Optimization and Applications of Deep Learning algorithms for Super Resolution in MRI

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Introduction

Single Image Super Resolution

What is Super Resolution?

Two main groups of techniques :

- SR microscopy, which aim is to overcome the diffraction limits with a complex laboratory setup.
- SR algorithm, which aim is to enhance the spatial resolution of an image for different purpose such as object detection, segmentation and improve its visual quality

Super resolution procedure

- Start from a prior-known High Resolution (HR) image;
- Rescale the image obtaining its Low Resolution (LR) counterpart;
- Feed a super-resolution model with the LR image trying to obtain as output its HR version;
- With the trained model we can re-apply the up-sampling procedure and further increase the HR quality*.

* This is even more efficient if we think about a **zoom** procedure.

Deep Learning model

- Neural Networks are mathematical models commonly used in data analysis.
- From a theoretical point-of-view we can define a Neural Network as **a series of non-linear multi-parametric functions**.
- Neural Networks are considered as **Universal Function Approximators**.

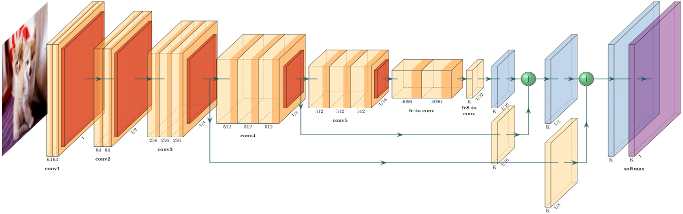


Figure: Neural Network model scheme. The model is composed by a series of layers made by interconnected computational units. The connections between layers can be serials or parallels and each layer models a pre-determined mathematical function.

Deep Learning

Neural Network models

- The supervised training of neural network happens by feeding the model with labeled example, that are couples of inputs and expected outputs.
- Then, the output is compared with the label by means of a **cost function**, which is a measure of the error made by the network. The objective is to modify the **parameters** of the model to minimize the cost function.
- Commonly, we think about Neural Network models as tools to **reduce** problems dimensionality, i.e. starting from high-dimensional data (e.g $w \times h \times c$ image) the model predicts a class (single number).
- In Super Resolution we have no classes but the desired output is also an image. Single Image Super Resolution tasks start from an image and the aim is to reconstruct its HR counterpart.

Byron

Build YouR Own Neural Network

Byron

- The library is written in **pure C++** with the support of the modern standard 17.
- The library is **optimized for image processing** (probably the most common task in biomedical research).
- Starting from the darknet project backbone, Byron introduces **numerous improvements and fixes**.
- The library is also **completely wrapped** using Cython to enlarge the range of users also to the Python ones.

Image Quality

Single Image Super Resolution

The most common image quality evaluator is given by our eyes.
Quantitative evaluations:

PSNR - Peak Signal to Noise Ratio

- It establishes the compression lossless of an image;
- Equation:

$$PSNR = 20 \cdot \log_{10}\left(\frac{\max(I)}{\sqrt{(MSE)}}\right)$$

where $\max(I)$ is the maximum value which can be taken by a pixel in the image and MSE is the Mean Square Error evaluated between the original and reconstructed images.

SSIM - Structural SIMilarity index

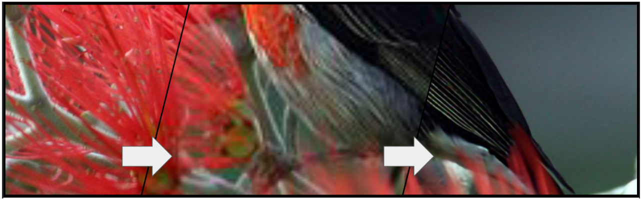
- It evaluates the structural similarity between two images taking into account also the visible improvement seen by human eyes.
- Equation:

$$SSIM(I,K) = \frac{1}{N}\sum_{i=1}^{N}\frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{({\mu_x}^2 + {\mu_y}^2 + c_1)({\sigma_x}^2 + {\sigma_y}^2 + c_2)}$$

where N is the number of arbitrary patches which divide the image and c_1 and c_2 parameters are fixed to avoid mathematical divergence.

EDSR - Enhanced Deep Super Resolution

Super Resolution Models



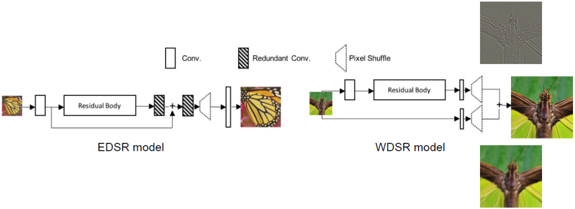
Architecture

Layer	Channels input/output	Filter dimensions	Number of Parameters
Conv. input	3/256	3×3	6912
Conv. (32 residual block)	256/256	3×3	589824
Conv. (pre-shuffle)	256/256	3×3	589824
Conv. (upsample block)	256/1024	3×3	2359296
Conv. output	256/3	3×3	6912

Average Time on 510×339 image: 576.92 s.
Winner of the **NTIRE 2017**. More than **40 million** of parameters

WDSR - Wide Deep Super Resolution

Super Resolution Models



Architecture

Layer	Channels input/output	Filter dimensions	Number of Parameters
Conv. input 1	3/32	3×3	864
Conv. 1 (32 residual block)	32/192	3×3	55296
Conv. 2 (32 residual block)	192/32	3×3	55296
Conv. (pre-shuffle)	32/48	3×3	13824
Conv. input 2 (pre-shuffle)	3/48	5×5	3600

Average Time on 510×339 image: 46.35 s.
Winner of the **NTIRE 2018**. ~ 3 million of parameters, **less than 10% of EDSR model**!

