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Brain Stroke Detection based on Fusion of Two Segmentation Model

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ABSTRACT

Diffusion-weighted magnetic resonance imaging (DWI) is sensitive to acute ischemic stroke and is a common diagnostic method for the stroke. However, the diagnostic result relies on the visual observation of neurologists which may vary from doctor to doctor under different circumstance. And manual segmentation is often a time-consuming and subjective process. The time from onset to thrombus removal has a significant impact on the prognosis of patients with acute ischemic stroke. The shorter the time, the better the prognosis. For this purpose we present a novel framework to quickly and automatically segment the ischemic stroke lesions on DWI. We mainly have three contributions: firstly, we design a detection and segmentation network (DSN) to solve the two kinds of data imbalance; secondly, we propose a triple-branch DSN architecture, used for extracting different plane feature respectively; thirdly, we propose a multi-plane fusion network (MPFN), which aims to make final prediction more accurate. Extensive experiments on ISLES2015 SSIS DWI sequence dataset demonstrate the superiority of our proposed segmentation method. The dice reached 62.2% and the sensitivity reached 71.7%.

Keywords: - Ischemic stroke, DWI, feature fusion, image segmentation, deep learning.

I. INTRODUCTION

Cerebrovascular accident (CVA) is a leading cause of dis- ability and death in the world. There will be an estimated 15 million new CVA cases and 5 million deaths in 2018 [1]. Ischemic stroke is the most common type, making up about 87 percent of all CVA. It's caused by a blockage in an artery supplying the brain with blood. Hemorrhagic strokes which account for the remaining 13 percent, can be caused by high blood pressure or an aneurysm [2]. Patients must be effec- tively treated within 4.5 hours of onset, otherwise they may have a high probability of disability or even death [3]. It has been proven that the key point to the diagnosis and treatment of ischemic stroke is to obtain the location and volume of the stroke lesion [4]. Magnetic resonance imaging (MRI) and Computed Tomography (CT) are the most commonly used diagnostic methods for ischemic stroke [5]. The advantages of CT are high popularity, fast, and affordable. However, DWI, a kind of MRI, is more sensitive to the ischemic stroke lesions than the CT [6], which makes it a great advantage in the diagnosis of early acute ischemic stroke.

The lesion detection and quantification are important for the treatment of ischemic stroke [7]. However, the neurol- ogists can only segment the the stroke lesions manually, this process can be extremely tedious and time-consuming, and the segmentation accuracy can be negatively affected by many factors, such as the complexity of the tissue struc- ture, and the ambiguous characteristics between lesions and artifacts [8]. Therefore, it is of great significance to design an automatic segmentation system for acute ischemic stroke lesions, but it is a complicated task [9]. Some methods have been proposed to assist doctors in solving these prob- lems [10], but the segmentation results often contain artifacts, which need to be corrected by the neurologists. In clinicalpractice, this kind of method is still time-consuming, so it is better to have a fully automatic segmentation method. The deep architecture of convolutional neural network can extract a series of effective features without human intervention [11], which makes it possible for fully auto- matic segmentation of ischemic stroke lesions. In recent years, the deep learning (DL) methods have been widely used in medical image processing tasks to assist physicians in improving the accuracy and efficiency of medical diagnosis [12].

Many attempts have been done to solve these problems. The basic idea is data augmentation. Nonnegative matrix factorization (NMF) method optimizes segmentation results through 3D information and shape prior [13]. 3-D fully con- volutional densenets (FCD) can learn more effective fea- tures from data due to its complex structure [14]. Automated region growing (ARG) method first reduces the range of region-growing [15] through image detection, and obtains segmentation results through seed points [16]. However, these researches have not take the two kinds of data imbalance and image artifacts into consideration. In this paper, we focus on the ischemic stroke lesion segmentation. A fully automated method based on feature pyramidal networks (FPN) [17] is proposed in our work. Considering that there are two kinds of data imbalance in our task, we design a FPN based architecture as the detection network for extracting the patches from the entire image and utilize the U-NET [18] architecture as the segmentation network for segmenting the lesions in image patches. We call the ensemble of detection network and segmentation network DSN. In addition, it is obvious that the spatial information is of great benefit to improve learning accuracy. On the one hand, spatial information can generate smoother segmenta- tion results, and on the other hand, it can suppress image artifacts to some extent. We introduce spatial information into our segmentation model, the DWI sequence is first segmented by the triple branches DSN, and then the segmentation results of DSN are fused by the MPFN. The most important innova- tion of our work is that we improve the segmentation accuracy through the information of different plane views.

