# Deep-Learning-based Image Denoising in Ophthalmology
# GR 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
- Different levels of zoom
- Preserve anatomical structure (vessels, etc. )

## State of the Art

### General Super-Resolution

Many different super resolution approaches.

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

Only CNNs fulfil **both** quality and speed constraints

### Opthamology

Uses CNN-Upscaling[1]

Solid results, not optimized for intraoperative use-case

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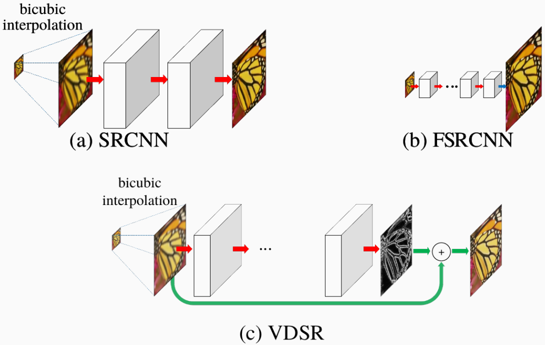
[1] D. Mahapatra, B. Bozorgtabar, S. Hewavitharanage and R. Garnavi (2017). 'Image Super Resolution Using Generative Adversarial Networks and Local Saliency Maps for Retinal Image Analysis'. In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*.

## Some common CNN-Topologies[2]

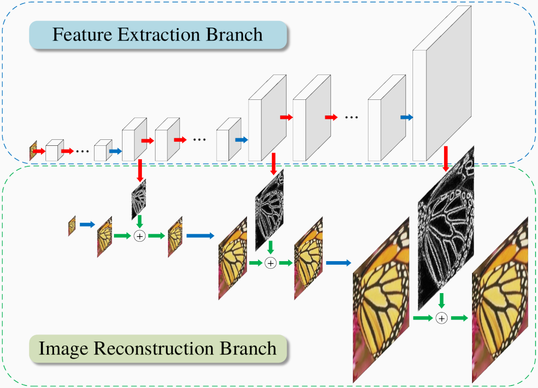



Common Topologies

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

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

# Laplacian Network[3]




Laplacian pyramid network

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

*Red*: $3 \times 3$ convolution, *blue*: transposed convolution, *green* summation

[3] Lai, Huang, Ahuja and Yang, see n. 2.

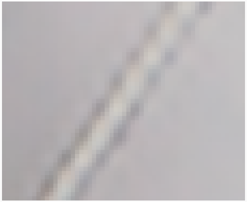
# Robust (Charbonnier) Loss[4]

(Relaxed) $L_1$ loss instead of $L_2$ loss

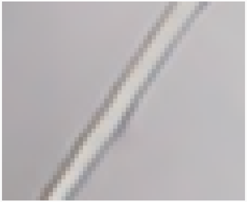
$$L(\hat{\boldsymbol{y}}, \boldsymbol{y}; \boldsymbol{\theta}) = \sum_n p\left(\hat{\boldsymbol{y}} - \boldsymbol{y}\right)$$

$$p(\boldsymbol{x}) = \sqrt{\langle x, x \rangle + \epsilon^2},$$

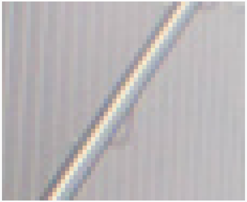
Robust, avoids **blurry** images



$L_2$ loss



$L_1$ loss



Ground truth

[4] Lai, Huang, Ahuja and Yang, see n. 2.

