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## Deep learning for vascular segmentation and tissue characterization in CT images

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# 6

## Summary and future work

Coronary plaque detection and intrahepatic anatomy analysis are two important topics in coronary artery disease diagnosis and preoperative planning for liver surgery based on CTA images. In this thesis, we aimed to develop novel deep learning-based approaches that address key challenges and substantially advance the state-of-the-art in both areas. In this chapter, we summarize the previous chapters and discuss potential research directions for future work.

### 6.1 Summary

We present deep learning solutions to address the three specific aims: non-invasive coronary plaque detection (Chapter 2), 2D model-based continuous liver vessel segmentation (Chapters 3 and 4), and lastly, vessel prior-free Couinaud liver segmentation (Chapter 5).

In **Chapter 2**, we focus on the detection and characterization of coronary plaque in CTA images, aiming to reduce the need for invasive imaging modalities in patients. The ground truth obtained from the invasive NIRS-IVUS modality was registered to the corresponding CTA images. The registered labels on the CTA images were used as targets for training the proposed deep learning models. We designed two convolutional neural network (CNN)-based methods to predict the plaque occurrence angle in the cross-sectional view. Both methods employ a 2.5D approach to introduce contextual information along the longitudinal direction of the coronary arteries. The first method is developed on top of a Dense U-Net, which is used to fit pie-shaped binary masks for both lipid-rich and calcified plaques. The predicted masks represent the plaque occurrence areas in the cross-sectional view. The angular range of the area is calculated through an additional post-processing step and visualized in a spread-out view, similar to the chemogram view used in the NIRS modality. Another method is developed on top of a Mask R-CNN architecture. Unlike the first method, this approach is applied to images in a polar coordinate system. The start and end angles of plaques can be directly predicted using bounding box regression. The proposed methods are trained and validated on an in-house dataset consisting of 64 patients, achieving a sixfold increase in the median F1-score compared to the conventional HU-based method at the lesion level for detecting lipid-rich plaques.

**Chapter 3** focuses on improving the continuity of the segmented liver vessel tree. We leverage both a graph attention mechanism and a diffusion model to facilitate continuous and complete liver vessel segmentation. To incorporate the vascular graph into the diffusion model, the ground truth vessel masks in each batch are transformed into graphs composed of nodes and edges, explicitly representing vascular connectivity. Edge weights can be learned through graph attention layers, which serve as a dynamic matrix representing the affinities between nodes distributed along the vessels. The weighted node features can be injected into the diffusion model as a condition to encourage the generation of continuous vessel segmentation. The proposed model is evaluated on two public datasets and outperforms other state-of-the-art medical segmentation methods in terms of Dice coefficient and connectivity metrics.

**Chapter 4** presents a top-k MIP prior, which preserves more depth information than the original MIP, for liver vessel segmentation. The proposed top-k MIP prior represents vessel connectivity through a sequence of 2D projection views, while preserving vessel diameter information using the top-k maxima of CT intensity. To learn the mapping between the top-k MIP and the integral projections of the ground truth vessel mask, we employ a 2D latent diffusion model. The top-k MIP prior is used as the condition for the latent diffusion model, which generates integral projections of the vessel tree. The generated integral projections can be reconstructed using the filtered back-projection method commonly employed in the CT reconstruction field. The evaluation results demonstrate that the proposed prior contributes to continuous vessel segmentation and achieves competitive performance compared to other medical segmentation baselines.

**Chapter 5** focuses on Couinaud liver segmentation without the use of explicit vessel guidance. To compensate for the absence of explicit vascular structures, we introduce 3D graph reasoning to dynamically learn intrahepatic anatomy. Additionally, to preserve the physical resolution of the CT images, we adopt a point-based architecture for this task. The learned implicit intrahepatic anatomy can serve as a replacement for explicit vessel priors, providing embeddings for the point-based model. The proposed point-based method with graph reasoning outperforms other point-based baselines in both Dice coefficient and surface distance, while eliminating the need for liver vessel priors in Couinaud segmentation.