Dataset

downscaled MRI description

- Dataset composed of 5 patients T1-weighted and T2-weighted with 176 slices 256 x 256
- Each sample has been donw-scaled with a bicubic algorithm with two different scale factors (x2 and x4)
- The LR images are then convoluted with a gaussian kernel with size 3, stride 1 and sigma 1

Upsample Comparisons

EDSR and Bicubic x2

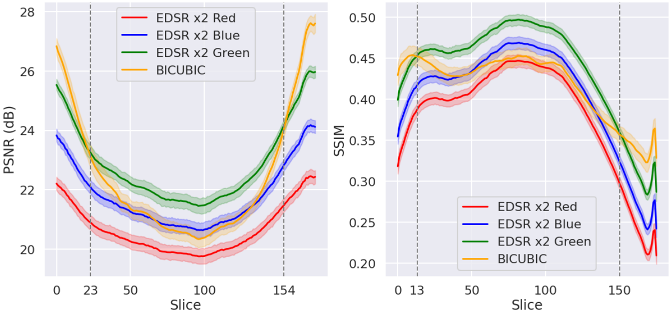


Figure: Average trends of PSNR (left) and SSIM (right) for the three channels (Red, Blue, Green lines) of the Super Resolution EDSR model compared with the bicubic al- gorithm scores (Yellow) as functions of the slices. The average is performed for every patients and for every rotation. The dotted lines highlights the slices where the bicubic and Super Resolution performances intersect.

Upsample Comparisons

WDSR and Bicubic x4

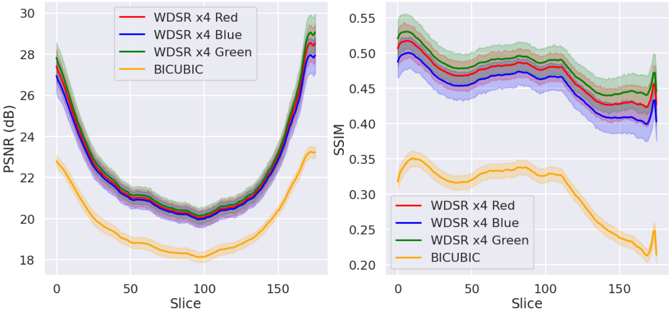


Figure: Average trends of PSNR (left) and SSIM (right) for the three channels (Red, Blue, Green lines) of the Super Resolution WDSR model compared with the bicubic algorithm scores (Yellow) as functions of the slices. The average is performed for every patients and for every rotation.

Upsample Comparisons

WDSR and Bicubic x4

Scores by angle

Error Localization

EDSR and Bicubic x2

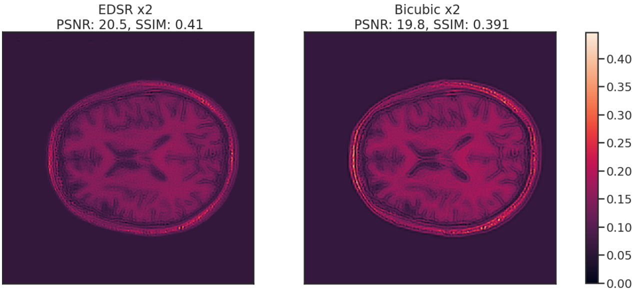


Figure: Absolute differences of Super resolved image (left) and bicubic (right). in both cases, the major differences seems to lies in the scalps of the subjecs. Though, it can be seen that the background is not zero, which means it has an impact on the scores.

Error Localization

EDSR and Bicubic x2

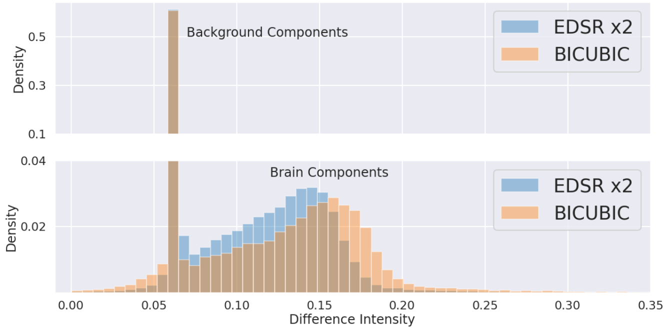


Figure: Histograms of the distribution of absolute differences for the reconstruction performed by EDSR (Blue) and by the bicubic algorithm (Orange). The histogram has been cut between 0.04 and 0.1 on the y axis to better represent the lower parts.

Conclusions

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- ciao
- ciao

Future Developments

Future aims may include:

- Applications to *Transfer Learning*: re-using previous knowledge to solve a different, but related, problem.
- Re-training from scratch: build two neural networks tailored around MRI reconstructions and compare results.
- Extension of the analysis after Brain Extraction for all patients and angle.