

Full Length Research Paper

Automated Segmentation and Extraction of Coronary Artery Tree Structures from Angiograms Using Gaussian Filtering and Thresholding

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Dynamic variations in the curvilinearity of coronary arteries pose significant challenges for study using current angiograms. Nonetheless, both experimental and clinical evidence indicates that vessel extraction is valuable for surgical treatment and clinical research. In this paper, we present an automated algorithm designed to identify the outlines of coronary artery tree blood vessels in angiograms. This approach serves as a practical tool for physicians. The algorithm automates the segmentation of coronary arteries from cineangiograms, followed by precise extraction of vessel features. Such preprocessing, in conjunction with a matched Gaussian filter, can significantly enhance results. The segmentation algorithm comprises two key processes: (1) Gaussian filtering of blood vessels and (2) thresholding. We evaluated the algorithm using a raw dataset of 100 angiogram images, validating the results through two methods. First, hand-labeled annotations provided ground truth segmentation for 20 images, revealing that our algorithm outperformed manual detection, even in cases of poor contrast that the naked eye could not recognize. Second, we employed a questionnaire to assess the effectiveness of the illustrated output. The hand-labeling matched our results with an accuracy of 98%, while the questionnaire validation rate was 90.84%. We conclude that our enhanced algorithm is effective for extracting coronary artery tree vessels, including smaller branches. Additionally, the algorithm operates efficiently, completing vessel extraction in approximately 14 to 15 seconds per image.

Key words: Angiocardiology, coronary artery segmentation, matched filter, adaptive thresholding, vessel extraction.

INTRODUCTION

Coronary angiograms are used to guide physicians in the medical diagnosis and also treatment of cardiac patients. Major advances in coronary angiography have been made with the help of medical imaging techniques including biplane angiography and digital subtraction angiography (DSA) (Saito et al., 1990). Such techniques allow the diagnosis of all structural anomalies in the cardiovascular system, that is, suitable for medical treatment and surgical revascularization. Since these

medical and surgical therapies are becoming more sophisticated, it is also becoming increasingly important to conduct quantitative analysis on angiographic images in order to understand the configuration of the coronary arteries. Coronary artery disease (CAD) concerns the narrowing or blockage of the arteries that provide blood to the heart muscles. Consequently, coronary angiograms have remained an indispensable tool in clinics for the diagnosis of CAD. In general, visual inspection of coronary angiograms suffers from inherent imprecision that has led to the development of the semi- and fully- automatic tools that apply computerized techniques for image analysis to the assessment of the

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coronary artery disease (Saito et al., 1990; Canny, 1983). Vessel extraction is an important task to guide physicians through vessel treatment procedures and which results in more medical benefits. However, extraction from angiograms did not take much space in previous work since this kind of images has low signal to noise ratio. Nowadays, most of the radiologists prefer angiograms because of the real-time diagnose and treatment they offer. In addition, vessel extraction considers as the first step in medical imaging pre-processing procedures that can lead for more helpful technical approaches in the future. One of those procedures is reconstruction of the coronary arteries in 3D at various phases of the cardiac cycle which was proven to be useful for analyzing the absolute motion of the myocardium as well as estimation of regional wall stress, as discussed in Saito et al. (1990) and Canny (1983). There are a number of earlier related works for estimating 3D features of coronary arteries through computer analysis (Saito et al., 1990; Chaudhuri et al., 1989).

Vessel centreline extraction was reported in many previous work papers. The procedure stands of tracking down the centrelines of vessels and produce the total tree of blood vessels. Even though this kind of work is very helpful and useful in many aspects, but it stays slow and does not offer information about vessel borders. The presented algorithms and approaches in vessel extraction used three different ways of solving the problem. Some of them used the geometrical topology information, others used the intensity information, and the rest combined between both of them to obtain the proposed tracking direction. The algorithm proposed in Xu et al. (2007) used the third way of combination between geometrical topology and intensity to track down the centerlines of vessels. The algorithm has been described as successful in extracting vessels centrelines with satisfactory accuracy. The paper investigated using matched filter on the eigenvalues which would make centreline extraction much easier. The work in Aylward and Bullitt (2002) presented the centerline extraction of tubular objects (blood vessels) in 2D and 3D images. The work was part of a task to analyze bunch of clinical images. This work was based on another paper for them was published in 1996 to handle noise using multi scale and optimal scale measurements (Aylward et al., 1996). The work was enabled as fast and accurate but was conducted on CT-scan, MRA and 3D-ultrasound images. Meanwhile, in Schreiner and Buxbaum (2002) work, an algorithm was presented to build a model of arterial vascular tree by adding terminal of vessel segments. The model was built by adding segments to the preexisting tree, then the new bifurcation is optimized geometrically. The work was compared to real coronary artery trees to demonstrate its strength points of showing structure of the arterial trees, pressure profile and morphometric parameters. We observed the output of this algorithm and it showed the coronary artery tree in full segments

(around 4000 segments and 2 days of computing time) which is not necessary in our work.

The vessel extraction from 3D angiograms took a space in this field also. Wherein, Wong and Chung (2008), we can find a method to segment blood vessels and extract their centerlines in 3D angiograms. The method involved discussing principal curvatures and vessel centerline extraction. Upon a user supplement of two end points to the algorithm, it can extract vessel centerline between the two points automatically. Another algorithm was presented in Sun (1989) adopted the same principal of initial start of search points. The algorithm would update tracking process by matched filter guidance. The algorithm was robust and efficient in tracking process in DSA and cineangiograms. Another algorithm was described in Wang et al. (2005) to extract vascular centerlines and contours in coronary angiography. By closely observing this work, we noticed that the algorithm used digital subtracted angiography (DSA) and it was to extract centerline and contours of vessels only. In addition, the algorithm needed seed points to start the extraction procedure. We tried DSA angiography and extracting was much easier than normal grayscale angiograms. Finally, a great amount of various vessel extraction approaches and techniques were reviewed and classified by means of the existence in Kirbas and Quek (2004). Previous works are based on the X-ray geometry of projections as well as the iterative identification of the matching structures from several views. The well-documented in accuracy in the visual interpretation of angiograms has motivated the development of the automated methods in order to quantify arterial morphology. Understandably, the accurate description of the arterial trees would be helpful for conducting quantitative diagnosis on atherosclerosis, as well as for treatment, surgery or associated planning. It would also be useful for monitoring the progress of disease or remission, and comparing the effectiveness of treatments.

The appearance of the blood vessels is regarded as an important indicator and is used for many diagnoses including diabetes, hypertension and arteriosclerosis. Arteries and veins have many observable attributes such as diameter, tortuosity or relative amount of curvature, colour and level of opacity (reflectivity). The crossing and patterns of artery-veins in small vessels could also be used as diagnostic tools. The accurate delineation of the boundaries of the blood vessels makes the exact measurements of these attributes possible. Such measurements might then be used for a variety of different tasks including diagnosis, evaluation of treatment and clinical study (Saito et al., 1990). We present here a semi-automatic algorithm for extraction of coronary artery trees blood vessels in angiograms. Our algorithm was inspired by Hoover et al. (2000) who demonstrated a vessel extraction in retina images. Since the algorithm in Hoover et al. (2000) was used for a

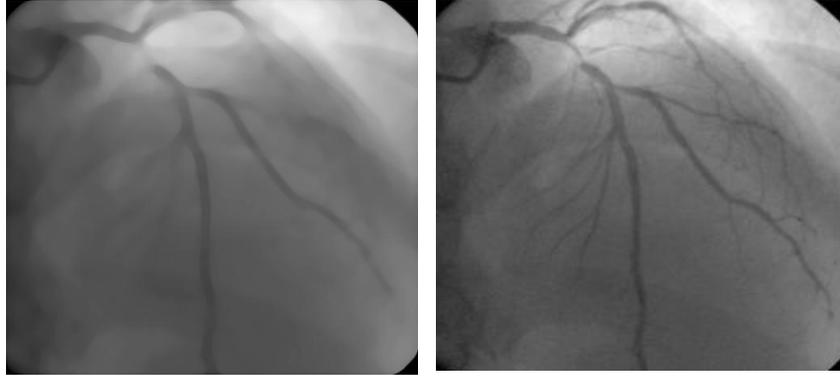


Figure 1. An example of angiogram with coronary artery tree vessels (left) and Gaussian filter response (right).

different type of images (retina) which have different functionality and features from our images (angiogram); we were inspired to design our algorithm that can work with angiograms even though it has been a big challenge. Such an algorithm can be regarded as very helpful tools that can assist heart specialists observe larger populations of vessel abnormalities. The exact measurements can be recorded more easily in, for example, treatment evaluation, clinical study and other applications as reported in Saito et al. (1990). The previous algorithms for automatic segmentation of blood vessels have concentrated mainly on the local features. Vessels can be characterized according to gradient (boundary strength), shape (that is, curvilinear) and contrast with their background. Regarding suitable ranges of such features, other image manifestations including boundaries of the optic nerves and also certain lesions and haemorrhages might also show the same local features as vessels (Cote et al., 1994).

The strength level of the Gaussian filter has been coded in greyscale, which means the stronger the response, the darker the pixel. Gaussian equation can work well as the determinant of an image threshold value by using controllable variance factor. The proposed idea in this paper is to make the variance value controllable by the user; the issue that can affect the Gaussian filter response itself. Therefore, the threshold value will be determined according to that response of the Gaussian filter. Figure 1 shows how Gaussian response can affect an image appearance. Our algorithm was applied on angiograms to extract coronary artery trees with full branches that could not be recognized in unprocessed angiogram images.

MATERIALS AND METHODS

Here, first, we briefly review the data acquisition (preparation and procedure) and the data pre-processing. Next, the Gaussian matched filter construction is explained upon which the improved algorithm is built. Then, we present the threshold examination

process by emphasizing both variance value and lighting effects on the thresholding process. Finally, the improved stages upon which the algorithm was built are presented. When using the previous algorithm, a blood vessel is tested by examining a certain area of the matched filter. During each iteration, the features of the blood vessel are tested to examine the continuation, and ultimately to decide whether the segment is from a vessel. Pixels that are not classified as a vessel will be re-examined.

Data acquisition

Angiograms are the data to be used in this paper to implement our algorithm. Angiography is defined as the X-ray investigation of blood vessels. Angiograms make use of a radiopaque dye or substance that allows blood vessels to be seen under applied X-ray (Saito et al., 1990). Arteriography is classified as a type of angiography that involves the examination of arteries. In fact, angiography is usually conducted in hospitals by trained radiologists and by assisting professional technicians and nurses (Saito et al., 1990). It is performed in X-ray or fluoroscopy suites. For most angiogram types, the patient's vital signs should be continuously monitored throughout the process.

Preparation for angiography

Angiography requires the injection of a contrast dye that makes the vessels visible under X-ray. The dye has to be injected through the procedure of 'arterial puncture' with the puncture generally being created in the groin area, inside elbow, armpit or neck. The site must be cleaned by using an antiseptic agent, and then injected with a local anaesthetic (Saito et al., 1990).

Procedure of angiography

The procedure was explained by Leigh (2010). It starts with positioning the patient on their back and may include fastening them with straps across the chest and legs to keep them safe. They may be given a sedative medicine to help them remain calm while their veins are connected to the IV lines. However, the sedative will not put them to sleep and they will remain aware throughout the procedure of any instructions from the doctors or nurses to move their arms or hold their breath. Leigh (2010) continues explaining the angiogram procedures that include monitoring the heart throughout the procedure through an electrode that is fixed to the

patient's chest. In addition, they should also measure the oxygen in the patient's blood and the blood pressure throughout the test procedure. The site must be cleaned by using an antiseptic agent, and then injected with a local anaesthetic. Initially, a small incision should be made in the skin to help the needle to pass through. Subsequently, a needle which contains a long inner wire called a stylet is inserted through the skin directly into the artery or the heart. The last stage of the procedure according to Leigh (2010) is when the catheter reaches its place near the heart. Then, a contrast dye will be injected into the veins. The doctor will be able to identify any blockage area(s) in the coronary artery vessels by the flow of the dye through the vessels.

