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

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Super Resolution:

- **Microscopy** -> diffraction limit
- **Softwares** -> enhance digital spatial resolution

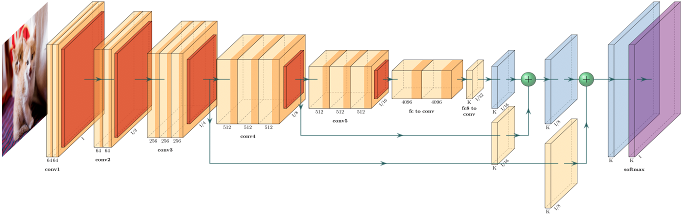
Standard procedure

- **prior-known** High Resolution (HR) image;
- **down-sample** for Low Resolution (LR) counterpart;
- Feed a Neural Network with **LR images**.

Deep Learning

What is a Neural Network

- Neural Network is a **series of non-linear multi-parametric functions**.



- Training by **examples**
- Super Resolution is an **image-to-image** process

Developed Frameworks

Byron and NumPyNet

NumPyNet

- Readable and Simple **Python** code.
- Overcomes the common "**black-box**" idea of Neural Network
- **Test** optimized code, **Experiment** with models and **Learn**

Byron

- Efficiency and flexibility of **C++**
- **Optimized for image processing**, common in biomedical research
- Tailored around **CPU** usage

Image Quality

Quantitative Evaluation

PSNR - Peak Signal to Noise Ratio

- Measure the quality of **lossy** reconstructions;

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

where MSE is :

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(I_i - K_i)^2$$

SSIM - Structural SIMilarity index

- It evaluates the structural similarity between two images taking into account **visible improvements**

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

Models

Models Implemented and Tested in Byron

Trained on **RGB Natural** images -> **Transfer Learning**

EDSR - Enhanced Deep SR

Layer	Number of Parameters
Conv. input	6912
Conv. (32 residual block)	589824
Conv. (pre-shuffle)	589824
Conv. (upsample block)	2359296
Conv. output	6912

Average Time on 510 $\times$ 339 image: 576.92 s.
More than **40 million** parameters

WDSR - Wide Deep SR

Layer	Number of Parameters
Conv. input 1	864
Conv. 1 (32 residual block)	55296
Conv. 2 (32 residual block)	55296
Conv. (pre-shuffle)	13824
Conv. input 2 (pre-shuffle)	3600

Average Time on 510 $\times$ 339 image: 46.35 s.
$\sim$ 3 million parameters

Dataset

MRI pre-processing description

Figure: T1-weighted downsamplings

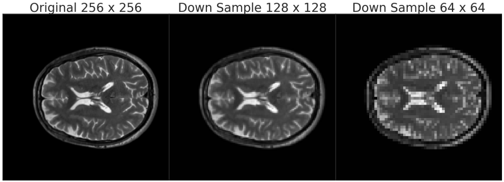


Figure: T2-weighted downsamplings

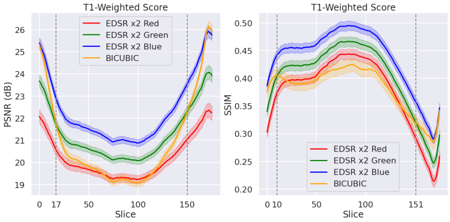
- Public NAMIC dataset of 5 patients -> originals HR
- Gaussian blurring
- Donwscaling (x2 and x4)
- Re-upsamples with NN and Bicubic Algorithm (BC)

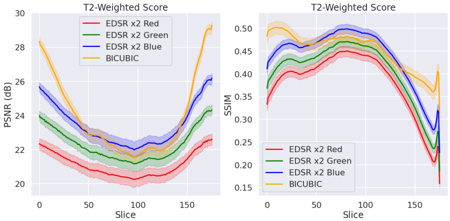
Upsample Comparisons

EDSR and Bicubic x2

T1-weighted:

- Mean trends on patient and angles.
- SR scores are higher than BC counterparts
- The three RGB channels perfoms differently



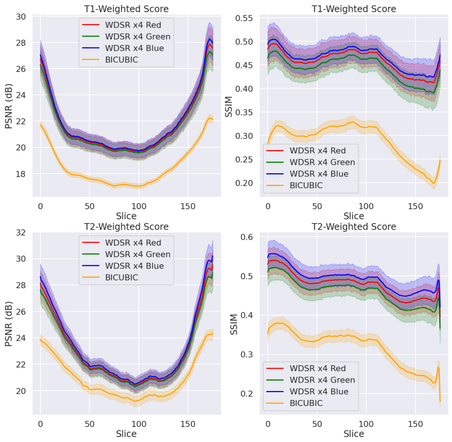


T2-weighted:

- RGB channels still have different performances
- BC and SR are comparable on most informative parts

