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Liver Segmentation from CT based on Multi-Scale Candidate Generation and Fractal Residual Network

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Abstract — *Liver malignant growth is one of the most widely recognized diseases. Liver tumor division is one of the most significant strides in rewarding liver malignant growth. Precise tumor division on Computed tomography (CT) pictures is a difficult errand because of the variety of the tumor's shape, size, and area. To this end, this paper proposes a liver tumor division technique on CT volumes utilizing multi-scale candidate generation(MCG), 3D fractal residual network (3D FRN), and active contour model (ACM) in a coarse-to-_ne way. To begin with, livers are fragmented utilizing 3D U-Net and afterward MCG is performed on these liver areas for getting tumor up-and-comers (all superpixel squares). Second, 3D FRN is proposed to additionally decide tumor areas, which is considered as coarse division results. At long last, the ACMis utilized for tumor division refinement. The proposed 3D MCG-FRN C ACM is prepared utilizing the 110 cases in the LiTS dataset and assessed on an open liver tumor dataset of the 3DIRCADb with dice per instance of 0.67. The experimentations and correlations exhibit the presentation favorable position of the 3D MCG-FRN + ACM contrasted with other division techniques.*

Key Words: Fractal residual network, multi-scale candidate generation method, active contour model, liver tumor segmentation, CT volume.

1. INTRODUCTION

As per the World Health Organization (WHO) reports, liver disease is one of the most widely recognized malignant growths on the planet and is a primary driver of death in all tumors. In 2012, 745,000 patients passed on of liver malignant growth overall [1], hepatic cell carcinoma (HCC) represents about 80% of all essential liver tumors and most patients with ceaseless liver ailment have HCC. Identification of HCC at a beginning phase can incredibly improve the fix pace of patients. Computed tomography (CT), included by its high spatial goal and quick checking speed, assumes a critical job in liver disease location and conclusion. The essential treatment techniques incorporate careful resection, interventional treatment, locoregional removal, and so forth. These treatment strategies need the detail data of tumors, for example, the size, shape, and area before treatment so as to build up a _ne treatment program [2].

In routine clinical practices, the segmentation of liver cancer can be done manually by radiologists with good expertise and experience. However, this is a time-consuming task requiring the radiologist to search through a 3D CT scan which may include hundreds of slices and multiple lesions. At the same time, automatic liver tumor segmentation is a difficult task due to different image acquisition protocols, various contrast-agents, and varying levels of contrast enhancements. In addition, dissimilar scanner resolutions lead to unpredictable intensity, and many different types of lesions, especially tumor sub-types, can occur in livers. Thus, these different types of tumors with varying contrast levels (hyper-/hypo-intense tumors) create obstacles for automated tumor segmentation [3]. In recent decades, with the development of computer-aided diagnosis (CAD) [4], several methods based on machine learning for automatic liver tumor segmentation on CT images have been developed which include traditional machine learning methods and deep learning methods. For traditional machine learning methods, Smeets *et al.* [5] proposed a combining level set method with supervised pixel classification for liver tumor segmentation.

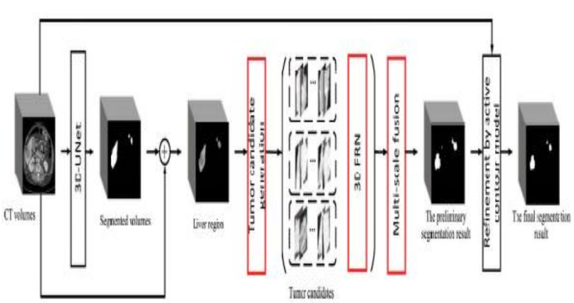

Fig-1 ARCHITECTURE OF PROPOSED METHOD

2.METHODOLOGIES

In this paper, we propose a method for liver tumor segmentation. First, 3D U-Net is used to segment liver regions. Then, liver regions are segmented to tumor candidates by multi-scale candidate generation. Tumor candidates are consequently classified and fused for the purpose of segmentation. This method can increase the proportion of liver tumor information compared with the liver information in candidate regions. In order to improve the classification accuracy and sensitivity of the network for liver tumor segmentation, a new network structure, namely, fractal-residual structure, was proposed.

2.1 Pre-processing

The main aim of pre-processing is to improve the quality of the input image by reducing the noise. The gaussian filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing. Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

2.2 3D U-Net

This paper use 3D U-Net for liver segmentation before liver tumor segmentation. Although the image after liver segmentation reduces a large number of non-interested regions, the tumor region of interest is still too small to be segmented in liver regions. To solve this problem, we decided to cut each segmented liver image into tumor candidates and then classify the tumor candidates to obtain the segmentation results.

2.3 3D Fractal residual network

3D FRN combining the fractal structure and the residual structure is proposed for classifying the liver tumor candidates. The original fractal network, due to the random discarding mechanism, has improved the generalization ability of the network, but has also led to the discarding of many effective features. In order to increase the generalization ability of the network as well as acquire more features of different resolutions, we add the shortcut connection in the FR structure. By means of building a deep network, the FR structure enlarges the width of the network, expands the dimension of the features extracted by the network, realizes the reuse of the features, and greatly improves the ability of the network to classify tumor candidates. FR structure can be expanded iteratively to an i-level structure, which is expressed as follows,

$$M_i = \begin{cases} res & if\ i = 1 \\ 2M_{i-1\oplus}M_1 \oplus z & otherwise \end{cases}$$

where res represents residual structure.

