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Liver CT Image Processing And Diagnosing Using Artificial Neural Networks And MATLAB

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Abstract

Segmentation is a grand challenge, and there are many contests are held around the world to solve this challenge, especially in biomedical image. There are many solutions to solve this challenge have been published.

Nowadays, neural networks, including deep learning is a powerful and state-of-the-art way to segment objects from the background. But to use deep learning effectively, beside design a good network architecture, the prepare of input data is also an important requirement. Active contour (other name: Snake) is a classical segmentation technique in image processing. But the accuracy of this technique is not as high as we need for health care problems, and soft techniques such as neural networks or deep learning can improve this problems. But in those researches, deep learning is supplied to change the parameters of active contour algorithm.

We propose a combination of two fields of solving segmentation problem, a classical one, and a modern one : using data from active contour to be the input of deep learning. The images to be used in this research are human liver CT images.

1 Introduction

Biological imaging is a rapidly evolving field that has seen the recent advent of a number of three-dimensional techniques such as confocal microscopy, magnetic resonance microscopy, micro-computed tomography or electron tomography that yield images of biological specimens at various scales from molecular complexes to organisms. High-throughput processing and analyzing schemes are required to cope with the large volumes of image data that can now be routinely produced. Image segmentation, whereby the contours of the structures of interest are determined, has long been recognized as one of the most important and most difficult step in image analysis. Manual segmentation is time consuming and suffers from both intra- and inter-operator variabilities.

As an alternative, numerous automatic segmentation methods have been developed. However, biological images generally present high noise levels, poor local contrasts and numerous structures or

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artifacts that surround the objects of interest. Consequently, it is not possible to extract the desired contours using fully automatic segmentation methods [1].

In this article, we propose a procedure to implement automatic liver CT image segmentation, which use CNN network of deep learning, and the support of active contour technique as a method for augmentation input training data. All simulations are done by the help of MATLAB 2018b environment.

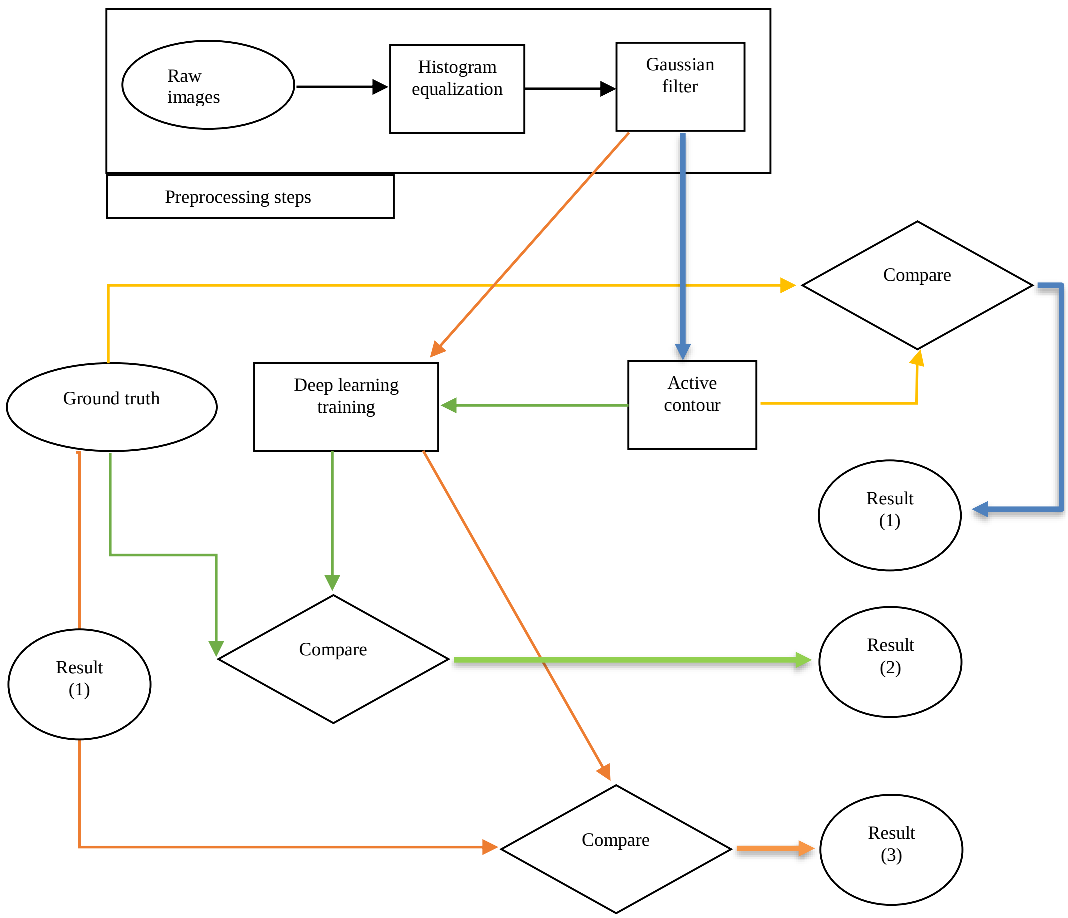

Figure 1: Flowchart of our proposed automatic segmentation procedure, with three different scenarios of result.

