Automatic Liver Segmentation by Using U-Net

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Abstract- Magnetic resonance imaging (MRI) has superb signal sensitivity to the various physiological response of liver disease. Therefore, with a special technique is used, MRI can easily calculate the percentage of fat in the liver and diagnose the fatty-liver issue. This project was designed to improve the fat-liver diagnosis. First, to obtain the details of image and fat fraction data from the Dicom file, this project implemented the fat-water separation Tool-box in Matlab. The multi-point Dixon method would be used to avoid the streak and improved the fat fraction measurement. Second, this project utilized a ROI method to build a binary mask for the training data. Third, this project used U-Net to generate the model and train the training data to obtain the model weight. Fourth, implementing the model to generate the predictive binary mask and separate the liver from the MRI slice. Finally, this project compared the predictive liver with the real liver and calculated the accuracy.

Keywords : MRI, fat-water separation, Automatic Liver Segmentation, U-Net

I. Introduce

Liver diseases such as cancer, fatty liver disease, and hepatitis seldom cause noticeable signs and symptoms until the situation is very serious. Therefore, there are lots of researches focusing on the early diagnosis of liver diseases. With the development of technology, there are more and more non-invasive imaging techniques such as echocardiography, MRI, CT, PET, and SPECT invented to provide a faster and easier way for liver diagnosis. The advantage of MRI is that it utilizes strong magnetic fields, magnetic field gradients, and radio waves to generate images of the organs in the body. These greatly reduce the risk of diagnosis. Moreover, MRI scans supply clear imaging to survey the detail of the liver.

II. Algorithm

A. Dixon Fat-water Imaging

The multi-point Dixon fat-water separation method, which is based on a graph cut field map estimation algorithm, was implemented to obtain the fat image, water image, and fat fraction image. The fat fraction measurement was reliable with arbitrary echo times. In figure [1] [2], compared to the three point Dixon, the multi-point Dixon improved the fat-water separation image and reduce the streak in the image.

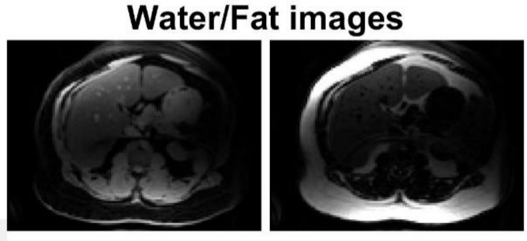


Figure [1] Water/Fat image using three point Dixon

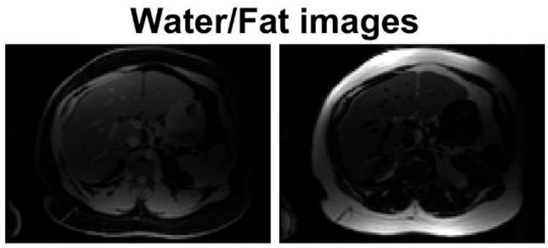


Figure [2] Wat/Fat image using multi-point Dixon

B. ROI

This project used polygon shape ROI to segment the liver from a MRI slice and set the binary mask training data. The points which were chosen would be stored in a cvs file. It also be considered as training data.

C. U-Net

1. U-Net is a convolutional neural network that was developed for biomedical image segmentation. It is composed of various fully convolutional network.
2. In figure [3], it shows that he U-Net consists of three sections, the first section is the contraction. It is composed of various contraction blocks. Each block implements two 3X3 convolution layers followed by a 2X2 max pooling on the input. This section works to extract the features of the input images. The second section is the bottleneck, which connects the contraction layer to the expansion layer. It utilizes two 3X3 CNN layers followed by a 2X2 up convolution layer. The third

section is the expansion (up-sampling layer), which is the most important section. It works similar as the contraction; however, this section of each blocks will convolution the feature maps of the corresponding contraction layer first and then appending to the input.

