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Improved Centerline Extraction in Fully Automated Coronary Ostium Localization and Centerline Extraction Framework using Deep Learning

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***Abstract*— Coronary artery extraction in cardiac CT angiography (CCTA) image volume is a necessary step for any quantitative assessment of stenoses and atherosclerotic plaque. In this work, we propose a fully automated workflow that depends on convolutional networks to extract the centerlines of the coronary arteries from CCTA image volumes, starting from identifying the ostium points and then tracking the vessel till its end based on its radius and direction. First, a regression U-Net is employed to identify the ostium points in the image volume, then these points are fed to an orientation and radius predictor CNN model to track and extract each artery till its end point. Our results show that an average of 96% of the ostium points were identified and located within less than 5mm from their true location. The coronary arteries centerlines extraction was performed with high accuracy and lower number of training parameters making it suitable for real clinical applications and continuous learning.**

Keywords—coronary artery disease, CCTA, angiography, deep learning, convolutional neural networks, ostium points, centerline extraction, vesselness.

I. INTRODUCTION

Coronary artery disease (CAD) is the most common type of heart disease leading to death of more than 365,000 death cases in the united states in 2020 [1]. Non-invasive imaging techniques, specifically Coronary CT angiography (CCTA), are usually preferred as the safest way to visualize the coronaries vasculature and assess stenosis or plaques [2][3][4]. However, investigating plaque location and sizes from CCTA is a complicated task, that requires considerable amount of experience. Therefore, it is prone to subjective image interpretation [5][6]. Across the last decade, several methods have been proposed to automate the detection and quantification of stenosis. While few methods use image features and pattern recognition for stenosis detection [6][8][9], most of the methods quantify stenosis by accurate lumen segmentation and centerline extraction [7][10][11][12]. This helps to estimate healthy and diseased lumen diameters and enables more quantifications to be calculated upon straightening the artery lumen using curved multiplanar reformation techniques [5][13]. In these methods (automating lumen segmentation and centerline extraction), two main approaches can be recognized. The first approach is to segment out the full vascular tree (coronary tree in this case) structure from the image volume and then extract the centerlines of this vessel structure [10][11][7][13]. This approach does not require any user input as start or end points and is less sensitive for vessels' discontinuities due to pathology or imaging artifacts, but it is more prone to errors due to appearance of multiple vessels in the vascular tree and the segmentation task is usually more time consuming and computationally exhaustive[11][7]. The second approach is to start with a point on the artery (placed manually or identified automatically) and then track the vessel iteratively based on its radius and orientation. This approach is more efficient and less prone to errors related to confusions in the vascular tree but it usually suffers from any gaps, discontinuities and stenoses that might exist in the artery [14].

Recently, convolutional neural networks (CNNs) became popular in the field of medical image analysis [15][16]. Several CNN models were proposed to address problems like vessel tree segmentation [11][17], landmarks or seed-points identification [18][19], and vessel tracking [20][21], which resemble different subproblems of the coronary lumen segmentation and centerline extraction problem. Specifically for the centerline extraction problem, branching points of the left and right coronaries, i.e. ostium points, were automatically identified using dilated convolutions [22] while the arteries centerline were extracted in [23], where a modified CNN that uses a dilated kernel over an isotropic image patch to determine the direction and radius of the coronary artery at any point. However, the employed models usually have a huge number of training parameters, around 1.9 billion training parameters, to achieve its reported results. This directly limits the application of such models in real clinical settings [24][25].

In this work, we propose a fully automated workflow for coronary arteries extraction from CCTA images using deep learning. Given a CCTA image volume, we develop a regression U-Net model to locate the coronaries ostium points by defining major seed points of both; right and left coronaries. Seed points are then used as input for our second CNN dedicated for centerline extraction process that starts from the seed point and terminates at the end of each artery. In this model, we a) introduced a tailored weighted loss function for the orientation classifier part and b) incorporated the vesselness information (in terms of the Hessian eigen values) as an extra input for the network (beside the image patch) to improve the learning process of the network. The proposed models achieve high accuracy with much lower training parameters and required computational power. This helps the presented models to be more appealing for real clinical settings and the continuous learning setups.

II. DATASETS

A. Local Dataset

Our local dataset was collected and annotated through a retrospectives study conducted in Suez Canal University hospital. The study was approved by the local institutional review board at the Suez Canal University with a waiver of informed consent. The dataset consists of 118 CTA scans for 118 subjects with resolution ranging from $0.36\times0.36\times0.4$ to $0.5\times0.5\times0.6$ mm^3 and fixed pixel size of 256×256. Scans were captured at different times from the contrast injection. The images were annotated by two expert radiologists (5 and 10 years of experience). For each case, the region of interest (ROI) was defined as the bounding box enclosing the cardiac walls inside. The seed points were annotated manually for each image in the series in which the coronary branching from the aorta appears.