2 Methods

2.1 Preprocessing procedures:

Because the CT image is usually low contrast, and it is difficult to distinguish between the object and the background, it is important to preprocess the image before segmentation. Due to noisy, inconsistent and incomplete data, preprocessing plays an important role. It is one of the preliminary steps that are required to acquire the high accuracy of steps. CT and MRI images consist of artifacts;

patient specific and equipment based artifacts; others are ring, staircase and volume effect artifacts. Before analyzing all these are removed by pre-processing procedures.

First of all, we use histogram equalization for the raw images, because CT images are low contrast. Histogram equalization is a technique for adjusting image intensities to enhance contrast.

Results show that the Gaussian Blur technique is to be used in images with high noise and with a Gaussian function of small variance whereas larger variance Gaussian function is more relevant in segmentation of images. So we use Gaussian filter, with the alpha = 1.

2.2 Active contour

Next, we want to reserve the full liver and the neighborhood pixels we have in active contour. For receiving good training result, we just keep the active contour versions which has full pixels of the liver, and delete the versions which the lost liver pixel, because those versions will cause bad prediction.

When we have all good versions of all images of many cases, it's time to start training.

2.3 Deep learning

The architecture we use in this research is a CNN segmentation network, with a down-sampling layer and an up-sampling layer.

After training, we receive a network which can predict and distinguish the liver pixel from the non-liver ones, in a whole new image.

We finish construct a segmentation method at this stage.

We do the research with all three scenarios, respectively.

3 Results

First, we show the results of the preprocessing, from the raw CT image to canny edge detection, steps by steps.

Figure 2: Raw liver CT image.

Figure 3: Image after using histogram equalization

Figure 4: Image after using histogram equalization

Result of active contour images are show as below. With each edged image, we can make many version active contour output result, by changing the size of mask windows from (1:256).

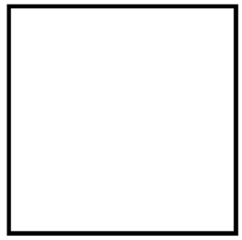

Figure 5: Mask size = 246. All of liver pixels and most of non-liver pixels reversed.

Figure 6: Result of active contour with mask size = 246.

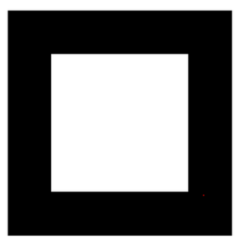

Figure 7: Mask size = 156. All liver pixel reversed, most of nonliver pixel have been removed.

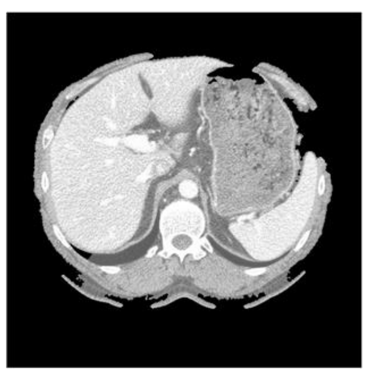

Figure 8: Result of active contour with mask size = 156.

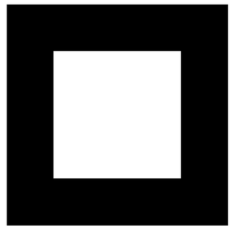

Figure 9: Mask size = 147, with is the threshold of this image. The most non-liver pixels have been removed, while all of liver pixels are reserved.

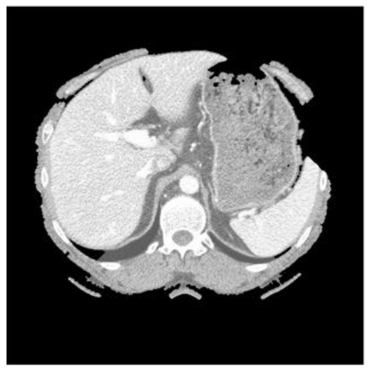

Figure 10: Result of active contour with mask size = 147.

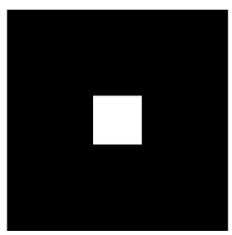

Figure 11: Mask size = 56. A lot of liver pixels have been lost.

