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Performance Comparison of Vesselness Measures for Segmentation of Coronary Arteries in 2D Angiograms

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Abstract

Objectives: In this paper, we aim to compare four different vesselness filters and propose a framework for segmenting coronary arteries from 2D angiograms with the aim of extracting accurate centerlines. **Methods/Statistical analysis:** Performance measures including noise suppression, edge smoothness, branch disconnection and centerline smoothness are used for comparing the performance of vesselness functions. Moreover, we have performed the segmentation of coronary arteries from the obtained vesselness measure using globalized region based active contour followed by median filtering to remove the artifacts such as unsmoothed edges. **Findings:** The study reveals that Frangi's vesselness performs well in suppressing the background noise, whereas, the other vesselness measures perform better at enhancing vessels throughout crossings and bifurcations. Except Frangi's vesselness, edges obtained by all the compared vesselness measure are prone to uneven and rough edges that will eventually lead to the extraction of wrong centerlines. **Application/Improvements:** Based on the findings, we have presented a segmentation method that produces more enhanced and smooth edges of coronary arteries and leads to the extraction of the smooth centerlines.

Keywords: Angiograms, Active Contour, Coronary Arteries, Segmentation, Vesselness Measure

1. Introduction

The exact delineation of coronary arteries is a vital step towards the computer aided analysis for Coronary Artery Disease (CAD). In developed countries, the majority of deaths are caused by Cardio Vascular Diseases (CVDs)[1]. In order to diagnose CVDs, coronary angiography is considered as an essential tool. The proper and exact segmentation of coronaries from the complex 2D angiogram images is required for a detailed visualization that may help the clinicians to assess the situation in a better way. However, in a complex background, the segmentation of vessels from spines and soft tissues in the X-ray angiograms is difficult due to intensity variation, low contrast or various shapes of vessels[2]. Other factors such as background noise and overlapped organs also contribute to the difficulties for delineating coronary arteries from X-ray angiograms. To cope with these situations vessel enhancement is highly needed as a pre-processing step which may lead to accurate segmentation of vessels along with the extraction of their centerlines.

The segmentation process is one of the pre-processing procedures extensively employed in the imaging field to extract the key features from the given data[3]. Segmentation methods based on thresholding normally do not perform well for delineating vessels from angiograms due to in homogeneity, background noise, low contrast and other factors. Therefore, it is a quite difficult task to trace the vessels efficiently in such a complex environment using threshold-based techniques. Hence vesselness measurement may be used as a guidance map for segmentation. The term vesselness actually measures the probability for a pixel to be on a vessel. Normally, the enhancement of vessels on the basis of Hessian matrix is considered as an important preprocessing step. The famous methods of examining an image in scale space have been reported in the literature[4–6]. These methods are considered to be a robust algorithm for enhancing tube-like components in medical images for a subsequent delineation. Generally, in a normalized Gaussian scale

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space the eigenvalues of the famous Hessian matrix are computed for different scales and the scale with the maximum response is selected to generate the optimal response. Among the most extensively used vesselness measures is the one presented by Frangi and his co-workers[6] in which they examine the Hessian matrix and its values geometrically to define the presence of vessels. The Frangi's vesselness[6] is a renowned filter function which can be thought as state of the art and therefore is used by many authors as the basis for more development.

Several vesselness functions for enhancement of coronary arteries have been reported in the literature which is based on conventional multi-scale Hessian based filter[6]. In[7] authors defined a transformed function based on the gray values and scale for efficient segmentation of coronary arteries in 2D angiograms. In[8] the authors presented an approach for vesselness measure by extracting feature map based on the relationship between the vessel morphology and the eigenvalues of Hessian matrix. Another vesselness measure for coronary angiograms is presented by in[9] where the authors have used a simple and easy function to obtain the vessel structures which finds out the probability whether the point belongs to the vessel or non-vessel components.

In this paper, we give performance comparison of four different vesselness measures described in[6–9] by performing different experiments and various performance measures. All the mentioned vesselness filters are developed by examining the eigenvalues of Hessian matrix. The vesselness filter in[6] is selected for the reason because it is most extensively used and recognized filter function and can be regarded as state of the art. Whereas, the other three vesselness measures are the further developments responsible for enhancing the coronary arteries by exploring the concept of Hessian matrix and its eigenvalues. In this work, the behaviors of the mentioned filter functions are examined for the purpose of enhancing coronary arteries in 2D angiograms to achieve the accurate segmentation and skeleton of coronary arteries.

The remaining paper is described in the order as follows: Section 2 concisely explains the idea of multi scale Hessian-based filtering for vessel enhancement. The experimental results on real 2D angiograms are presented in Section 3 and finally Section 4 makes the conclusion of this study.

2. Materials and Methods

The objective of enhancing vessels is to suppress the background containing the non-vessel components by highlighting the vessel structures. It is to be noted that the diameter of the vessels and the points located on the centerlines must be preserved after carrying out the operations. Generally, the coronary arteries in angiograms regarded as tubular objects each comprising of different widths. The examination of local partial derivatives is done to recover the geometric structure and also differential operators are built on the basis of sign and values of eigenvalues. It is required that the answer of operator is built for different scales due to the different widths of the vessels.

