Automated Segmentation of Coronary Arteries

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***Abstract*—To segment coronary arteries automatically in cardiac computed tomography angiography (CCTA) can significantly improve the diagnostic result and treatment for cardiovascular disease (CVD). In this article, it offers a method that has fully automated segmentation of coronary arteries from 3D type of images. The dataset includes a real patient with CVD and healthy patient to minimize the uncertainties. Firstly, images are extracted from 3D to 2D type for implementation. Secondly, preprocessings of images include image enhancement and vessel enhancement are implemented, and preprocessed images and original images are divided as two different groups, which are images with coronary arteries and images without coronary arteries. Thirdly, original images and images after preprocessing are appended on the training dataset for deep learning process. The deep learning process involves the convolutional neuron network (CNN) training. After the training process, test image is classified and proceed the segmentation step. The Hausdorff distance and dice score are used for analysing the final output. The result presented an automated system that is capable of correctly classifying image with or without coronary arteries in all patients, and performing fully automated segmentation.**

***Index Terms*—Coronary Arteries, Automated Segmentation, CNN training**

I. INTRODUCTION

Cardiovascular disease (CVD) is a prevalent heart disease among many countries nowadays, and it is a major cause of death. Computed tomography angiography (CCTA) is a widely used imaging modality to diagnose and treat different types of CVD. Because due to the non-invasive nature of CCTA, it is also a prevalent methodology for evaluating and reconstructing heart and coronary vessel structures. In order to find the possible disease and image artefacts that relating with CVD, the small size of the coronary arteries is an intractability for automated implementation. Changing of diameter of coronary artery lumen indicates the patient whether they have CVD or not. The accurate diagnosis and image segmentation, therefore, will hugely enhance the result of early diagnosis as well as help doctors to treat patients. The majority of methods of segmentation of coronary arteries used semi-automatic methods that needed a human expert to guide the algorithm and correct errors. Semi-automatic method, however, leads to a limitation that when processing the large amount of medical images, which are the time used for implementation [1]. The most valuable or important thing for any treatment or diagnosis is time. Hence, to construct a method that process fully automated segmentation is crucial for diagnosis and treatment, and can save more lives. One existing method [4] uses an automated segmentation system for stenosis detection on 2D projection images. It uses image smoothing, vessel enhancement, localized threshold and connected component labeling for implementation. This method can eliminate the number of false negative responses by finding out all suspected parts of the coronary arteries for detailed and final investigations by a human expert, which is limited by a large scale of dataset . Another method [5] is built on a statistics region growing together with a heuristic decision to obtain the fully automated coronary artery segmentation from cardiac data volume. It firstly extracts the heart region by using a multi-atlas-based approach, followed by the vessel structures that are reinforced via a 3D multi-scale line filter. Seed points are then used for region growing, and heuristic decision is used for automatically obtaining the desired result. This 3D type algorithm, however, is to segment the whole structure of coronary arteries, which limit the analysis or requirement of types of CVD . In method [3], it based on the minimal directional path and the level-set segmentation in the 2D fused image to segment the coronary lumen in a fully automatic model. The minimal directional path can automatically obtain the coronary centerliens of the main branches, which provide the center location of the coronary lumen. Then the cross-sectional planes and 3D stacking of the cross-sectional planes are calculated in 3D CCTA images with gray filtered and vesselness-enhanced images respectively, in order to increase the accuracy of lumen segmentation. After two enhanced images are fused, the level-set algorithm will segment the coronary lumen in the cross-sectional planes of the fused image. However, this method is also to find the whole structure of coronary lumen, which cannot meet the requirement of this proposed project.

In this proposed algorithm, the disease classification is based on medical images that extract coronary artery from different images, and can precisely obtain coronary arteries in images from both healthy and real patients. Firstly, preprocessing of image from 3D type with image enhancement. Secondly, the preprocessed images will be loaded on the training set for training purpose. The training process will implement classification for deep learning with convolutional neuron network (CNN) in order to automatically identify coronary arteries from every type of images. After that, the test image will be classified as with coronary arteries or without them. Lastly, the automatic segmentation will proceed to do a watershed and contour drawing on each identified image with coronary arteries. The evaluation metrics include the Hausdorff distance and dice score.