Upsample Comparisons

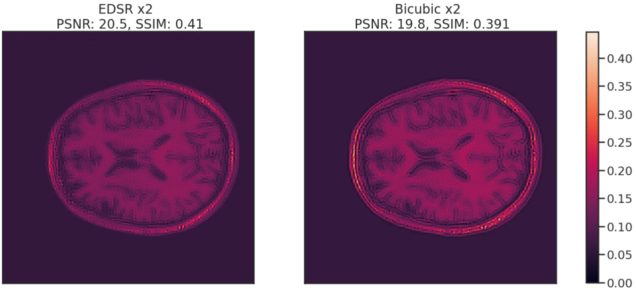
WDSR and Bicubic x4



- Much less variance between channels
- Both SSIM and PSNR shows better performances

Error Localization

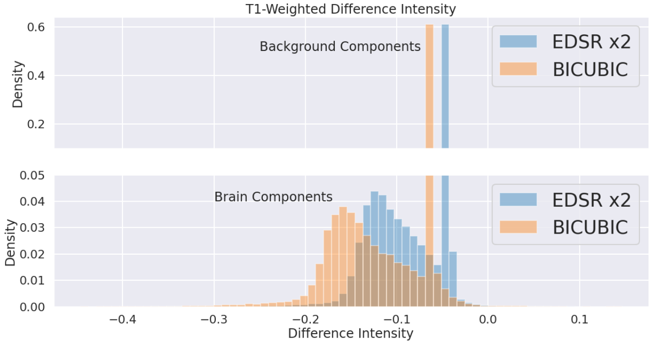
EDSR and Bicubic x2



- Pixel-wise absolute difference between reconstructions and originals
- Higher differences located around scalps
- Background $\neq 0$

Error Localization

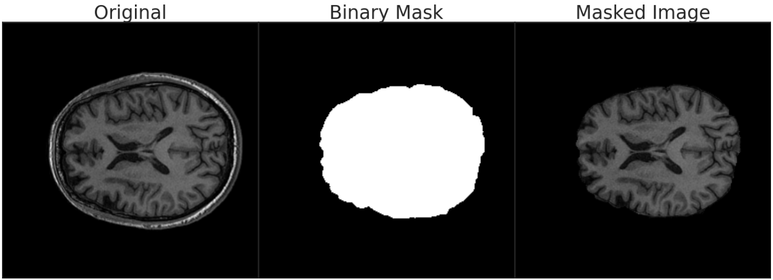
EDSR and Bicubic x2 On T1-weighted patients



- Clear distiction between two components
- Heavy background components
- Pixel values are overestimated

Brain Extraction

BET - Brain Extraction Tool

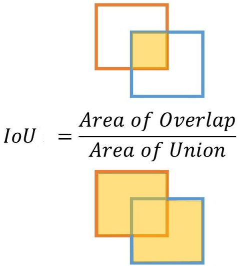


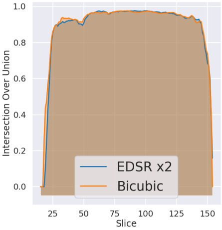
- BET is a standard tool in MRI analysis. Two approaches:
  1. Extract masks for originals and reconstructions and compare
  2. Use the masks obtained from HR originals to evaluate reconstructions.

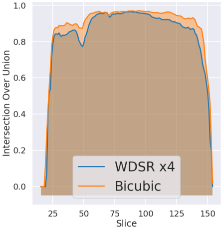
Brain Extraction

BET - Masks Analysis

- Three masks from originals and reconstructions
- Intersection over Union:



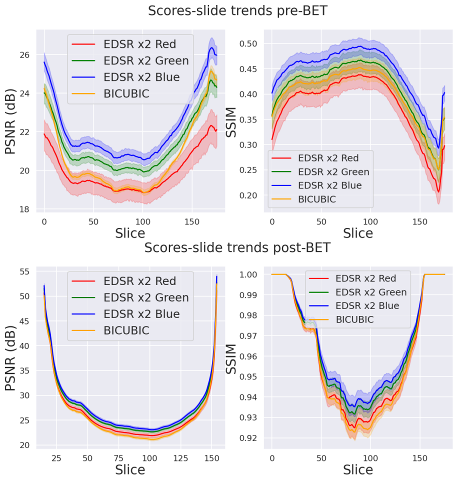




- IoU > 0.90
- EDSR comparable results
- WDSR not adapt for BET

Brain Extraction

BET - Background Removal



- The same mask is applied to each reconstruction.
- Removes background and scalp.
- The relative results change:
  - channels much more consistent
  - SR still better than bicubic

Conclusions

- Two new libraries were proposed:
  - **NumPyNet** Focused on readability and educational purposes;
  - **Byron** a tool for efficient implementations in CPUs environment;
- Promising results for super-resolution on biomedical images
- NN can **generalize** well, applying their "knowledge" to new datasets.
- extensions on **explainability** for DL

Future Developments

Future works may include:

- Extensions of *Transfer Learning* with **training**
- Re-train from scratch
- Analysis after Brain Extraction for all patients and angles

Thanks for your attention