

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 approaches¹.

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

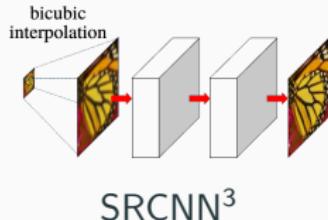
Uses CNN-Upscaling²

Solid results, not optimised for intraoperative use-case

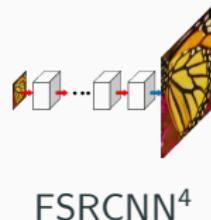
¹K. Nasrollahi and T. B. Moeslund. 'Super-resolution: a comprehensive survey'. In: *Machine vision and applications* 25.6 (2014).

²D. 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.

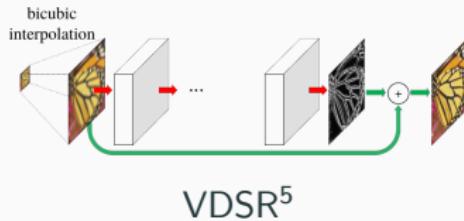
Some common CNN-Topologies⁶



SRCNN³



FSRCNN⁴



VDSR⁵

*Red: Convolution
Blue: Transposed Convolution
Green: Summation*

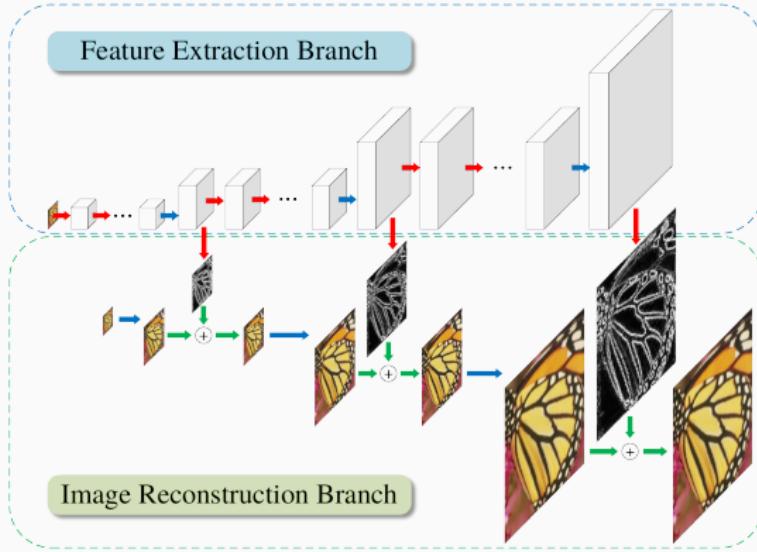
³C. Dong, C. C. Loy, K. He and X. Tang. 'Learning a deep convolutional network for image super-resolution'. In: *European Conference on Computer Vision*. 2014.

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

⁵J. 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.

⁶W.-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 Network⁷



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

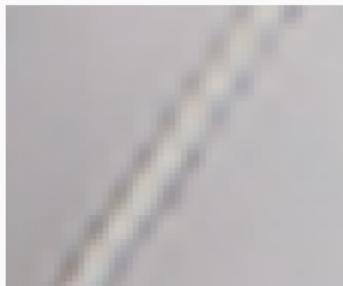
⁷W.-S. Lai, J.-B. Huang, N. Ahuja and M.-H. Yang. 'Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution'. In: *IEEE Conference on Computer Vision and Pattern Recognition*. 2017.

Robust (Charbonnier) Loss⁸

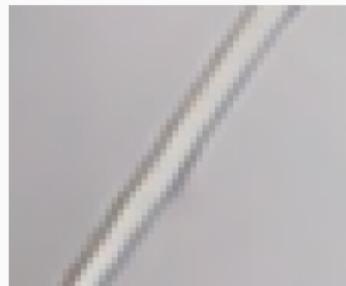
(Relaxed) L_1 loss instead of L_2 loss

$$L(\hat{\mathbf{y}}, \mathbf{y}; \theta) = \sum_n p(\hat{\mathbf{y}} - \mathbf{y})$$
$$p(\mathbf{x}) = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle + \epsilon^2},$$

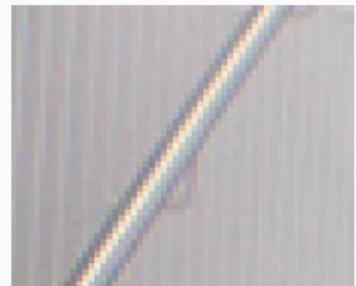
Robust, avoids **blurry** images



L_2 loss



L_1 loss



Ground truth

⁸W.-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-based⁹

Transform images before calculating loss, with feature map ϕ :

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

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

Extract feature maps from pre-trained VGG16-Network



L_2 loss



Perceptual loss



Ground truth

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

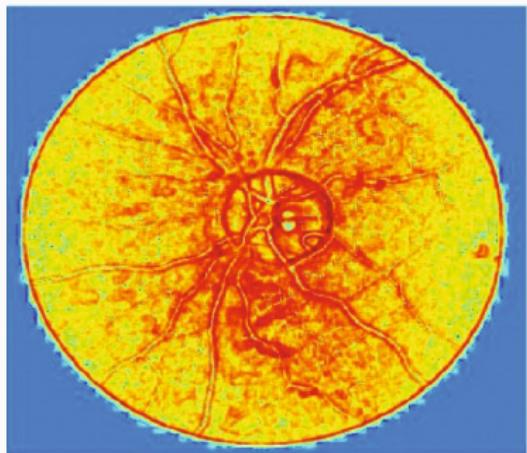
Perceptual Loss—Saliency Maps¹⁰

Possibility 2: Saliency Maps

Handcrafted features



Retina image



Resulting saliency map

¹⁰D. 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.