II. RELATEDWORKS

Most of the early acute ischemic stroke imaging researches are tested on the CT data and design the image features manually [19]. First, they extract the designed image features and then use traditional machine learning algorithms to clas- sify or detect. In fact of CT is not sensitive enough to the ischemic stroke lesions, many features only have limited con- tribution to the prediction accuracy. One feature that has been proven effective and widely used in researches is the sym- metrical of brain, compare the differences in brain symmetric regions can identify the abnormal regions easily [20]. Further analysis can determine the lesion location and volume [21]. The performance of these methods depends on the features designed by the researchers, which may have poor gener- alization capability. So, it is preferable to make the model learn the feature maps from the data by itself. The deep learning algorithm has a deeper network structure that can extract more complex and abstract features from the data [22]. In recent years, it has been widely applied to tasks such as classification and semantic segmentation. Initially, deep learning algorithms were mainly used for classification tasks and achieve good results on various datasets [23]. However, there are many problems arise in applying the deep learning methods to the medical images. For example, the labeled data is scarce, which may lead to overfitting. And the label with insufficient accuracy, which severely prevent the model extracting features from the training data set.

Despite these limitations, many DL-based methods have achieved good performance on the brain tumor segmentation task [24]–[27]. Because image segmentation of medical images is often regarded as a pixel-level classification problem and most of the pixels are normal tissue, which means serious imbal- ance in the dataset. Chen *et al.* design the ensemble of two deconvnets (EDD) first segment roughly and than the mul- tiscale convolutional label evaluation network (MUSCLE) supress the image artifacts [28]. Partial Differential Equa- tion (PDE) [29] model is proposed for image reconstruction, so that brain tumors will be more obvious. Other researchers use the multimodal MRI to optimize brain tumor segmen- tation results and achieve better performance [30]. MRI can also be used for ischemic stroke lesion segmentation, since the region of DWI abnormality can act as a gold standard for irreversible brain infarction in clinical prac- tice. Multimodal MRI can be used to classify the onset time of ischemic stroke [31] and they may help to elimi- nate the artifacts in segmentation results [32]. For example, the method uses fuzzy C-means algorithm to segment the lesion on DWI, then eliminate artifacts through T1, T2 and Flair [33]. The segmentation of sub-acute ischemic stroke lesion is one of the tasks in ISLES 2015, which attracts many entries. This challenge is to segment sub-acute ischemic stroke lesions on the multi-modal MRI sequences automat- ically. Among the top ranked approaches, DeepMedic per- form best. DeepMedic is a multi-scale 3D CNN with fully connected conditional random fields (CRFs) achieving a Dice score of 0.59 in testing. The second best performing method use a modified level-set approach embedded with the fuzzy C-means algorithm [34] while the third best method is based on random forests and contextual clustering [35]. R. Karthika's team proposed a U-NET improvement model to segment the ischemic stroke lesion on the multimodal MRI [36].

III. PROPOSED SYSTEM ARCHITECTURE

Our proposed approach is reffered as Multi-Plane Informa- tion Fusion Network, employs a triple branches DSN and a MPFN. The DSN first finds candidate regions of inter- est (ROIs) through detection, and then performs lesion seg- mentation on the candidate ROIs, MPFN is dedicated to smooth segmentation results and suppress image artifacts. The architecture of our work is shown in Fig. 1 and fig.2 . This section is organzied as follows: the illustration of DSN; the illustration of MPFN; the illustration of evaluation metrics; the illustra- tion of implementation details. We find that there are two types of data imbalance in the ischemic stroke lesion segmentation task. First is pixel-level imbalance, there are more normal tissues than the abnor- mal. Second is slice-level imbalance, normal slices more than the abnormal. The current segmentation model does not address these data imbalance effectively. For the image level imbalance problem, we use the image augmentation method, and convert this task into a detection and segmentation task. First, DSN detects the lesion on the DWI sequence. Second, it segments the lesion on the detection results. Our DSN is an improvement of the Mask-RCNN archi- tecture [40]. Mask-RCNN also detects objects before seg- menting. However, Mask-RCNN is an instance segmenta- tion model, so its network structure is very complicated and have large amount of the parameters. We modify the model structure based on the characteristics of the ischemic stroke segmentation task and reduced the amount of parameters.

