A Hybrid Approach for Coronary Artery Anatomical Labeling in Cardiac CT Angiography

Chen Zhou
School of EECS, Peking University
Email: zhouch258@pku.edu.cn

Abstract. Automated anatomical labeling plays an essential role in the effort of developing a computer-aided diagnosing system for coronary artery diseases. The large variation between individuals, presence of vascular stenosis or blockages, and possible image degradations makes the problem extremely challenging. In this paper, we propose a hybrid approach that combines the strength of traditional rule-based methods and recent deep learning methods, ensuring interpretability and consistency of the labeling process while being capable of learning parameters in a data-driven scheme. Our method is composed of two major components. First, we present our method of artery tree building from possibly noisy initial segmentation. The proposed algorithm links missing vessel segments while reducing noise, resulting in a complete and clean centerline based artery tree representation. Next, our labeling algorithm combining gated graph convolutional network (GGCN) and logical rules is elaborated. Experiments have demonstrated encouraging results both for completeness of artery tree building and accuracy of anatomical artery labeling.

1. Introduction
Coronary computed tomography angiography (CCTA) is a widely used imaging modality for diagnosing coronary artery diseases (CADs), providing detailed information about the anatomy of the coronary arteries. In practice, radiologists and physicians report pathological areas along with their anatomical locations, following established medical guidelines (E.g. the guidelines developed by the Society of Cardiovascular Computed Tomography (SCCT) [1] or the American Heart Association (AHA) [2]). For a computer-aided diagnosis system, such a capability of correctly identifying anatomical locations would also be essential. On one hand, it facilitates the diagnostic process for radiologists and cardiologists. On the other hand, the information is necessary for a number of subsequent applications, including automatic medical report generation and visualization.

In this work, we follow the SCCT guideline [1] for anatomical labeling of the coronary arteries. The coronary arteries are composed of two major parts, i.e., the left and right sub-trees, both originating from the aorta. The left sub-tree usually consists of three main arteries, i.e. left main (LM) artery, left anterior descending (LAD) artery and left circumflex (LCX) artery. Multiple side branches may derive from the main arteries, e.g. left ramus-intermedius (RI), obtuse margin (OM) from LAD, and diagonal artery (D) from LCX. The main artery of the right sub-tree is the right coronary artery (RCA), with common side branches such as right posterior lateral branches (R-PLB) and right posterior descending artery (R-PDA) [3,4].

Existing works have tackled the problem in different ways. Earlier works solve the problem by registration techniques or by manually defined logical rules. [5,6] first identify the main arteries (LM,
LCX, LAD, RCA) by registering the main branches to a pre-built atlas model, and then side branches are labeled and refined by manually defined rules. These methods are vulnerable to large individual variations, and have been validated only on relatively small datasets (less than 100 samples). Recent works have approached the problem utilizing deep learning methods. [7] proposed TreeLab-Net, utilizing multi-layer perceptron networks to encode features of vessel segments, and further exploits bidirectional tree-LSTM [8] to aggregate and pass information through the artery tree. The very recent work of Yang et al. [9] proposed to use graph convolutional network (GCN) to pass information across the artery tree. While deep learning methods has demonstrated clearly superior performance, challenges still remain: Annotating the ground truth requires tedious labor from experienced physicians, rendering the ground truth acquisition process time-consuming and expensive. Besides, the dependencies between anatomical labels, which are essential for consistent labeling, are not explicitly enforced.

In this paper, we present a hybrid method that combines the advantages of rule-based methods and deep learning methods to solve the above-mentioned problems. First, we present our method of artery tree building from possibly noisy initial segmentation. Aiming at a complete and noise-reduced artery tree, our proposed algorithm efficiently links missing vessel segments while reducing noise. Next, our labeling algorithm combining gated graph convolutional network (GGCN) and logical rules is detailed. Experiments have demonstrated encouraging results both for completeness of artery tree building and accuracy of anatomical artery labeling.

In summary, the contributions of this paper are as follows:
- We propose a hybrid method for anatomical labeling, combining the advantages of traditional rule-based methods and deep learning methods. It ensures interpretability and consistency of the labeling process, while enabling parameter learning in a data-driven scheme.
- We develop a complete and robust pipeline. Starting from possibly noisy segmentation, our method first robustly builds a centerline-based artery tree representation, and then graph convolutional network combined with logical rules is utilized for consistent, robust branch labeling.
- We collected a large dataset consisting of 350 patients, and demonstrate state-of-the-art performance.

