A Fully Automated Approach to Preprocessing and Segmentation of Coronary Arteries in X-ray Angiography Images

Ognjen Pavić, Lazar Dašić, Tijana Geroski, Nenad Filipović

Abstract—**In medical practice, X-ray coronary angiography (XRA) represents a gold standard in diagnosing coronary artery (CA) disease. Although deep learning methods achieve high accuracy results, large number of labeled imaging data are often unavailable. As a result, unsupervised methods based on filters should be prioritized. This paper focuses on methodologies for tackling preprocessing steps and segmentation of coronary arteries in X-ray angiography images, only to improve the 3D reconstruction of the CA in the later stages. Dataset with X-ray coronary angiography images of 147 patients from a local database was used for segmentation of left and right coronary artery. Several preprocessing steps after which ridge and edge detection and global Otsu's thresholding was applied, showed that several techniques can be applied in order to detect coronary arteries without unwanted noise, additional details and with connectivity among detected centerlines. The results of this study will represent and input to further steps included on 3D reconstruction of coronary arteries.**

Index Terms— **X-ray angiography, segmentation, detection, filters, coronary artery disease.**

I. Introduction

Coronary artery disease (CAD) is a serious cardiovascular condition characterized by coronary artery wall stiffness and lumen narrowing due to plaque creation. Coronary arteries (CA) are tiny and dynamic vessels that branch from the aorta and feed oxygen-rich blood to the myocardium [1]. Clinical studies show that CAD is the main cause of mortality in the developed world [2], making the timely diagnosis and suitable treatment of upmost importance. In medical practice, there are numerous diagnosis tools that can be used to monitor heart (EKG, echocardiogram, etc.), but X-ray coronary angiography (XRA) still remains a gold standard, despite its invasiveness [3]. This diagnostic procedure consists of placing a catheter into the patient and taking a series of X-ray images as radio-opaque dye is injected into the coronary arteries, thus providing a clear visualization of coronary blood vessels and their structure [4]. Despite its widespread use, XRA images are plaqued with numerous imperfections, such as imaging artifacts, wrongly chosen projection angles, vessel overlap, low contrast, low signal-to-noise ratio, etc. which results into a loss of important informations [5]. Due to the aforementioned shortcomings and two-dimensional nature of the XRA imaging data, other issues with the usage of XRA is intraobserver and interobserver variablity, that could lead to wrong estimation of lesion severity and risk of intracoronary intervention [6].

Over the years, there have been increasing needs for methods that could overcome disadvantages of XRA imaging data [7], which resulted into many studies with the common goal of 3D reconstruction of CA. The majority of the methods for reconstructing CA from XRA are semi-automatic and include the following five steps:

1. pairing of frames acquired from different views,
2. vessel segmentation, decomposition, and tracking in the XRA dynamic runs,
3. calibration of the parameters defining the device orientations,
4. modeling of the CA centerline from its synchronized segmentations,
5. reconstruction of the CA tree surface.

Multiple angiography image segmentation methods have been developed based on both traditional image processing techniques, as well as machine and deep learning. Convolutional neural networks (CNN) have been shown to be particularly useful in the segmentation task and various CNN architecture have been proposed for this task [8-10]. However, these supervised segmentation methods require large quantity of labeled XRA imaging data, which is often not available. This resulted into developing of unsupervised image segmentation techniques, mostly based on the usage of image filters. One of the earliest, and still widely used filtering techniques, have been developed by Frangi et al. with the goal of suppressing the noise and background and enhancing the vessels [11]. Recently, Yin et al. proposed methodology that uses regional parameter expansion and optimal cover tree algorithm in order to segment blood vessels from coronary angiography images [12].

In order to improve the 3D reconstruction of the CA in the later stages, in this paper, we focus on methodologies for tackling preprocessing steps and segmentation (namely steps 1 and 2).