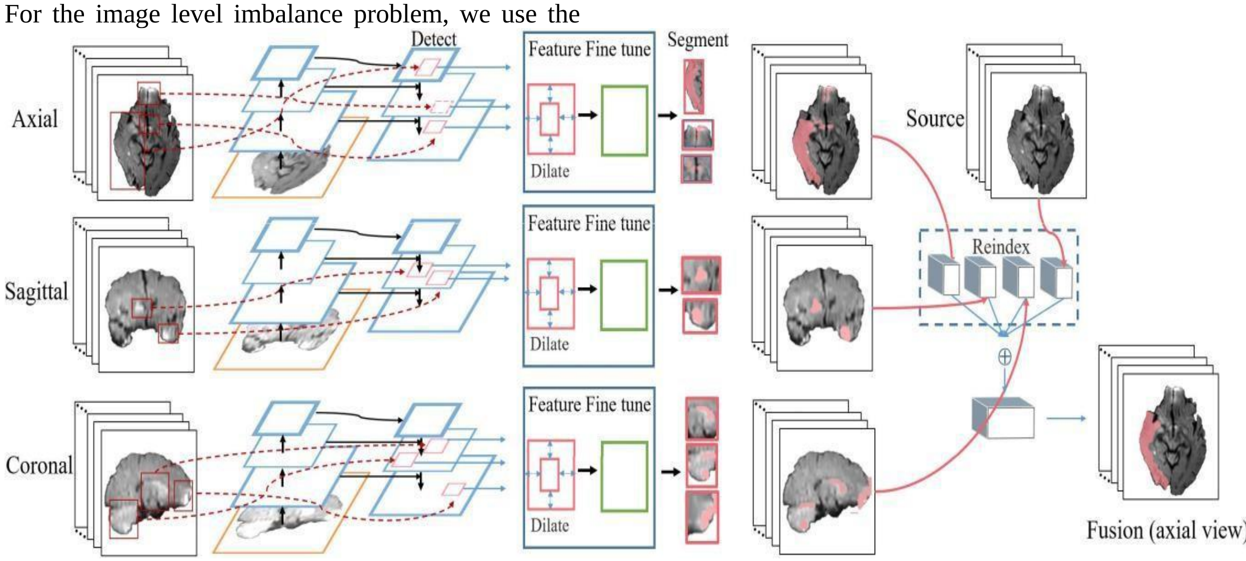

FIG 1. Illustration of the MULTI-PLANE Information Fusion Network. Triple branches take the different planes as input respectively. The red rectangles represent the candidate patches, red masks indicate possible lesions.

The input is a full image, which has been resized at 1024× 1024. The back- bone is FPN-resnet101, which is used to extract lesion features at different scales. We choose the FPN for the following reasons: first, objects of different scales will be assigned to different image feature levels, which addresses objects of different scales; second, FPN has a high resolution feature map for small objects. Note all scales of FPN feature maps share the same afterwards network architecture and the same model weights. In the detection task, contextual information often provides important knowledge for labeling the detection bounding boxes [41]. However, it is difficult to determine the optimal level of contextual information. On the one hand, too much contextual information may hide the true lesion. After a trade-off between performance and effectiveness, We set the depth of the FPN to 5, so we can obtain feature maps at five scales: 32×32, 64×64, 128 ×128, 256×256, and 512×512. These feature maps can contain Most cases. Region proposal network (RPN) is used to generate the candidate regions, which are used for subsequent lesion seg- mentation. In order to reduce the information loss caused by RPN detection, the candidate regions need to be dilated, and different scale has different dilate coefficient. On the other hand, the features used for detection may not necessarily suitable for segmentation task, We design feature fine tune module modifies the multi-scale feature maps of FPN. Then we map the dilated candidate regions to the fine tuned feature maps. The prediction of DSN contains many false positive clus- ters which have similar appearance with the small stroke lesions. So we use DSN to segment data from three different plane view, and design MPFN to combine these segmentation results and generate a more accurate ones. MPFN can greatly suppress errors in DSN prediction.

