FLAIR MR Image Synthesis By Using 3D Fully Convolutional Networks for Multiple Sclerosis

Wen Wei, Emilie Poirion, Benedetta Bodini, Stanley Durrleman, Olivier Colliot, Bruno Stankoff, Nicholas Ayache

HAL Id: hal-01723070

https://inria.hal.science/hal-01723070

Submitted on 5 Mar 2018

FLAIR MR Image Synthesis By Using 3D Fully Convolutional Networks for Multiple Sclerosis

Wen Wei[1,2,3], Emilie Poirion[2], Benedetta Bodini[2], Stanley Durrleman[2,3]
Olivier Colliot[2,3], Bruno Stankoff[3], and Nicholas Ayache[1]

[1] Asclepios project-team, Inria, Sophia Antipolis, France
[2] Sorbonne Universités, UPMC Univ Paris 06, Inserm, CNRS, Institut du cerveau et la moelle (ICM), AP-HP-Hôpital Pitié-Salpêtrière, Boulevard de l'hôpital, Paris, France
[3] Aramis project-team, Inria, Paris, France

Synopsis. Fluid-attenuated inversion recovery (FLAIR) MRI pulse sequence is used clinically and in research for the detection of WM lesions. However,in a clinical setting, some MRI pulse sequences can be missing because of patient or time constraints. We propose 3D fully convolutional neural networks to predict a FLAIR MRI pulse sequence from other MRI pulse sequences. We evaluate our approach on a real multiple sclerosis disease dataset by assessing the lesion contrast and by comparing our approach to other methods. Both the qualitative and quantitative results show that our method is competitive for FLAIR prediction.

1 Introduction

Multiple sclerosis (MS) is a demyelinating and inflammatory disease of the central nervous system.[1] MS has been characterized as a white matter (WM) disease with the formation of WM lesions, which can be visualized by magnetic resonance imaging (MRI).[2,3] FLAIR is commonly used clinically and in research to detect WM lesions which appear hyperintense compared to normal WM tissue. Additionally, observer performance is better with FLAIR,[4] as shown in Fig. 1. However, in a clinical setting, some MRI pulse sequences can be missing because of patient or time constraints. Hence, there is a big need for predicting the missed FLAIR when it was not acquired during a patient's visit. Furthermore, it was shown in some publications[5,6] that synthesized MR images can improve brain tissue classification and segmentation results, which is an additional motivation for this work. FLAIR may also be absent in some legacy research datasets, that are still of major interest due to their number of subjects and long follow-up.

We propose 3D Fully Convolutional Neural Networks (3D FCNs) to predict FLAIR. The proposed method can learn an end-to-end and voxel-to-voxel mapping between other MRI pulse sequences and the corresponding FLAIR. Finally, the feasibility of our approach is validated qualitatively and quantitatively.
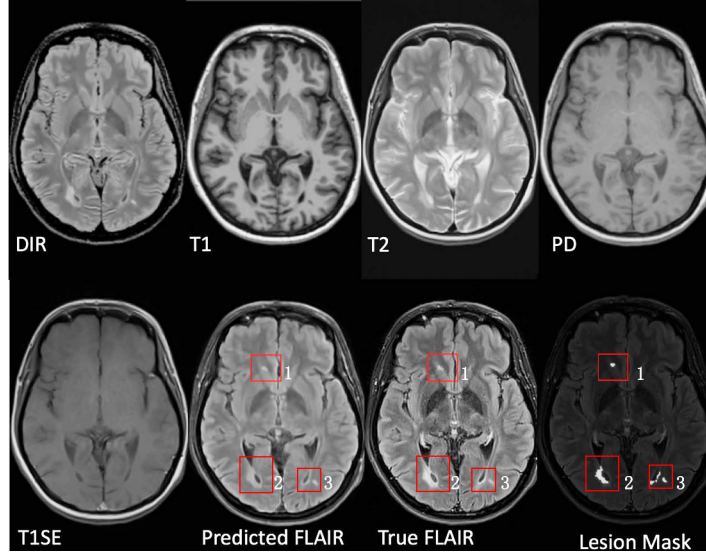
Fig. 1: FLAIR has better observer performance in the detection of multiple sclerosis (MS) lesions on magnetic resonance (MR) images of the brain. The lesions 2 and 3 can be detected in other pulse sequences. However, it could be very time and labor consuming for the detection of lesion 1 even for an expert.