B. CAT08 Dataset

The centerline extraction network was trained over the CAT08 dataset publicly available under the Rotterdam Coronary Artery Algorithm Evaluation Framework [13]. The dataset includes 32 cardiac CTA volumes for 32 cases. Images are reconstructed with mean voxel size of $0.32\times0.32\times0.4$ mm^3. The CAT08 organization has split the data into train and test sets; where 8 cases had the reference centerline data were considered for training; and 24 cases which does not contain reference annotations were left for testing. The reference data for each case contained the coordinates of the centerline as well as the estimated radius of the coronary artery branch at this point. Four vessels are annotated for each case which respectively are right coronary artery (RCA), left anterior descending (LAD), left circumflex (LCX) and the fourth artery was an arbitrary side branch of one of the previously mentioned arteries.

III. METHODS

A. Seed Points Locator

To identify the ostium points, we used a regression U-Net. U-net architecture is well known in medical image segmentation problems [24] but being originally designed for segmentation tasks, the network has no dense output layer, and the output is a mask of the same dimensions as the input image. Thus, to fit the regression task; two consecutive convolutional layers were added with resolution of 16 and 1 respectively, and to achieve the desired output; a fully connected dense layer with linear activation was added as the output layer of the network. The expected output is the x and y coordinates of the coronary ostium.

B. Centerline Extractor

To extract the coronary arteries' centerlines, we proposed a modified version of the CNN model in [23] where the centerline is extracted point by point using an iterative workflow. The original model input is a small 3D volume (19×19×19 voxels) of the input dataset. The center of the input volume is the current point on the centerline. The output is the predicted direction to the next centerline point and the estimated radius of the artery at the current point. The next centerline point is obtained by moving from the current point by the estimated radius in the predicted direction. Then, the next centerline point is considered as the new current point and a new input volume is calculated. The directions are discrete orientations in the spherical coordinates. The CNN model consists of 7 convolutional layers and one fully connected layer. Each convolution layer is followed by a batch normalization layer. The kernel size of the first 5 layers is 3 and 1 for the last two layers. The number of kernels is 32, 32, 32, 32, 64, 64 and (number of directions + 1) respectively. The dilation factor for layers 3 and 4 is 2 and 3 respectively. All other layers have dilation factor equal to 1.

The original model uses 500 directions which generate 1,927,563,895 trainable parameters and was trained using 50K epochs. Our proposed model uses 180 directions (224,866,567 trainable parameters) 250 epochs to achieve approximately similar performance. The following subsections describe the modifications that applied on the original CNN model.

- *Geometric/shape information:*

A unique feature in coronaries appearing in CCTA images is its tube (vessel) like morphology, referred to as vesselness [25]. Most vesselness calculations includes hessian matrix computation, from which eigen values are computed and then fed into the vesselness calculations. In our model, we modify the CNN to accept a 4-channel input isotropic image patch; one channel contains the normal grayscale image intensities, while the other three channels contain the eigen values of the image in 3D directions. Eigen values are fed barely to the network without any further computations in order to give the CNN the freedom to extract the vesselness feature from them in the optimal way.

- *Weighted Loss Function:*

Instead of the categorial loss function in [23], we introduce a weighted loss function that considers the proximity of the predicted direction to the ground truth. For each of the discrete directions; the cosine of the angle (α) between the predicted vector (P) and the discrete directions unit vector (U_i) is computed as follows:

$$\cos\alpha = \vec{P}.\vec{U_i}$$

Then, a weight value is assigned to each direction (i):

$$W_i = 2 - \cos\alpha,$$

where W_i values ranges from 3 to 1; where 3 indicates the totally opposite direction, and 1 indicates the same direction. The network is fed with 3D isotropic image patches. Isotropic patch requires resampling the image equally in all dimensions to maintain equal voxel spacing. A voxel size of $0.5\times0.5\times0.5$ mm^3 was used to ensure covering a receptive field of 9.5mm which is sufficient to cover the widest coronary artery. The network stacks dilated convolutional layers by implementing an increasing stride between kernel elements to increase the receptive field of the kernel and to aggregate many features at multiple scales [26], while maintaining linear growth of number of trainable parameters. This controlled number of parameters avoids costy computations and prevents overfitting. The network final output combines orientation classification over discrete directions, besides a radius regression to estimate the radius. Linear and softmax activation functions were used for the regression and classification tasks respectively. ReLU activation function was employed for the rest of the network.

To evaluate the results, both the reference and the predicted centerlines are then resampled equidistantly at 0.03mm and then we calculated the percentage of the clinically relevant part of the artery which was predicted through the workflow and compared it to the reference centerlines manually annotated.