Data pre-processing

The pre-processing of the plain data obtained from the hospital is a very important step. The data is saved in CD-ROMs during the treatment procedure as a cineangiogram. Dealing with the data in its original moving DICOM format is quite difficult; therefore, the data is converted into a series of 2D BMP (bitmap) angiogram images. Later on, each single-view angiogram image can be used at a time (input) to extract the output (coronary artery trees). Currently, there are many types of software available to convert moving DICOMs into BMP images. The popular software which works well to read DICOMs is the DICOM viewer. There are numbers of DICOM viewers available on the Internet such as DICOM viewer, Sante DICOM viewer, Philips DICOM Viewer R2.5L1 SP4 and others. The DICOM viewer software reads moving DICOMs and transfers those into still BMP angiogram images. Finally, the process of separating the still angiograms from each run of each cineangiogram starts from the period of injecting the contrast dye into arteries until the end of the procedure. The optimum angiogram image that shows the complete coronary artery network is chosen - according to the scope of this paper - to serve as subsequent input to the extraction algorithm. The number of images is different from one run (a sequence of motion images from a specific angle) to another because it depends on the time each run consumes. The complete process of angiograms separation from moving DICOMs is illustrated in Figure 2. At the end of data pre-processing, a series of single-view angiogram images are obtained for each patient. Images belonging to each patient are saved individually in order to use the images in the extraction process. It is important to enhance the images after each pre-processing procedure by removing the noise that might occur through the pre-processing stage and also to enhance the contrast. Fortunately angiograms, due to the nature of their imaging systems making use of X-ray radiation do not suffer much from contamination by noise except for some unnoticeable White Gaussian noise that might occur through the pre-processing stage. Angiogram noise removal, if any such noise exists is done at the step of coronary artery tree extraction through a smoothing process. However, there exists a problem in the contrast enhancement of the vessels in the angiograms. This issue is such a challenge in angiograms because of the similarity in contrast between some blood vessels and the background after the completion of injecting the contrast dye.

Figure 3 illustrates three examples of angiogram images showing the contrast similarity between parts of the background and vessels indicated in the green boxes. Therefore, contrast enhancement is important for highlighting and extracting coronary arteries from angiograms. The proposed coronary artery trees extraction algorithm in this paper performs the contrast enhancement automatically by using Gaussian filter. Therefore, no extra software is needed in this work to enhance the contrast and the original angiogram can be input directly into the coronary artery tree extraction algorithm. In summary, the pre-processing stage is a vital

process to ensure the success of the following stages of the methodology. The optimum angiogram nomination is a necessary step in the extraction process to guarantee accurate extraction process. Therefore, this step is responsible for automatically choosing the optimum angiogram image among the set of angiograms of each patient. Then, this optimum image will be the input for the coronary artery trees extraction algorithm. The automated optimum angiogram nomination proposed algorithm will be explained in the part of this paper that deals with angiogram images.

Gaussian matched filter

A matched filter, the Gaussian filter shows the appearance of the desired signals. In this paper we propose using a Gaussian function as introduced by Canny (1983), for a blood vessel profile that is further extended to 2D by assuming that a vessel must have a fixed width as well as a fixed direction and with short length. Since, in reality, vessels are seen in any orientation, a set of 2D profiles of segments in equiangular rotations must be used. Eichel et al. (1988) and Hoover et al. (2000) applied kernels for matched filters by using twelve sets of 16×16 pixel kernels. Further details regarding computation of the actual values in the kernels can be found in Eichel et al. (1988) and Hoover et al. (2000). For our purposes, we applied a Gaussian matched filter to an angiogram by convolving it with all of the twelve kernels. The filter is essential in the vessel extraction as well as segmentation. However, we propose to use a controllable variance factor in the Gaussian function to segment our angiogram images. The idea comes from the strong relationship between the Gaussian response influences over images which can produce the threshold value automatically for an image. The Gaussian function is the function that is responsible for image intensity, however, changing the variance throughout the Gaussian filter equation will change the response upon that image and as a result the threshold value will be determined according to that response. In addition, choosing to control the variance value is because this value controls the width of "bell" shape of the Gaussian output, therefore, we will be controlling the thresholding value itself. Figure 4 shows the Gaussian bell shape for different variance values.

Threshold examination

The basic task of the algorithm presented in this paper is to examine the Gaussian response over images. For each examination, a criteria set is tested in order to determine the threshold, and eventually to decide whether the area being examined belongs to a blood vessel (Hoover et al., 2000). The flowchart of threshold examination and vessel extraction is presented in Figure 5. The pixels will be set in a queue and initialized, where each point will be used for the examination. When the examination is completed, and if the segment is found to be a vessel, then its endpoints is added to the queue. Accordingly, different examinations (and therefore different thresholds) could be applied to the whole image. The previous algorithm is used to extract blood vessels within retina images. However, it inspired us to come up with our algorithm of angiograms. Our contribution is to improve the functionality of their algorithm to become a coronary artery trees extraction algorithm. We should keep in mind that in angiograms we are dealing with two intensity values, vessel and background. According to our measurements, the vessel intensity always larger than backgrounds ones since vessel are filled of contrast dye at the moment of angiography process. We propose to use the Gaussian function with variable controllable variance (σ^2) in order to efficiently extract blood vessels using angiograms. Angiograms are a type of X-ray images that has low signal to noise

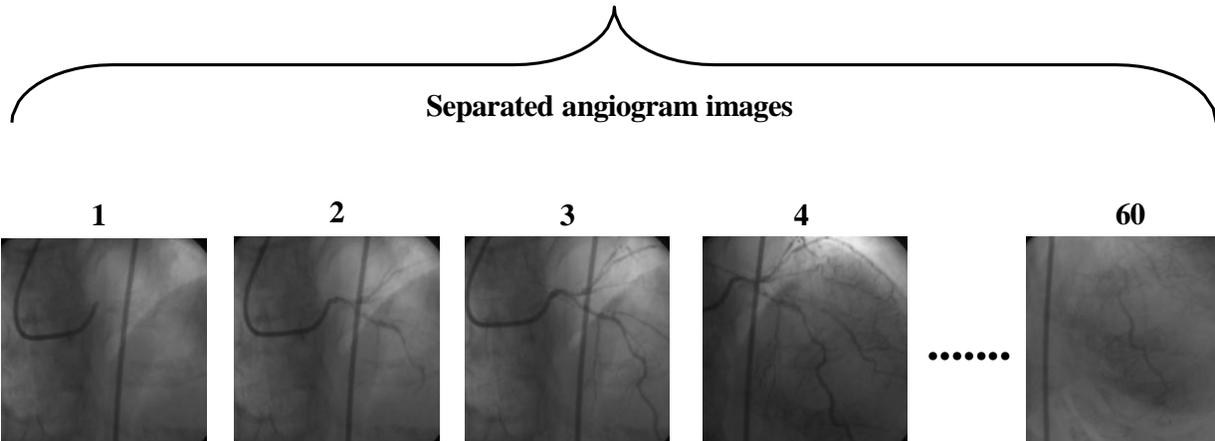
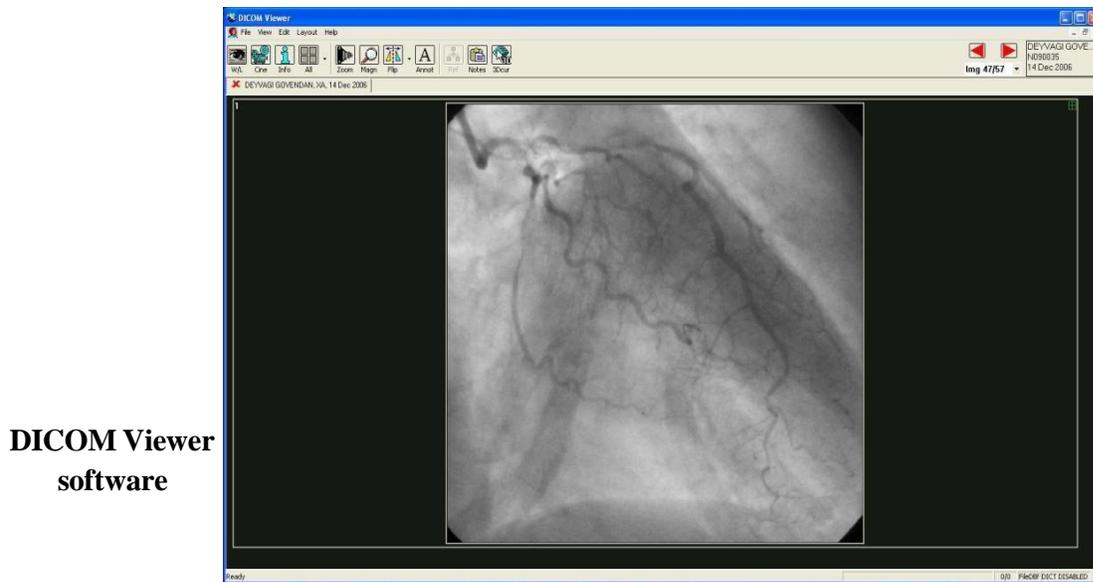
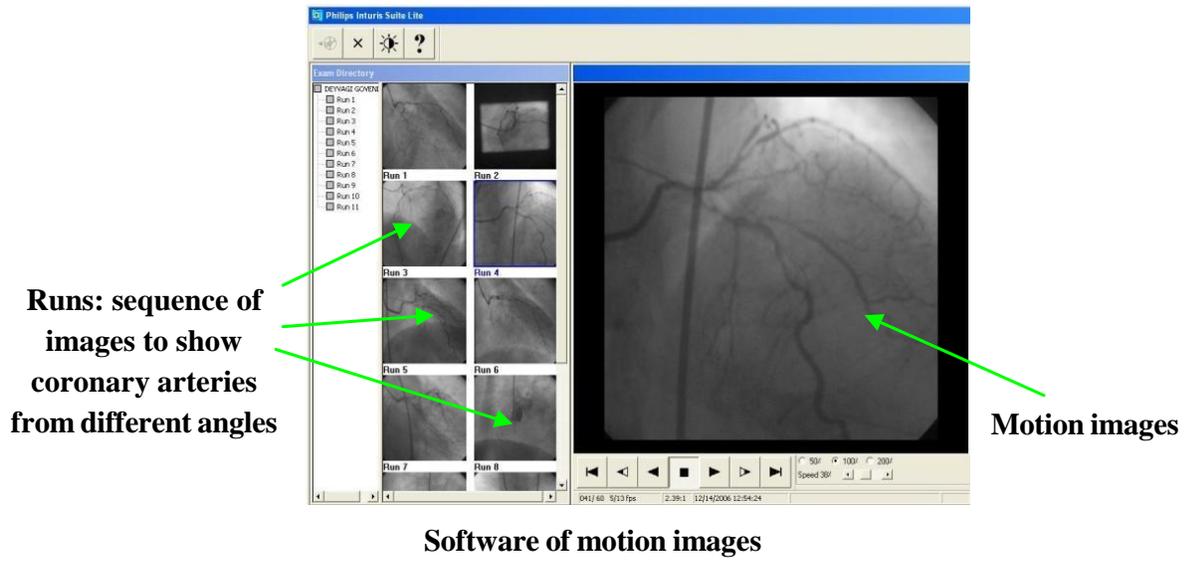


Figure 2. Process of separating still BMP angiogram images from moving DICOMs.

