A DEEP SYMMETRY CONVNET FOR STROKE LESION SEGMENTATION

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ABSTRACT

Stroke is one of the leading causes of death and disability. Clinically, to establish stroke patient prognosis, an accurate delineation of brain lesion is essential, which is time consuming and prone to subjective errors. In this paper, we propose a novel method call Deep Lesion Symmetry ConvNet to automatically segment chronic stroke lesions using MRI. An 8-layer 3D convolutional neural network is constructed to handle the MRI voxels. An additional CNN stream using the corresponding symmetric MRI voxels is combined, leading to a significant improvement in system performance. The high average dice coefficient achieved on our dataset based on data collected from three research labs demonstrates the effectiveness of our method.

Index Terms— Stroke, MRI, Image Segmentation, Deep Learning, Brain Quasi-symmetry

1. INTRODUCTION

According to the World Health Organization (WHO), stroke is the second leading cause of death for people above the age of 60 years, and the fifth leading cause for people aged 15 to 59 years old. Each year, nearly six million people worldwide die from stroke. It is important to have accurate diagnosis for proper treatment as well as good prognosis to help the patient and their family prepare for rehabilitation. Fast and accurate identification of the stroke lesion is critical for these tasks. Clinically, a radiologist will review thousands of MRI slices to delineate lesions, which is laborious process (more than 20 hours per brain) and susceptible to operator-bias. Therefore, automatic identification of chronic stroke lesion on brain MRI images is a necessity to assist the radiologists and clinicians.

The problem we pose here is: given 3D T1 MRI images, can a computational model automatically classify its voxels into lesion and non-lesion categories? The irregular shape and location of the stroke lesion, as well as the variance of lesion scale among patients are major challenges for automatic stroke lesion segmentation, as shown in Figure 1. Traditional methods such as SVM [1] and Random Forest [2] often do not exhibit enough distinguishing capabilities to satisfy the request. To address this, we utilize a deep convolutional neural network, which has demonstrated improved learning ability on many visual recognition tasks (e.g., LeNet [3], ImageNet [4]). Differently from most tasks which work on normal 2D images, our problem relies on 3D MRI images. Therefore, we construct an 7-layer 3D convolutional neural network with 5 convolutional layers and 2 fully connected layers. In addition, a symmetrical structure is applied to the network, which utilizes the brain quasi-symmetry property. This network has been shown to be effective on identifying lesion voxels especially when combined with the bilateral voxel descriptors.

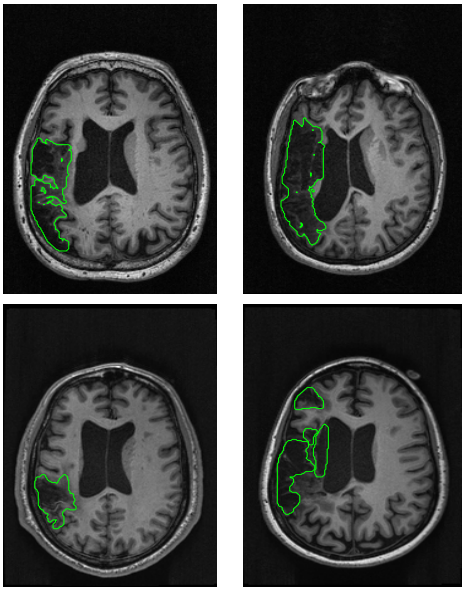

Fig. 1. Example slices of four brain MRI images. The green line delineates the region of lesion.

This paper makes the following two important contributions:

- We propose a Deep Lesion Symmetry ConvNet segmentation pipeline. To the best of our knowledge, there is no existing work developing a 3D convolutional neural network with convolutional layers and fully-connected layers for the modeling of brain lesion segmentation.