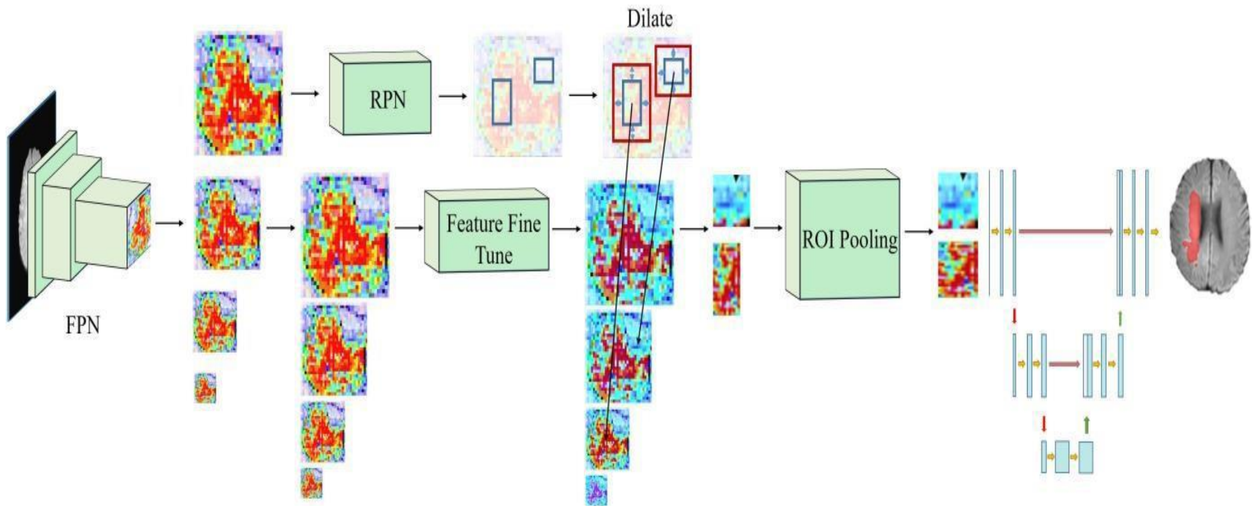

FIG. 2. Illustration of the detection and segmentation network (DSN). The different size heatmaps represent the multi-scales feature maps.

The input of MPFN is 4 sequences, which are the original image sequence, axial classification probability maps, sagittal classification probability maps, and coronal classification probability maps. MPFN aims to eliminate false recognition artifacts in DSN's prediction. The volumetric slices are spatially related, the closer the distance is, the greater the correlation coefficient. Acute ischemic stroke lesions are spatially continuous in the brain. So, the segmentation results can be optimized by the information provided by the adjacent slices. Channel Adjustment (CHA) is used to adjust the combination order of input sequences. For convenience of description, let us give an example, if the index of a picture is *i*, and each sequence is arranged from small to large according to the distance from the *i-th* slice. This adjustment ensure that the features learned by MPFN include the spatial correlation between the slices. Considering computational power is limited and the farther slices have smaller correlation coefficients with *i-th* slice, which means that they contribute a little to the segmentation result of *i-th* slice. So, the MPFN only take 50 slices from each kinds of sequence at a time. The workflow of the method is shown in Fig.3