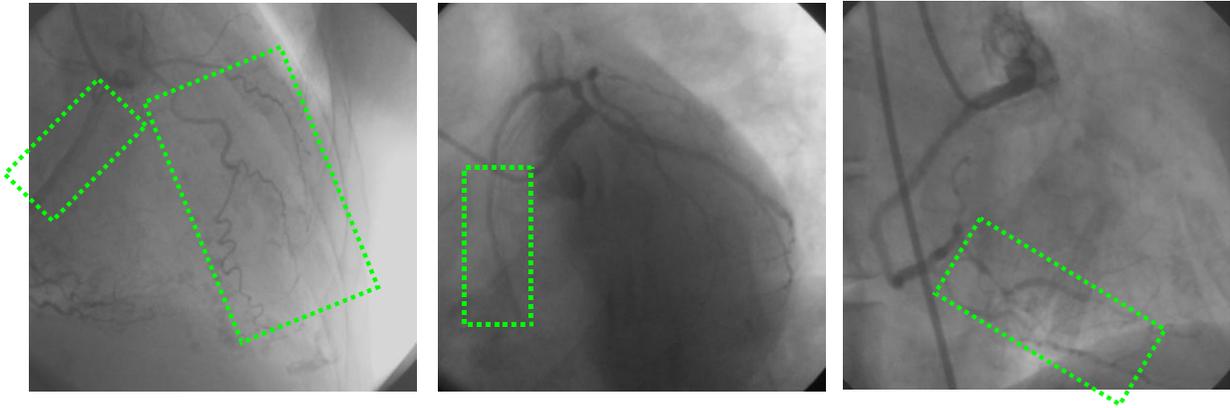


Figure 3. Examples of angiograms with contrast similarity between the vessels and the background.

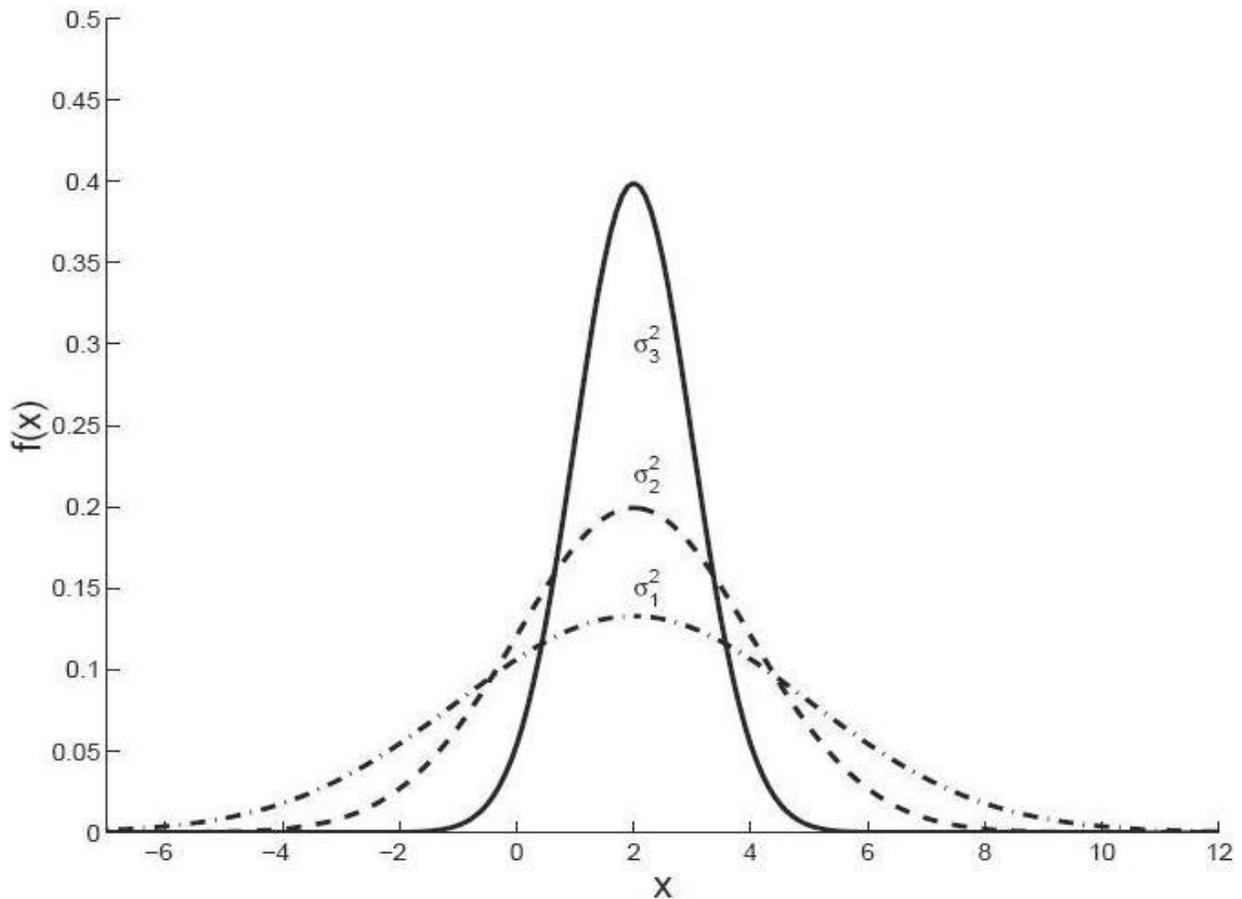


Figure 4. Gaussian bell shape with different variances ($\sigma_1^2 = 3^2$, $\sigma_2^2 = 2^2$, $\sigma_3^2 = 1$) (Ribeiro, 2004).

ratio, that is, it does not provide much information unless they are pre-processed to highlight objects and remove backgrounds. There is a considerable difference in the intensity among an angiogram's pixels. We attempted to design our algorithm keeping in mind previous information and came out with algorithm presented in Figure 5.

Details of the flowchart in Figure 5 are listed in the following

steps:

- 1) Start the algorithm by input of an angiogram image.
- 2) Convolve the image with Gaussian filter while the variance (σ^2) value is been set up in the range of $1 \leq \sigma^2 \leq 2$. This process is to clear the image from any noise (if any), enhance the contrast and

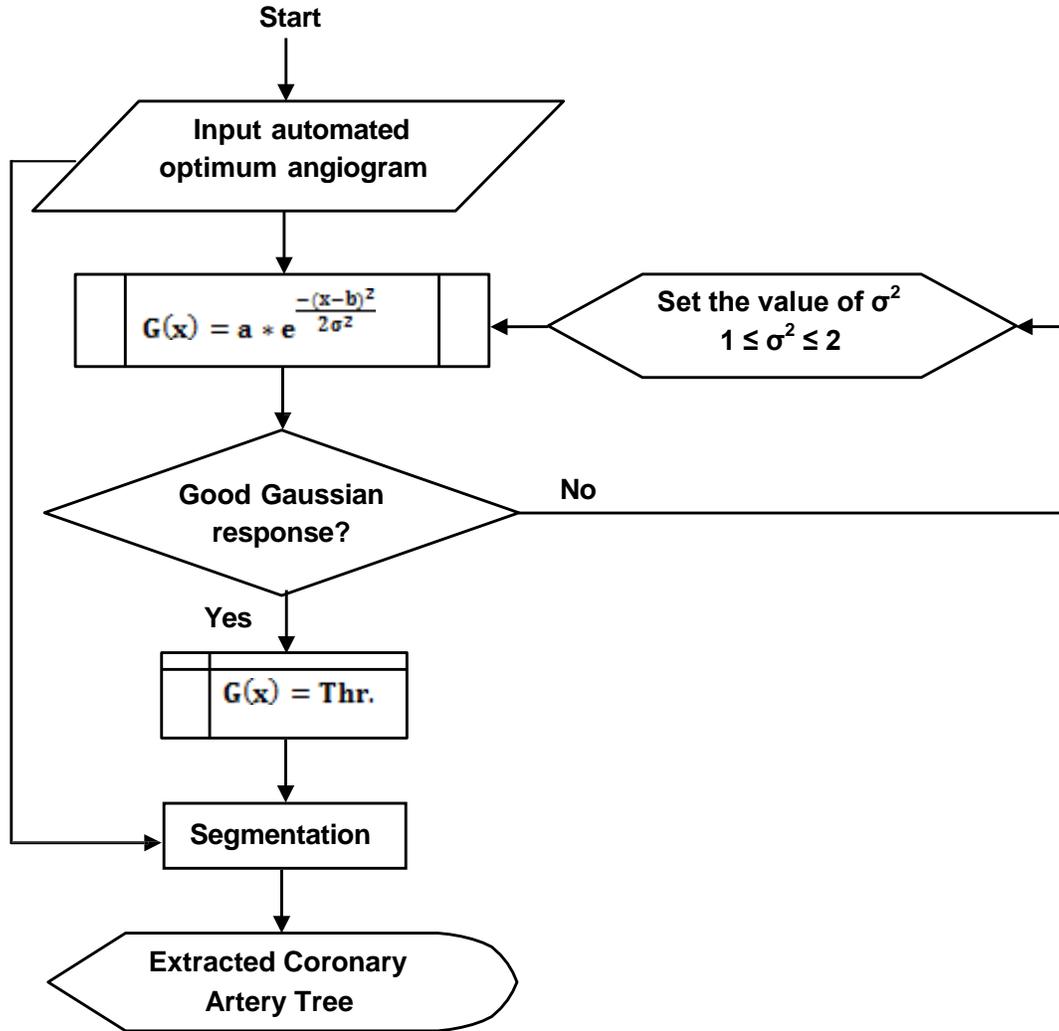


Figure 5. Flowchart of threshold value examination and coronary artery trees extraction.

examine the filter's response upon the image which will determine the threshold of each pixel in the image. The Gaussian function is shown in Equation 1.

$$G(x) = a * e^{\frac{-(x-b)^2}{2\sigma^2}} \quad (1)$$

Where a, b > 0 are constants, σ^2 is the variance and x is an image's pixel.

3) Check the response of the Gaussian filter on each pixel of the image. If it was good, that is, the image is clear and no loose of information (vessels) as shown in Equation 1, then the response of the filter per each pixel can be set, internally in the program, as the threshold value for that pixel. If the response was poor and there is amount of information loosing, then repeat step 2 which will set a new value for σ^2 in the specified limit. This process will be done for pixels which are part of vessels but if they were part of the background then they will be omitted.

4) The set threshold values of pixels will be used to automatically segment them and the complete coronary artery tree will be extracted as the final step.

5) Display the extracted coronary artery tree in a binary format standing alone or superposed with the original angiogram.

