Reference-less SSIM Regression for Detection and Quantification of Motion Artefacts in Brain MRIs

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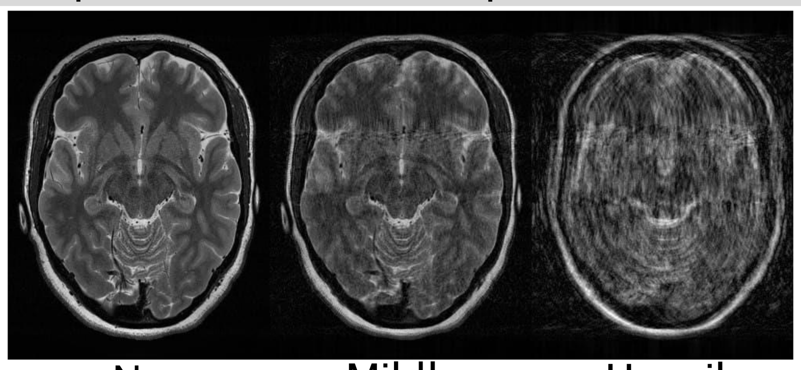
Introduction

Abstract

Motion artefacts in magnetic resonance brain images are a crucial issue. The assessment of MR image quality is fundamental before proceeding with the clinical diagnosis. If the motion artefacts alter a correct delineation of structure and substructures of the brain, lesions, tumours and so on, the patients need to be re-scanned. Otherwise, neuro-radiologists could report an inaccurate or incorrect diagnosis. The first step right after scanning a patient is the "image quality assessment" in order to decide if the acquired images are diagnostically acceptable. An automated image quality assessment based on the structural similarity index (SSIM) regression through a residual neural network has been proposed here, with the possibility to perform also the classification in different groups - by subdividing with SSIM ranges. This method predicts SSIM values of an input image in the absence of a reference ground truth image.

Examples of Motion Corruption



No corruption | Mildly corrupted | Heavily corrupted

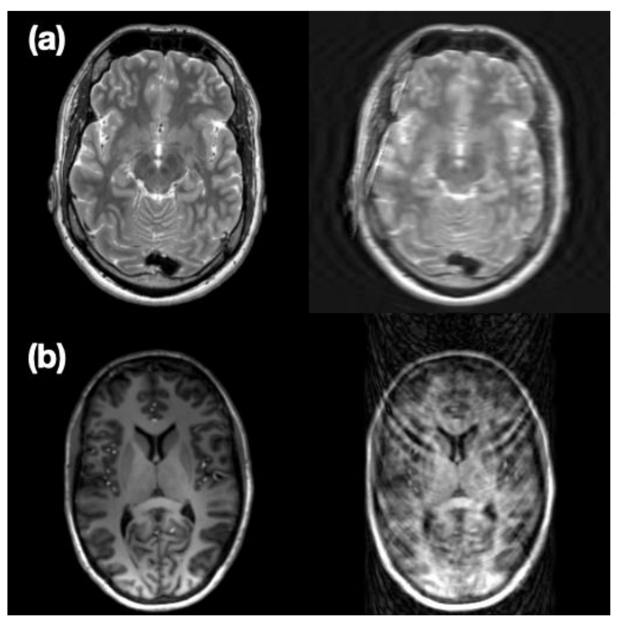
Methodology

Data

DATA FOR TRAINING, VALIDATION AND TESTING.