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II. METHODOLOGY

Dataset included X-ray coronary angiography image data from 147 patients, that underwent medical examination at Clinical Centre of Kragujevac. Every patient had a sequence of X-ray images taken of both right and left coronary arteries. Out of every sequence, only the frames that show the full-vessel tree and that are in the end-diastole state have been selected, since they are considered as the best frames for diagnosis and analysis by experts and computer methods [13]. It should be emphasized that there were no available manually segmented masks for the dataset. This means that evaluating the performance of segmentation without ground truth data, i.e., unsupervised evaluation, is at this point challenging task, which is important for the comparison of segmentation algorithms and the automatic selection of optimal parameters and will be the topic of future research.

In this paper we have created and compared two distinct methodologies for coronary artery extraction from angiography images. Both proposed methods work as a pipeline of image transformation and thresholding filters. In both methods, the input coronary artery angiography image is subjected to multiple preprocessing steps including cropping, image filtering and detail selection. The first step in image preprocessing is the cropping of unwanted frames that remained from DICOM pixel data extraction. These frames, in cases in which they cover a significant area of an image cause future image processing steps to produce lower quality results because of the lowering of mean pixel data values as well as the increase in global histogram disparity, so it is of great importance for these frames to be eliminated properly. After the image cropping, multiple cascading filters are applied to the image with the goal of extracting the main region of interest in as much detail as possible.

Adaptive histogram equalization (AHE) is a technique typically used for processing foggy images with the goal of increasing visibility through histogram equalization [14]. In the case of the available left coronary artery angiography, the coronary arteries are distinct from the background heart muscle tissue, but are not distinct enough to allow precise feature extraction. A global AHE filter applied to the image produces a high amount of noise. Contrast limited adaptive histogram equalization (CLAHE) equalizes histograms in smaller patches of the image which limits the value to which a histogram can grow or shrink [1]. The application of a CLAHE filter to the image allows for future increase in precision regarding coronary artery extraction, while also avoiding the appearance of unnecessary overabundance of noise.

After the application of the CLAHE filter it is necessary to apply a top hat transformation to the image to differentiate between the region of interest [15], which is in this case the coronary artery and the background, that being, the rest of the heart muscle tissue. The main goal of the preprocessing process is to create a binary image within which the foreground will be represented with a value of 1 in white pixels and the background will be represented by the value 0 in black pixels. To achieve this goal, it is necessary to invert the colors of the image so that the coronary artery becomes brighter than the surrounding background pixels. After the pixel values are inverted a black top hat transform is applied to the image. The size of the filter which achieves the best results is 11x11 with 6 gray levels. The output of the black hat transformation is an image with increased contrast between the region of interest and the background.

A. Coronary artery extraction through the utilization of ridge and edge detection

After the preprocessing steps of image cropping and the application of the CLAHE filter, pixel value inversion and black top hat transform, the result is an increased contrast within the image. This increase in contrast allows for a more precise extraction of the region of interest through the use of a series of filters consisting of a hessian matrix filter, Gaussian blur filter and an ensemble of Gabor filters.

The hessian matrix filter is an image processing filter used for ridge detection. The ridges contained within the image are eigenvalues of a matrix of second derivatives of the image. This matrix of second derivatives is also known as a hessian matrix. Ridges represent a local maximum of smaller patches within the image. Ridges are important to identify and extract because they contain information on the positions and surfaces of individual shapes, which are necessary for the improvement in edge detection and thus the extraction of the region of interest. In the case of coronary artery extraction, the background heart muscle tissue is not a smooth, flat surface, but is instead very rigid. If an edge detection filter alone was to be applied to the input image, without prior ridge detection, the result would be a very large number of thin edges laced throughout the entire surface area, most importantly near the coronary artery which would be very hard to single out due to the proximity of this unwanted noise.

After the hessian matrix filter, we filter the image using a Gaussian blur filter. A Gaussian filter is a low pass filter typically used for the purposes of noise removal and detail reduction. Image blur and detail reduction are used for multiple reasons during the preprocessing phase of coronary artery image processing. Mainly, the image blur effect enables the connection of close ridges identified by the hessian matrix filter into larger shapes. The joining of shapes that are close to one another further distances the coronary artery from the background shapes that are present in every image, while also having the ability to close gaps in the region of the artery itself. Secondly, the blur effect enables edge detection filters to take into account the transition area between the main body of the coronary artery and the background which is lost during the ridge detection step of preprocessing. In this case a Gaussian blur filter with a standard deviation of 3 yielded best results.

