AN UNSUPERVISED IMAGE SEGMENTATION WORKFLOW FOR EXTRACTION OF LEFT CORONARY ARTERY FROM X-RAY CORONARY ANGIOGRAPHY

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Abstract:

Coronary heart disease (CHD) is a serious cardiovascular illness that is among the top causes of death worldwide. Using X-ray coronary angiography, it is possible to detect and monitor CHD by visualizing coronary vessels. One of the most important steps in analyzing angiographic images is image segmentation, where the coronary arteries are separated from the background. In this work, we propose an unsupervised image segmentation workflow that uses different filters in order to minimize the limitations of X-ray coronary angiography and achieve satisfactory segmentation of the left coronary artery. During the preprocessing step, the X-ray angiographic image of coronary artery is processed with CLAHE, the Wiener filter and gamma correction in order to overcome the shortcomings of the X-ray imaging data. These preprocessing steps greatly reduce the background noise and improve the separation of the artery from the rest of the image. The preprocessed image is then segmented using Otsu's thresholding method, which results in a binarized image. This image has left coronary artery successfully segmented, but unfortunately a lot of non-vessel segments have been wrongly labeled as well. In the postprocessing step, connected components are obtained, and then using information about their size the largest connected component represents a segmented left coronary artery, while the rest is marked as background.

Key words: left coronary artery, unsupervised image segmentation, x-ray coronary angiography

1. Introduction

Coronary heart disease (CHD) is a serious cardiovascular illness that is among the top causes of death worldwide, making the early detection and treatment of disease of upmost importance [1]. Coronary arteries are small blood vessels branching from aorta and they supply heart with oxygen-rich blood [2]. This disease is caused by plaque creation that results in wall stiffness and lumen reduction, making the coronary arteries unable to supply blood to the heart. In order to diagnose and monitor CHD, various imaging modalities are widely used (echocardiogram, EKG, etc.). Most commonly used method of assessing CHD is invasive X-ray coronary angiography and is still considered the gold standard [3]. X-ray coronary angiography provides visualization of blood vessels and their anatomical structure by utilizing X-rays during the injection of radiopaque contrast material [4]. Unfortunately, X-ray coronary angiography is not a perfect method since a lot of information can be lost due to imaging artifacts, wrongly chosen projection angles, vessel overlap, etc. [5]. Another problem is intraobserver variability, that could lead to a wrong assessment of lesion severity and stent dimensions [6]. Because of the aforementioned shortcomings, there has been numerous research efforts to use angiographic images as a means for 3D reconstruction that would give better insight into the anatomical structure of the coronary arteries.

Over the years, numerous approaches for 3D reconstruction of coronary arteries that differ drastically in both technology and workflow have been developed. However, one common step for the majority of these approaches is segmentation of coronary arteries from digital angiography images. Process of image segmentation consists of separating region of interest from the background. Various unsupervised, as well as supervised and deep learning, ideas have been developed for angiographic image segmentation. Convolutional neural networks (CNN) achieved great results in many image segmentation tasks, so it was only natural that numerous CNN architectures have been developed for the task of coronary artery segmentation [7-9]. Even though deep learning approaches achieve great results, they require large amount of labelled data that is often not available. As a way of overcoming the need for labelled data, unsupervised learning methods have been developed. Most of the developed unsupervised approaches have been based on the use of different types of image processing filters [10-12]. These approaches achieved suboptimal results due to the aforementioned shortcomings of X-ray coronary angiography as well as complexity of coronary vessels (especially the left coronary artery with larger number of bifurcations and small blood vessels).

2. Methods

In this work, we propose an unsupervised image segmentation workflow that uses different filters in order to minimize limitations of X-ray coronary angiography and achieve satisfactory segmentation of left coronary artery.

2.1 Dataset

Dataset used in this research consists of X-ray coronary angiography imaging data from 147 different patients, collected during medical checkups at the Clinical Centre of Kragujevac. During the procedure, patients' coronary arteries have been imaged from different angles in order to give better insight into the vessel structure. Collected dataset is provided in the standard DICOM format. For the methodology development, only the X-ray images that are in the end-diastole and that shows whole coronary tree have been selected. These frames are considered as the best option for both diagnosis by medical experts and analysis by computer methods [13].

2.2 Workflow

All the steps of developed methodology are shown in Figure 1. The methodology consists of three main parts: preprocessing, filtering and segmentation and postprocessing.

Since the DICOM format, besides imaging pixel data, contains additional information and metadata, it was important to convert data into a format that is easier to work with, such as PNG. The extracted PNG images contained large black borders that didn't contain any relevant information, so the images were cropped. Example of the left coronary artery is shown in Figure 2a.