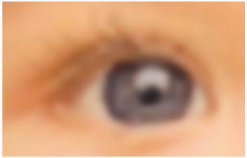
# Perceptual Loss—VGG-based[5]

Transform images before calculating loss, with feature map $\phi$:

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

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

Extract feature maps from pre-trained VGG16-Network



$L_2$ loss

Perceptual loss

Ground truth

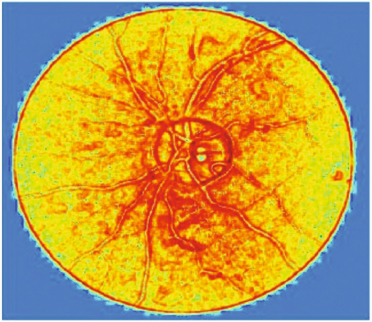
[5] J. Johnson, A. Alahi and L. Fei-Fei (2016). 'Perceptual losses for real-time style transfer and super-resolution'. In: *European Conference on Computer Vision*.

# Perceptual Loss—Saliency Maps[6]

Possibility 2: Saliency Maps

**Handcrafted** features

Retina image



Resulting saliency map

[6] Mahapatra, Bozorgtabar, Hewavitharanage and Garnavi, see n. 1.

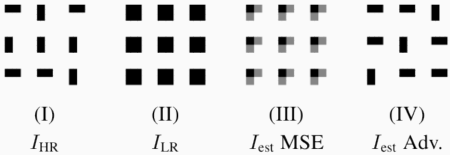
# Adversarial Loss

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[7]

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

# Possible Modifications for Network

Weight sharing

Replace stacked convolutions

Replace transposed convolutions (avoid checkerboard artifacts)[8]

Example of block artifacts (from[9])

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

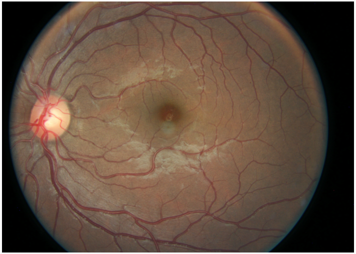
[9] Johnson, Alahi and Fei-Fei, see n. 5.

# Dataset

Use 1000 images from Eyepacs dataset[10] (ca. 300k HR) for training

Crop black borders, rescale to $1024 \times 1024$

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



Eyepacs example

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

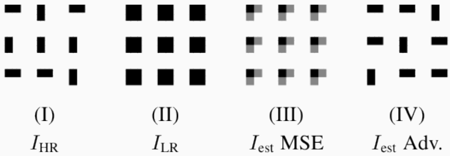
# Evaluation

Normally: Compare pixel-wise reconstruction error

**Useless** in our case.

Perceptual & adversarial loss improve perceived quality but increase error!

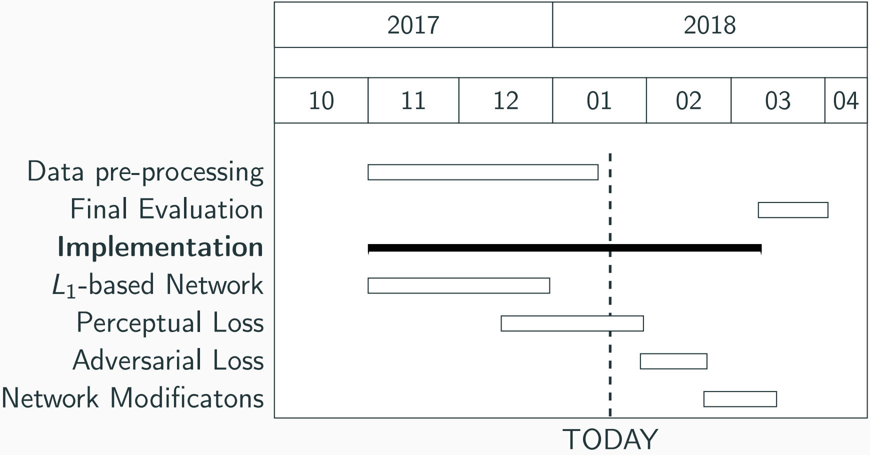
Rather compare effectiveness as a pre-processing tool.




Adversarial loss higher quality with larger error[11]

[11]Sajjadi, Schölkopf and Hirsch, see n. 7.

# 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 Modificatons
TODAY

# Summary

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