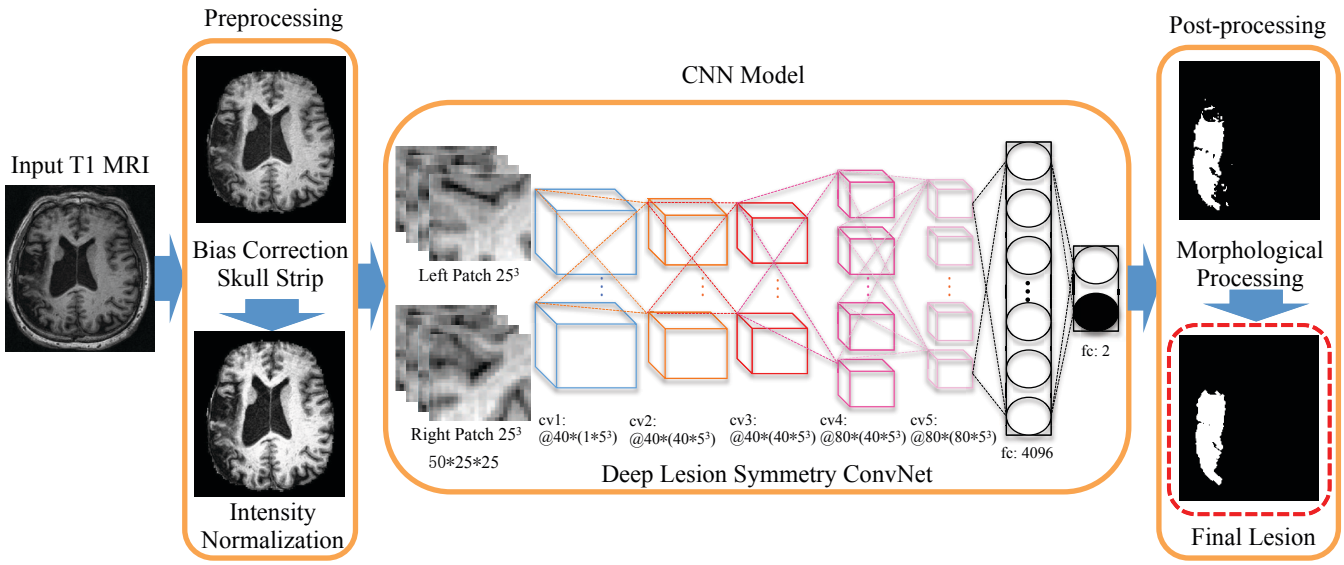

Fig. 2. Overview of our Deep Lesion Symmetry-based ConvNet segmentation pipeline for stroke lesion segmentation on T1 MRI image. Number and size of the kernels are depicted in the format (@number*size). 'fc'stands for fully connected layer, 'cv'stands for convolutional layer.

- We combine a unilateral voxel descriptor (local) and a bilateral voxel descriptor (global) through CNNs for voxel-wise classification. This provides critical insights in utilizing the brain quasi-symmetry property for solving this challenging problem.

The paper is organized as follows. Section 2 introduces the related work on stroke lesion segmentation. Section 3 describes our proposed pipeline including three steps: preprocessing, network construction, and post-processing. Section 4 shows the experimental details and results. Finally, Section 5 presents our conclusions.

2. RELATED WORK

Previous attempts to delineate brain lesions are semi-automated, which still require expert supervision [5] [6] [7]. Recently, statistical machine learning methods, such as SVMs [1] and Random Forests [2], have been tried to solve the problem, but suffer from complicated parameter tuning for different scanning parameters and patient populations.

There are three papers [8], [9], [10], which are related to the work described in the paper. The authors in these papers utilized convolutional layers to obtain the voxel-wise prediction models. In [8], the authors proposed a 3-layer, 2-pathway convolutional network applied to each 2D slice. In [9], the authors designed a 3-convolutional-layer with 2-fully-connected-layer network applied to 2D image slice. The 2D networks, [8], [9], failed to take advantage of the lesion coherence at vertical plane. In [10], the first 3D convolutional network for stroke lesion segmentation was presented, which consists of 11 convolutional layers and double-pathway based on two different image scales.

Although promising results are observed in these works, the quasi-symmetry property of the brain, which exploits one important characteristic in chronic stroke lesion segmentation, is not used. In this paper, we demonstrate that proper utilization of the quasi-symmetry property is very useful.

3. THE PROPOSED PIPELINE

Figure 2 shows our framework which consists of three steps: preprocessing, model construction, and postprocessing. We briefly describe each of them below.

3.1. Preprocessing

The 3D T1 weighted (1mm isotropic) MRI data have an intensity inhomogeneity (bias field) due to magnetic field inhomogeneities (Tx/Rx), patient movement, and head coil characteristics. We correct the bias field by using AFNI [11]. The corrected images are then fed into the processing blocks that follow.