Variance (σ^2) value

The variance value was chosen to be in the range of $1 \leq \sigma^2 \leq 2$, why? We have done a series of experiments regarding the issue of Gaussian filter response and how it can be good enough to extract vessels. That inspired us to use the value of the variance to control the Gaussian response knowing that it is an important factor in the Gaussian equation. Even though the value is important, but it cannot be open to all values and we had to test the best values. Our experiments proved that Gaussian filter can response well with angiograms when the value of σ^2 is in the limit of $1 \leq \sigma^2 \leq 2$ and as a result the extraction process would be efficient. The efficiency of vessel extraction can be determined according to the clear and less noise extraction process. Vessel extraction meant to highlight the vessels only and remove the background; therefore, if the response of Gaussian filter was poor, then the extraction process will detect part of the background as vessels which will be called false alarm

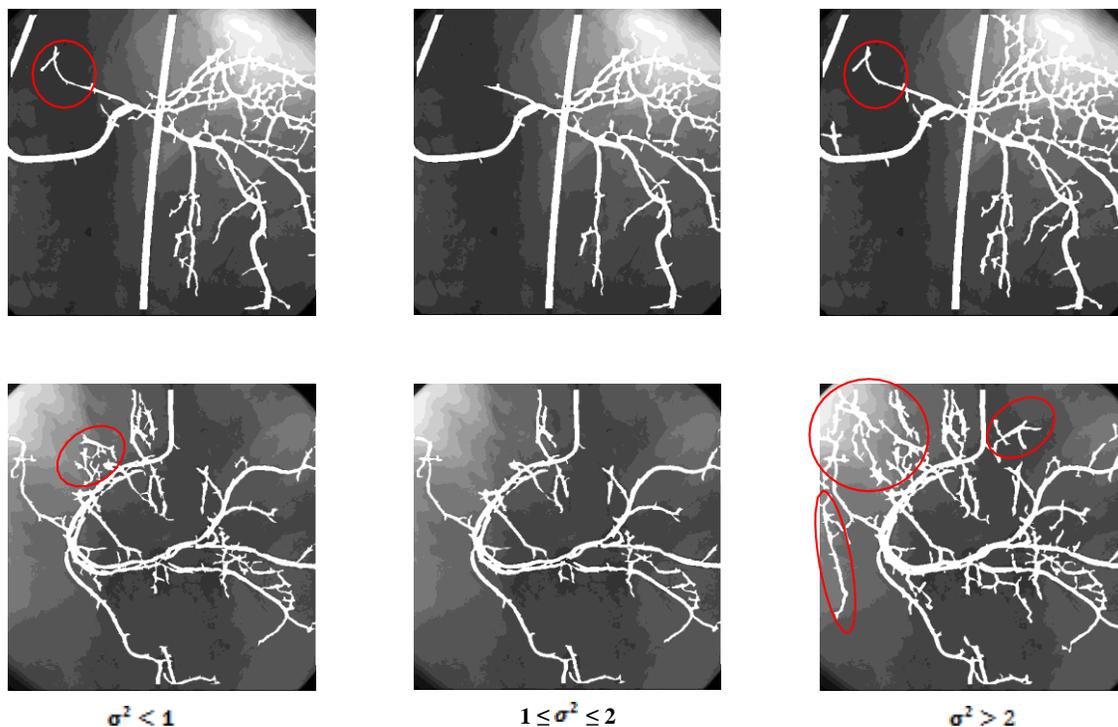


Figure 6. Some examples of extracted coronary artery trees in different σ^2 limit values. the extracted trees are superposed on the original images with red circles to show false alarms (noise).

(noise) in this case. To validate our finding, we have done a questionnaire to evaluate the efficient illustration output of coronary artery trees extraction from angiograms. The questionnaire will be detailed in the results and discussion section. Figure 6 shows examples of images were extracted in different σ^2 values. The figure shows three columns of images and we can notice that when the value of σ^2 falls in the proposed limit ($1 \leq \sigma^2 \leq 2$), the extraction could be more efficient, that is, less noise. Now, are all threshold values generated within the limit $1 \leq \sigma^2 \leq 2$ can work well without any noise occurrence?

First the threshold value will depend on the Gaussian filter response and secondly, some noise may occur within our proposed limit but it will always be less noise that may occur within other limits.

Lighting effect

One of the difficulties that may obstruct good object extraction in any kind of images is the lighting. The lighting in images has always been considered as a big challenge. The light value could be added to the values of the pixels but this would cause problems. Light elimination and approaches involved in this issue are not our concern here because lighting has no effect on angiograms because X-rays are the main source used to capture angiograms. So, what is the lighting that appears in some angiograms? According to radiologists and cardiologists from PPUKM hospital (the hospital that provided the data for us), the light areas that appear in some parts of angiograms are the effect of X-ray reflections from the Operating Theatre (OT) table that is placed under the patient through the imaging process. As explained earlier,

the C-arm system is set to different angles as part of the coronary angiography procedure. In some of the specified angles, the X-ray source may shoot outside the patient's body and hit the table or the radiation may hit some parts of the body without thick organs or bones and then pass through to the table. In this case, the Charge-Coupled Device (CCD) camera captures the reflections of the radiation from the OT table and light areas appear in the angiograms. Therefore, according to the effect of radiation, the intensity of the pixels will be changed to different levels and so affect the extraction process. Thus, the importance of a Gaussian filter to concentrate on vessel extraction in order to clear angiograms of noise (if any) and enhance the intensity levels (attenuate the lighting effects). Figure 7 illustrates some angiograms with x-ray reflections and Figure 8 shows the differences in the intensity levels using histograms. Therefore, we can say that Gaussian filter is an essential step in the pre-processing because besides its response is the main factor to determine the threshold value, it can also clear the angiogram from any noise (if any) and enhance its intensity levels as well.

The x-ray reflection can obstruct vessels extraction process in the absence of Gaussian filter. We can summarise the Gaussian filter advantages in three points:

- 1) Threshold value determinant,
- 2) Enhance intensity value levels, that is, lessening x-ray reflections,
- 3) Clear the image from any noise (if any).

Usually, angiograms are not contaminated by noise because of the special environment of image capturing which involves x-ray only. However, noise may occur through the pre-processing step. Data comes from hospitals in CD-ROMs and we need to extract still

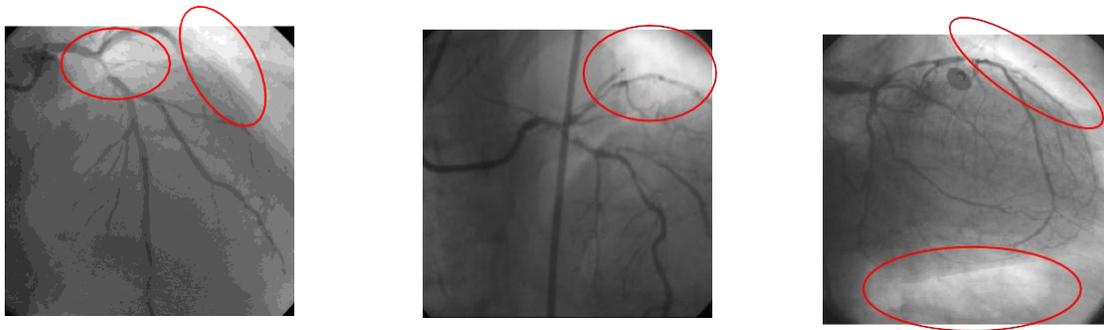


Figure 7. Angiogram images with x-ray reflections.

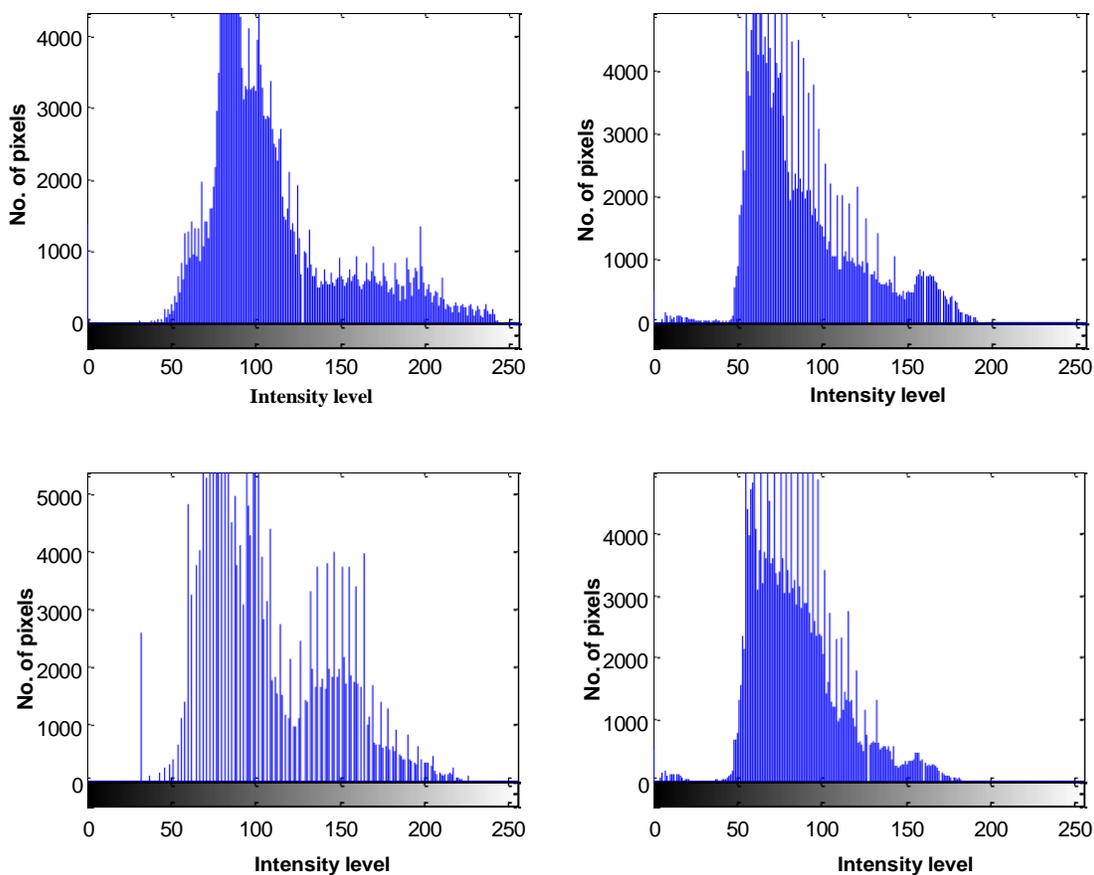


Figure 8. Different intensity levels for four different angiograms shown by histogram.

angiograms out of them. The pre-processing step of separating moving angiograms into still images may cause some noise (White Gaussian Noise). Therefore, different examinations and, accordingly, different thresholds can be applied throughout the extraction process until Gaussian response is good and subsequently the extracted coronary artery tree. The tiny vessels extraction is a challenging process because their intensity values could be very close to their neighbours (background). Our algorithm in this paper could efficiently extract the whole coronary artery tree including tiny vessels.

Angiogram images

It is worth mentioning briefly that the data set of angiograms was used to perform the algorithm was proposed in this chapter. The dataset which included 100 angiogram images was obtained from PPUKM hospital, Malaysia. As mentioned earlier, data were saved in CD-ROMs and the pre-processing stage was used to extract a set of still BMP angiograms of 512×512 pixels size and 24-bit gray scale levels. The optimum angiograms, the input for the vessel extraction algorithm were chosen to build our dataset according to

three categories: 1) most of the referenced strategies only demonstrated normal vessel appearances that are easy to observe, 2) abnormal vessel appearances that were recommended for clinical usage, and 3) both normal and abnormal cases that were suitable for evaluation of the performance of the proposed algorithm. Therefore, the optimum angiograms in our dataset should view as much as possible the complete coronary artery trees with normal and abnormal arteries. Choosing the optimum angiogram image from a set of images is a vital process in the coronary arteries extraction algorithm to guarantee accurate output. The optimum image must be having the following attributes to be nominated as optimum; less noise, less bright spots (X-ray reflections) and homogeneity image intensity values. The concerns of noise and bright spots of X-ray reflections can be solved by the Gaussian filter of the extraction algorithm itself afterwards. As for the homogeneity of image's intensities, it was not that easy to solve this problem since we are dealing with kind of images that have different intensities from one angiogram to another depending on the angle of imaging. Therefore, a preliminary experiment was done in this chapter to guarantee choosing the optimum image automatically by the program and without any user interference.