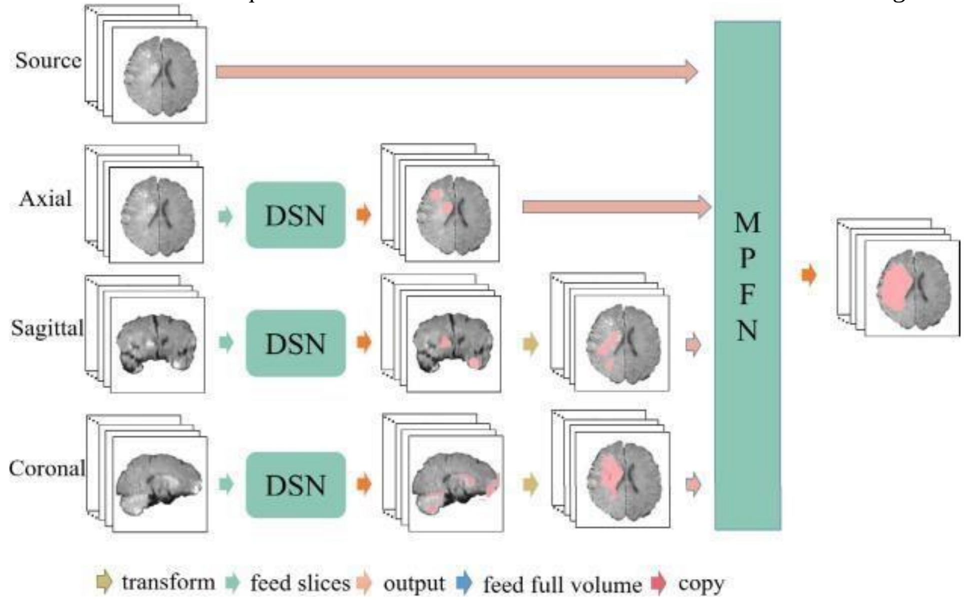

Fig.3 The workflow of our method.

IV. RESULTS AND DISCUSSION

In this section, we conduct a number of experiments to analyze MULTI-PLANE Information Fusion Network on ISLES2015 SSIS DWI sequence dataset. The acute ischemic stroke lesion segmentation is an essential task, so, we try many existing image segmentation models. Our experiments found that the N4Bias preprocessing method not only fail to improve the learning performance of the model, but also weak the features of the lesions. We compare the characteristics of the data before and after N4bias preprocessing, and find that N4bias algorithm consider the lesions are caused by the intensity in homogeneities. Table I shows the performance comparison. We can see that the overall results obtained with the N4bias preprocessing are worse than without the N4bias preprocessing.

Table I Performance comparison using N4bias preprocessing and without N4bias.The best performance is highlighted in bold.

method	without N4Bias		N4Bias preprocessing	
	Precision	DICE	Precision	DICE
U-NET	**35.35%**	**0.82%**	9.53%	0.33%
FCN [45]	**23.14%**	**0.53%**	10.64%	0.37%
DeepLabv3 [46]	**35.21%**	**1.23%**	26.95%	0.62%
DeepLabv3+ [47]	**16.93%**	**0.39%**	**0%**	**0%**
SegResnet [48]	**29.97%**	0.70%	20.15%	**0.71%**
UPERNET [49]	**26.25%**	**0.61%**	13.52%	0.47%

V. FUTURE SCOPE AND CONCLUSION

In this paper, we have presented a novel framework to seg- ment the acute ischemic lesions on DWI. And several visual examples of the segmentation results are shown in Fig. 7. To solve the two kinds of data imbalance, we designed DSN architecture, which includes detection and segmentation modules. The detection one is use to extract patches with IOU greater than 0.7, which can solve the data imbalance prob- lems effectively. Besides, we use the segmentation module to segment the lesions in the extracted patches. Experiments show that our data has rich information on the z-axis, and this information is helpful for lesion segmentation. We designed a triple branches DSN architecture, which trained on three kinds of plane. And the fusion network combines the seg- mention results. Different from the many other related works, our work combines the advantages of 2D and 3D segmen- tation models. The evaluation process is conducted using performance metrics like DICE, IOU, and average f1 score. Extensive experiments on ISLES2015 SSIS DWI sequence dataset demonstrate the high accuracy and efficiency of our proposed segmentation method. In the future, the experience of the neurologists will be involved to produce the attention-based model. We will try to highlight areas in a given input image that provide useful evidence for lesion segmentation.

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