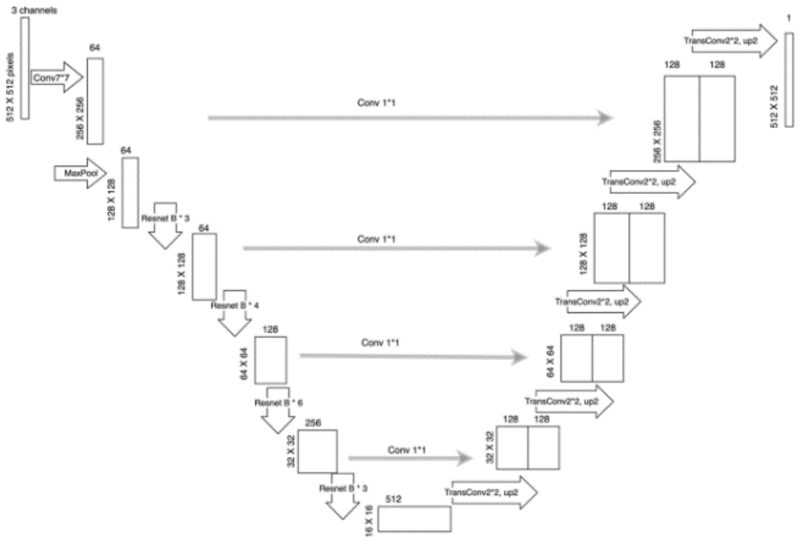


Figure [3] U-Net

3. The advantages of U-Net:
   a. The expansion sections and the convolution channel allow more texture features in the images to be extracted and conveyed.
   b. It can ensure the segmentation results are based on unlost context features.

III. The Flow of the project

Figure [4] is the steps of the automatic liver segmentation.

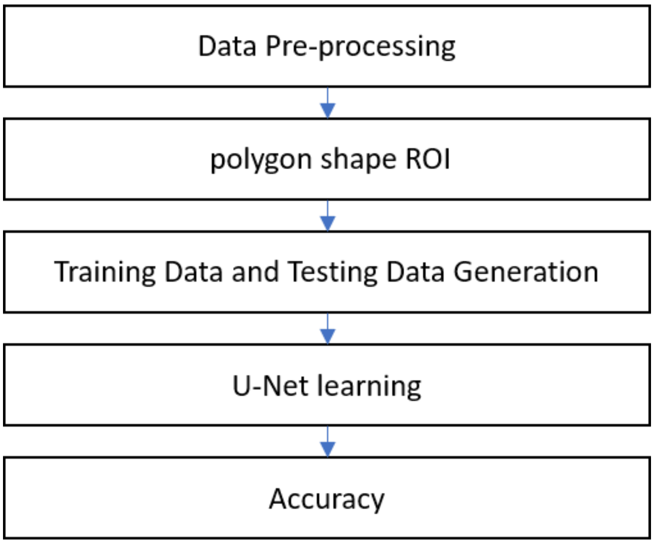
First, this project resized images and implemented the fat-water separation Toolbox in Matlab to pre-processing the data. It will enhance the images' texture features which are useful for liver classification.

Second, this project utilized polygon shape ROI to generate the binary mask for the training data.

Third, this project separated the total dataset into training data and testing data. There were 560 samples for the training dataset and 51 samples for the testing dataset.

Fourth, the U-Net was used for automatic liver segmentation. It will train the training dataset first to create the model weight and then testing the testing dataset to obtain the predictions from the U-Net model.

Finally, comparing the predictions to the real segmentation, observing the predictions segmentation, and calculating the accuracy.



Figure[4]

IV. Result and Discussion

A. Data Pre-processing

This project exploited the read_Dicom function to read the iFeld, voxel size, matrix size, CF, delta TE, TE, B0_dir, files information from the MRI Dicom files and permuted the data for the fat-water separation Tool-box. Subsequently, loading the data into the Tool-box. This project chose the multi-point Dixon to get the water and fat images that is showed in figure [1]. Eventually, using the postprocessing to compute fat fraction map, which is showed in figure [5].

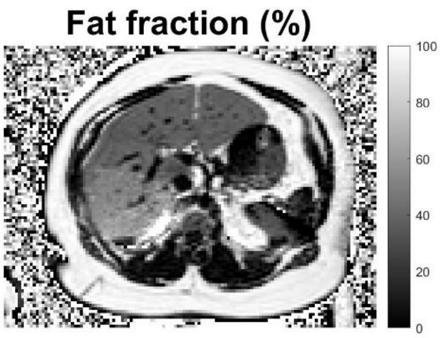


Figure [5] Fat Fraction Map

B. Polygon Shape ROI

This project utilized the polygon shape to create a binary mask.

It set the left button for choosing a point and the right button for defining the ROI area. After choosing the last point and right-click, we got the binary mask and the region of interest which are showed in figure [7][8]. And all of the points showed in figure [6] were saved in the config.pkl file. It would be extracted out and saved in a CSV file for defining the ROI location.