2. Methodology
In this paper, we assume that the segmentation of the coronary arteries has been obtained by existing methods, e.g. the tubular structure segmentation method of [10]. First, our tree tracing process robustly identifies the artery tree topological structure from the segmentation result. Next, we combine graph convolutional network and logical-based rules to label the anatomical artery tree.

2.1. Artery Tree Tracing
In this section, we present our method of building structured artery trees given the initial segmentation result. Our method is capable to cope with possibly noisy or partially broken segmentation. Stated succinctly, our artery tree tracing method is composed of three steps: centerline extraction, tree tracing, isolated vessel linkage and noise removal. Fig. 1 demonstrates the overall process.

Centerline Extraction. We first extract the centerlines utilizing the thinning-based method of [11]. The centerlines are ensured to preserve the connectivity of the original segmentation, but when the input segmentation is non-perfect, the results can be noisy, non-smooth, and may contain bogus branches or loops.

Tree tracing. The extracted centerlines are in the form of unstructured point cloud, and in this step, the point cloud is processed to build a structured artery tree. First, the starting points of the left and right sub-trees are identified. Utilizing the fact that the aorta and the artery vessels drastically differ in radius and size, morphological opening on a down-sampled mask eliminates the relatively thin artery vessels and preserves the aorta. Centerline points closest to the aorta are identified as starting point candidates and are used as roots for tree tracing. Next, the artery tree is built by graph traversal through the point cloud. Bogus connectivities are detected by heuristic rules (e.g. thick vessels joined
by a very thin, short vessel, and by setting large traversal penalties to these points, loops caused by bogus connectivities can be correctly broken into trees. In Fig. 1, b) shows intermediate results of centerline extraction and tree tracing, d) shows an example of loop ambiguity revolving (magenta box).

**Isolated vessel linkage and noise removal.** In real world applications, various factors including vessel blockage (occlusion), motion artifacts, veins close to arteries, etc., cause broken vessel segments and bogus branches. The possibly broken vessel segments could be identified by detecting vessel segment ends in proximity, and linked by line segments.

Figure 1. Artery tree building.

This figure demonstrates the process of our artery tree building algorithm. a) The input segmentation mask. b) The initially extracted centerlines and artery trees. c) The final artery tree after post-processing. d) Zoomed in views of highlighted areas in c), in each colored box, the results before and after our hybrid processing algorithm are compared. The red and green boxes show results of tree linkage, the magenta box shows our algorithm resolves loops, and the blue box shows elimination of bogus branches. Best viewed in color.

However, the naïve linkage doesn’t respect natural shapes of arteries nor image information, and may result in problems in subsequent applications such as CPR image generation. Instead, we dump information from the segmentation network. We add a prediction branch, parallel to the segmentation-prediction branch, to predict a signed distance map (SDM) inside the segmentation. During training, the SDM can be readily computed by applying distance transform on the ground truth segmentation, and during inference, the local maximums of the SDM corresponds to the centerline of the vessel. The graph traversing weight from p to q is defined by scaling and inverting SDM values: \( w(p,q) = 1 - \frac{SDM(q)}{\max(SDM)} \). The broken vessel segments can then be connected by shortest path tracing in a similar manner of the Dijkstra’s algorithm.

The bogus branches are eliminated by branches with small sizes, to avoid eliminating true branches with small sizes, we also check whether the branch is visible from the main artery centerline, i.e. whether the straight lines connecting branch ending and a range of points on the main artery centerline
are all in the segmentation mask. Fig. 1c shows our final tree tracing result and Fig. 1d shows a closer view. Fig. 2 shows the CPR view [12] of the SDM of one vessel.

