Cardiac fat analysis in low-dose CT with deep learning

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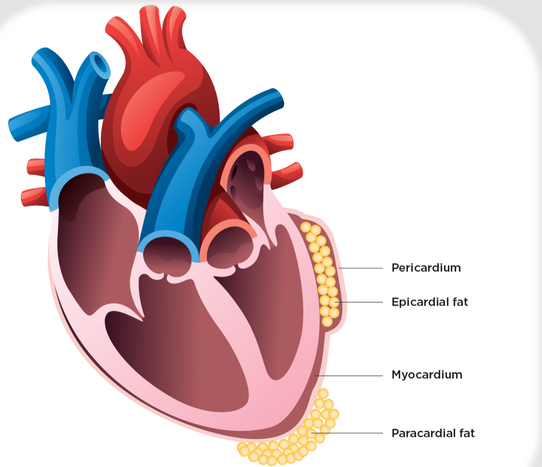

Source: El Khoudary, et al., Journal of the American Heart Association, 2017

Introduction

Epicardial adipose tissue (EAT) locates between the pericardium and the myocardium. It has various distributions and is commonly found on the heart surface, in the atrioventricular and interventricular grooves, in the right ventricle lateral wall, and near the coronary arteries. In many studies, it has been considered as a source of inflammatory mediators and cytokines and EAT volume has been associated with coronary artery disease. EAT volume has been evaluated as an imaging biomarker for the diagnosis of pathological states such as metabolic syndrome and visceral obesity.

Although radiologists can measure the EAT volume manually or semi-automatically, it is time-consuming and not feasible for a large clinical practice. Thus, automated EAT volume quantification methods are proposed to solve this problem. Clinically, most EAT volume quantification is measured on non-contrast or contrast cardiac computed tomography (CT). In this project, we utilize non-contrast CT (NCCT). There are many challenges in the EAT segmentation in NCCT. Compared to other cardiac structures, EAT has an irregular and noncontinuous shape and spatial distribution. Due to the anatomical structure of the heart, there are other fat tissues like mediastinal fat that locates outside of the pericardium.
In CT images, these structures look like EAT and locate very close to EAT. The crucial reference to distinguish EAT from the other similar structures is the thin layer of pericardium. Compared to contrast CT, NCCT has much lower contrast on the coronary structure and has a different thickness. Therefore, segmentation and quantification of EAT in NCCT is more challenging.

In this project, All CTs are from the coronary artery calcium CT scans of the Risk Or Benefit IN Screening for CArdiovascular diseases (ROBINSCA) trial provided by the University medical center Groningen (UMCG).

In the following blocks, I show my past works and the ongoing work in this project.

Data collection

A subset of 154 NCCT were selected and annotated by an experienced radiologist using the open-source medical imaging processing software 3D Slicer. Two kinds of label maps are obtained as shown in: (1) the region inside, (2) EAT volumes. To reduce the workload, all the annotations are made in the axial view semi-automatically. The radiologist annotated the region inside the pericardium on some 2D slices, and the annotations in between were generated automatically with the 'fill between slices' effect of the 3D Slicer. Finally, the radiologist checked and corrected the generated annotations. To get the EAT, the thresholding of -190HU to -30HU is applied, and then morphological operations of erosion and dilation are used to reduce the noise.

