

A.S.



AND RESEARCH IN MULTIPLE SCLEROSIS



Lesion synthesis for extending MRI training datasets and improving automatic multiple sclerosis lesion segmentation

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1. Introduction and purpose:

Magnetic resonance imaging (MRI) synthesis has attracted attention due to its various applications in the medical imaging domain. Segmenting MS lesions using supervised machine learning algorithms on MRI images requires a large number of samples to be annotated by expert radiologists. Moreover, obtaining the annotations of medical images is a tedious and time consuming task. This lack of labeled datasets is considered one of the main limitations of the performance of supervised machine learning algorithms, since training with a small number of images may result in overfitting and an increase in the generalization error of the model. We present here a fully convolutional neural network (FCNN) for MS lesion synthesis. The model takes as inputs T1-w and FLAIR images without MS lesions and outputs synthetic T1-w and FLAIR images that contain MS lesions. The lesion information is encoded as different binary masks passed to the model stacked with the input images. One of the applications of our synthetic MS lesion pipeline is to generate new MS lesion samples on patient or healthy images and use these synthetic images as data augmentation to increase the MS lesion segmentation and detection performance.

2. Material and methods:



dataset

Clinical

MS lesion generation model

Data augmentation application: Generating new synthetic MS lesions:

The main idea is to modify the original eight intensity level masks of the target image before passing it through the generator network. At testing time, if the intensity level masks are used without any modification, the output images are a generated synthetic version of the input ones containing all the WMHs found in the input image. Passing modified intensity level masks to the generator network will generate these desired modifications (i.e., new MS lesions) on the output images.

4. Results:

a) MS lesion generation on healthy subjects:

Healthy Original	Synthetic MS lesions on healthy			
	T1-w	FLAIR	Lesion Mask	





b) Data augmentation results (one-image scenario):

Clinical MS dataset					
Method		DSC	Sensitivity	Precision	
One image with 7.6 ml (42 lesions)	ORG	0.57 ± 0.25	0.41 ± 0.16	0.53 ± 0.23	
	DA	0.63 ± 0.20	0.50 ± 0.16	0.65 ± 0.21	
One image with 49.4 ml (53 lesions)	ORG	0.57 ± 0.25	0.58 ± 0.20	0.56 ± 0.22	
	DA	0.58 ± 0.25	0.67 ± 0.18	0.60 ± 0.13	
ISBI2015 dataset					
/lethod		DSC	Sensitivity	Precision	
ISBI01	ORG	0.41 ± 0.13	0.30 ± 0.12	0.75 ± 0.19	
	DA	0.54 ± 0.13	0.45 ± 0.15	0.75 ± 0.17	
ISBI02	ORG	0.53 ± 0.18	0.44 ± 0.19	0.76 ± 0.21	
	DA	0.59 ± 0.15	0.51 ± 0.19	0.78 ± 0.18	



Datasets:

Clinical MS dataset: This dataset consists of 15 healthy subjects and 65 different patients with a clinically isolated syndrome or early relapsing MS. **ISBI2015 dataset**: This dataset consists of 5 training and 14 testing subjects with 4 or 5 different

image time-points per subject from the ISBI2015 MS lesion challenge.

3. Evaluation:

To qualitatively evaluate the generation of MS lesions on healthy subjects, the MS lesions of the clinical MS dataset were generated on the healthy images using linear and non-linear registration. Then, we evaluated quantitively the use of the proposed MS lesion generator as a data augmentation method by generating images from the same domain using registration. The two deformed generated lesion masks (from linear and non-linear registration) and the correspondent two synthetic images were added as data augmentation to the original patient image during training. We tested a state-of-the-art MS lesion segmentation approach (Valverde et al. 2017) on a clinical MS dataset and the public ISBI2015 challenge dataset, analyzing the effect of synthetic images as data augmentation in the one-image training scenario.

NOTE: For each coefficient, the reported values are the mean ± standard deviation when evaluated on the enire testing set. The reported values for the ISBI dataset are extracted from the challenge results board.

5. Conclusion:

The proposed CNN was able to generate T1-w and T2-FLAIR images with synthetic MS lesions. The combination of original images with synthetic ones of the same domain increased the lesion segmentation accuracy, reducing also the number of manually annotated images needed in the database.

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