Gabor filter represents a modulation product of a sinusoidal wave of frequency ω and a Gaussian envelope of duration σ occurring at epoch θ [16]. The frequency ω dictates the frequency of the texture being looked for in the image, standard deviation σ the size of the image region being analyzed, while θ defines the orientation of the texture. Because of the irregularity of the shape of the coronary artery, multiple Gabor filters needed to be used for detecting the edges of the region of interest. A total of 16 Gabor filters were used for detecting edges. One unique filter was created for every possible combination of values for θ ranging from 0 to π in increments of π/4, σ = {1,3} and ω = {0.05, 0.25}. The resulting image was produced as a convolution between the Gaussian blurred image and every subsequent Gabor filter.

After conducting edge detection using the 16 aforementioned Gabor filters, the coronary artery was extracted from the image. However, there existed multiple other shapes contained within the resulting image which needed to be eliminated from the final image. These smaller shapes which do not belong to the region of interest were dropped by calculating the area in pixels of each shape belonging to the foreground and moving those with the surface area smaller than 1000 pixels to the background. The entire preprocessing process is shown in Figure 1.

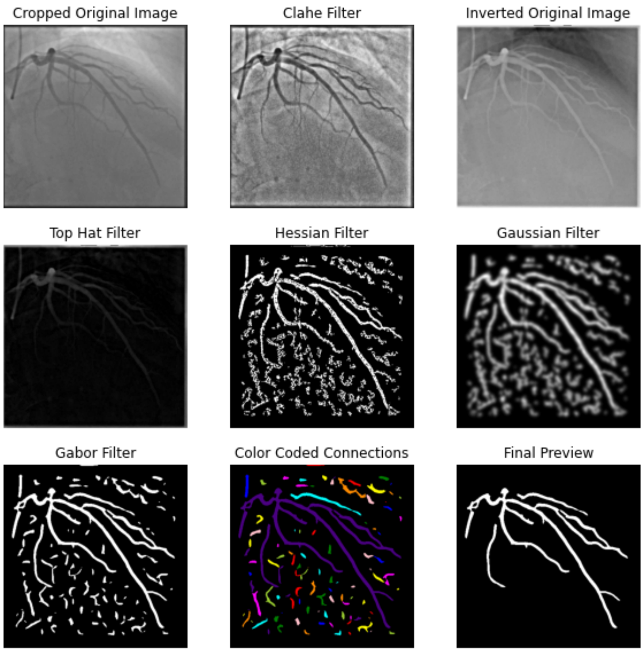

Fig 1. Coronary artery extraction through the utilization of ridge and edge detection

B. *Coronary artery extraction through the utilization of global Otsu's thresholding*

After the steps taken during the preprocessing of the image, including image cropping and the application of the CLAHE filter, pixel value inversion and black top hat transform, the result is an image with the increased contrast. However, contrast enhancement also increased the noise in the image making image grainy and background bone structure more prominent. To solve this issue, image is processed using the pixel-wise adaptive low-pass Wiener filter which is the mean square error optimal stationary linear filter for images degraded by additive noise and blurring.

Wiener filter successfully removed some of the noise, but in this process, it also smoothed the edges that separate blood vessel from the background, making the task of segmentation challenging. In order to enhance the edges of CA, the Wiener-filter processed image underwent the procedure of gamma correction. Gamma correction is a nonlinear operation used to encode and decode luminance or values in video in images thereby changing the saturation of the image. The level of saturation is controlled with the γ parameter, where $\gamma < 1$ is called encoding gamma and results in enhancing of saturation in the image; conversely $\gamma > 1$ is called decoding gamma and results in lowering of saturation in the image. For this research, encoding gamma of 0.97 was selected in order to slightly saturate the image, and make bright blood vessels more prominent.