3.1.1. Skull Strip SymROBEX

A fundamental first step for most quantitative analysis algorithms on brain MRI is skull-stripping. We use ROBEX [12]

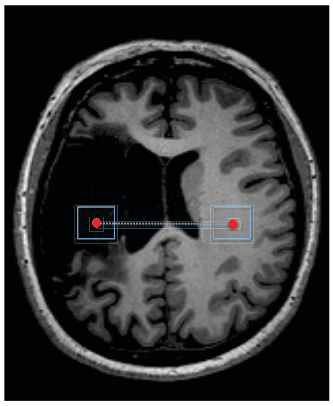

Fig. 3. Sample show of the brain quasi-symmetry property. The two rectangles indicate the corresponding patches in left and right hemispheres.

for skull stripping since it is the most effective one we have tried. ROBEX adopts a Random Forest classifier to find the brain contour with highest likelihood, and then applies graph cuts to refine the contour. However, due to susceptibility changes along the skull, ROBEX produces inaccurate masks on the lesion side, while it produces good skull strip result on the other side. Therefore, we proposed SymROBEX [13] by improving the skull stripping mask through the union of the flipped unaffected hemisphere mask and the affected one.

3.1.2. Contrast Enhancement and Normalization

We increase the contrast of each brain MRI image by using histogram equalization. For better identification, we want the area between lesion and grey matter exhibit a higher contrast, especially when the whole image is dark. Histogram equalization achieves this by spreading out most frequent intensity values using the cumulative distribution function. Here we set the minimum threshold to 100 and the maximum threshold to 600 based on our observation of the T1 image intensity from data from 3 different scanners. Then we use zero mean and unit variance to normalize images and prepare them for network training.

3.2. Network Construction

We approach the brain lesion identification problem by solving it voxel by voxel in 3D space on T1 modality. The problem is thus converted into a voxel-wise classification problem. The input to the network is a patch of voxels, and the output is the probability of the central voxel of that patch, indicating whether this voxel is pathology or normal brain region.

The main drawback of the above setting is that the segmentation of each voxel is performed solely by processing the contents of a small neighborhood patch (unilateral descriptor) around it, which is not consistent with the actual gold standard labeling. One critical prior for doctors to identify lesion is the brain Quasi-symmetry property: MR imaging of the human brain demonstrates a symmetrical property on axial (left/right) and coronal (front/back) planes. When the stroke lesion occurs, the symmetrical property breaks down, as shown in Figure 3. Based on this intuition, we extract two patches to describe one voxel, one is the original patch surrounding that voxel and the other corresponds to the symmetric patch in the opposite hemisphere (bilateral descriptor). The two patches are fed into the network at the same time.

Our system consists of 8 layers with 6 convolutional layers and 2 fully connected layers. The size of each input patch is 25^3, resulting in the final size (2 patches) of $25 \times 25 \times 50$. Basically, the convolutional layer has 40 to 80 kernels of size $5 \times 5 \times 5$ connected to the outputs of the previous convolutional layer. The first fully-connected layer has 4096 neurons and the final layer has 2 neurons, indicating the lesion and non-lesion categories, respectively. The final prediction is made with the softmax non-linearity.

In the training phase, the parameters of the kernels are optimized by gradient descent, with the aim of minimizing the error between the prediction and the ground truth. We adopted the ReLU as the activation function. Initial learning rate was set at 0.001 and was gradually reduced during training, along with constant momentum equal to 0.9.

3.3. Postprocessing

In the postprocessing phase, we use morphological operations including opening, dilation and erosion to eliminate isolated small regions and smooth lesion edges to further improve the lesion segmentation.

4. EXPERIMENTAL RESULTS

4.1. Dataset

Eighteen participants with aphasia resulting from a single left hemisphere stroke were recruited from three research laboratories. All participants were monolingual English speakers and were right handed, at least one-year post onset of stroke. The participants underwent imaging that included a standard T1-weighted 3D MPRAGE scan acquired in the sagittal plane with isotropic resolution of 1mm. The gold standard measure of manual tracing was generated using MRIcro on the 3D T1 volume in the native space.

