Tool for Medical Data Processing and 3D Model Reconstruction of Tissues in Blender

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Introduction

BDICOM tool is a blender add-on that provides users with the ability to read medical data such as images from computed tomography (CT) and magnetic resonance imaging (MRI) in DICOM format and visualize the human anatomy in 3D. Data can be processed and used to create the 3D reconstructed model by utilizing Poisson surface reconstruction. The pipeline of Bdicom functions is shown in Figure 1. The user can further work on the 3D reconstructed mesh with the existing Blender's functionalities.

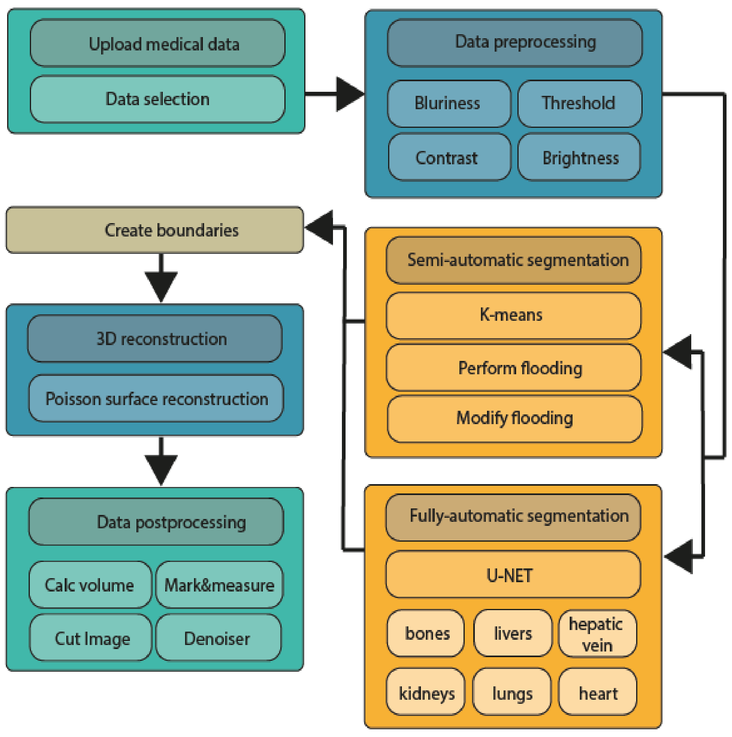

Figure 1: BDICOM Add-on Flow Diagram.

The add-on is based on the organ segmentation. Our tool allows the use of **semi-automatic** and **fully-automatic segmentation** methods. These methods are implemented to **recognize bones, abdominal organs, tissues** and even **hepatic liver vessels**.

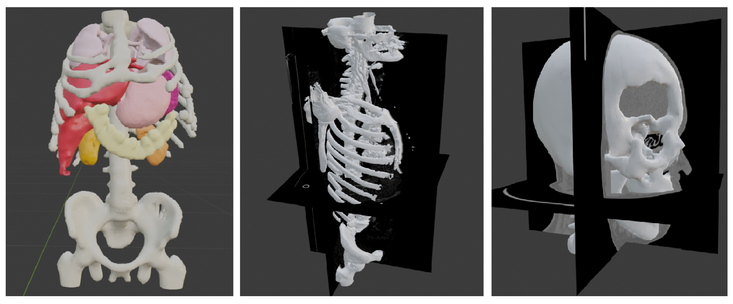

Figure 2: 3D reconstruction of organs and tissues with correspondence to axial, sagittal, and coronal view.

The challenging task is to segment hepatic vessels inside the liver by using fully-automated methods. The problem is caused by low contrast resolution between the vessels and the liver area. We present the state-of-the-art approach which is based on the convolutional neural network architecture.

Data Pre-processing

For livers, we use Constrast Limited Adaptive histogram equalization (CLAHE) to improve contrast with limited amplification to suppress the image noise. For veins, we use the pipeline of functions which are shown in the Figure 3 [1].