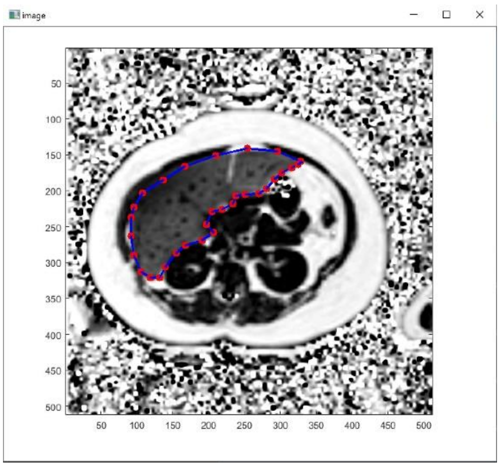
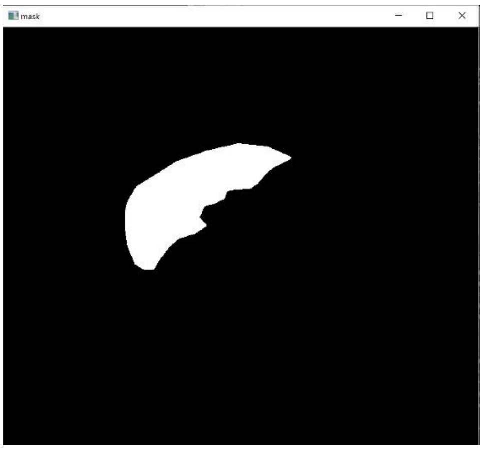


Figure [6] ROI



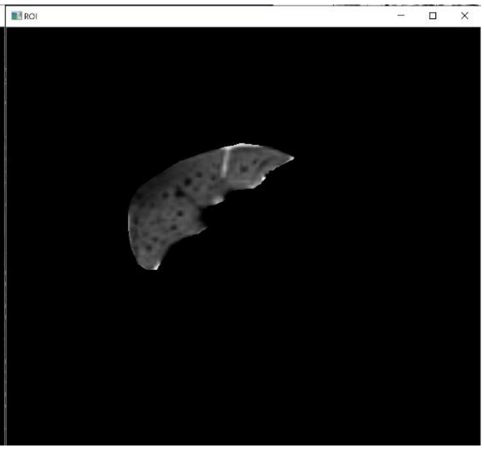


Figure [7] Binary Mask

Figure [8] ROI Liver

C. Training set and U-Net model

1. Training set

   This project defined that the training sample number equaled to 560, batch size equaled to 2, and epoch equaled to 5. Since the steps per epoch should be equal to number of samples in database divided by batch size, it would be 560/2=280.

2. U-Net

The U-Net architecture consists of a contraction path, bottleneck path, and expansion. The contraction path has four blocks where each block is composed of two times of 3X3 2D convolution and one time of 2X2 2D max pooling. The activation function is ReLU. This path will improve the features extraction; however, it may reduce the size of feature maps. The bottleneck path which mediates between the contraction layer and expansion layer consists of one time of 3X3 2D convolution. The expansion path has four blocks where each block contains one time of 2D transposed convolutional layer, one concatenate function, and two times of 3X3 2D convolution. The final block implemented a 1X1 convolution layer to obtain the output segmentation map. The model utilized Adam optimizer what the learning rate is 0.001. In figure [9], it showed that the accuracy of training in each epoch becomes better than the last one.

```
Epoch 1/5
280/280 [==============================] - ETA: 0s - loss: 0.1554 - accuracy: 0.9460
Epoch 00001: loss improved from inf to 0.15540, saving model to unet_model.hdf5
280/280 [==============================] - 10460s 37s/step - loss: 0.1554 - accuracy: 0.9460
Epoch 2/5
280/280 [==============================] - ETA: 0s - loss: 0.1116 - accuracy: 0.9539
Epoch 00002: loss improved from 0.15540 to 0.11157, saving model to unet_model.hdf5
280/280 [==============================] - 10181s 36s/step - loss: 0.1116 - accuracy: 0.9539
Epoch 3/5
280/280 [==============================] - ETA: 0s - loss: 0.0891 - accuracy: 0.9620
Epoch 00003: loss improved from 0.11157 to 0.08915, saving model to unet_model.hdf5
280/280 [==============================] - 9251s 33s/step - loss: 0.0891 - accuracy: 0.9620
Epoch 4/5
280/280 [==============================] - ETA: 0s - loss: 0.0770 - accuracy: 0.9668
Epoch 00004: loss improved from 0.08915 to 0.07698, saving model to unet_model.hdf5
280/280 [==============================] - 10337s 37s/step - loss: 0.0770 - accuracy: 0.9668
Epoch 5/5
280/280 [==============================] - ETA: 0s - loss: 0.0696 - accuracy: 0.9741
Epoch 00005: loss improved from 0.07698 to 0.06961, saving model to unet_model.hdf5
280/280 [==============================] - 9447s 34s/step - loss: 0.0696 - accuracy: 0.9741
```