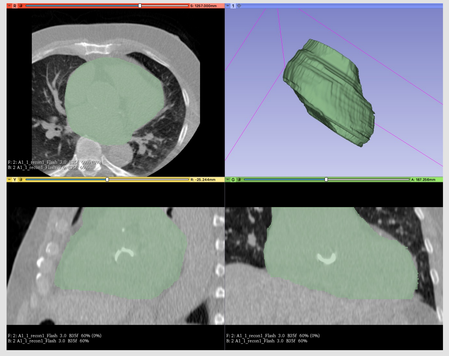

Figure 1. 3D slicer user interface for annotation

Anatomy-aided deep learning for medical image segmentation: a review

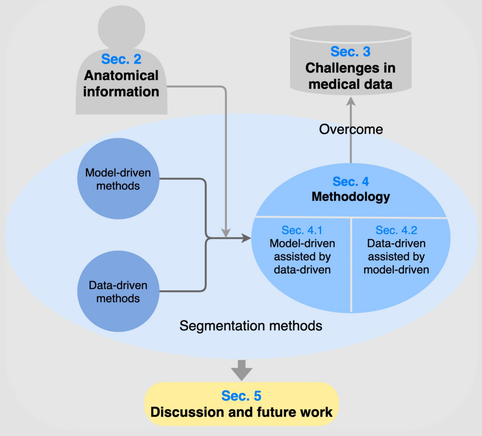

Figure 2. Overview of the review paper. **published in Physics in Medicine and Biology.**
Liu L, Wolterink JM, Brune C, Veldhuis RNJ. (2021) Anatomy-aided deep learning for medical image segmentation: a review. Physics in Medicine & Biology, **66** 11TR01. https://doi.org/10.1088/1361-6560/abfbf4

Using the U-Net family for EAT segmentation and quantification in NCCT

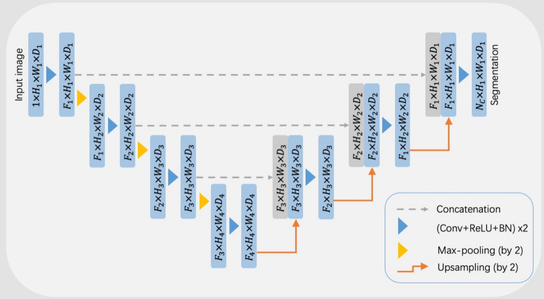

Figure 3. The 3D U-Net architecture. Blue boxes are feature maps, while grey boxes are concatenation maps.

Considering representativeness and diversity, we selected four methods from the U-Net family: 3D U-Net, 3D attention U-Net, U-Net++, and the recent deep attention U-Net (DAU-Net) by He et al. as the EAT segmentation model. For evaluation, four-fold cross-validation and hold-out tests are used. Quantitative analysis of EAT volume is shown with the Pearson correlation and the Bland-Altman analysis.

Table 1: Cross-validation results of the selected models.

Model	Label type	Dice (%)	mIoU (%)	sensitivity (%)	specificity (%)	correlation
3D U-Net	Pericardium	74.90±1.30	60.92±1.47	77.67±2.15	99.53±0.00	0.7588
	Epicardial fat	59.04±0.92	42.45±0.74	70.99±2.42	98.96±0.00	0.5648
3D attention U-Net	Pericardium	68.52±6.38	56.62±5.97	70.50±10.22	99.69±0.00	0.2085
	Epicardial fat	54.94±6.43	41.56±4.78	57.34±9.92	99.47±0.00	0.3883
DAU-Net	Pericardium	80.06±0.50	67.30±0.91	91.80±0.46	99.34±.00	0.8448
	Epicardial fat	71.91±0.49	56.58±0.69	83.01±0.28	99.17±0.00	0.8596
U-Net++	Pericardium	**86.16±0.23**	**75.97±0.51**	**88.31±0.55**	**99.72±0.00**	**0.9123**
	Epicardial fat	77.42±0.71	63.78±0.90	84.61±1.61	99.47±0.00	0.7303

Table 2: Hold-out test results of the selected models.