The experiment was done to mimic the way of choosing the optimum image visually by bare eyes. The bare eyes check for the complete appearance of coronary artery networks plus the three factors that were mentioned earlier, noise, bright spots, and homogeneity, before announcing the optimum. The experiment adopted the histogram technique to act as the main factor of choosing optimum angiograms. The histogram technique is one of the powerful techniques for images' information extraction, frequencies and intensities representation (Gonzalez et al., 2004). The histogram in a range (0 to 255) is defined in the discrete Equation 2 as follows:

$$h(l_k) = m_k \quad (2)$$

Where l_k is the k^{th} intensity level in the interval (0 to 255) and m_k is the number of pixel in the image whose intensity level is l_k .

The experiment was handled on two phases; first, with segmentation and secondly, without segmentation. The purpose of proposing to use the segmentation process in the experiment was to extract the arteries from images and calculate the histogram for them only without focusing on the background. However, using segmentation will cost us more processing time and results will be compared with the visually chosen images to judge using this step. As for the segmentation (vessel extraction) part of experiment, the proposed algorithm in this chapter was used to segment the original angiograms in order to calculate their histograms after this. Therefore, the histogram will be calculated for the coronary arteries only because they are the objects under consideration and in the optimum image they should occupy no less than 50% of the angiogram. The steps of conducting the preliminary experiment with the segmentation part are listed as follows and the framework was illustrated in Figure 9:

- 1) Input a set of angiograms as they were separated from one Run (cineangiogram),
- 2) Segment the angiograms and extract the gray scale arteries only,
- 3) Calculate the histograms for the segmented angiograms,
- 4) Find the average histogram for all histograms in step 3,
- 5) Calculate the Sum Square Error (SSE) for each histogram in step 3 with the average histogram in step 4,
- 6) The optimum angiogram image will be the one with the minimum SSE. Thus, minimum SSE is for the closest image's histogram to the average histogram.

Angiograms are first separated from each cineangiogram, as it

was mentioned earlier in the pre-processing of data in this study, then the test will be applied of the preliminary experiment. SSE is calculated from Equation 3 as follows (Searle, 1971):

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3)$$

Where n is the number of angiograms in one set, y_i is the histogram of an angiogram and \hat{y}_i is the average histogram of all angiograms.

The assumption of using the average histogram came from assuming that when the complete coronary artery tree appears in an angiogram image, it will occupy at least 50% of the frequencies of that image. Therefore, calculating the average of histograms and comparing it with each image's histogram (SSE) can be good enough to nominate the optimum image. The results of choosing the optimum image while the segmentation process is included are acceptable compared with the visually chosen images. However, the process is time consuming that each image is required to be segmented separately. We eliminated the segmentation part from the experiment and calculated histograms for the complete set of pixels for each angiogram image. We then compared the results of the optimum images with the visually chosen ones. Therefore, Figure 9 illustrates the same steps of the experiment that were shown in Figure 10 except for the segmentation part. The proposed algorithm's performance was evaluated on the basis of segmentation of the major vessel correctly, and without premature termination during the extraction process. Although, in normal cases, the separation process between vessel and non-vessel (background) pixels in the extraction procedure is better even though there is no much difference between normal and abnormal (blocked) vessels as shown in Figure 11. The classification of most pixels is often clear to a human observer. However, in contrast with Hoover's algorithm (Hoover et al., 2000) where some of the pixels, for example, those on the vessel's boundary, those on the small vessels, and those on vessels near pathology are classified less easily. Our algorithm easily and efficiently extracts vessels in the whole angiogram.

RESULTS

To evaluate our proposed algorithm using a computer with Windows-XP, 3G-RAM and 1.5 GHz, we applied on a clinical data set of 100 angiogram images. The application was to extract the coronary artery tree out of each angiogram image. Later on, we validated the results of our algorithm by comparing it with two different approaches using two ways. First of all, the experiment of nominating optimal angiograms is applied as in Figures 9 and 10; and the results shown in Table 1 together with the results of the nomination of the optimum images using the bare eyes (the visual part). The images used in the experiment were taken from 15 different runs (cineangiograms). In Table 1, it can be clearly seen that the results of the experiment without the segmentation part are closer to the visually nominated results than the results of the experiment when the segmentation part was included. Table 1 includes five columns. The first is for the number of the Run, the second is for the number of images per each Run, the third is for the visually

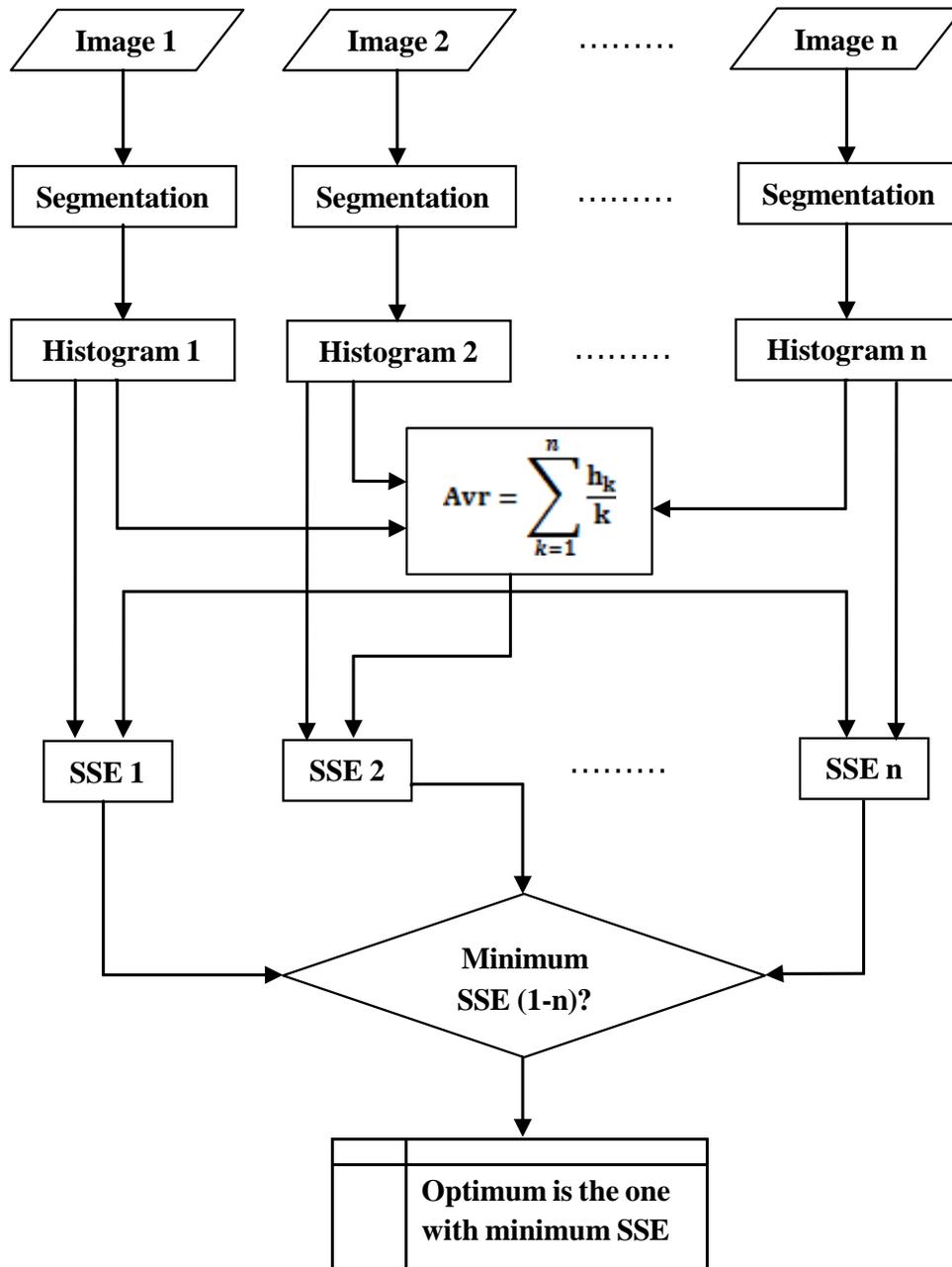


Figure 9. The framework of optimum angiogram image nominating with the segmentation part.

chosen images from the total number of images per Run, the fourth is for the results of the experiment with the segmentation part, and finally the fifth column is for the results of the experiment without the segmentation part. The criterion of visually chosen images depends on visual aspects such as full coronary artery network, not poor angiogram and less x-reflection spots. The second column in Table 1 shows the number of angiograms in each Run (frames per each cineangiogram). Same goes for the 3rd, 4th and 5th columns whereas each number

refers to the index of an angiogram in the series of frames per each Run.

Figure 12 illustrates a comparison between the results of the experiment in Figures 9, 10, and the results of the visual part. Figure 12 clearly illustrates that the curve of 'Optimal image without segmentation' has greater similarity to the curve of 'Visually Optimal' than the curve of 'Optimal image with segmentation'. This proves that the experiment without the segmentation part can give better results (closer to the visual part) and of course

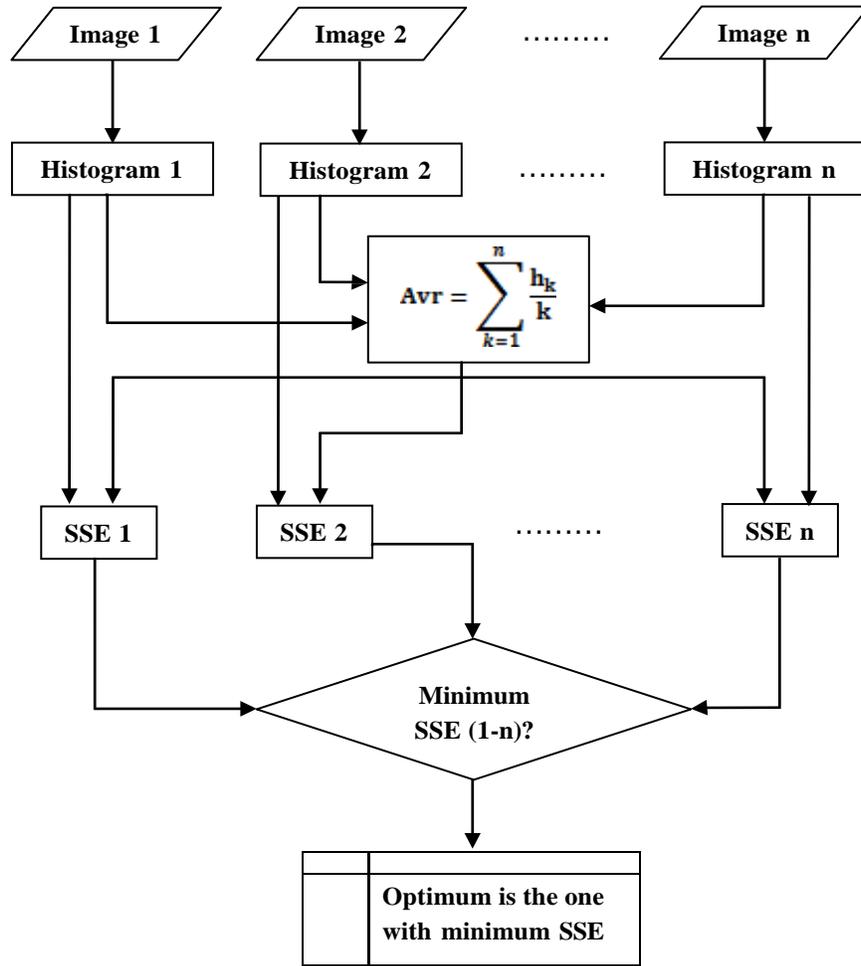


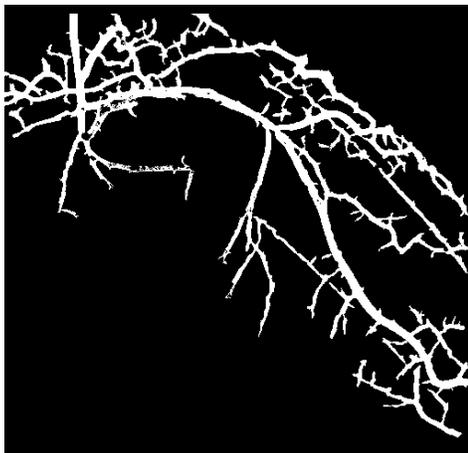
Figure 10. The framework of optimum angiogram image nominating without the segmentation part.