## 6.2 Discussion and future work

The overarching aim of the thesis was to develop novel deep learning-based approaches that address key challenges and substantially advance the state-of-the-art in both areas. This was realized by developing automatic methods for non-invasive coronary plaque detection and intrahepatic anatomy analysis, including liver vessel segmentation and Couinaud liver segmentation. First, coronary plaque detection was explored

in Chapter 2. We develop two deep learning methods to detect and characterize coronary plaques in cross-sectional CTA images. Although the proposed methods outperform the conventional HU-based approach in quantitative metrics, several challenges remain in coronary plaque detection. The overlapping HU range between lipid-rich plaques and the surrounding myocardial tissue makes accurate distinction of the plaque area challenging. Calcified plaques with high intensities can also cause artifacts, resulting in low-attenuation shadows that resemble the appearance of lipid-rich plaques. Additionally, blooming artifacts caused by implanted metal stents present another challenge, as they can obscure plaque features. Current methods do not perform well on artifact-affected CTA images; therefore, coronary arteries with implanted stents were excluded from the experiments. Most of the existing challenges are closely related to CTA image quality—specifically, whether the features of different plaque types are clearly distinguishable. Although the results presented in Chapter 2 demonstrate that deep-learning methods have the potential to extract more implicit features from CTA images and achieve more accurate plaque detection than the conventional HU-based method, essential improvements will rely on advanced CT imaging techniques, such as photon-counting CT (PCCT) [1]. Developing deep-learning methods based on the PCCT modality will be an important direction for future research.

In Chapters 3,4 and 5, Intrahepatic anatomy analysis was investigated. Chapters 3 and 4 primarily address continuous liver vessel segmentation, while Chapter 5 focuses on Couinaud segmentation without using vessel priors. Both liver vessel segmentation and Couinaud segmentation are essential steps in the preoperative planning of liver surgery. However, the challenges of these two tasks differ: connectivity is the main concern for vessel segmentation, while accurate boundary determination is key for Couinaud segmentation. The two proposed methods in Chapters 3 and 4 start from different image views (cross-sectional and projection views) and employ diffusion model-based architectures to improve the connectivity of the segmented vessel tree. Unlike most existing segmentation methods, which are typically based on deterministic models, diffusion models can learn the underlying data distribution and intrinsic class characteristics. We utilize this advantageous property of the diffusion model in our vessel segmentation task. To better control the stochasticity of the diffusion model and guide the generation toward the desired output, we use graph attention as a condition in Chapter 3 and mimic the CT reconstruction process in Chapter 4. These chapters demonstrate that these strategies are all beneficial for enhancing vessel connectivity in 3D. The quantitative and qualitative results show that vessel connectivity can be significantly improved compared to the other advanced segmentation methods. However, current methods have two main limitations. First, the proposed models are supervised, and their performance can be adversely affected

by inaccurate vessel annotations. Second, inference with diffusion models is more computationally expensive compared to other deterministic segmentation methods. Thus, future work should aim to overcome these two limitations. Weakly supervised methods may help mitigate the negative impact of inaccurate vessel annotations. Additionally, developing more advanced mathematical frameworks for diffusion models could improve the efficiency of both training and inference.

Couinaud segmentation, the second focus of intrahepatic anatomy analysis, also faces the challenge of inaccurate vessel annotations, as conventional methods used in clinical practice rely heavily on vessel priors to determine the boundaries between liver segments. This challenge is addressed by our proposed prior-free method presented in Chapter 5. We adopt graph reasoning to learn implicit intrahepatic anatomy instead of relying on explicit liver vessels. Consequently, the proposed method is independent of vessel annotation quality and eliminates the need for a labor-intensive vessel annotation process. However, neither the proposed method nor the baseline methods that were compared can handle livers with large tumors effectively. This is because parts of the intrahepatic structures are deteriorated by the tumor, making it difficult for the neural network to capture anatomical features in the tumor-occupied regions. Therefore, future research could focus on strategies to compensate for missing anatomical structures. Enhancing the learning of long-range dependencies could be a potential solution, allowing the tumor-occupied regions lacking anatomical features to be associated with neighboring tumor-free regions.

All the chapters in this thesis are centered on the two main topics of coronary plaque detection and intrahepatic anatomy analysis based on CTA/CT images. Although all the proposed methods are developed based on the CT modality, they can potentially be applied to similar clinical tasks using other imaging modalities.

### **6.3 General conclusions**

In conclusion, this thesis proposes deep learning methods for two important clinical topics: noninvasive coronary plaque detection and intrahepatic anatomy analysis based on CTA/CT images. Specifically, we first explore the mapping of plaque features between invasive images and noninvasive CTA images in the cross-sectional view, achieving more accurate and finer angle-wise plaque detection. Moreover, we efficiently leverage the advantages of different models such as diffusion models, graph neural networks, and point-based models, and adapt them appropriately to facilitate continuous liver vessel segmentation and eliminate the need for vessel priors in Couinaud segmentation. All deep learning methods proposed in this thesis have been validated both quantitatively and qualitatively, demonstrating superior performance compared to other state-of-the-art baselines.

## References

- [1] A. Meloni, F. Frijia, D. Panetta, et al. “Photon-counting computed tomography (PCCT): technical background and cardio-vascular applications”. In: *Diagnostics* 13.4 (2023), page 645.