Data	Weighting	Volumes	Matrix Size m(M) x m(M) x m(M)†	Resolution (mm^3) m(M) x m(M) x m(M)†
TRAINING				
IXI	T1,T2,PD	15,15,15	230(240)x230(240)x134(162)	1.00 isotropic
Site-A	T1,T2,PD,FLAIR	20,20,20,20	168(168)x224(224)x143(144)	1.00 isotropic
Site-B	T1,T2,FLAIR	20,20,20	156(156)x224(224)x100(100)	1.00 isotropic
Site-C	T1	3	192(512)x256(512)x36(256)	0.45(1.00)x0.45(0.98)x0.98(4.40)
Site-C	T2	11	192(640)x192(640)x32(160)	0.42(1.09)x0.42(1.09)x1.00(4.40)
Site-C	FLAIR	1	320x320x34	0.72x0.72x4.40
VALIDATION				
IXI	T1,T2,PD	1,5,7	230(240)x230(240)x134(162)	1.00 isotropic
Site-A	T1,T2,PD,FLAIR	4,4,4,4	168(168)x224(224)x143(144)	1.00 isotropic
Site-B	T1,T2,FLAIR	6,6,4	156(156)x224(224)x100(100)	1.00 isotropic
Site-C	T1	3	176(240)x240(256)x118(256)	1.00 isotropic
Site-C	T2	1	240x320x80	0.80x0.80x2.00
Site-C	PD	1	240x320x80	0.80x0.80x2.00
TESTING				
IXI	T1,T2,PD	2,4,4	230(240)x230(240)x134(162)	1.00 isotropic
Site-A	T1,T2,PD,FLAIR	6,4,4,4	168(168)x224(224)x143(144)	1.00 isotropic
Site-B	T1,T2,FLAIR	6,6,5	156(156)x224(224)x100(100)	1.00 isotropic
Site-C	T1	2	288(320)x288(320)x35(46)	0.72(0.87)x0.72(0.87)x3.00(4.40)
Site-C	T2	2	320(512)x320(512)x34(34)	0.44(0.72)x0.45(0.72)x4.40(4.40)
Site-C	FLAIR	1	320x320x35	0.70x0.70x4.40

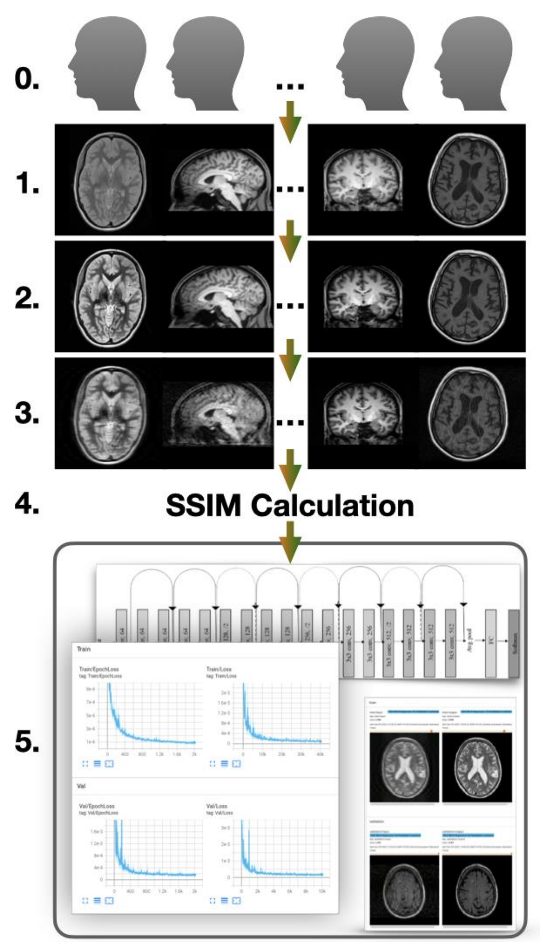
†: "m" indicates the minimum value while "M" the maximum.



All the images were artificially corrupted with:

a) A modified version of the RandomMotion transformation of TorchIO with 10 simulated movements and rotation between -1.75 to +1.75 degrees
b) In-house algorithm – randomly rotating phase-encoding lines