Once the livers and veins are contrast enhanced adequately, data augmentation technique are applied to artificially expand the size of the training and test dataset by creating rotated, height-width shifted, zoomed and along an axis distorted versions of images.

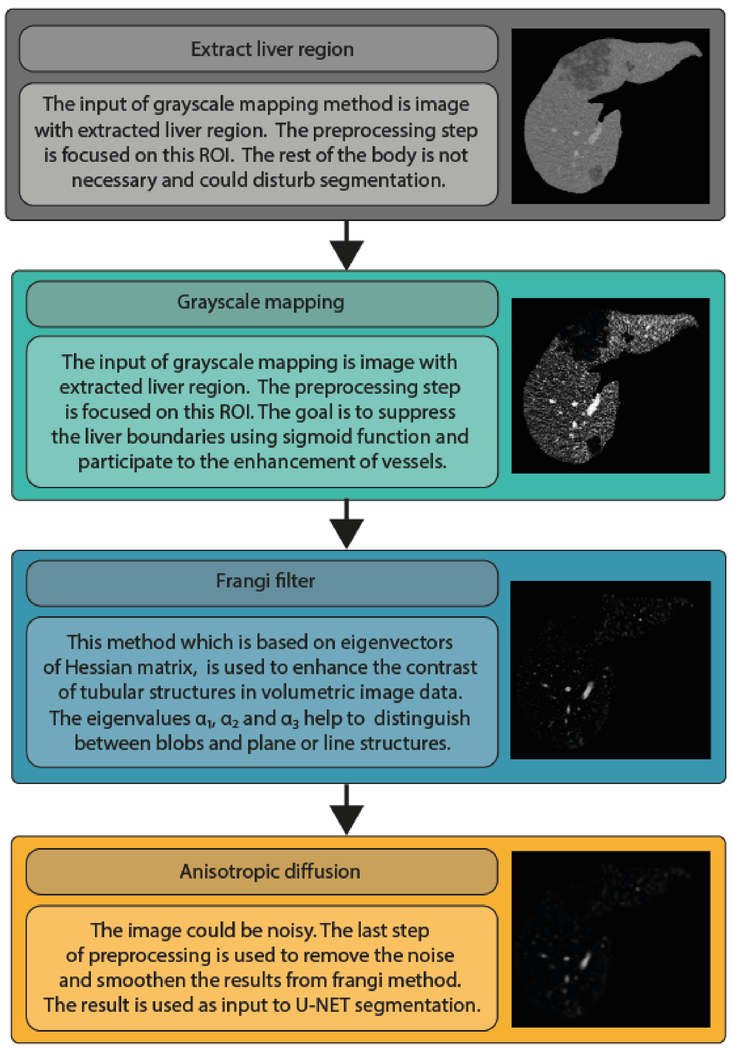

Figure 3: Flow Diagram of vascular system pre-processing [2]

Segmentation

We provide a fully automatic segmentation algorithm based on the U-net (2-D DenseUNet) architecture [3]. First, the liver segmentation is done. We remove the non-liver area which could have negative influence on subsequent processes. The result of this operation is used for hepatic vessel segmentation.

Using similar deep learning architecture we can segment other internal tissues as well.

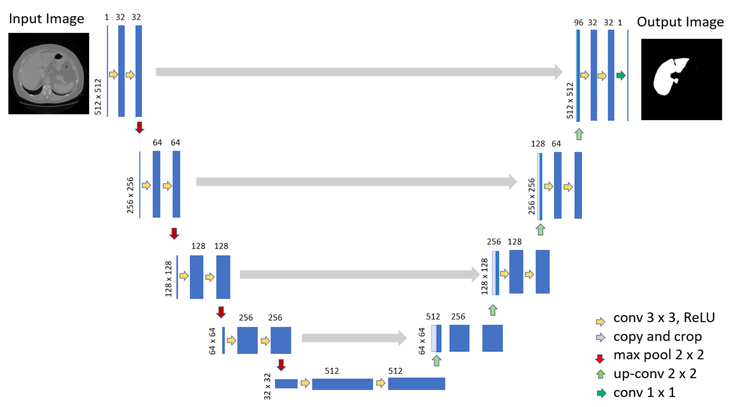

Figure 4: Our U-net Architecture for segmentation. The convolutional layer uses RELU activation function, except the final layer which uses softmax function to classify target voxel. The model uses Adam optimizer to reduce the losses