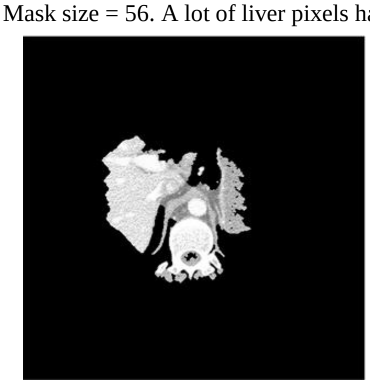

Figure 12: Result of active contour with mask size = 56

For receiving good training result, we just keep the active contour versions which has full pixels of the liver, and delete the versions which the lost liver pixel, because those versions will cause bad prediction.

When we have all good versions of all images of training cases, we begin to train the data.

After training and processing the training and testing data, we compare these result of three scenario in Fig.1 with the ground truth: (1). Only using active contour; (2). Only using deep learning (we use cascade convolutional neural network for training and validating), (3). Using cascade system, which the output of active contour is the input of cascade convolutional neural network.

Validation metric we use are the Sensitivity (True Positive Rate - TPR), Specificity (True Negative Rate - TNR), Precision (False Positive Rate - FPR) and Miss Rate (False Negative Rate – FNR), which are calculated as shown below:

Pixel(i,j) in image	Pixel(i,j) in ground truth	Values
Liver	Liver	TP(i,j) = 1 FP(i,j) = 0 TN(i,j) = 0 FN(i,j) = 0
Non liver	Liver	TP(i,j) = 0 FP(i,j) = 1 TN(i,j) = 0 FN(i,j) = 0
Non liver	Non liver	TP(i,j) = 0 FP(i,j) = 0 TN(i,j) = 1 FN(i,j) = 0
Liver	Non liver	TP(i,j) = 0 FP(i,j) = 0 TN(i,j) = 0 FN(i,j) = 1

Table 1: Confusion matrix for pixel comparation

TPR = sum(TP)/(sum(TP)+sum(FN))
TNR = sum(TN)/(sum(TN)+sum(FP))
TR = TPR+TNR;
Sum : summation operation is calculated with all of the pixels in the images.

Table 2: Our pixel comparation result

	TPR	TNR	TR
Only using active contour	0.1967	1.000	1.1967
Only using deep learning	0.2531	1.000	1.2531
Combining active contour and deep learning	0.4532	1.000	1.4532

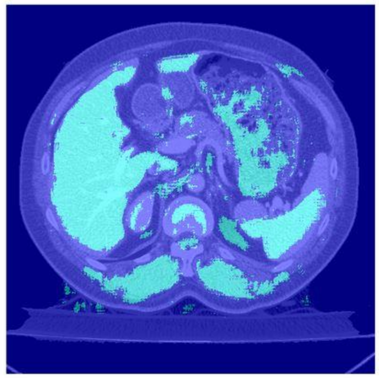

Figure 13: Result image of segmentation using combination of deep learning and active contour.

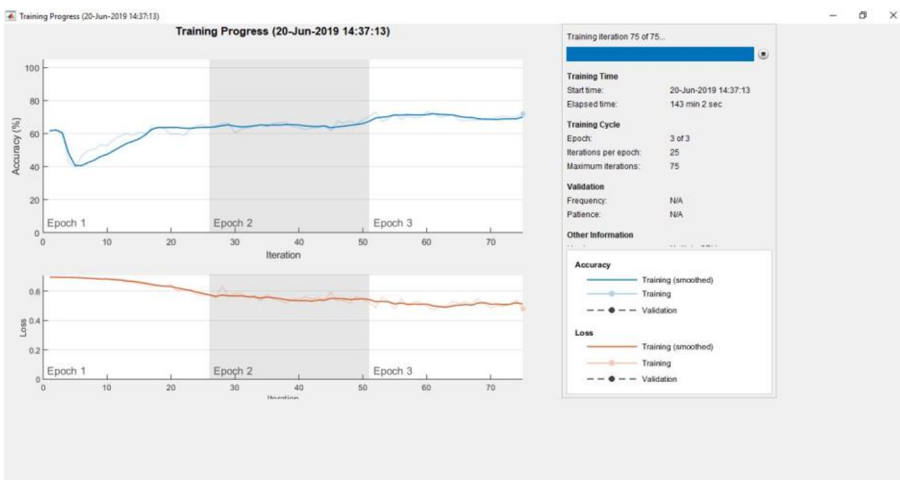

Figure 14: Results of accuracy and loss of training deep learning with normal images

Figure 15: Results of accuracy and loss of training deep learning with active contour multi-version input images

In figure 14 and 15, we show the training progress of two scenarios, for the normal input images, and for active contour multi-version input images, respectively. The accuracy of the case in figure 14 is about 69%, while that in figure 15 is 81%. And the loss function result in figure 14 is 0.5, and figure 15 is lower, 0.35, respectively.

4 Conclusion

In this paper, we proposed an automatic liver segmentation algorithm based on combining active contour as a data enrichment method to be used as input for deep learning network. This could be used as a solution to improve the accuracy of segmentation problem.

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