2 Method

Our goal is to predict FLAIR by finding a non-linear function s, which maps multi-sequence source images I_{source}, e.g. $I_{\text{source}} = (I_{\text{T1}}, I_{\text{T2}})$, to the corresponding target sequence I_{target}. The non-linear function can be found by solving the following optimization problem:

$$\hat{s} = \arg\min_{s \in S} \sum_{i=1}^{n} Error(I_{\text{target}}^{i}, s(I_{\text{source}}^{i}))$$ (1)

where S denotes potential mapping functions, n is the number of subjects. The error function above calculates the difference between the predicted and the true image.

Our 3D FCNs is shown in Fig. 2. It contains three convolutional layers followed by rectified linear functions ($relu(x) = max(x, 0)$). Every layer $l \in [1, L]$ has C_l feature maps. The first layer extracts C_l-dimensional feature from input images. Then, the second and third layers find a non-linear mapping between the feature representations of source images and the target image feature representations, which are used to reconstruct our target image. The m_{th} feature map in the l_{th} layer is defined as follows:

$$y_l^m = max(0, \sum_{c=1}^{C_{l-1}} k_l^{m,c} * y_{l-1}^c + b_l^m)$$ (2)
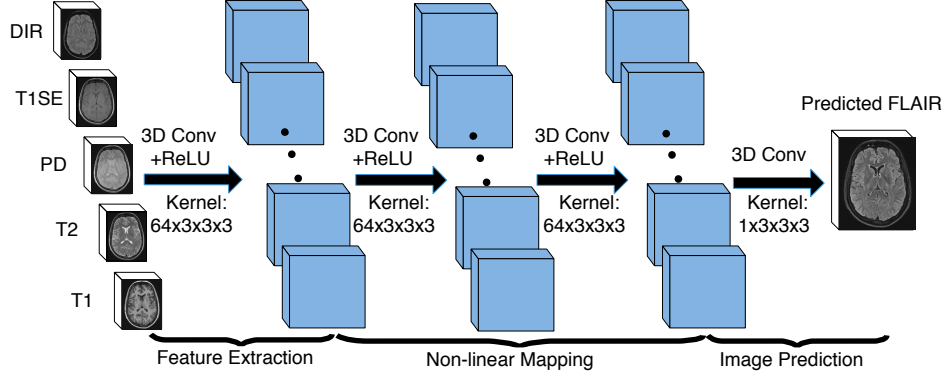
Fig. 2: The proposed 3D fully convolutional neural networks. The first layer extracts a set of feature maps. The second and third layers find a nonlinear mapping for image prediction.Our networks use three convolutional layers with 64 filters and the filter size is 3x3x3.

where k denotes a 3-dimensional trainable kernel and b is a learned bias. The parameters k, b can be learned by minimizing the error function, which is mean-square-error (MSE) in our model.

$$MSE = \frac{1}{H \times W \times D} \sum_{h=1}^{H} \sum_{w=1}^{W} \sum_{d=1}^{D} (y_{h,w,d} - \hat{y}_{h,w,d})^2 \qquad (3)$$

where H, W, D indicate the height, weight, and depth of target image, while y and $\hat{y}$ are the ground truth and the predicted image, respectively.

To evaluate our method, we compare it qualitatively and quantitatively with three other approaches : modality propagation,[7] random forests (RF) with 60 trees,[8] and voxel-wise multilayer perceptron (MLP). Specifically, two metrics are used to evaluate quantitatively: 1). Mean-Square-Error (MSE); 2). Peak Signal-to-noise-Ratio (PSNR).