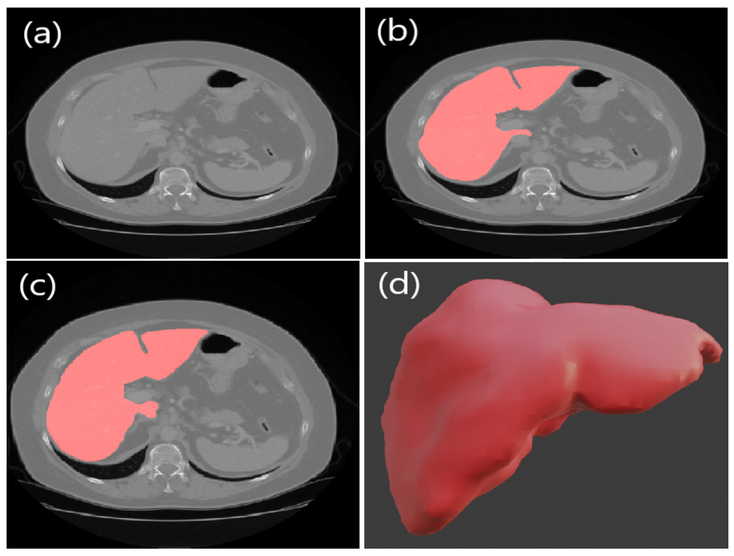

Figure 5: Liver Segmentation: (a) Original CT Slice, (b) Ground Truth Liver, (c) Predicted Liver, (d) 3D Model

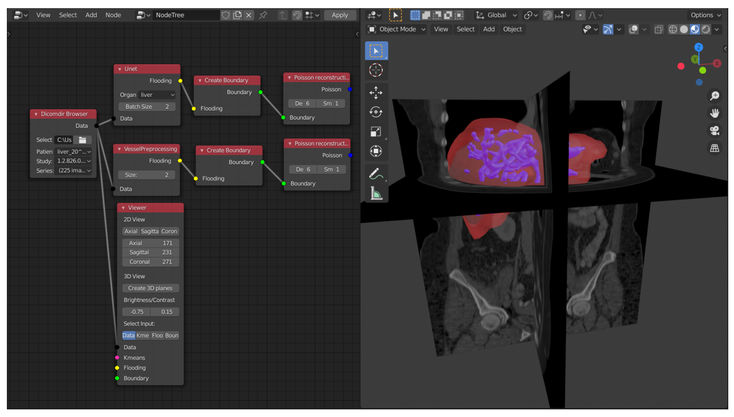

Figure 6: 3D Reconstruction of Liver & Vessels

Parallelization

We use OpenMP for multithreading of selected C++ algorithms.

For training the neural networks we utilize GPU acceleration to achieve faster training times.

Results

We tested the proposed algorithm on the 3DIRCADB dataset for liver and vein segmentation. From these 20 patients, we took 19 patients as training and the remaining one patient as test data to maximise the training dataset for both liver and vein segmentation.

For livers

ID	Dice Coefficient	Sensitivity	Precision
18	0.913	0.861	0.972
19	0.942	0.918	0.968
20	0.957	0.989	0.926

Table 1: Quantitative analysis of Liver Segmentation results using IRCAD dataset.

For veins:

ID	Dice Coefficient	Sensitivity	Precision
18	0.577	0.643	0.523
19	0.567	0.569	0.565
20	0.576	0.455	0.455

Table 2: Quantitative analysis of Vein Segmentation results using IRCAD dataset.

Conclusion & Future Work

This tool provides effective segmentation techniques to segment various body organs. However, there are also some drawbacks in our method. In the future, we will develop more effective vessel enhancement, better vessel segmentation and separate portal vein and venous system.

Acknowledgements

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