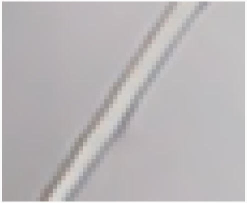
(Relaxed) L_1 loss instead of L_2 loss

$$L(\hat{\boldsymbol{y}}, \boldsymbol{y}; \boldsymbol{\theta}) = \sum_{n} p\left(\hat{\boldsymbol{y}} - \boldsymbol{y}\right)$$
$$p(\boldsymbol{x}) = \sqrt{\langle x, x \rangle + \epsilon^2},$$

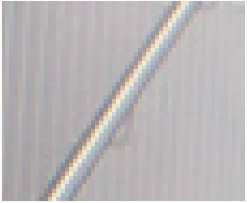
Robust, avoids **blurry** images



L_2 loss



L_1 loss



Ground truth

[8] W.-S. Lai, J.-B. Huang, N. Ahuja and M.-H. Yang. 'Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution'. In: *IEEE Conference on Computer Vision and Pattern Recognition*. 2017.

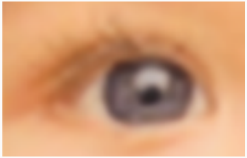
Perceptual Loss—VGG-based[9]

Transform images before calculating loss, with feature map ϕ:

$$L_p(\hat{\boldsymbol{y}}, \boldsymbol{y}; \boldsymbol{\theta}) = \sum_n \|\phi(\hat{\boldsymbol{y}}) - \phi(\boldsymbol{y})\|$$

Possibility 1: Neural Network based loss, **automatic** features

Extract feature maps from pre-trained VGG16-Network



L_2 loss

Perceptual loss

Ground truth

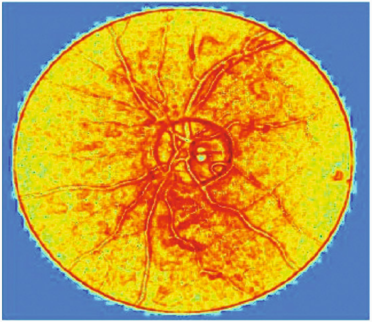
[9] J. Johnson, A. Alahi and L. Fei-Fei. 'Perceptual losses for real-time style transfer and super-resolution'. In: *European Conference on Computer Vision*. 2016.

Perceptual Loss—Saliency Maps[10]

Possibility 2: Saliency Maps

Handcrafted features

Retina image



Resulting saliency map

[10] D. Mahapatra, B. Bozorgtabar, S. Hewavitharanage and R. Garnavi. 'Image Super Resolution Using Generative Adversarial Networks and Local Saliency Maps for Retinal Image Analysis'. In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. 2017.

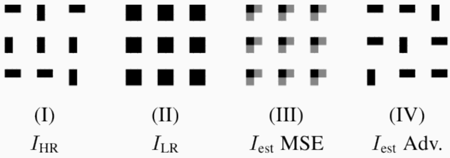
Adversarial Loss

Two player game between

Generator Super-resolution network

Discriminator Tries to decide, whether images are **real** high-resolution images or **generated** by our network

Leads to realistic looking images



Toy example for adversarial loss[11]

[11] M. S. M. Sajjadi, B. Schölkopf and M. Hirsch. ‘EnhanceNet: Single Image Super-Resolution through Automated Texture Synthesis’. In: *IEEE International Conference on Computer Vision (ICCV 2017)*. 2017.

Possible Modifications for Network

Weight sharing

Replace stacked convolutions

Replace transposed convolutions (avoid checkerboard artifacts)[12]

Example of block artifacts (from[13])

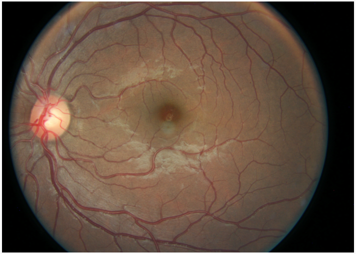
[12] A. Odena, V. Dumoulin and C. Olah. 'Deconvolution and Checkerboard Artifacts'. In: *Distill* (2016).