Table 1. Results of optimal image nomination.

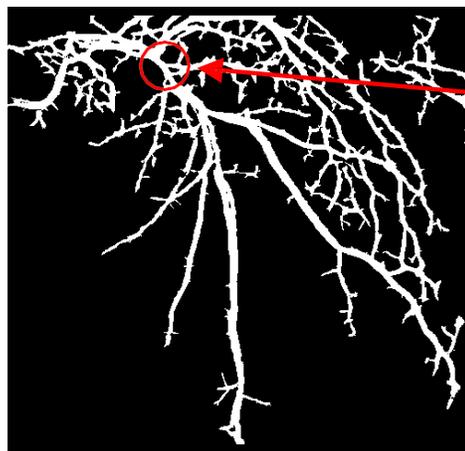
Run #	No. of images/run	Visually optimal	Optimal image with segmentation	Optimal image without segmentation
1	44	32	9	21
2	45	27	29	22
3	47	30	23	25
4	32	20	18	32
5	31	20	28	23
6	34	14	7	19
7	44	17	14	13
8	46	23	5	15
9	45	18	15	3
10	85	48	45	46
11	56	18	18	15
12	36	18	22	15
13	38	22	30	29
14	77	26	56	28
15	50	18	41	42

Table 2. The distribution of 10 angiograms in the questionnaire's slides.

Question / image	Limits of variance		
	$\sigma^2 < 1$	$1 \leq \sigma^2 \leq 2$	$\sigma^2 > 2$
1	a	b	c
2	a	c	b
3	b	a	c
4	a	c	b
5	c	b	a
6	a	b	c
7	b	a	c
8	c	a	b
9	c	b	a
10	a	c	b



(a)



(b)

Blockage in the main artery

Figure 11. Examples of angiogram images showing segmentation, (a) normal vessels, (b) abnormal vessels.

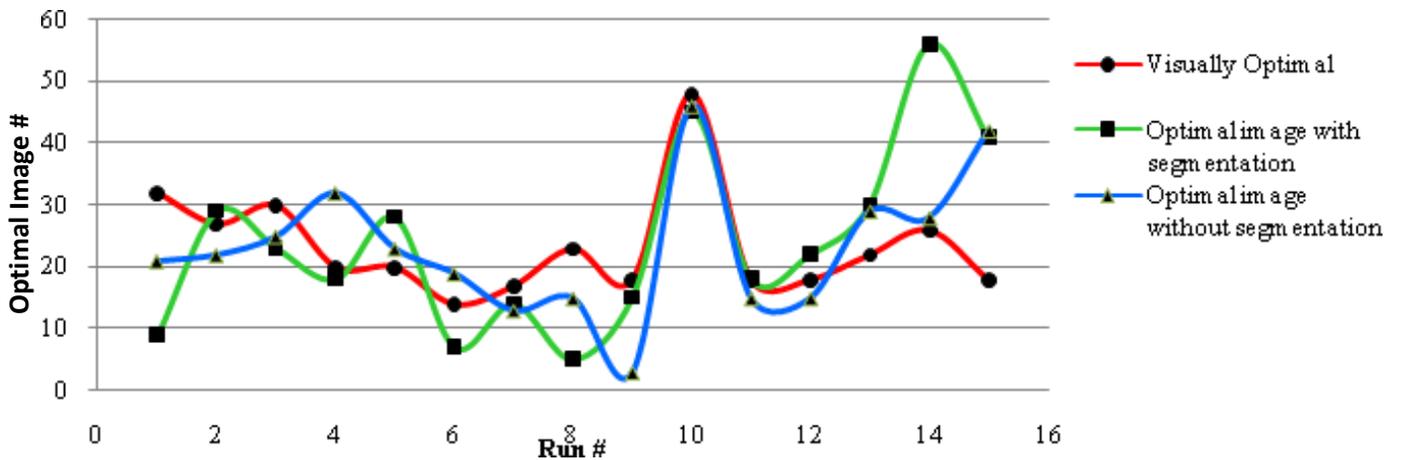


Figure 12. Comparison between results of visually nominated optimal images, results of the experiment with segmentation part and results of the experiment without segmentation part.

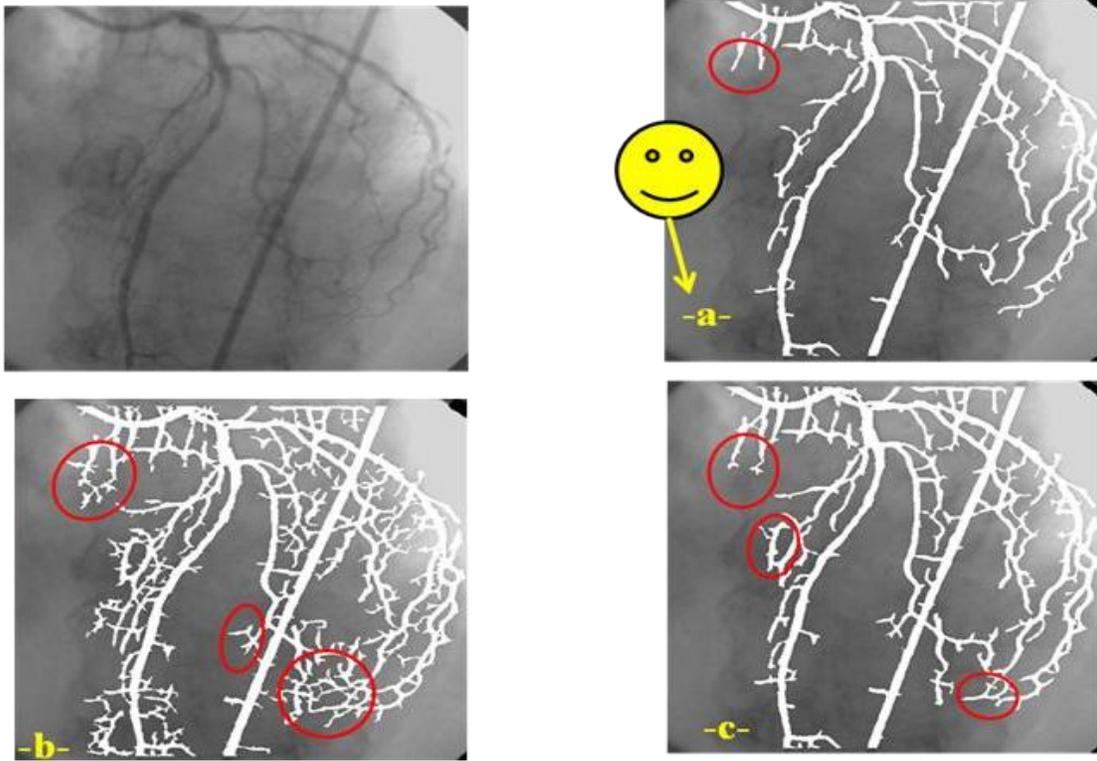


Figure 13. Example from the questionnaire of how to choose the best output image.

provide greater savings in processing time. However, the experiment designed as shown in Figure 10 is a good way to automatically choose the optimum image for the coronary artery trees extraction algorithm without any user interaction. We conducted an experiment of setting a questionnaire to validate the efficient illustration output. The questionnaire was held in one room (same environment) and 12 professional participants were attended to validate the output. We showed the participants 10 different slides each with 4 angiograms. First image is the original angiogram and the rest 3 images are its coronary artery trees extracted in three different variance values ($\sigma^2 < 1$, $1 \leq \sigma^2 \leq 2$, $\sigma^2 > 2$). As we mentioned earlier about the variance value and how it can affect the Gaussian response and threshold value itself and we mentioned that our proposed limit of controllable value is $1 \leq \sigma^2 \leq 2$ that can give better coronary artery tree extraction in angiograms. The 3 extraction images were marked by letters 'a, b, c' and the participants had to choose one of them which represent the better extraction output according to his expertise in medical imaging and medical applications. To guarantee the impartiality, our images which were processed according to our proposed variance limit were located randomly among the 3 images. The questionnaire included 10 angiogram images. Figure 13 shows an example of how to choose the best output image

presented to participants in the questionnaire. The best output image that will be selected is the one with less false alarms and focuses on extracting the main coronary arteries. As we can notice in the figure that image (a) is the one which represents the best output of extraction and therefore we will choose it to be the supported one and supported limit of variance.

In order to calculate the validation rate of participants' support to our proposed limit of thresholding, the questionnaire results were analysed as follows. First, in Table 2, we presented how the images (a, b, c) were distributed in the slides according to each limit of extraction. Next, in Table 3 we showed the selections (results of supporting for our proposed limit) of each participant. Finally, in Table 4 we calculated how many of the participant's selections supported our limit ($1 \leq \sigma^2 \leq 2$). As a final step of the analysis, the validation rate was calculated from the results of Table 4 and according to Equation 4.

$$\text{Validation rate} = \frac{\sum_{i=1}^n (\text{number of supporting choices (i)})}{\text{number of questions for all participants}} * 100\% \quad (4)$$

Where n is the number of participants.

The validation rate can be calculated from the statistical Equation 4 aforementioned and depending on the results of Table 4 as follows:

Table 3. The supported images for each participant.

