Draw and Erase to Learn Better

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Abstract. In order to segment new Multiple Sclerosis (MS) lesions, automatic methods need longitudinal data to learn the joint information contained in both time points. However, longitudinal dataset for MS are expensive and difficult to build. In this paper, we propose an innovative pipeline to simulate two realistic time points with new MS lesion from a single FLAIR scan.

Keywords: Synthetic data · New lesion segmentation · Lesion generation.

1 Introduction

The detection of new lesions is an important bio-marker in Multiple Sclerosis (MS) that allows clinicians to adapt the patient treatment and assess the evolution of the disease. Recently, the automation of MS segmentation has shown encouraging results. In some conditions, many techniques showed performance comparable to clinicians. Those methods use a single time point scan to segment all appearing lesions at the time of the acquisition. These techniques are not specialized in the detection of new lesions. Indeed, they repeatedly run the segmentation process for each time-point to detect the new appearing lesions. Unlike the human reader, these methods do not jointly exploit the information contained at each time point. In order to propose automatic methods specifically designed for the scenario of new lesions detection, it requires a longitudinal dataset of MS lesions with an evolution in their lesions. The organizers of the MICCAI 2021 - Longitudinal Multiple Sclerosis Lesion Segmentation Challenge [5] provided such a dataset. However, training state-of-the-art deep learning algorithms and achieving generalizing results on unseen domains [10, 1, 11] may require more data. Thus, we propose in this paper an innovative pipeline for generating synthetic training data suited to the scenario of new lesions detections. First, we propose a lesion generator model to simulate new lesions on healthy white matter regions. Second, we propose a lesion inpainting model to simulate healthy tissue on regions with existing lesions. Finally, we combine the lesion generator and the lesion inpainting to inpaint two realistic time points from a single FLAIR scan.

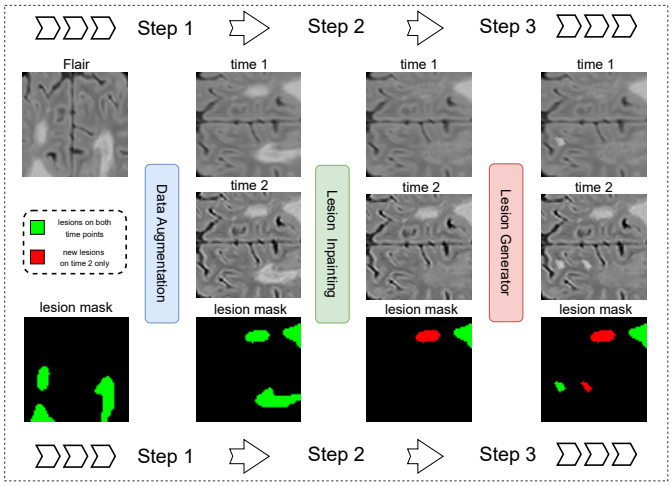

Fig. 1. Synthetic time points with new MS lesion generation pipeline

2 Method and Material

2.1 Method Overview

The proposed method is based on the simulation of new MS lesions between two time points. As shown in Fig1, our pipeline generates "on the fly" synthetic 3D FLAIR patches corresponding to two time points and their respective new lesion masks from a single FLAIR image. The synthetic data is generated in 3 steps. In the first step, a 3D FLAIR patch and its MS lesion mask are randomly sampled from MS lesion segmentation datasets [3, 4, 2]. Then, this FLAIR patch and lesion mask are randomly augmented with flipping and rotations. A copy of the FLAIR patch is performed to represent the two time points. Then, both identical patches are altered with different data augmentation [7], where noise, blur, edge enhancement, and subsampling distortion randomly differentiate the two patches. At this point, the lesion mask from the two synthetic time points are identical. Thus, there are no new lesions. In the second step, a connected component operation is used to separate each independent lesion from the lesion mask. Each lesion is either inpainted (*i.e.* removed) from one of the time points or both of them or neither time point. The lesion inpainting model is used to inpaint the lesion region with hallucinated healthy tissue (see 2.2). Next, the new lesion mask is constructed from lesion regions that have been kept in the second time point but not the first one. In the third step, the lesion generator model is used to simulate synthetic lesion at realistic locations. Synthetic lesions are generated for one of the time points or both of them (see 2.3). Similarly to the previous step, the new lesion mask is updated to include only the generated lesions on the second time point.

2.2 Lesion Inpainting Model

The lesion inpainting model is trained, independently and priorly to our proposed pipeline, with randomly selected 3D FLAIR patches which do not contain MS lesions or white matter hyperintensities. Similarly to [9], the 3D U-Net network is optimised to reconstruct altered input image. The input patch is corrupted with inpainting (random regions are replaced with noise) and other alterations. When the model is trained, it can be used to synthesize healthy regions in lesion locations that are replaced with random noise.

2.3 Lesion Generator Model

The lesion generator is trained before our proposed pipeline to simulate realistic lesions. The generator is a 3D U-Net network with two input channels and one output channel. The first input channel receives an augmented version of 3D FLAIR patch containing MS lesions where lesions are replaced with random noise. The second input channel receives the MS lesion mask of the original 3D FLAIR patch. The output channels predict the original 3D FLAIR patch with lesions. Thus, the trained model is able to simulate synthetic MS lesion from a 3D patch of FLAIR and its corresponding lesion mask.

2.4 New Lesions Segmentation

For the new lesion segmentation, a 3D U-Net architecture similar to the one proposed by [7] has been selected. As input, the network receives a concatenation of FLAIR patches from the two time points. The model output predicts the new lesion mask. The Dice loss is used during training to quantify similarity between the ground truth and the predicted mask.

The new lesion model is trained with mini-batches from both the generated data using the proposed pipeline and the challenge dataset [5]. Specifically in our implementation, the ratio of the real data from the challenge dataset over synthetic data in a mini-batch is 1/3. The total loss of the mini-batch is a weighted combination of the Dice loss of each element. Since challenge data are considered more reliable compared to synthetic data, a weight of 1/3 is attributed to synthetic data Dice loss whereas a weight of 1 is selected for challenge data.

2.5 Data

The dataset provided by the MICCAI 2021 - Longitudinal Multiple Sclerosis Lesion Segmentation Challenge [5] was used to train our method. For preprocessing, our strategy used the docker [6] built with the Anima scripts proposed by the challenge organizers. It includes bias correction, denoising and skull stripping.

3 Implementation Details

The networks are trained with FLAIR patches of size 64^3. Image quality data augmentation [7] is used when training the new lesion segmentation model. The models are optimized with Adam [8] using a learning rate of 0.0001 and a momentum of 0.9.

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