2.4 Active contour model

The active contour model is introduced to refine the boundary of the liver tumor. Consequently, in the boundary of the tumor, many candidate regions contain only part of tumors because the border of candidates overlap with tumor edges, but they tend to be classified as tumor regions due to the generalization process of 3D FRN. As a result, the final segmentation result will be larger than the real tumor. Therefore, the active contour model is applied as a simple post-processing procedure to fine tune the obtained boundary since 3D FRN could provide an excellent initial boundary.

RESULT AND DISCUSSION

Input image is taken from LiTS dataset. The number of slices per patient varies greatly. Most CT scans are pathological, including tumors of different sizes, metastases and cysts.The input image is 3D medical images.3D imaging creates an innovative opportunity to more accurately represent medical data in 3D than traditional imaging technologies, which can then be viewed simultaneously from different locations around the world. The input images are Computed tomography (CT), Magnetic Resonance Imaging (MRI), Posterior Emission Tomography (PET) and single-photon emission computed tomography (SPECT).

Most CT scans are pathological, including tumors of different sizes, metastases and cysts. It is worth noting that the 3DIRCADb dataset1 is a subset of the LiTS dataset.2 In order to evaluate our model fairly, we use 3DIRCADb dataset as the testing data and the remaining data in LiTS dataset is considered as the training data.

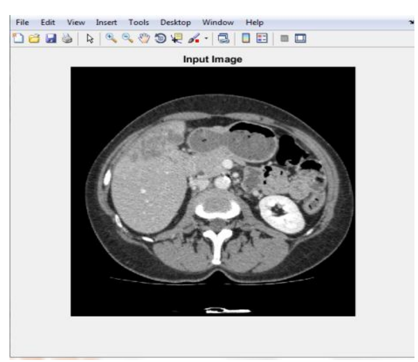

Fig-1 Input image

Fig-2 Pre-processing image

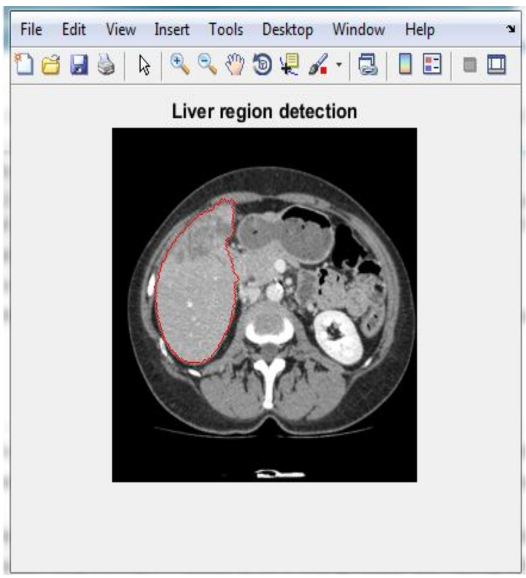

Fig-3 Liver region detection

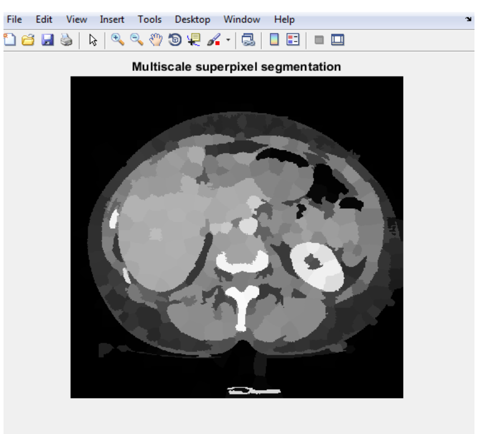

Fig-4 Multiscale super pixel segmentation

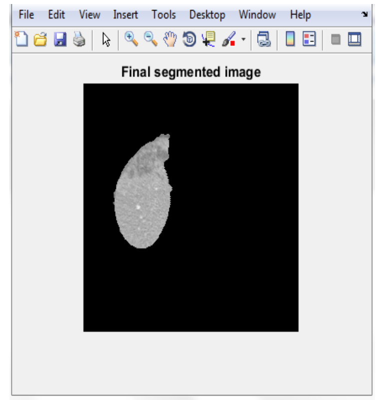

Fig-5 Final segmented region

CONCLUSION

In this paper, they propose another strategy for liver tumor division in CT pictures, including liver division, multi-scale tumor up-and-comer age, tumor applicant grouping, and the dynamic form model. Initially, they utilize 3D U-Net for liver division and getting tumor competitors utilizing MCG technique. At that point, with respect to competitor order, they propose 3D FRN. At last, for better division results, dynamic shape model is chosen for post handling. they played out the division errands on 3DIRCADb dataset, the examination results and correlations with related work show that our proposed model can accomplish a superior division execution.

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