Participant	Question / Image	Supported image
1	1	b
	2	c
	3	a
	4	c
	5	b
	6	b
	7	a
	8	a
	9	b
	10	c
2	1	b
	2	c
	3	a
	4	c
	5	b
	6	b
	7	c*
	8	a
	9	b
	10	c
3	1	b
	2	c
	3	a
	4	c
	5	b
	6	b
	7	c*
	8	b*
	9	b
	10	c
4	1	b
	2	c
	3	a
	4	c
	5	b
	6	b
	7	a
	8	a
	9	b
	10	c
5	1	b
	2	c
	3	a
	4	c
	5	b
	6	c*

Table 3. Contd

	7	c*
	8	a
	9	b
	10	a*
	1	b
	2	c
	3	a
	4	c
6	5	b
	6	b
	7	a
	8	a
	9	b
	10	c
	1	b
	2	c
	3	a
	4	c
7	5	b
	6	b
	7	a
	8	a
	9	c*
	10	c
	1	b
	2	c
	3	a
	4	c
8	5	b
	6	b
	7	a
	8	a
	9	b
	10	c
	1	b
	2	c
	3	a
	4	c
9	5	b
	6	b
	7	a
	8	a
	9	b
	10	c
10	1	b
	2	a*

Table 3. Contd

	3	a
	4	c
	5	b
	6	b
	7	c*
	8	a
	9	b
	10	c
	1	b
	2	c
	3	a
	4	c
11	5	b
	6	b
	7	a
	8	a
	9	b
	10	c
	1	b
	2	c
	3	a
	4	c
12	5	b
	6	b
	7	a
	8	a
	9	a*
	10	b*

*: unsupported selection.

$$\text{Validation rate} = \frac{\sum_{i=1}^{i=2} (\text{number of supporting choices (i)})}{\text{number of questions for all participants}} * 100 \% \quad (5)$$

$n = 12$, the number of participants.

$$\text{Validation rate} = \frac{(10 + 9 + 8 + 10 + 7 + 10 + 9 + 10 + 10 + 8 + 10 + 8)}{120} * 100 \%$$

$$\text{Validation rate} = \frac{109}{120} * 100 \%$$

Validation rate = 90.84 %

The validation rate shows that medical imaging and applications experts highly support our proposed limit of variance to produce the threshold limit that can give better output with it. The support rate was 90.84% which can prove the robustness of our proposal. The extraction

process was quiet fast as it consumes between 14 to 15 s to extract the whole coronary artery tree in angiogram images of 512×512 pixels size and 24-bit gray-scale levels. We applied the algorithm on a data set of 100 images for vessel extraction and calculate the time; and Table 5 presents the results for 20 images of them. The whole images were processed in proposed limit of variance $1 \leq \sigma^2 \leq 2$. Figure 14 illustrates the processing time for results in Table 5.

Comparison with previous work

Most previous algorithms and computer models focused on centerline and contour extraction of vessels. They ignored most of the details that involve tiny vessels and their bifurcations. As we mentioned in the introduction of this paper also, algorithms were divided into three

Table 4. No. of supported selections per each participant.

Participant	No. of supported selections
1	10
2	9
3	8
4	10
5	7
6	10
7	9
8	10
9	10
10	8
11	10
12	8

Table 5. Processing time to extract coronary artery trees.

No. of image	Extraction time/s
1	14.6943
2	13.9604
3	14.1240
4	13.1873
5	15.2917
6	15.2818
7	15.7903
8	15.0156
9	15.2247
10	15.5708
11	14.3477
12	14.4099
13	14.3453
14	14.3423
15	14.7318
16	14.6505
17	14.3586
18	14.5543
19	14.3339
20	14.3291

categories in terms of processing images to extract vessels. The first part deals geometrically with images, the second deals with intensity and the third and last combines both ways. Our work involves with intensity to extract vascular arterial trees from angiograms because our algorithm segment the image depending on the threshold value going to be generated from Gaussian response and variance value. In this section, we are going to compare our algorithm with two previously done approaches in terms of qualitative and quantitative samples. First, we used hand-labelled annotations on 20

images of our data set to prove the accuracy of our results of extraction. Three angiogram images are presented in Figure 15 illustrating our hand-labelling superimposed with original angiograms. The labelled vessels are what we could see that contrast of vessels comes similar to background in most parts of arteries. By comparing the results of Figures 15 and 16, we can notice that Figure 16 illustrated more accurate extraction process that the entire main artery have extracted accurately with all their bifurcations. Figure 16 illustrates three examples of extraction in angiograms. The three

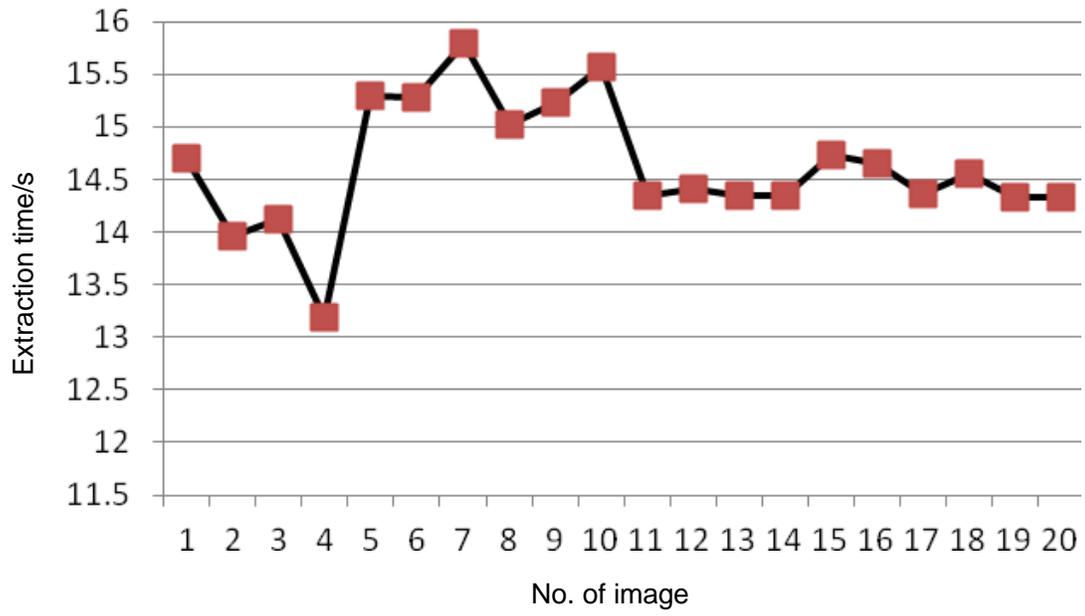


Figure 14. Extraction time in seconds for a sample of 20 angiograms.

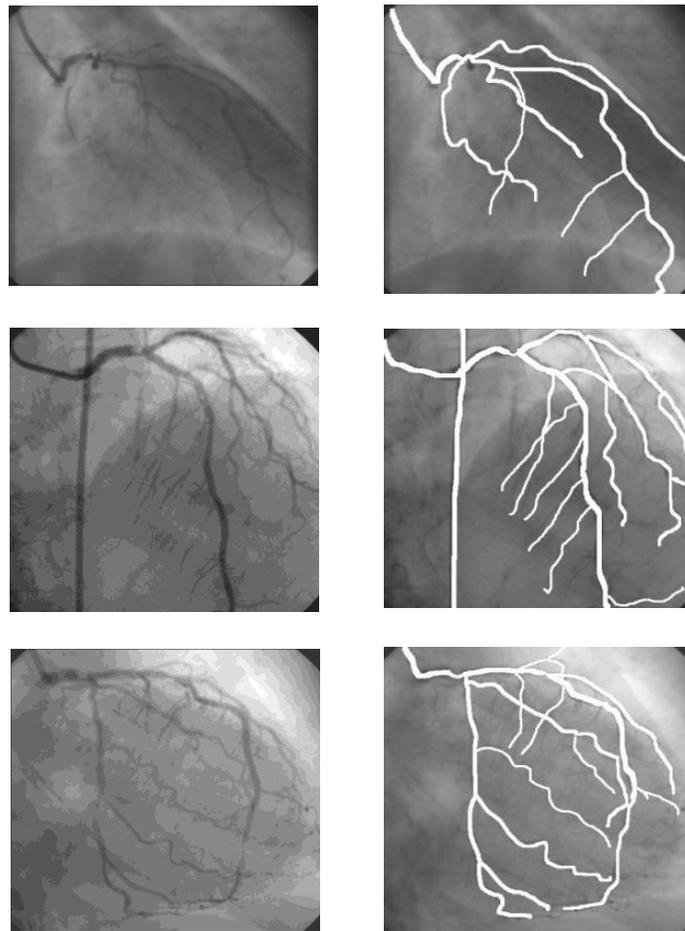


Figure 15. Examples of hand-labeling annotations.

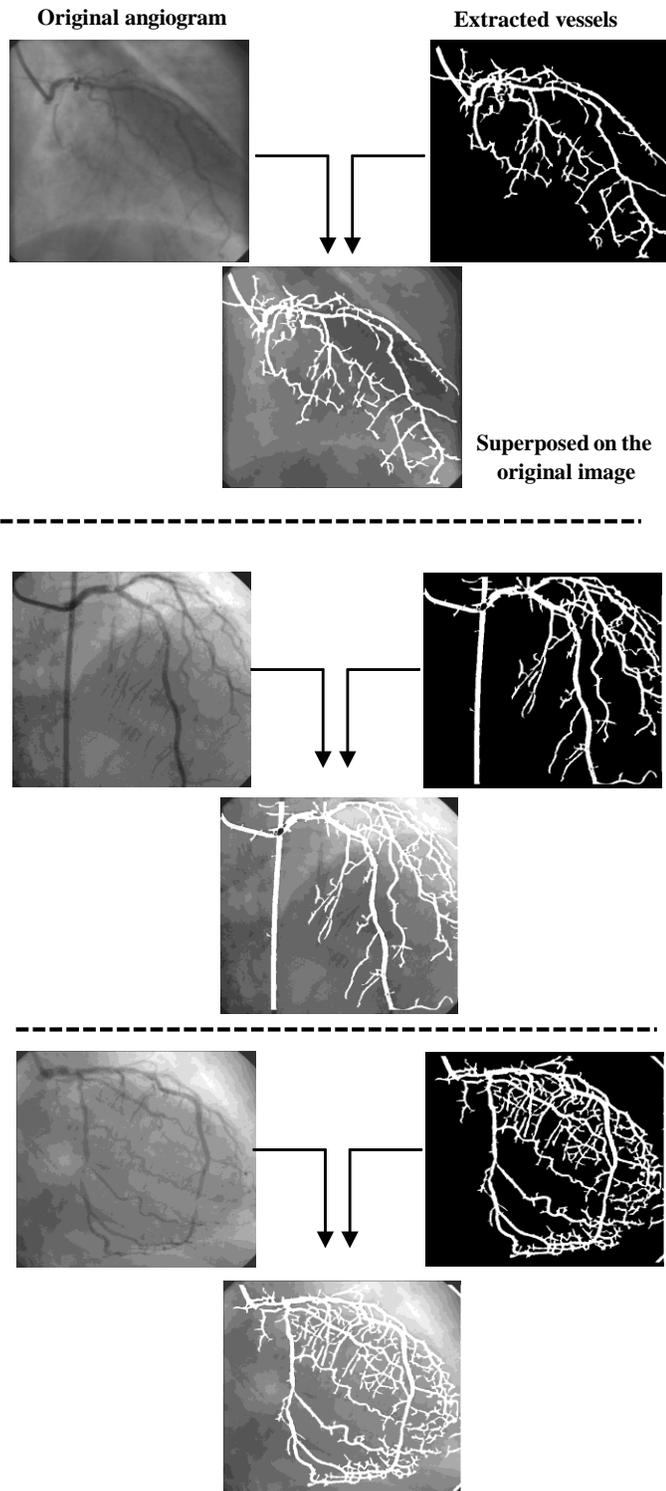


Figure 16. Examples of vessel extraction using our algorithm.

angiograms were processed in variance values 1.5, 1.1 and 1.8, respectively. Next, we compare our output with the algorithm in Wang et al. (2005). Figure 17 illustrates the output for both and from that we can demonstrate the

following:

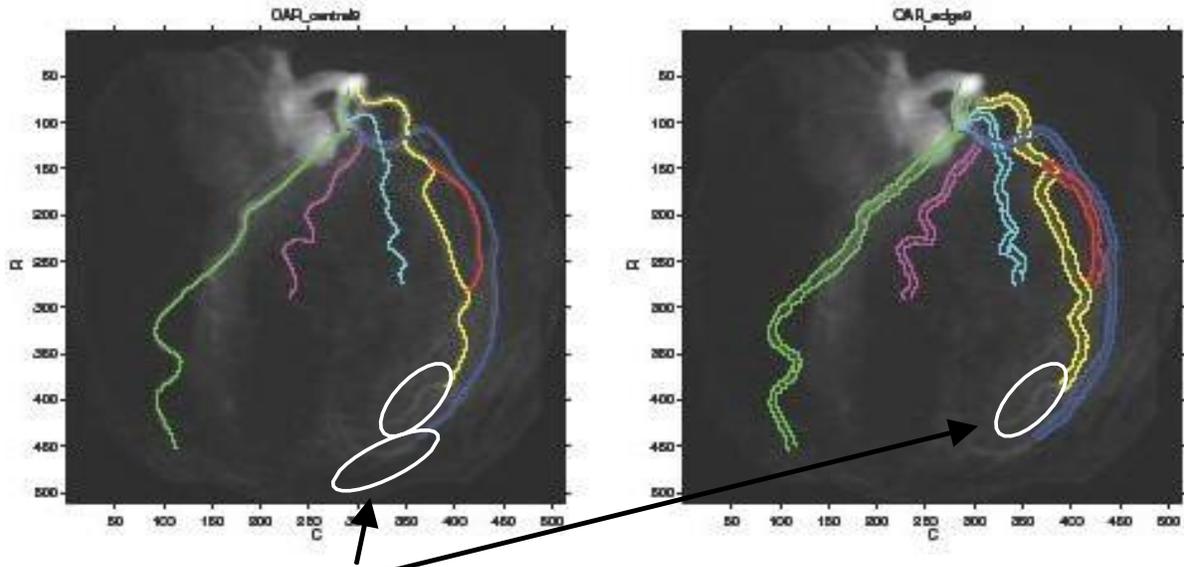
- 1) Algorithm in Wang et al. (2005) used sequences of DSA images while ours adopts the plain angiocardiography. We should know that extraction from plain angiograms is a larger challenge since gray scale values between the vessel and its background are similar most of the time. In addition, the plain angiogram's background has different gray scale values, shadows and reflection of x-ray (lighting).
- 2) In the previous algorithm and in each image, first, the centerlines would be extracted and next would be the contours of vessels. In our algorithm, whole vessel would be extracted for the whole image, that is, the result will be a full coronary artery tree (network).

The previous processing time was 10 s per image on a PC with 1.5 GHz CPU and 512 Mb RAM and our algorithm took between 14 to 15 s on a PC with 3 GB-RAM and 1.5 GHz CPU. Our time is longer in few seconds because previous algorithm was devoted for centreline and contour extraction and ours for a whole coronary artery tree with full network (step 1 aforementioned). The previous algorithm in some images cannot extract the whole artery network in Figure 17. In contrast, our algorithm can start from the main artery tree stent with full network extraction until the end. Finally, the algorithm in Li et al. (2008) has been compared with our algorithm. The previous algorithm was applied on data of theirs and data of ours and we discussed the results that are shown in Figure 18. Results shown in Figure 18 were obtained from applying algorithm in Li et al. (2008) on samples of theirs and our data respectively. The first and second rows illustrate results of two images, synthetic and real object image respectively. In the first one, the background is darker than the object (vessel). Meanwhile, in the second image, the object is darker than the background. In both images, the extraction was efficient with no disturbance and with a number of iterations in 150 and 300, respectively. The third and fourth rows in the figure are for the results from our data images. Same as before, the image in the third row has dark background while image in the fourth row has darker vessel. We can easily notice that both rows of results obtained from our data were not efficient and extraction got a lot of disturbance (background was detected as a vessel).

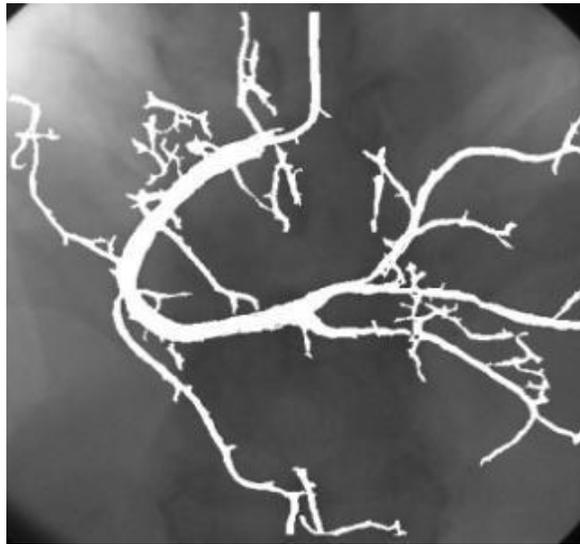
The extraction was done in 50 and 300 iterations respectively. We can clearly demonstrate that the method of this paper is performing better in angiocardiography than algorithm in Li et al. (2008).

DISCUSSION

Vessel extraction is an important task to guide physicians through vessel treatment procedures and which results in



Missing vessels (a)



(b)

Figure 17. Comparison between a) Wang et al. (2005) output and b) output of our algorithm

more medical benefits. However, the extraction approach in this paper is different from previous works. This paper improved retina images of previous algorithm to extract the complete coronary artery trees. The extraction is for the main arteries plus the small branches. Currently, angiography images are preferable by specialists since they are able to provide online monitoring of blood vessels. Vessels extraction process is the first vital step in any medical pre-processing because of other technical approaches that might rely on it in future. The 3D rendering of coronary arteries is one of those important approaches. There are strong evidences in the presented results that the proposed algorithm in this paper is

accurate in extracting coronary arteries. All the achieved experiments clearly demonstrated that the proposed algorithm has the power and ability to extract the complete arteries and their bifurcations. In addition, the processing time of extraction is short compared with other previous algorithms. The most convincing way for representation of the proposed algorithm is obtained through observation of its iterative dynamic operation. To achieve this purpose, an application in Windows O/S using an executable file is made available that shows the process of the real-time execution of the algorithm. The algorithm offers clinical benefits and considers a helpful tool to make physicians work easier by better

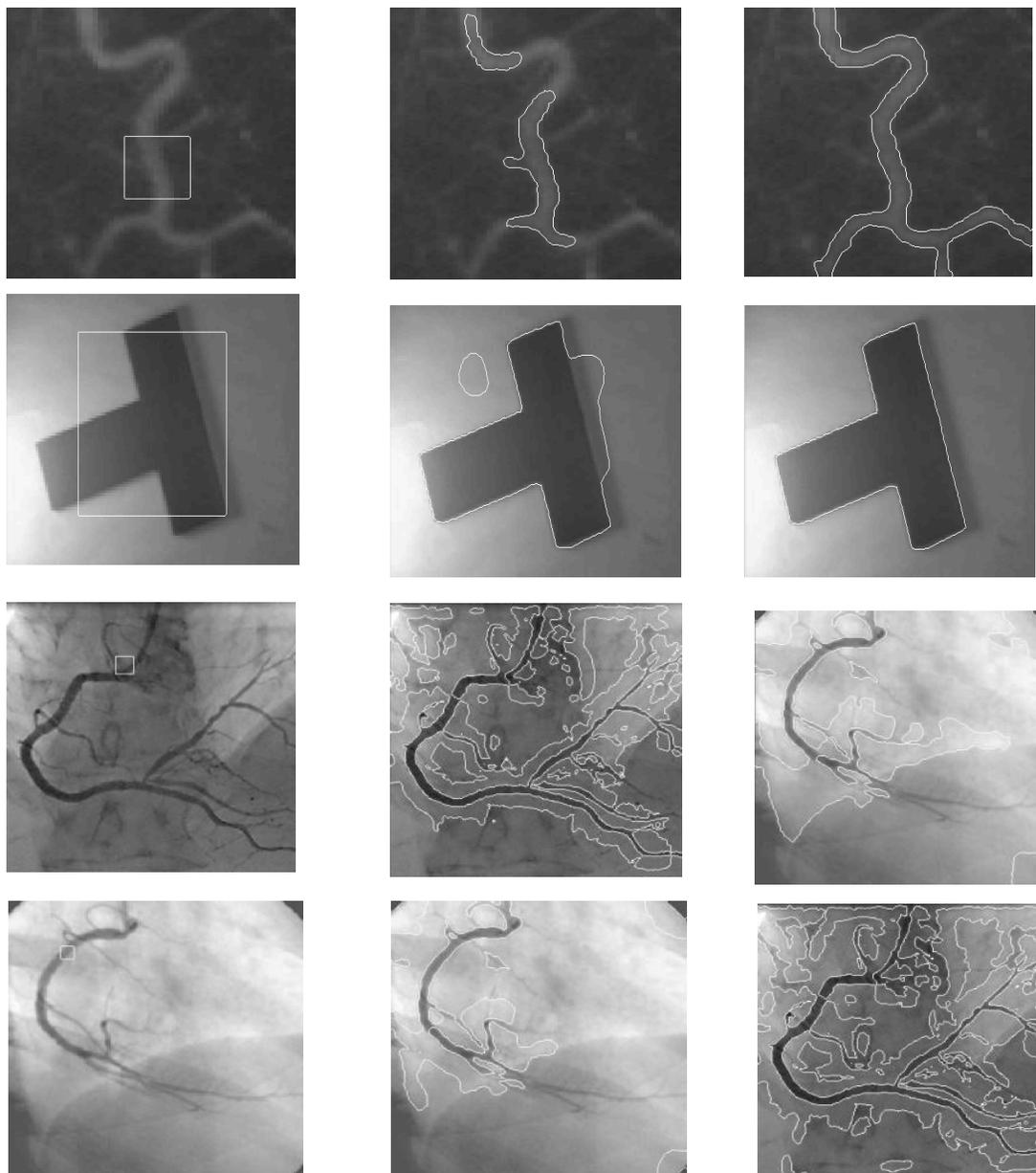


Figure 18. Results of method in Li et al. (2008) which was applied on four images. First and second rows had shown images of synthetic and real images of the same data used in the previous method. Third and fourth rows had shown images of our vascular angiography images.

visualisation of coronary artery trees and in a short time. One aspect of the approach that has been reported earlier in Hoover et al. (2000) is the evaluation of the connectedness property. By design, their approach produced a labelling (right or wrong) of the continuous segments.

The basic thresholding algorithm is likely to produce small groups of isolated pixels. Although, these pixels might in fact be correctly classified, their utility for measurement is probably limited. The proposed algorithm in this paper solved this problem in terms of

connectedness.

Conclusions

With the increased need for the use of real-time angiogram images, it became importantly to analyze and extract as much information as possible from them. Angiograms are a helpful tool to physicians in many cases, especially if they have been pre-processed to highlight objects (vessels) out of them. We have

proposed in this paper a robust algorithm for coronary artery trees extraction. The algorithm depends on the variance factor - controllable value ($1 \leq \sigma^2 \leq 2$) - in Gaussian equation to affect its response which can lead to extract suitable threshold value for the image under consideration. Specialists may use this approach for diagnosing the abnormality in vessels purposes, that is, by measuring the thickness of healthy, blocked, including all the tiny vessels, and by managing to insert a stent through the blocked vessels. The core of the algorithm, vessel extraction was validated by using hand-labelling ground truth segmentation annotations of 20 images and the results matched 98% of the extracted images. In addition, the results were validated by conducting a questionnaire meant to show the output to 12 medical imaging experts. The validation rate was 90.84% support from them to the presented extracted images, that is, the variance and threshold limit itself. Finally, the algorithm was fast in terms of processing time that it takes between 14 to 15 s per image. In addition, it worked well on angiograms; however, it can be elaborated to work with other types of medical images that have different features and structures. As a final perspective, using a masking process on the original image superposed with the artery tree can extract the tree in gray scale format. This would help in further future work for a coronary artery tree 3D reconstruction.

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