Super Resolution of T1w and T2w MRI using Deep Neural Networks:

Brain Images from CamCAN Dataset

Cristiana Fiscone[1], Nico Curti[2], Mattia Ceccarelli[3], David N. Manners[1], Gastone Castellani[4], Raffaele Lodi[1,5], Daniel Remondini[6,7], Caterina Tonon[1,5], Claudia Testa[5,6,7]

[1] Department of Biomedical and NeuroMotor Sciences,University of Bologna,IT
[2] eDIMESLab,Department of Experimental,Diagnostic and Specialty Medicine,University of Bologna,IT
[3] Department of Agricultural and Food Sciences,University of Bologna,IT
[4] Department of Experimental, Diagnostic and Specialty Medicine,University of Bologna,IT
[5] IRCCS Istituto delle Scienze Neurologiche di Bologna, Functional and Molecular NeuroImaging Unit, Bologna,IT
[6] Department of Physics and Astronomy,University of Bologna,IT
[7] INFN, Bologna, IT

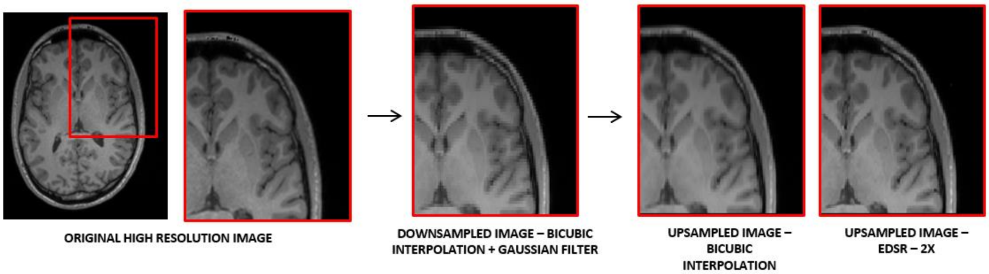
Keywords: Super Resolution, Deep Learning, Convolutional Neural Networks, MRI

e-mail: cristiana.fiscone2@unibo.it

Background:
Super-resolution models are deep learning algorithms which enhance image spatial resolution. Their use on biomedical images has been explored, through *ad hoc* training stages [1]. EDSR (Enhanced Deep Super Resolution) [2] and WDSR (Wide activation for efficient and accurate Deep Super Resolution) [3] are convolutional neural networks, trained on general purpose images, which perform 2x- and 4x- upsampling. This work aimed to validate their application to MR brain images, comparing the results with traditional upsampling methods.

Methods:
Data used in this work were provided by the Cambridge Centre for Ageing and Neuroscience (CamCAN) [4],[5].
3D sagittal high-resolution T1w and T2w images (3T Siemens Magnetom Trio, 1mm isotropic spatial resolution) of 70 subjects were convolved with a Gaussian filter and then down-sampled. EDSR and WDSR were used to up-sample low-resolution images. The reconstruction time for each image was ~ 1 min and ~ 15mins respectively (Ubuntu 20.04.2 LTS, 80 processors Intel(R) Xeon(R) Gold 6138 CPU, 20 cores each). Byron was used as custom library, released with MIT license and available on Github [6]. The results were compared to bicubic interpolation upsampling. The processing pipeline is shown in Fig. 1.
After the brain extraction, pixel-wise and whole-brain average analysis was performed. RMSE (Root Mean Square Error), pSNR (peak Signal-to-Noise Ratio), SSIM (Structural SIMilarity index) and HFEN (High Frequency Error Norm) were chosen as quantitative similarity parameters, and they were evaluated over the entire T1w and T2w images reconstructed by different upsampling techniques for all the subjects, using the original high-resolution images as ground truth.
Since the two models work with 2D images, sagittal, axial and coronal directions were analyzed separately.

Fig. 1 Scheme of the pipeline implemented to test EDSR-2x and WDSR-4x models on MR images
In this figure, 1w image from one subject of CamCAN database is shown.