![Figure 2. Signed Distance Map of one vessel in CPR view, larger SDM values visualized by red color.](image)

### 2.2. Hybrid GCN Representation Learning and Rule-based Refinement

In this section, we present our method combining residual gated graph convolutional network and logical rule-based refinement. The residual gated graph convolutional network [13] is defined as follows:

$$h_i^{t+1} = f_{GCNN}^t(h_i, \{h_j^t : j \rightarrow i\}) + h_i^t = ReLU \left( U^t h_i^t + V^t \sum_{j \rightarrow i} h_j^t \right) + h_i^t$$  

(1)

Where $h_i^t$ denotes the representation vector for graph node $i$ at layer $t$. $f_{GCNN}^t$ denotes the nonlinear transform function, aggregating information from all neighbouring nodes of $i$, denoted as $\{h_j^t : j \rightarrow i\}$. $U^t$ and $V^t$ are the parameter matrices to be learned. In our GCN learning framework, a node is defined for each vessel segment from the artery tree. More specifically, a segment is the centerline extracted between two bifurcations. We used features similar to [7] and [9], including the relative angles between the parent segment and two child branches, and the directions extracted at the beginning, middle and ending of the vessel segment. Our GCN is composed of 4 layers with a hidden unit size of 128.

**Rule-based Refinement.** The predictions made by the deep network may be inconsistent regarding the dependencies between anatomical labels. We solve the problem by enforcing syntactic rules as a refinement method. At each node of the artery tree, the probability of the parent-child derivation (e.g. LM $\rightarrow$ LAD|LCX) is utilized as a prior term, and the predictions made by the network acts as likelihoods. The parent-child derivation with the largest posterior is chosen as the final labeling. Using this scheme, the unlikely or impossible derivations (e.g. LAD $\rightarrow$ LAD|OM) is effectively down-weighted or eliminated. A more sophisticated dynamic programming-based algorithm is possible to arrive at a tree labeling with globally optimal posterior probability, however, our greedy algorithm works well in practice. Fig. 3 shows an example of our labeling algorithm.

### 3. Experiments

Unfortunately, there is no publicly available dataset in this field, as pointed out in [7,9], and existing works evaluated their method only on private datasets. To systematically validate the performance of our method, we have collected a dataset of 350 patients. The ground truth segmentation and vessel segment anatomical labeling are annotated by physicians.

We measure the performance of our artery tree building algorithm in terms of completeness, accuracy and F1 score. Given the initial segmentation, the artery trees extracted by our method or baselines are compared to the artery tree extracted by thinning and tracing the ground truth segmentation. We calculate completeness as the percentage of ground truth artery tree points for which at least one traced artery tree point is within a distance of $\tau=1$ voxel. Similarly, we calculate accuracy as the percentage of traced artery tree points for which at least one ground truth point is within a distance of $\tau=1$ voxel.
Figure 3. Anatomical Labeling of Coronary Arteries.
This figure shows the final result of our anatomical labeling algorithm. Best viewed in color.
The result is shown in Table 1. It’s evident that our method significantly improves the completeness and the overall artery tree building result.

Table 1. Quantitative results of artery tree building.

|                              | Completeness | Accuracy | F1 Score |
|------------------------------|--------------|----------|----------|
| Our method                   | 0.863        | 0.825    | 0.844    |
| Thinning-based method [11]   | 0.610        | 0.822    | 0.700    |

Our labeling algorithm is evaluated as follows: Among all the 350 samples, 50 is reserved as test set, and 300 samples are used to train our method. We use five-fold cross-validation strategy to train our model and select the one with the best average F1 score for testing. For comparison, we implemented AdaBoost as the baseline. The quantitative results of our method are listed in Table 2, and our method clearly outperforms the baseline.

Table 2. Quantitative results of anatomical labeling.

| Label | Our method | AdaBoost |
|-------|------------|----------|
|       | Precision  | Recall   | F1      | Precision  | Recall   | F1      |
| LM    | 1.000      | 1.000    | 1.000   | 0.900      | 0.920    | 0.910   |
| LAD   | 0.972      | 0.966    | 0.969   | 0.872      | 0.854    | 0.863   |
| LCX   | 0.935      | 0.947    | 0.941   | 0.847      | 0.822    | 0.834   |
| RCA   | 0.951      | 0.977    | 0.964   | 0.883      | 0.906    | 0.894   |
| D     | 0.894      | 0.913    | 0.903   | 0.788      | 0.830    | 0.808   |
| OM    | 0.836      | 0.869    | 0.852   | 0.766      | 0.722    | 0.743   |
| LPLB  | 0.948      | 0.634    | 0.760   | 0.753      | 0.221    | 0.342   |
| RPDA  | 0.893      | 0.902    | 0.897   | 0.778      | 0.852    | 0.813   |
| RPLB  | 0.910      | 0.923    | 0.916   | 0.760      | 0.613    | 0.679   |
| Average | 0.927    | 0.903    | 0.911   | 0.816      | 0.749    | 0.765   |

4. Discussion
In this paper, we propose a hybrid approach to anatomical labeling of coronary arteries for CCTA images. Our method combines the advantages of traditional rule-based method and deep learning methods, ensuring interpretability and consistent labeling, while allowing for data-driven parameter
learning. Our method is composed of two major parts: centerline-based artery tree building, and GCN-Rule based anatomical labeling. Experiments have shown superior performance for both components of our methods. Currently, end-to-end training is not viable for our method. In our future work, this would be an interesting direction to investigate.