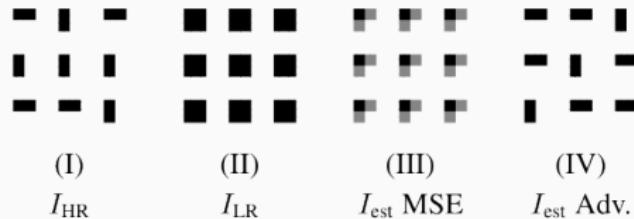
Adversarial Loss

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 loss¹¹

¹¹M. 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 (from¹³)

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

¹³J. 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 dataset¹⁴ (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>

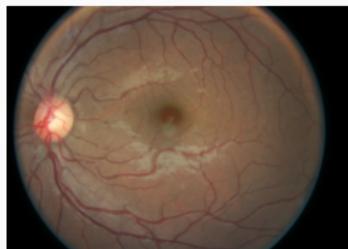
Evaluation

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



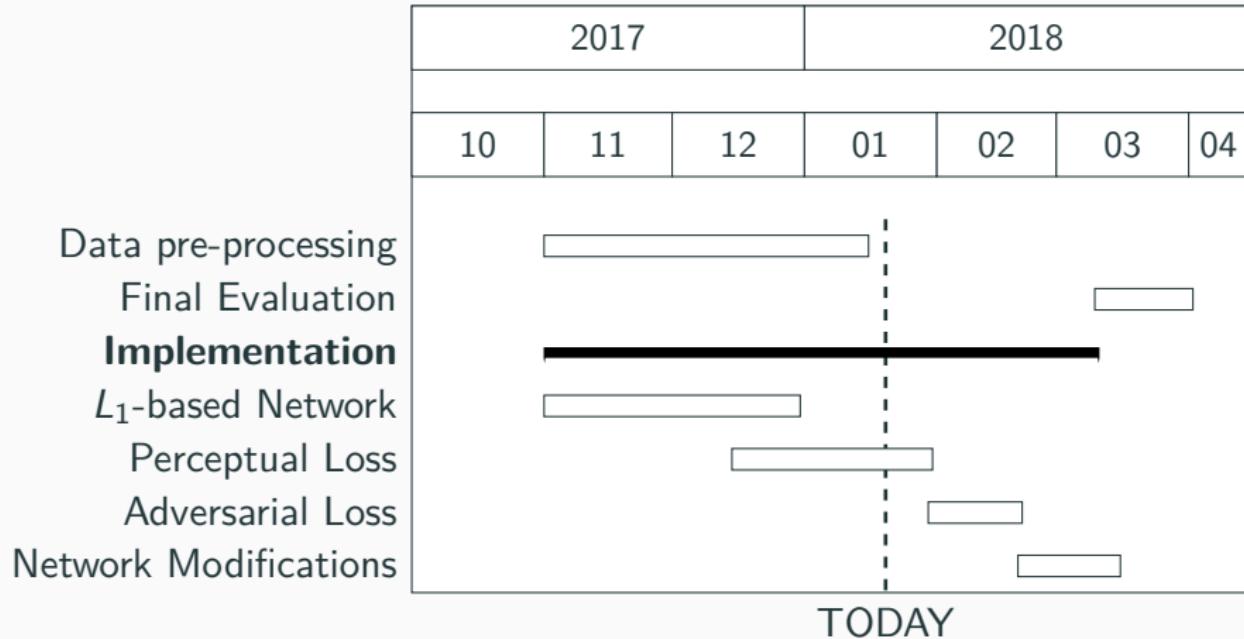
Sharpened



Ground truth¹⁵

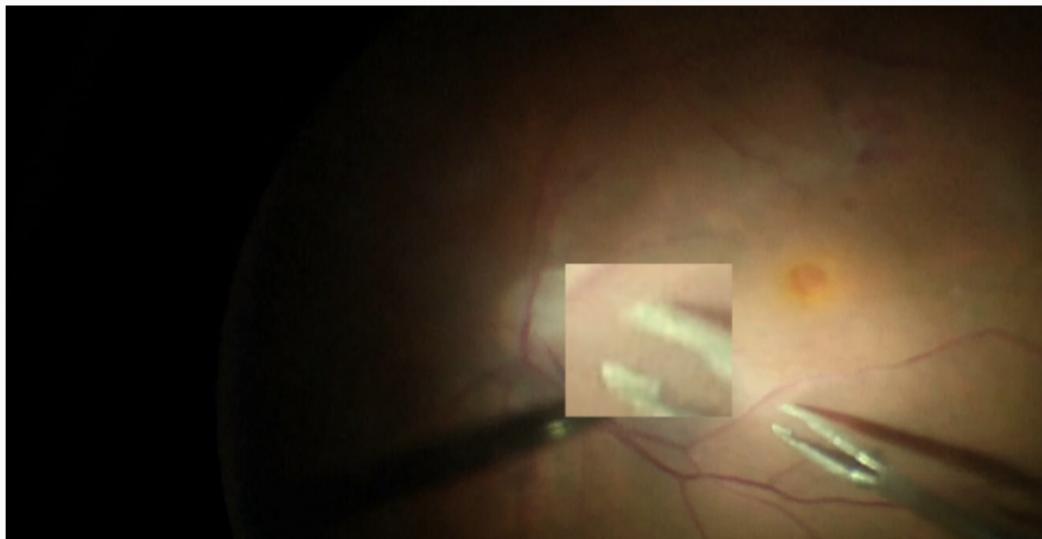
¹⁵<https://www.kaggle.com/c/diabetic-retinopathy-detection>

Timeline



Summary

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



Use case: Digital Window