3   Experiments and Results

We used our in-house dataset for FLAIR prediction, which contains 4 healthy volunteers and 20 MS patients, including T1-w, T2-w, T1 spin-echo (T1SE), proton density (PD), and double inversion recovery (DIR) weighted images and the corresponding FLAIR. Five-fold cross validation is used for evaluating performance. In 5-fold cross validation, the dataset is partitioned into 5 folds. Subsequently 5 iterations of training and validation are performed such that within each iteration one different fold is held-out for validation and remaining four folds are used for training.

Figure 3 shows the inputs and outputs. As shown with arrows, some regions can be better predicted by our method. The modality propagation method got the worst result, so we do not show it here.
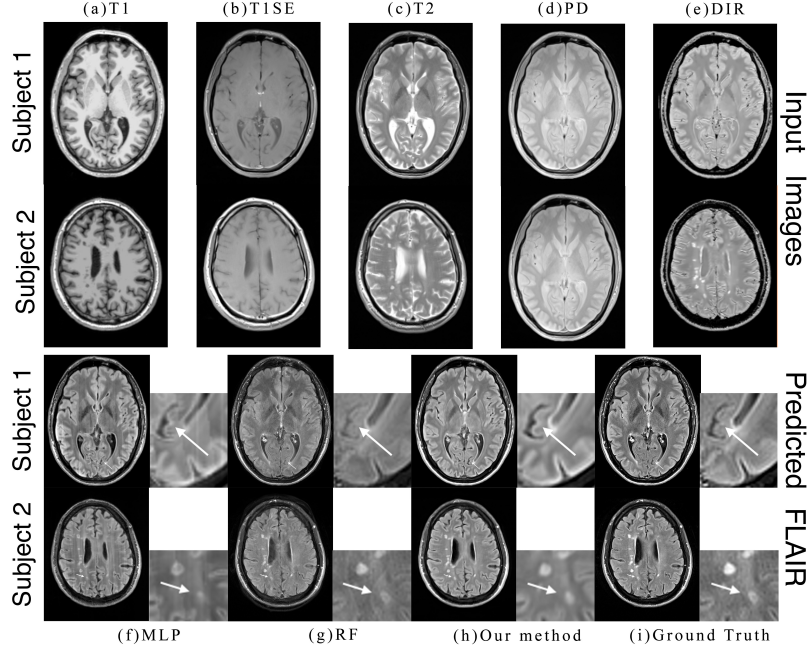

Fig. 3: The first two rows are input images for two subjects, including T1-w, T2-w, T1 spin-echo (T1SE), PD, and double inversion recovery (DIR) weighted images. The last two rows are qualitative comparison of the predicted FLAIR results obtained by our method and the other methods. As shown with arrows, some regions can be better predicted by our method.

Figure 4 shows the result on 5-fold cross validation. Our method gets the best result on four folds. Even though RF gets the best performance on fold-4, the error difference is very small.

Figure 5 is the evaluation result for MS lesion contrast. MS lesions, normal-appearing WM (NAWM), and the surrounding NAWM are extracted using lesion and WM masks. Then we calculated the mean intensity of these three regions in the predicted images and ground truth. Our method keeps a good contrast between MS lesions and white matter, which is clinically very useful.

4 Conclusion

We introduced 3D FCNs for FLAIR prediction from multi-sequence MR images. The nonlinear relationship between the source images and FLAIR can be captured by our network. Both the qualitative and quantitative results show its

Table A: Mean Square Error

	Random Forest 60	Modality Propagation	Multilayer Perceptron	Our Method
Fold 1	993.68	2194.79	1532.89	**905.05**
Fold 2	1056.76	2037.69	1236.53	**913.34**
Fold 3	945.38	1987.32	1169.78	**898.76**
Fold 4	**932.67**	2273.58	1023.35	945.33
Fold 5	987.63	1934.25	1403.57	**927.88**
Average	983.22	2085.53	1273.22	**918.07**