In order to label pixels into the classes of blood vessel and background, image thresholding was used. This technique binarizes the image based on pixel intensities. If the intensity of a pixel in the input image is greater than a threshold, the corresponding output pixel is marked as white (blood vessel), and if the input pixel intensity is less than or equal to the threshold, the output pixel location is marked black (background). In order to find optimal thresholding value global Otsu's thresholding algorithm was used. This threshold is determined by minimizing intra-class intensity variance, or equivalently, by maximizing inter-class variance [17].

Otsu's thresholding successfully segmented coronary artery, but it also wrongly classified some of the background as blood vessel. These non-vessel areas are considered noise and have to be removed from the image in order to correctly label only CA. Fortunately, these wrongly labeled areas are small in size and can be easily eliminated using connected component analysis. Every connected contour in the image is marked as a single segment and all the components are sorted by size (number of pixels in each connected component). The largest connected component is marked as coronary artery, while the rest of the segments are considered background. The entire preprocessing methodology of extraction through the utilization of global Otsu's thresholding is shown in Figure 2.

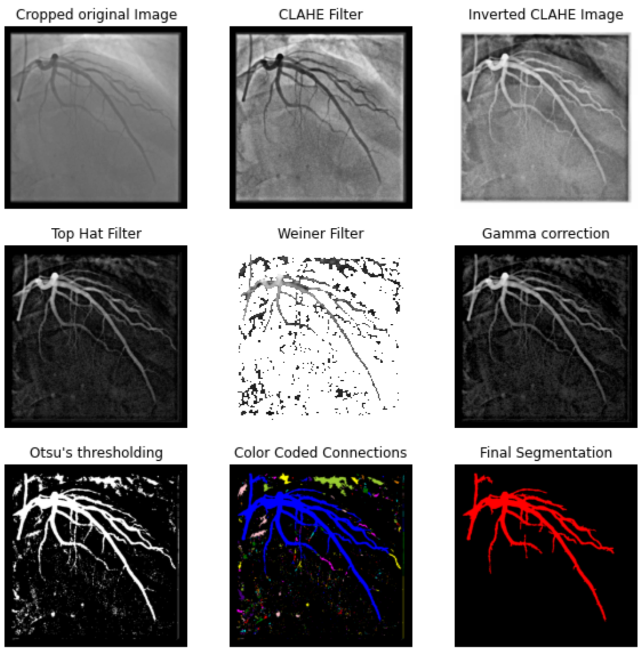

Fig 2. Coronary artery extraction through the utilization of global Otsu's thresholding

III. Main Result

Although both methodologies proved high accuracy for detection and segmentation of arteries, there is some differences in the level of details.

A. *Left coronary artery segmentation*

It can be seen that both proposed methodologies are able to perform segmentation of left coronary artery. However, by visually comparing the results of left coronary artery extraction through the utilization of ridge and edge detection (Figure 3) and through the use of global Otsu's thresholding (Figure 4), it is visible that second method is able to detect even smaller arteries, without the breaks in the detected lines.

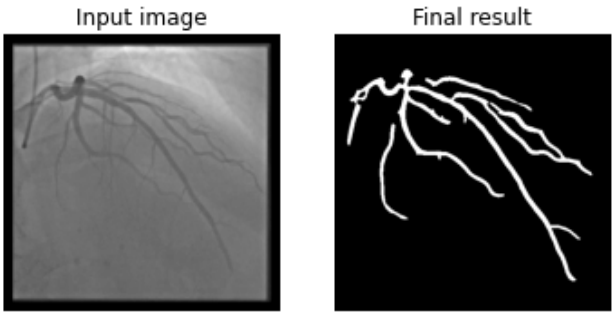

Fig 3. The results of left coronary artery extraction through the utilization of ridge and edge detection