[13] J. Johnson, A. Alahi and L. Fei-Fei. 'Perceptual losses for real-time style transfer and super-resolution'. In: *European Conference on Computer Vision*. 2016.

Dataset

Use 1000 images from Eyepacs dataset[14] (ca. 30k HR) for training

Augment, then select random crops of size 128×128, create low-resolution images by downscaling and blurring



Eyepacs example

[14] https://www.kaggle.com/c/diabetic-retinopathy-detection

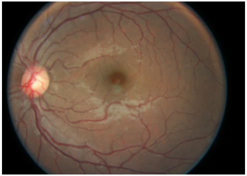
Evaluation

Normally: Compare pixel-wise reconstruction error

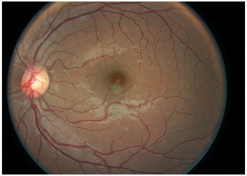
Difficult in our case.

Perceptual & adversarial loss improve perceived quality but increase error!

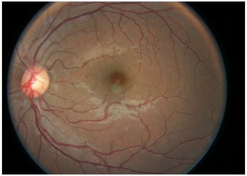
Rather compare effectiveness as a pre-processing tool.



Blurred



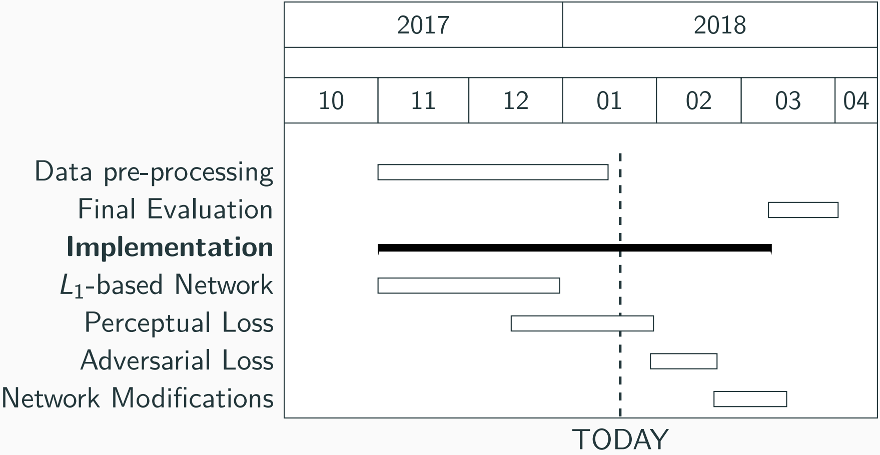
Sharpened



Ground truth[15]

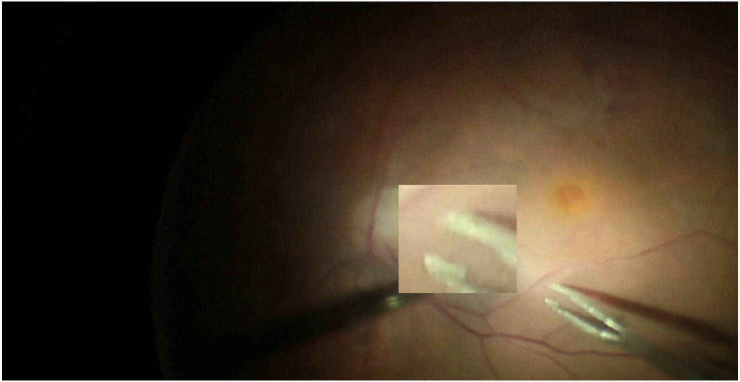
[15] https://www.kaggle.com/c/diabetic-retinopathy-detection

Timeline


2017
2018
10
11
12
01
02
03
04
Data pre-processing
Final Evaluation
Implementation
L_1-based Network
Perceptual Loss
Adversarial Loss
Network Modifications
TODAY

Summary

- Real-time super-resolution is realistic
- Selection of loss function is important
- Need for careful evaluation



Use case: Digital Window