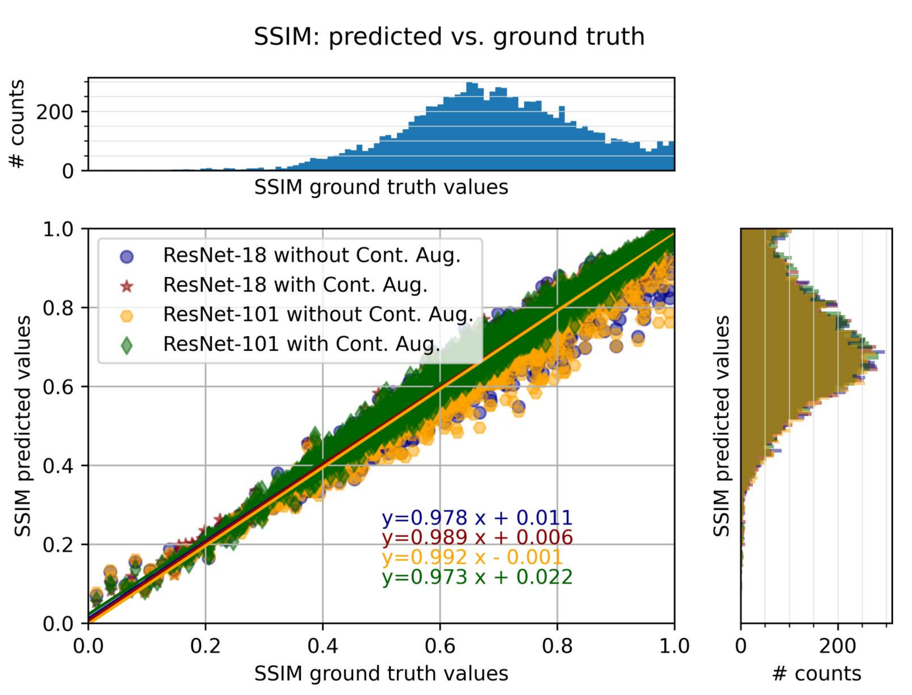
Pipeline



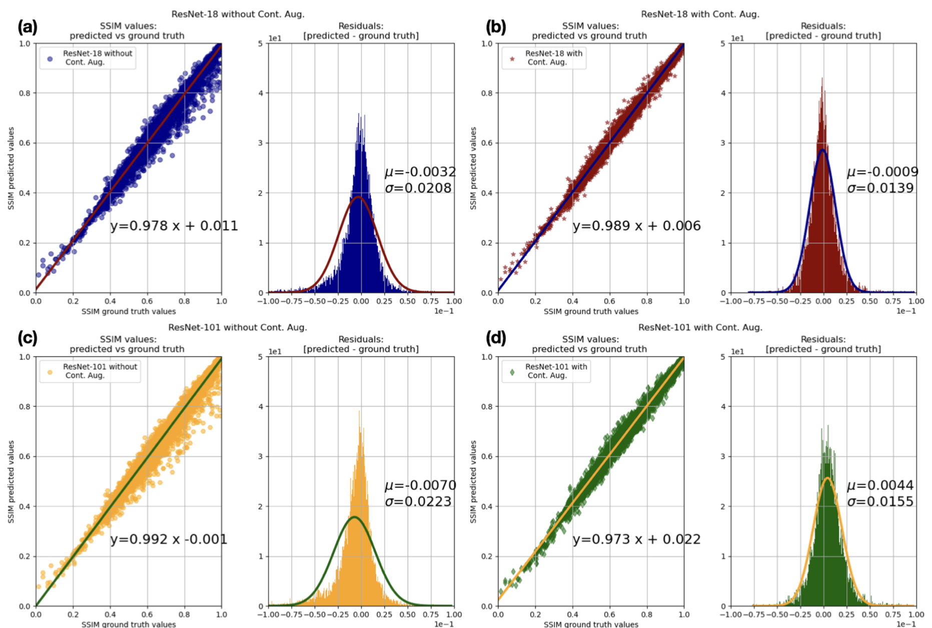
0. Input 3D volume
1. One random 2D slice from the 3D volume is selected in one of the possible orientations - axial, sagittal and coronal
2. In case of contrast augmentation is enabled, one random contrast augmentation algorithm is applied - Gamma, Logarithmic, Sigmoid, Adaptive histogram adjustment
3. Motion corruption is applied on the 2D image with one of the two methods.
4. The SSIM is calculated between the input 2D image and the corresponding corrupted one
5. The calculated SSIM value and the corrupted image are passed to the chosen model (ResNet-18 or ResNet-101) for the training