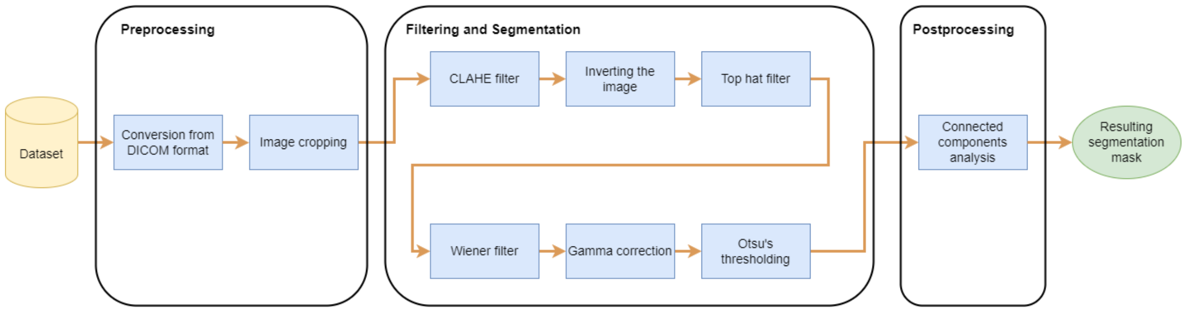

Fig. 1 Proposed methodology workflow

One of the biggest problems working with any X-ray based imaging data is the low contrast in the image, which makes segmentation of the region of interest from the background challenging. In the case of available angiography data, coronary arteries are not distinct enough from the background muscle and bone tissue. In order to improve contrast, the grayscale image of the left coronary artery is processed using the Contrast Limited Adaptive Histogram Equalization (CLAHE) filter. CLAHE operates on small regions in the image and introduces clipping limit of the histogram, which results in reduced over-amplification of the contrast in the image. Results of the application of the CLAHE filter are shown in Figure 2b.

Fig. 2 Original grayscale image of left coronary artery (a); Results of application of the CLAHE filter (b)

Following the CLAHE filtering, pixel values in the image are inverted so the coronary artery is represented with white color and background is represented in dark color. With the goal of suppressing the background in the images, top hat filter that enhances bright objects of interest is applied. Even though CLAHE filter significantly improved contrast in the image, it also made image grainy and background bone structure more prominent, as shown in Figure 2b. In order to suppress the noise that is present in the picture a Wiener filter has been applied. Wiener filter is an adaptive low-pass filter that applies varying smoothing based on local mean and variance of the pixels in the patch of size $M \times N$. Wiener filters are usually applied in frequency domain, where resulting image represents a product between Wiener filter and image spectrum.

In order to further enhance the separation between blood vessels and the background, the Wiener filter-processed image underwent a gamma correction procedure. Gamma correction is a nonlinear operation used to encode or decode luminance in the image, thus 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, while $\gamma > 1$ is called decoding gamma and results in lowering of saturation in the image. For the task of coronary artery segmentation, encoding gamma of 0.97 was selected in order to slightly saturate the image and make bright blood vessels more prominent. It would've been better if image was more saturated, but this would result in the amplification of background noise as well.

The pixel values in the processed image are in the range of 0 to 255. For binary segmentation, we want to group all of the pixels that belong to coronary artery and label them with one pixel value and mark the other pixels with 0. To achieve binary segmentation, thresholding technique was used where image is binarized based on pixel values. If the intensity of a pixel is greater than the given threshold, the pixel is marked as white and represents coronary artery region. If the input pixel value is less than the given threshold, the pixel is marked as black (background). Deciding what is the optimal threshold is crucial and it can drastically affect the quality of resulting segmented image. In order to find optimal threshold value Otsu's thresholding algorithm was used. This algorithm finds threshold value by minimizing intra-class intensity variance, or equivalently, by maximizing inter-class variance [14].

Looking at the results of Otsu's thresholding, it can be seen that it adequately segments coronary artery region, but in the process, it also wrongly classifies some of the background areas as region of interest. These wrongly labelled areas are considered noise and have to be removed in order to correctly finalize process of binary segmentation. Due to the small size of these areas, connected components analysis can be utilized for the noise removal. Every connected area in the image is marked as a single component and all of the components are sorted by their size (number of pixels in each component). The largest component is marked as coronary artery, while the rest of the segments are considered background. Figure 3 shows the whole methodology of coronary artery segmentation.

