LIVER CLASSIFICATION IMPLEMENTATION FOR FAST AUTOMATIC LIVER SEGMENTATION IN CT SCAN IMAGES

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Introduction

Liver segmentation has remained a challenge in computer-aided diagnosis and surgery, due to its various shape and unclear borders with surrounding organs in computed tomography (CT) images. Various automatic methods have been developed to obtain faster and more precise segmentation [1], such as methods based on region growing [2], level set [3], statistical shape model [4], and deep neural network [5]. In this study, the aim is to perform fast automatic liver segmentation by introducing liver classification in the pre -processing step to reduce the processing time.

Method and Materials

The proposed model is the combination of Fully Connected Neural Network (FCNN) as a classification network and Deep Convolutional Neural Network (DCNN) using modified Encoder-Decoder architecture as a segmentation network. A total of 56 CT volumes and segmentation masks (from manual segmentation by clinical experts) were used from Liver Tumour Segmentation (LiTS) challenge for training (n=41) and testing (n=15) both network model. To speed up the segmentation process, an improvement was made in the pre-processing step where FCNN was employed to classify every slice from the image dataset into two classes: background and liver. Afterward, only slices with a liver label were proceed using segmentation network to obtain the initial liver regions. Post processing was applied by selecting the largest 3D connected component as the final liver segmentation. The performance was measured by calculating the accuracy of the detection for the classification network and the Dice score of the segmented liver volume for the segmentation network. Moreover, processing time was compared between the tests with and without implementation of the classification network.

Result

The training process for both classification and segmentation network took 39 minutes and 10 hours respectively using a single GPU with 8GB memory. Classification network was able to label the image slices with an average accuracy of 92.6±5.7%. Meanwhile, the volume result from the segmentation network achieves an average dice score of 94.1±1.4%, where an example of liver segmentation result is shown in figure 1. Processing time varies depending on the number of slices, from 10-85 seconds. Test that implemented the classification network in the pre-processing step shows 1.7 to 4 times faster processing time compare to the test without the classification network as seen in figure 2.
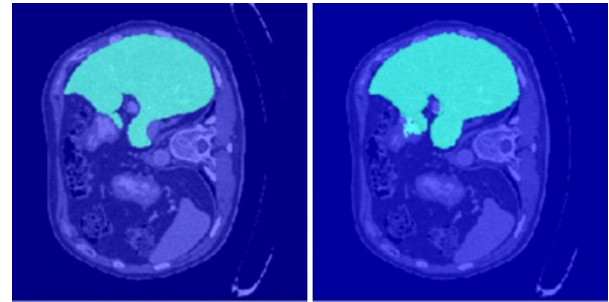

Figure 1: Liver segmentation on 2D slice image, manual segmentation as the ground truth (left) and from our segmentation network (right)
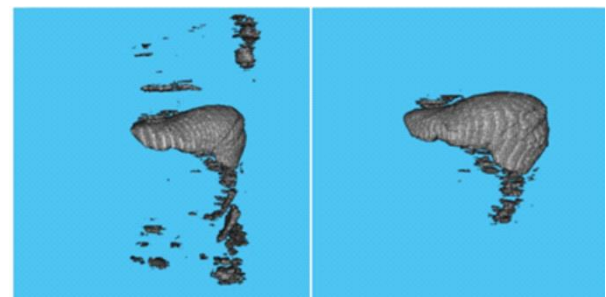

Figure 2: 3D reconstruction result, without (left) and with (right) implementation of liver classification.

Discussion

The proposed approach is able to perform automatic, accurate and fast liver segmentation. Implementation of classification network in the pre-processing part drastically reduces the processing time, hence more data can be computed, and the liver diagnosis can be sped up. An automated, accurate and faster liver segmentation may contribute to an improvement of clinical diagnosis (e.g. liver parenchymal heterogeneity) and treatment decision making.

References

1. L. Fernández-de-manuel *et al, Annual International Conference of the IEEE Engineering in Medicine and Biology Society.* pp. 3625–3628, 2009.
2. L. Ruskó, G. Bekes, G. Nemeth, and M. Fidrich, *MICCAI Wshp. 3D Segmentation Clin. A Gd. Chall.*, vol. 2, no. 7, pp. 1–8, 2007.
3. D. Furukawa *et al, MICCAI - Work. 3D Segmentation Clin. a Gand Chall.*, pp. 117–124, 2007.
4. D. Seghers *et al.*, *Proc. Work. 10th Int. Conf. MICCAI, Work. 3D Segmentation Clin. A Gd. Chall.*, pp. 135–142, 2007.
5. G. Chlebus *et al*, no. Midl 2018, pp. 1–9.