Results

Regression Results

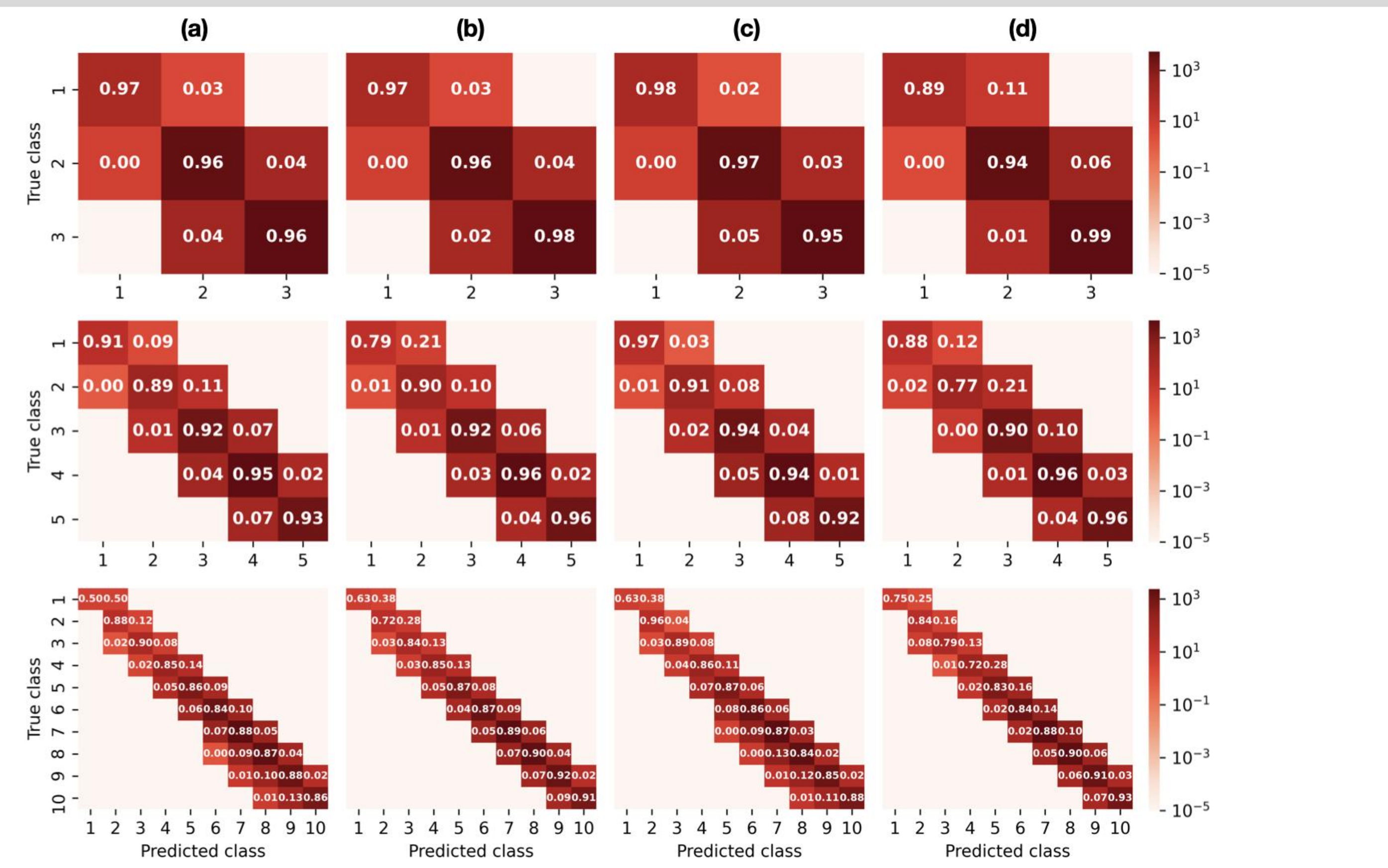


Scatter plots for all the methods
On the top: distribution of the ground-truth SSIM values
On the right: distributions of the predicted SSIM values for each group of data



Scatter plots of predicted vs ground-truth SSIMs and residual distributions: (a) ResNet-18 without contrast augmentation, (b) ResNet-18 with contrast augmentation, (c) ResNet-101 without contrast augmentation, and (d) ResNet-101 with contrast augmentation

Classification Results



Confusion matrices for the classification tasks – by equally dividing the SSIM range into 3 classes (1st row), 5 classes (2nd row), and 10 classes (3rd row). Models: (a) ResNet-18 without contrast augmentation, (b) ResNet-18 with contrast augmentation, (c) ResNet-101 without contrast augmentation, and (d) ResNet-101 with contrast augmentation

Conclusion

- The method managed to predict the SSIM values of artificially motion corrupted images without the ground-truth (motion-free) images with high accuracy (residual SSIMs as less as -0.0009±0.0139)
- The motion classes obtained from the predicted SSIMs were very close to the true ones and achieved a weighted accuracy of 89±2%
- Considering the complexity of the problem in quantifying the image degradation level due to motion, the variability of the type of contrast, resolution, etc., the results obtained are promising

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