P-value (* < .05) and *Cohen's d* (* > 0 .8), which measures the effect size, were evaluated to compare the quantitative parameters' distributions of super resolution and bicubic interpolation as upsampling methods for T1w and T2w images, along sagittal, axial and coronal reconstructions.

Results:
EDSR generally showed better performance than bicubic interpolation. Results are summarized in Tabs 1 and 2:

- T1w images: there was significant difference in favour of EDSR for all the considered criteria in sagittal, coronal and axial reconstructions, confirmed by both *p-value* and *Coehn's d*
- T2w images: there was significant difference in favour of EDSR for two out of four criteria (SSIM and HFEN) in sagittal, coronal and axial reconstructions confirmed by both *p-value* and *Coehn's d*. The trend of the other two criteria (RMSE and pSNR) was similar in the two upsampling methods leading to a not significant difference

No correlations were found between similarity parameters and subjects attributes (sex, age, handeness and total intracranial volume).
WDSR was not found to be suitable, since it enhances and creates line-like artifacts.

Tab.1 P-value for sagittal, axial and coronal T1w and T2w images, comparing EDSR-2x and bicubic interpolation.
The method with better perfomance is noted in brackets.

p-value		RMSE	pSNR	SSIM	HFEN
YZ – Sagittal	T1w	<.000 * (EDSR)	<.000 * (EDSR)	<.000 * (EDSR)	<.000 * (EDSR)
	T2w	0.711 (BC)	0.860 (BC)	<.000 * (EDSR)	<.000 * (EDSR)
XY - Axial	T1w	<.000 * (EDSR)	<.000 * (EDSR)	<.000 * (EDSR)	<.000 * (EDSR)
	T2w	.389 (EDSR)	.446 (EDSR)	<.000 * (EDSR)	<.000 * (EDSR)
XZ - Coronal	T1w	<.000 * (EDSR)	<.000* (EDSR)	<.000 * (EDSR)	<.000 * (EDSR)
	T2w	<.008 * (EDSR)	<.003* (EDSR)	<.000 * (EDSR)	<.000 * (EDSR)

Tab.2 Cohen's d for sagittal, axial and coronal T1w and T2w images, comparing EDSR-2x and bicubic interpolation.
The method with better perfomance is noted in brackets.

Cohen's d		RMSE	pSNR	SSIM	HFEN
YZ – Sagittal	T1w	1.10 * (EDSR)	1.17 * (EDSR)	2.21 * (EDSR)	2.20 * (EDSR)
	T2w	0.06 (BC)	0.03 (BC)	3.53 * (EDSR)	2.24 * (EDSR)
XY - Axial	T1w	1.17 * (EDSR)	1.22 * (EDSR)	2.75 * (EDSR)	3.43 * (EDSR)
	T2w	0.15 (EDSR)	0.13 (EDSR)	3.00 * (EDSR)	1.96 * (EDSR)
XZ - Coronal	T1w	0.92* (EDSR)	1.27 * (EDSR)	1.98 * (EDSR)	1.63* (EDSR)
	T2w	0.45 (EDSR)	0.51 (EDSR)	2.75 * (EDSR)	3.13 * (EDSR)

Conclusions:
EDSR, that performs 2x-upsampling, outperforms the bicubic interpolation without needing fine-tuning, showing its ability of transfer learning. It is flexible with respect the analyzed MR sequence and subject characteristics.
In particular, in T1w images it shows significant better performance by all the considered metrics.

References:
[1] K. Zeng *Computers in Biology and Medicine.* 99, 133-141 (2018)
[2] R. Timofte *2017 IEEE CVPRW*. 1110-1121 (2017)
[3] J. Yu *arXiv:1808.08718*. (2018)
[4] J.R. Taylor *NeuroImage.* 144, 262-269 (2017)
[5] M.A. Shafto *BMC Neurology.* 14 (2014)
[6] N. Curti, https://github.com/Nico-Curti/ByronTesting (2019)