4.2. Classifier and Evaluation

Among the 18 cases of patients with chronic stroke lesions, we randomly select 10 brains for training and 8 brains for testing. It is worth noting that the distribution of lesions is very imbalanced, since in most cases 90% voxels of the brain are normal brain tissue. To avoid the negative effect of strong class imbalances, for each training case, we construct our patch datasets with equal number of lesion and non-lesion

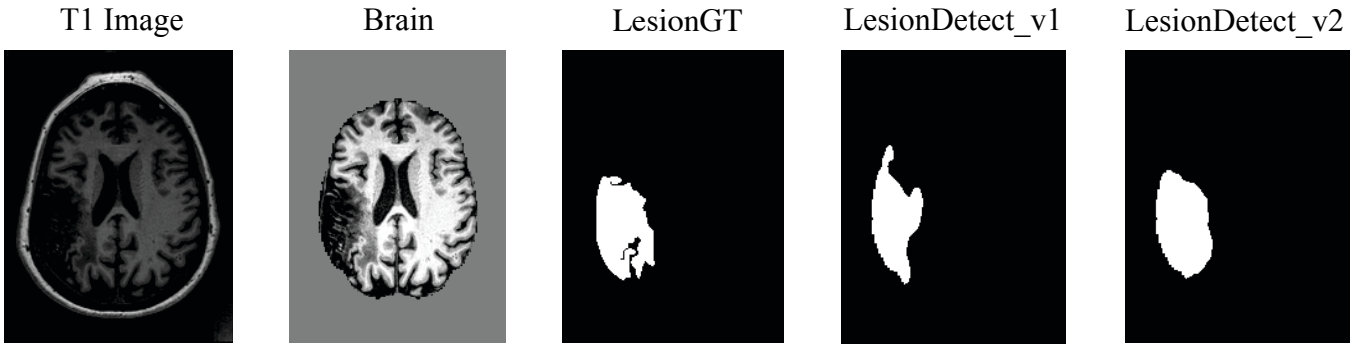

Fig. 4. One example produced by our pipeline. T1 image is the original T1 scan. Brain is the image without skull, LesionGT is the lesion drawn by experts, LesionDetect_v1 is the lesion detected by a unilateral model, LesionDetect_v2 is the lesion produced by a bilateral model.

samples. The Dice Similarity Coefficient (DSC) was used to evaluate the performance of the CNN models.

4.3. Results and Discussions

Subject ID	Hand Drawn Lesion Size (ml)	DSC_v1	DSC_v2
1	253.09	0.70	**0.85**
2	124.10	0.53	**0.75**
3	141.93	0.63	**0.73**
4	246.11	0.70	**0.84**
5	137.35	0.55	**0.73**
6	262.56	0.75	**0.76**
7	162.21	0.53	**0.75**
8	254.33	0.65	**0.79**
Mean	197.21	0.63 ± 0.08	$\mathbf{0.78} \pm 0.04$

Table 1. Performance on eight test cases measured by Dice Similarity Coefficient (DSC). DSC_v1 is the performance achieved by a unilateral model and DSC_v2 is the performance achieved by a bilateral model.

In this section, we trained two models using a unilateral voxel descriptor (local) and a bilateral voxel descriptor (global) and measure their DSC on our datasets. Table 1 shows the detailed performance on each test brain. We see that the model with unilateral voxel descriptor produces a mean DSC of 0.63. Using a bilateral voxel descriptor leads to substantial performance gains (0.63->0.78), which clearly shows the value of combining the symmetry property and convolutional neural network.

It is worth noting that medical images are private and thus usually not open to the public. We cannot have direct comparison with other methods. As reported in [10] and [8], the industry standard is around 0.60 DSC, indicating that our results are quite promising.

5. CONCLUSIONS

In this paper, we proposed a Deep Lesion Symmetry ConvNet segmentation pipeline for stroke lesion identification. We constructed an 8-layer convolutional neural network, which has been proven to be effective in identifying lesion regions without any parameter tuning once the network has been trained. In addition, we evaluated the performance of both unilateral and bilateral voxel descriptor, demonstrating that the brain symmetry property plays a very critical role in stroke lesion segmentation.

While our initial results are very encouraging, the topic deserves further investigations, especially in the special cases where stroke lesions spread not only in one hemisphere but in the whole brain.

6. ACKNOWLEDGES

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