II. Proposed Methodology

In order to automatically segment coronary arteries from different types of images with the highest accuracy, the method contains four steps as follow: (1) preprocessing of training images, (2) CNN training, (3) prediction and classification, and (4) segmentation. The programming language that used is Python, and the deep learning tool is implemented by using Tensorflow.

A. Preprocessing of images

The dataset includes the training set, which contains 20 CCTAs with contrast agent which is the mask that will be used for segmentation, and the 20 CCTAs in the dataset include 10 healthy patients, 10 patients with coronary artery disease. The datasets are all three-dimensional images, and the format is NRRD file. In this proposed method, it randomly selects patients from 20 patients to reduce the size of training data. It uses patients from 0 to 8, and 15 to 19 for the training process. First of all, the NRRD file will be decomposed to '.png' in order to implement image enhancement in 2D. After original image in 2D type will be classified manually by two different categories, which are images have coronary arteries and without them, based on the ground truth. Image enhancement then will be implemented based on the classified image. For this proposed algorithm, patient 0 uses all images that are extracted from 3D data type, which are 204 images in total. Patients 1, 5, 6, and 8 use images from number 61 to 129 . Patients 2 and 15 to 18 use images from number 0 to 60. Patients 3 and 4 have images from number 61 to 179. Patient 19 uses images from number 61 to 199. The randomly selecting can minimize uncertainties by eliminating the situation that all images are presenting coronary arteries or all images all without arteries present, while the size of the training data is smaller than using all images from training dataset. After reconstruction of images, one enhancement method is the Canny edge detector, which is also a vessel filter. The Canny filter is a multi-stage edge detector, which uses the derivative of a Gaussian to compute the intensity of the gradients. As Gaussian can remove the effect of noise present in the image, the potential edges, therefore, are thinned down to 1-pixel curves by removing non-maximum pixels of the gradient magnitude. Edge pixels are then kept or removed using hysteresis thresholding on the gradient magnitude [6]. As figure 1 shows, the image indicates an example of image after applied with Canny filter, coronary arteries are clearly identified as two circles in the middle of the images. Another implementation before the training step is to draw the contours on the original training images by using the mask. As the figure 2 shows, contours are indicated on the image when coronary arteries presence. This can augment the training dataset in order to classify images with less uncertainties. The last image enhancement is to use the unsharp masking, which is a linear image processing technique which can

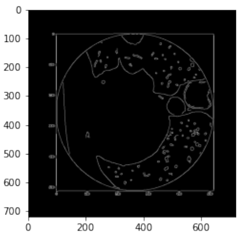

Fig. 1. The figure shows the example of image with coronary artery after applied Canny filter

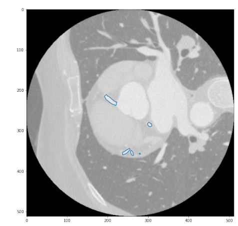

Fig. 2. The figure shows the example of image with coronary artery after applied contour drawing

sharpen images. As the equation 1 shows, the sharp details are depended on the difference between the original image and its blurred version, and the original images will be added with these details by a specific scale. The radius parameter in the unsharp masking filter related to the sigma parameter of the Gaussian filter.

$$enhanced\,image = original + amount * (original - blurred) \tag{1}$$

The figure 3 shows the image after applied unsharp masking filter. The coronary artery is clearly presented in the middle part of the image, which are two white lines. This vessel filter algorithm can strengthen the classification ability, which also called data augmentation techniques in deep learning method. The training datasets, therefore, are constructed in two categories (with coronary arteries and without them) with three four different training image paths.