References
[1] Leipsic J, Abbara S, Achenbach S, Curry R, Earls JP, Mancini GJ, Nieman K, Pantone G, Raff GL. SCCT guidelines for the interpretation and reporting of coronary CT angiography: a report of the Society of Cardiovascular Computed Tomography Guidelines Committee. Journal of cardiovascular computed tomography. 2014 Sep 1;8(5):342-58.
[2] Austen, W.G., Edwards, J.E., Frye, R., Gensini, G., Gott, V.L., Griffith, L.S., McGoon, D., Murphy, M., Roe, B.: A reporting system on patients evaluated for coronary artery disease. report of the ad hoc committee for grading of coronary artery disease, council on cardiovascular surgery, American Heart Association. Circulation 51(4), 5–40 (1975)
[3] Tanaka, A., Imanishi, T., Kitabata, H., Kubo, T., Takarada, S., Kataiwa, H., Kuroi, A., Tsujioka, H., Tanimoto, T., Nakamura, N., et al.: Distribution and frequency of thin-capped fibroatheromas and ruptured plaques in the entire culprit coronary artery in patients with acute coronary syndrome as determined by optical coherence tomography. The American journal of cardiology 102(8), 975–979 (2008)
[4] Cademartiri F, La Grutta L, Malago R et al (2008) Prevalence of anatomical variants and coronary anomalies in 543 consecutive patients studied with 64-slice CT coronary angiography. EurRadiol 18(4):781–791
[5] Qing Cao, Alexander Broersen, Michiel A de Graaf, Pieter H Kitslaar, Guanyu Yang, Arthur J Scholte, Boudewijn PF Lelieveldt, Johan HC Reiber, and Jouke Dijkstra. Automatic identification of coronary tree anatomy in coronary computed tomography angiography. The international journal of cardiovascular imaging, 33(11):1809–1819, 2017.
[6] Guanyu Yang, Alexander Broersen, Robert Petr, Pieter Kitslaar, Michiel A de Graaf, Jeroen J Bax, Johan HC Reiber, and Jouke Dijkstra. Automatic coronary artery tree labeling in coronary computed tomographic angiography datasets. In 2011 Computing in Cardiology, pages 109–112. IEEE, 2011.
[7] Dan Wu, Xin Wang, Junjie Bai, Xiaoyang Xu, Bin Ouyang, Yuwei Li, Heye Zhang, Qi Song, Kunlin Cao, and Youbing Yin. Automated anatomical labeling of coronary arteries via bidirectional tree lstms. International journal of computer assisted radiology and surgery, 14(2):271–280, 2019.
[8] Yang Z, Yang D, Dyer C, He X, Smola A, Hovy E. Hierarchical attention networks for document classification. InProceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies 2016 Jun (pp. 1480-1489).
[9] Han Yang, Xingjian Zhen, Ying Chi, Lei Zhang, Xian-Sheng Hua. CPR-GCN: Conditional Partial-Residual Graph Convolutional Network in Automated Anatomical Labeling of Coronary Arteries. The IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 3803-3811
[10] Wang Y, Wei X, Liu F, Chen J, Zhou Y, Shen W, Fishman EK, Yuille AL. Deep distance transform for tubular structure segmentation in ct scans. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition 2020 (pp. 3833-3842).
[11] T.-C. Lee, R.L. Kashyap and C.-N. Chu, Building skeleton models via 3-D medial surface/axis thinning algorithms. Computer Vision, Graphics, and Image Processing, 56(6):462-478, 1994.
[12] Kanitsar, A., Fleischmann, D., Wegenkittl, R., Felkel, P., & Groller, E. (2002). CPR - Curved planar reformation. Visualization, 2002. VIS 2002. IEEE.
[13] Bresson X, Laurent T. Residual gated graph convnets. arXiv preprint arXiv:1711.07553. 2017 Nov 20.