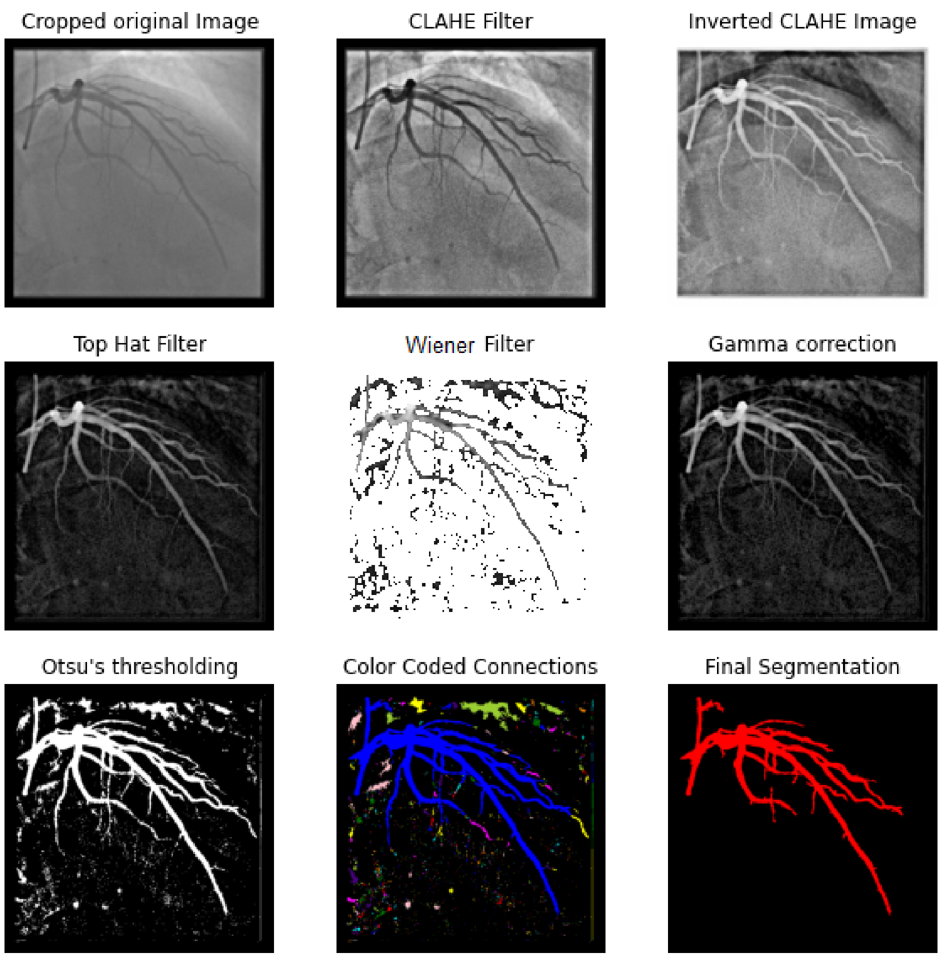

Fig. 3 Unsupervised coronary segmentation workflow

3. Results

Figure 4 shows final results of the image segmentation workflow on examples of left coronary artery images. It is clear that methodology is capable of achieving great segmentation results even on the smaller arteries that are hard to correctly segments even by medical experts.

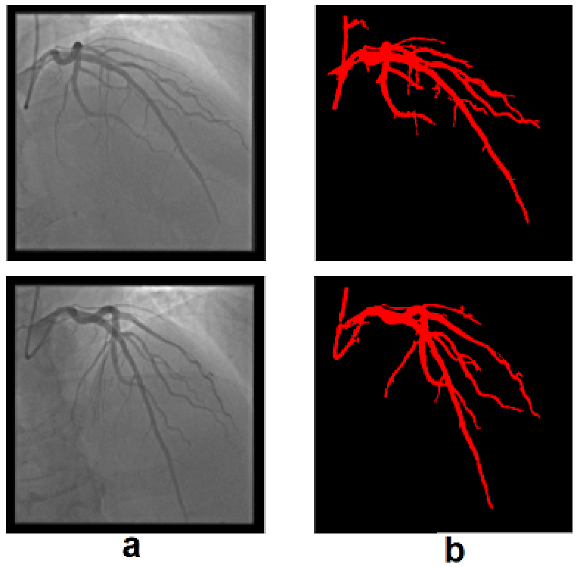

Fig. 4 X-ray angiographic images of left coronary artery (a); Result of proposed segmentation workflow (b)

Since the proposed methodology is considered unsupervised learning technique, there isn't any available labelled data that can be compared with resulting segmentation mask. This results in the lack of any quantitative metrics that could show segmentation performance of the developed methodology.

4. Conclusions

In the field of medicine, segmentation of certain region of interest for diagnostic purpose is a common problem. The task of image segmentation is especially difficult when working with X-ray images that suffer from imaging artifacts and noise. In this paper we describe robust unsupervised segmentation method that extracts left coronary artery from the angiographic imaging data.

The proposed workflow correctly segments major branches of the left coronary artery as well as smaller diagonal branches. The achieved results are satisfactory, even with the previously mentioned shortcomings of X-ray images. Proposed methodology showed that it is possible to segment left coronary artery even when there isn't any labelled data. Future research is going to focus on adapting the methodology for the task of segmentation of right coronary artery and the usage of proposed workflow in a larger project that focuses on 3D reconstruction of coronary arteries.

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