Model	Label type	Dice (%)	mIoU (%)	sensitivity (%)	specificity (%)	correlation
3D U-Net	Pericardium	74.42±1.37	60.37±1.57	72.95±2.67	99.64±0.00	0.6661
	Epicardial fat	63.94±1.20	47.84±1.20	69.83±2.17	99.22±0.00	0.6293
3D attention U-Net	Pericardium	74.99±4.79	63.48±4.36	80.29±7.27	99.57±0.00	0.5120
	Epicardial fat	55.39±5.26	41.32±3.96	60.11±9.39	99.35±0.00	0.1386
DAU-Net	Pericardium	82.33±0.39	70.43±0.80	90.11±0.45	99.49±0.00	0.8445
	Epicardial fat	72.13±0.40	56.78±0.61	82.69±0.20	99.21±0.00	0.8047
U-Net++	Pericardium	**87.99±0.12**	**78.71±0.30**	**91.45±0.17**	**99.72±0.00**	**0.9606**
	Epicardial fat	80.18±0.20	67.13±0.39	81.47±0.43	99.64±0.00	0.9405

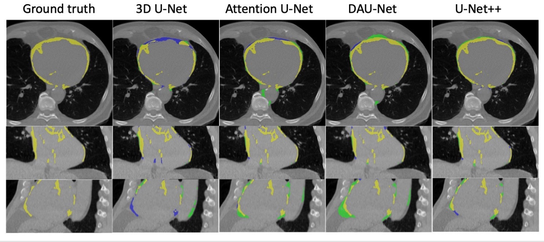

Figure 4. Visualization of segmentation results trained with pericardium masks. The first row shows the segmentation in axial view, the second row is for the coronal view, and the third row is for the sagittal view. In the segmentation results, the true positive is highlighted in yellow, false positive is highlighted in green, and false negative is highlighted in blue.

Generally, compared with the model trained with epicardial fat labels, the models trained with pericardium labels show better results. The state-of-the-art deep learning method U-Net++ outperforms the other methods. DL-based methods have the potential to perform better for EAT segmentation in NCCT.

Fourier shape descriptors in deep learning for EAT segmentation in NCCT

The anatomical information of the pericardium shape/contour is the key information to segment EAT. There are two ways to use this information: (1) loss function, (2) physics-informed deep learning. Now, pixel-wise loss functions like cross entropy loss and dice loss are commonly used in medical segmentation. Recently, shape descriptors (volume, centroid, average distance to the centroid, and the length of the boundary) represented by shape moments to replace the pixel-wise loss function and obtained surprisingly good performance. Our idea is to use the Fourier-based shape descriptors which can encode the shape of two-dimensional objects in the loss function.

A shape can be described by several Fourier descriptors and the original shape can be recovered from the inverse Fourier transform. Fourier shape descriptors are defined as:

$$u_n = \frac{1}{N}\sum_{t=0}^{N-1} s(t)\exp\left(\frac{-j2\pi nt}{N}\right), \qquad n = 0,1,\dots,N-1$$

Where s(t) is a shape signature formula that representing two dimensional areas or boundaries. Commonly used shape signatures includes complex coordinates, shifted coordinates, centroid distance, curvature signature, and cumulative angular function. Here, we the shifted coordinates representation as an example:

$$s(t) = [x(t) - x_c] + i[y(t) - y_c]$$

$\{t|t \in C\}$ are the pixels on the contour C sorted clock-wisely. The Fourier transform generates a vector of N shape descriptors, where is the number of pixels on the boundary (usually 300 to 500). To reconstruct the original shape, we could use all the shape descriptors but not necessarily. Below we visualize the reconstruction with number of p shape descriptors.

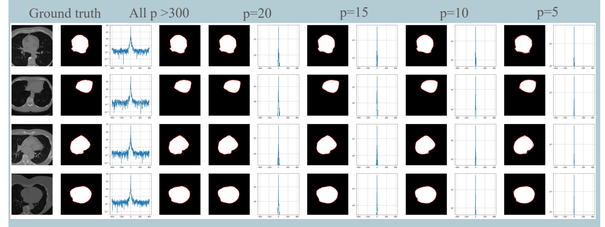

Figure 5. Reconstruction of the pericardium contours with p Fourier shape descriptors. The plots show the absolute value of the used Fourier descriptors.

So far, we are working on this work. There will be more details, further experiments and ideas expected soon.

Future plan

Project 5: Smooth shells from optimal transport in deep network for EAT segmentation in NCCT

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