C. *Workflow:*

Figure 1 shows a schematic diagram for the proposed workflow. First, the images are fed to the seed points locator model which predicts the seed points of right and left coronaries. Seed points are then fed to the centerline extraction model; where each centerline is tracked starting from the input seed point till the end of the vessel when the radius remains clinically insignificant (< 0.2mm) for more than three iterations.

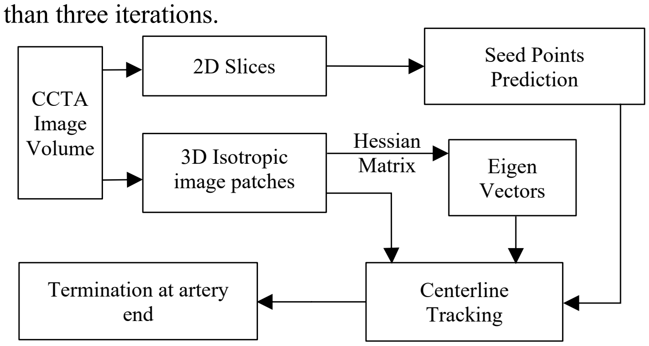

Figure 1. Block diagram for the employed workflow

D. *Training Strategy:*

Training of the seed points locator U-Net was performed using the local dataset. The subjects were split into 94 subjects (80%) for training of the network and 18 (20%) subjects for validation. Data was fed to the model as 2D images with dimensions 256×256 which represents a window enclosing the aorta. The target is an array containing the locations of the seed point, relative to the enclosing window. Adam optimizer with 0.0001 learning rate was used for updating weights, and the mean squared error loss was the loss function of the model. Data was fed to the model in batches of 4. The training elapsed 76 epochs before early stopping. For the centerline extractor, the 8 training cases given in CAT08 dataset were used as leave-one-out for validation. Images of each case were resampled at the new voxel spacing of 0.5 and a target of N+1 corresponded to each isotropic patch; where N+1 represents N number of directions and a radius. We considered 180 discrete directions only due to hardware resource limitations. Two CNNs were constructed; the first used normal categorical cross entropy loss, the second implements weighted loss function besides the 4-channel network. Both CNNs were trained for 250 epochs. Each full training loop lasted on average for 37 hours for each of the two models. All CNNs were trained on a NVidia GeForce RTX 2070 GPU, 8 GB RAM.

IV. RESULTS

The seed points locator was evaluated on the local dataset showing an average error of less than 5mm in more than 95% of the results. Detailed accuracies are illustrated in Table 1.

Table 1. Ostium Points Locator Performance

Error	***LCA***	***RCA***
Less than 2mm	68.3 %	74.1 %
2 – 5mm	24.4 %	24.0 %
More than 5mm	7.3 %	1.9 %

The centerline extraction accuracy was assessed using CAT08. The average distance between the reference and extracted centerline for automatically extracted points that are within the radius of the reference centerline (DE) was measured for three models. The first has 500 directions and 50K epoch for training (similar to [23]). The second has the same architecture with 180 directions and was trained for 250 epochs. The third is the proposed model with 180 directions and 250 training epochs. The DE for the three models was 0.23, 0.58 and 0.45 mm respectively. Figure 2 shows examples for the straightened vessels results using the proposed model.

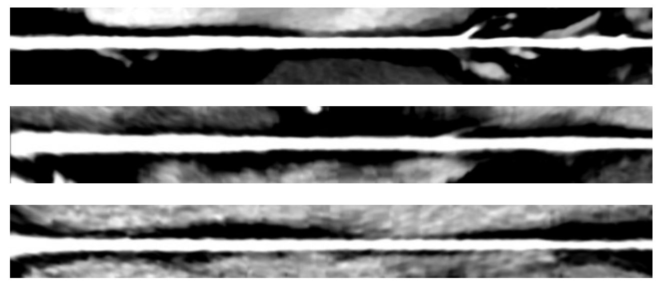

Figure 2. Examples for straightened vessels after centerlines extraction

V. DISCUSSION

The proposed framework first employs a regression U-Net to identify the ostium points then feed these points to modified CNN that tracks the artery via estimating its orientation and radius. Our results show that modifying the loss function to consider the proximity of the predicted direction to the ground truth and feeding the vesselness information (in terms of the eigen values of the Hessian matrix) helps to significantly improves the performance of orientation estimation. The proposed model has comparable accuracy to the model in [23] with much less utilized directions (180 vs 500) and training epochs (250 vs 50K) leading to a significantly reduced number of training parameters (224,866,567 vs 1,927,563,895, i.e. ~11%). This allows the integration of the proposed model in clinical settings and opens the opportunity to employ the continuous learning framework.

VI. CONCLUSION

A fully automated framework for coronary arteries centerlines extraction from CCTA images was proposed with high accuracy and low number of training parameters that makes it suitable for real clinical applications and continuous learning.

VII. ACKNOWLEDGMENT

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