B. CNN Training

For CNN training construction, firstly, all images from image preprocessing will be loaded on the training datasets. Further, images will be resized as 512 times 512 in grey scale, and this size is the minimum size for training images because coronary arteries are too small to find when they are presented with the image, small size will remove them. In order to train all images with minimum uncertainties, images will be randomized to avoid the case that training all images with coronary arteries before all images without them. After images are loaded, Keras in Tensorflow function will proceed the CNN training process [2]. There are three convolutional

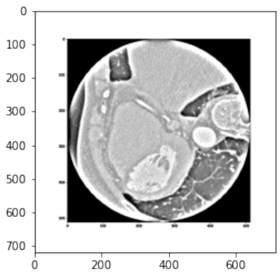

Fig. 3. The figure shows the example of image with coronary artery after applied unsharp masking filter

layers in total (3x3) with size of 64, activation function of rectified linear unit, the loss function is using binary cross-entropy, and the low learning rate of 0.0001. Based on the small coronary arteries in the image, the batch size needed as small as possible. The batch size, therefore, is implemented as 2, epochs are 6 in total, and validation split is 0.3 in order to use 30% of trained images to improve the result accuracy. After finishing 6 epochs, the model can predict the test datasets.

C. Predication and Classification

The dataset for testing images include 10 patients that contain both unknown number of real patients and healthy people also in 3D type. In order to test images, after transformed 3D images to 2D type, three different methods to test images are implemented to compare the result. The test data that used in this proposed method are implementing 212 images from patient 10, which are from image number 0 to number 211. The first method is to test the original image after resize of 512 times 512. The second one has preprocessing of images which use unsharp masking filter, and resize to the same image size as trained images. The last one is to use canny edge detection before resizing of images. After constructed three different methods. CNN training model will be loaded to predict every test image that whether it has coronary arteries present or not. According to the prediction, two separate paths for predicted images are constructed for each condition. If the test image is identified that has coronary arteries present, the image will be classified as 0 and proceed to segmentation part. The other condition, shows in figure 4 image does not have presence of coronary arteries, will be classified as 1 and reveal the original test image as the result.

D. Segmentation

In order to present the automated segmentation correctly by comparison, there are three different segmentation methods in total that are shown in the figure 5 and figure 6. The first one is a contour drawing by using the unsharp mask filter. It draws contour in the region of interest (ROI) on the original image. By using ROI, the required result will be more accurate by eliminating unnecessary regions and uncertainties.

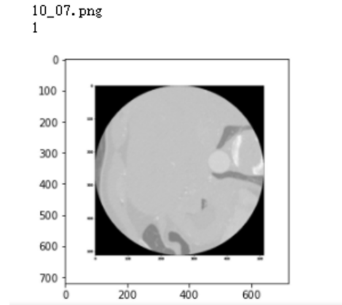

Fig. 4. The figure shows the example of image without coronary arteries, and indicated as 1 in image #58 from patient #10

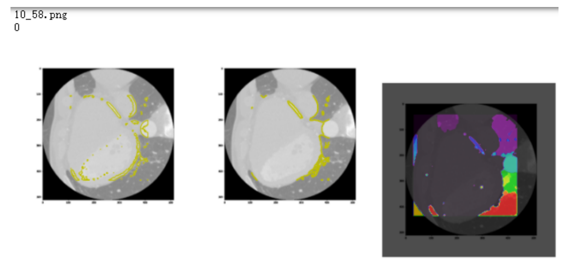

Fig. 5. The figure shows the example of image with coronary arteries and indicated as 0 after implemented segmentation in image #58 from patient #10

The second method is to draw contours from canny edge detection on the ROI of original images. The last method is to use markers for watershed transform to segment coronary arteries from each classified image. The watershed algorithm can separate different objects in an image, which can segment each identified coronary artery as needed. It firstly denoises the images by using the median function in the rank filters. Then it finds the continuous region by utilizing low gradient in order to construct a marker inside the image. In a gradient image, the areas of high values provide barriers that can help to segment the image. Using markers on the lower values can ensure the segmented objects, which are coronary arteries, are extracted. The disk value is 4.9, and the low gradient value is 64. These two values can be adjusted based on the ROI in different images.