Table B: Peak Signal-to-Noise Ratio

	Random Forest 60	Modality Propagation	Multilayer Perceptron	Our Method
Fold 1	29.62	26.18	27.73	**30.02**
Fold 2	29.35	26.50	28.67	**29.98**
Fold 3	29.84	26.61	28.91	**30.05**
Fold 4	**29.90**	26.03	28.71	29.83
Fold 5	29.65	26.73	28.12	**29.91**
Average	29.67	26.41	28.43	**29.96**

Fig. 4: Table A and Table B are evaluation results for MSE and PSNR, respectively. Our method got the best result on Fold 1-2-3-5. Even though random forest algorithm got the best result on Fold-4, the difference with our method is very small.

	Lesions	NAWM	Surrounding NAWM	Ratio 1	Ratio 2
Random Forest 60	0.54	0.36	0.48	1.50	1.13
Modality Propagation	0.49	0.35	0.44	1.40	1.11
Multilayer Perceptron	0.63	0.41	0.55	1.54	**1.15**
Our Method	0.65	0.40	0.57	**1.63**	1.14
Ground Truth	0.60	0.34	0.51	1.76	1.18

Note: NAWM is normal-appearing white matter. Ratio 1 and 2 are the ratio of lesions to NAWM and surrounding NAWM respectively.

Fig. 5: Evaluation result for lesion contrast. Our method keeps a good contrast between MS lesions and white matter. Even though MLP got a better contrast between lesions and the surrounding NAWM, the difference with ours is small.

good performance for FLAIR prediction. Moreover, the generated FLAIR has a good contrast for MS lesions so that it can be useful clinically. In the future, it would be interesting to also assess the utility of the method in the context of other WM lesions (e.g. age-related hyperintensities).

References

1. A. Compston and A. Coles. Multiple sclerosis. *Lancet*, 372(9648):1502–1517, 2008.
2. D. W. Paty, J. J. Oger, L. F. Kastrukoff, S. A. Hashimoto, J. P. Hooge, A. A. Eisen, K. A. Eisen, S. J. Purves, M. D. Low, and V. Brandejs. MRI in the diagnosis of MS: a prospective study with comparison of clinical evaluation, evoked potentials, oligoclonal banding, and CT. *Neurology*, 38(2):180–185, 1988.

3. F. Barkhof, M. Filippi, D. H. Miller, P. Scheltens, A. Campi, C. H. Polman, G. Comi, H. J. Ader, N. Losseff, and J. Valk. Comparison of MRI criteria at first presentation to predict conversion to clinically definite multiple sclerosis. *Brain*, 120 (Pt 11):2059–2069, 1997.

4. John H. Woo, Lana P. Henry, Jaroslaw Krejza, and Elias R. Melhem. Detection of simulated multiple sclerosis lesions on t2-weighted and flair images of the brain: Observer performance. *Radiology*, 241(1):206–212, 2006.

5. Juan Eugenio Iglesias, Ender Konukoglu, Darko Zikic, Ben Glocker, Koen Van Leemput, and Bruce Fischl. Is synthesizing mri contrast useful for inter-modality analysis? In *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2013*, volume 8149 of *Lecture Notes in Computer Science*. Springer.

6. Gijs van Tulder and Marleen de Bruijne. Why does synthesized data improve multi-sequence classification? In *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, volume 9349 of *Lecture Notes in Computer Science*. Springer.

7. Dong Hye Ye, Darko Zikic, Ben Glocker, Antonio Criminisi, and Ender Konukoglu. Modality propagation: Coherent synthesis of subject-specific scans with data-driven regularization. In *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2013*, volume 8149 of *Lecture Notes in Computer Science*. Springer.

8. A. Jog, A. Carass, D. L. Pham, and J. L. Prince. Random Forest FLAIR Reconstruction from T1, T2, and PD -Weighted MRI. *Proc IEEE Int Symp Biomed Imaging*, 2014:1079–1082, 2014.