Figure [9] Epoch=1~5

D. Accuracy

1. This project utilized the single histograms to calculate the accuracy of each segmentation liver. It seems that when pre-processing the MRI slice becomes more texture features, the accuracy of prediction liver segmentation will also become higher.

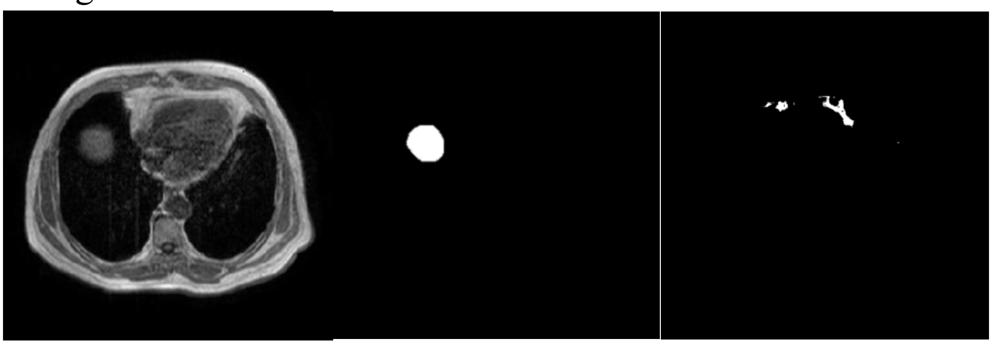


Figure [10] [11] [12]MRI slice Figure, Real liver segment, predict
Accuracy= 0.22262071

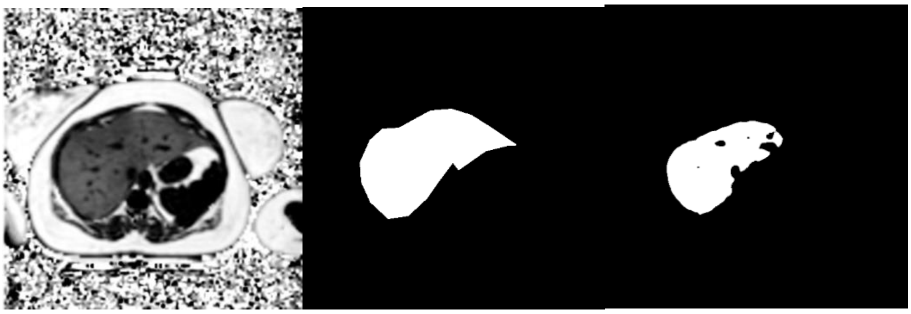


Figure [13] [14] [15]MRI slice Figure, Real liver segment, predict
Accuracy = 0.99984884

V. Summary

The purpose of this project was to investigate the possibility of using machine learning for the automation of liver segmentation in magnetic resonance imaging.
First, this project implemented the fat-water separation toolbox to enhance the texture features in the fat-liver image and generate the fat fraction images. Second, this project used polygon shape ROI to build a binary mask and define the bounds of the liver in the MRI slice. The training data included the binary mask dataset for the model. Third, this project utilized U-Net to establish the model and start to train the data. Since the project only used CPU to train the data, it took around 7 hours to finish the 560 training samples. Finally, this project applied the model to test the rest data and created the prediction liver mask to separate the liver from the MRI slice. The single histogram method was used to calculate the accuracy of the segmentation liver.

As future work, inserting a GPU to the design to speed up the model learning. Moreover, put more texture features method into the design to improve the classification.

References

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[2] https://kharshit.github.io/blog/2019/08/09/quick-intro-to-semantic-segmentation

[3] https://github.com/BUAAXZzz/Unet_liver_seg

[4] https://www.csie.ntu.edu.tw/~fuh/personal/LiverSegmentationwith2DUNet.pdf