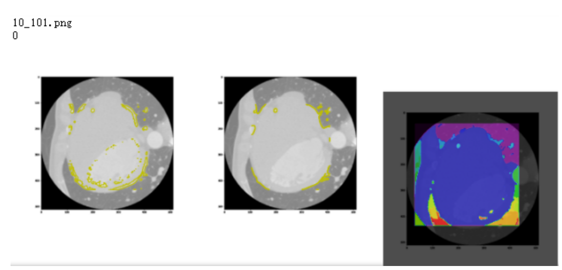

Fig. 6. The figure shows the example of image with coronary artery and indicated as 0 after implemented segmentation in image #101 from patient #10

TABLE I
THE TABLE SHOWS THE HAUSDORFF DISTANCE AND DICE SCORE FROM THE EVALUATION RESULT BASED ON THE AUTOMATED SEGMENTATION AFTER CNN TRAINING.

	Mean	standard derivation
Hausdorff distance	262.0	124.6
Dice score	0.501	0.499

III. RESULT AND DISCUSSION

A. Evaluation

From three test methods, the classification reaches the highest standard when it uses the original image. By using images after unsharp mask filter and canny filter will distract the prediction that makes many images without coronary arteries as 0, which has the coronary arteries. Therefore, only original images will be used for prediction. In CNN training model, the training accuracy reaches to 0.9880 with only 0.0353 losses. Each epoch takes 1509 seconds in total of 2584 samples, but time cost is based on the hardware. From the final output, the CNN model can precisely classify 205 out of 212 test images in patient 10, which reaches the accuracy of 96.70%. The evaluation also uses Hausdorff distance and dice score to validate the final output as the result shows in the table I, which uses binary metric in Medpy model.

B. Discussion and future improvement

Based on the final result, the classification accuracy meets the requirements. The classification accuracy can be improved by using more images (use all datasets in 20 patients) for the training data. As for CNN model, the accuracy can be improved by changing the learning rate, increase the number of epochs, construct more neuron layers, and add padding to the CNN model. The Hausdorff distance and dice score, however, are definitely required to improve or reconstruct. The ROI in each test image mainly causes significant uncertainties for evaluation. The ROI, right now, is a fixed region for all images, but all images are obtained from 3D image type. Therefore, ROI changes in every image will lead the segmented image contains noise or redundant points, that leads the Hausdorff distance and dice score cannot obtain the required data. By constructing another deep learning model (CNN training) to set ROI in each image can significantly improve the accuracy. Each image has its own ROI can remove the unnecessary data in the image in order to eliminate uncertainties in the evaluation part. Moreover, by constructing this CNN model, parameters in the watershed algorithm can also be adjusted based on each image. In this way, each final output will have its specific ROI as well as a precise watershed segmentation. In addition, Unet algorithm also tried in order to match the result. However, coronary arteries are so small that the Unet cannot automatically generate the segmentation based on the test images. Last but not least, images that used for testing are patient 10 in the training set, because the ground truth in the test images are missing. Therefore, potential uncertainties may exist to affect the final result, and it cannot decide whether the patient is real patient or healthy people.

IV. CONCLUSION

In this algorithm, it proposed an automated segmentation of coronary arteries that uses CNN to train the deep learning model in order to classify images. The automated algorithm includes classify images whether have coronary arteries or not automatically, and automatic segment every images that are identified as have coronary arteries present. After images are obtained from a 3D type to 2D, images will be assigned in two categories. Secondly, preprocessing of images include canny filter and unsharp mask filter can improve the accuracy of the classification. Then three convolutional layers with size of 64 are trained, and result of classification shows that they can provide the accuracy of 96.7%. Each test image can be predicted by the CNN model, the prediction result include image contains coronary arteries or without arteries. If the image is classified without coronary arteries, the result will just provide the original test image. Otherwise, automated segmentation will proceed based on the predicted image. Two contour drawings and the marker for watershed transform is implemented to segment coronary arteries from each classified image. The watershed segmentation separates each identified coronary artery in ROI automatically. Last but not least, the consequence will be validated by the Hausdorff distance and dice score function. Based on the result, this automated segmentation method requires several improvements include constructing another deep learning model for ROI and parameter adjustment, dataset augmentation, and CNN model modifications. Overall, the proposed method can automated classify every test image accurately, and every coronary arteries in the image can be precisely separated and segmented by using the watershed segmentation. This algorithm is capable of performing automated segmentation of coronary arteries, and any other tasks like abnormal tissues in medical images by some simple modification on the parameters. Therefore, it is a sustainable and helpful algorithm in the biomedical area.

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