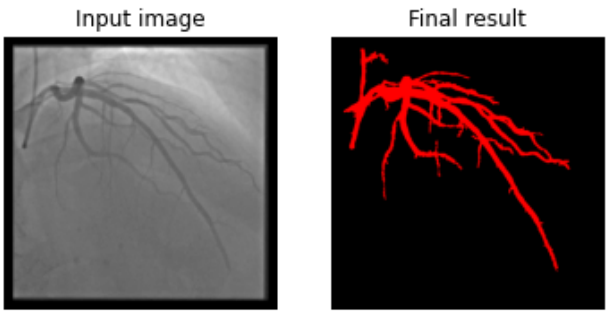

Fig 4. The results of left coronary artery extraction through the utilization of global Otsu's thresholding

B. *Right coronary artery segmentation*

On the other hand, in the case of right coronary artery segmentation through the utilization of ridge and edge detection (Figure 5) and through the use of global Otsu's thresholding (Figure 6), it is visible that first method was able to detect CA, as second method detected too many unwanted artifacts (noise) and unnecessary details.

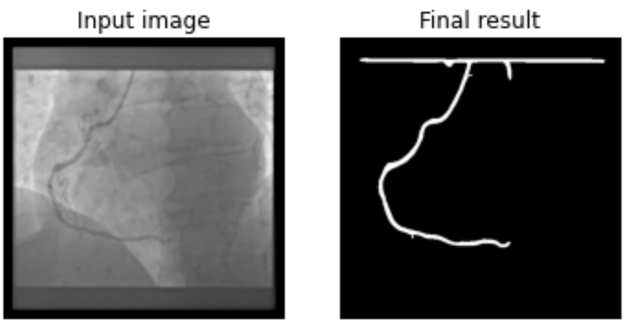

Fig 5. The results of right coronary artery extraction through the utilization of ridge and edge detection

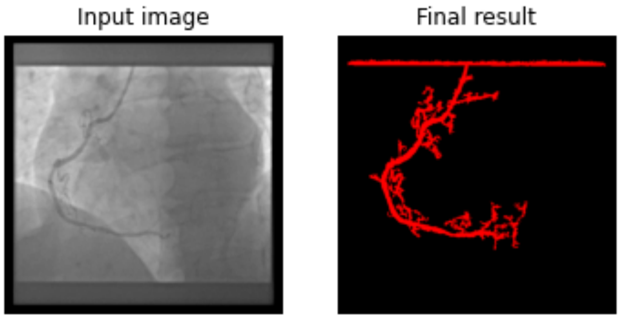

Fig 6. The results of right coronary artery extraction through the utilization of global Otsu's thresholding

IV. Conclusion

Region of interest extraction from images is a common problem especially in the field of medicine with regards to radiographic images. In these cases, region of interest extraction is usually used during the diagnostics process or for the purposes of segmentation mask creation.

In this paper we succeeded in our efforts to create a methodology for automatic region of interest extraction from X-Ray Angiography images by creating two distinct image filtering pipelines. Although both methodologies are capable of automatic coronary artery extraction, the first methodology works better with right coronary artery extraction, while the second methodology works better with left coronary artery extraction. Coronary artery extraction through the utilization of ridge and edge detection is capable of avoiding background surface noise and separating it from the main region of interest especially in the case of right coronary artery images where background surface noise is more abundant. However, this methodology creates gaps within the body of the coronary artery and is thus riskier to use on left coronary artery images which contain a higher branching count. On the contrary, coronary artery extraction through the utilization of global Otsu's thresholding is capable of filling in the gaps in the body of the left coronary artery better, but is incapable of avoiding the forming of long and connected shapes which would in the end be recognized as a part of the image foreground.

In conclusion both image processing methods can be combined into a single system within which, each would work on their own respective branch of the coronary artery tree. Limitation of the current methodology is that evaluating the performance of segmentation without ground truth data is very challenging. Our future steps will focus on obtaining manually segmented masks for available dataset and validation of the proposed methodology against manually segmented masks.

Acknowledgment

The research was funded by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia, contract number [Agreement No. 451-03-47/2023-01/200378]. This research is also supported by the project that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 952603 (SGABU project). This article reflects only the author's view. The Commission is not responsible for any use that may be made of the information it contains.

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