From the concept of differential geometry it is familiar that the second derivatives of an image are analyzed in a geometric fashion by exploring their eigenvalues at each point. The concept lies in analyzing the eigenvalues is to find out the directions in which second order structure of the image can be decomposed. Let the eigenvalues of Hessian matrix H be λ_1 and λ_2 and let v_1 and v_2 be their normalized eigen vectors, respectively. The eigenvalues are analyzed and used for defining the vesselness measure by sorting them as $\lambda_1 < \lambda_2$ where $\lambda_1 = \lambda_2 < 0$ for an ideal vessel structure. The values of Hessian matrix at each point in an image are defined by (1).

$$H = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix} \tag{1}$$

where $I_{xx} = \dfrac{\partial^2 I}{\partial x^2}$, $I_{yy} = \dfrac{\partial^2 I}{\partial y^2}$, $\mathrm{I}_{xy} = \dfrac{\partial^2 I}{\partial xy}$

Information regarding relationship of eigenvalues and shapes of objects can be exploited to build a vesselness measure that can be further used for differentiating background and the vessel components. In this paper we make a comparison among the vesselness filters presented in[6–9] which are used for enhancing the coronary arteries in angiograms. They are explained in the following sub sections.

The information near a small local region of each point is contained in Hessian matrix. To detect the tubular objects comprising of larger diameters, scale space theory is utilized. Therefore, vesselness response is computed at various scales. All the vessel enhancement filters[6–9] derives structural information from the Hessian eigenvalues $|\lambda_1| \le |\lambda_2|$. The Hessian H is calculated using Gaussian derivatives at a scale σ. For obtaining the image representation using scale space, the image is convolved with various standard deviations for each scale. The Gaussian second order derivative of image *I* at scale *σ* and point *(x, y)* is defined by (2).

$$I_{xx}(x, y; \sigma) = \frac{\partial^2}{\partial x^2} G(\sigma) * I(x, y), \tag{2}$$

Where $G(\sigma)$ is a Guassian distribution function with scale σ and * denotes a convolution operator. Finally for a given image, calculating second order scale space (1) and (2) can be combined. Hence, the Hessian matrix at a given scale σ is computed using (4).

$$H(x, y; \sigma) = \sigma^{\lambda} \begin{bmatrix} I * \dfrac{\partial^2 G_\sigma}{\partial^2 x}, & I * \dfrac{\partial^2 G_\sigma}{\partial x \partial y} \\ I * \dfrac{\partial^2 G_\sigma}{\partial y \partial x} & I * \dfrac{\partial^2 G_\sigma}{\partial^2 y} \end{bmatrix} \tag{3}$$

The factor σ^{λ} is the normalization factor that normalizes the intensities across scale space and is required to compare the outputs of vesselness at various scales. Lindeberg[10] introduced the factor λ for defining a series of normalized derivatives. The vessel filter function is computed for each scale σ after computation of eigenvalues of H to find out the final vesselness response $V(x, y; \sigma)$. All the filters discussed here can work in multi-scale environment by using the following equation (4).

$$V(x, y) = \max(V(x, y; \sigma)), \qquad \sigma_{\min} \le \sigma \le \sigma_{\max} \tag{4}$$

2.1 Vesselness Function

In[6] Frangi and his co-workers explored the concept of eigenvalues and presented a model to differentiate the shapes including plate-like, blob-like and tubular structures on the basis of eigenvalues of Hessian matrix. Specifically, to capture the knowledge of the image geometrically, they built a measure of unlikeness that includes a geometric ratio. Moreover, they also added the concept of Frobenius matrix norm to decrease the uncertain filter responses for non-vessel components. The blobness measure is defined by the following ration defined by (5).

$$R_B = \frac{\lambda_1}{\lambda_2} \tag{5}$$

The final vesselness filter function is given by (6),

$$f = \begin{Bmatrix} 0, & if\, \lambda_2 > 0 \\ e^{-\frac{R_B^2}{2\beta}} \left(1 - e^{-\frac{S^2}{2\gamma}}\right), & otherwise \end{Bmatrix} \tag{6}$$

where β and γ are the sensitivity control parameters of the filter and S defines the Hessian's norm. The vesselness value f is achieved in between [0 1] for the curvilinear structure, where the 1 specifies a perfect agreement.

2.2 Vesselness Function by Ying et al

Ying and his co-workers obtained the vesselness structure in[7] by defining a transformed function based on the gray values and scale for efficient segmentation of coronary arteries in 2D angiograms. In their work, vessel detection is based on the analysis of eigenvalues of multi-scale Hessian matrix. They have used λ_2 as vessel feature because the dark vessel structure in a bright background usually has a large positive eigenvalue λ_2. They have defined an adaptive transform function which comprises of gray value and the scale to improve the vesselness outcome because it is quite possible that eigenvalues may be very similar for vessel and non-vessel components and in such case it is hard to discriminate vessel and non-vessel components.

In order to distinguish the vessel and the non-vessel points in a better way, the eigenvalues at each point of an image are adjusted by using the enhanced gray level as a refinement factor. Therefore, instead of using the original image intensity, they have first applied the enhancement function given in the following equation (7) to enhance the contrast of the original image by lessening the gray level of vessels.

$$I_t(x, y) = \begin{Bmatrix} I(x, y) - T_2, & if\; I(x, y) < T_1 \\ 255, & else, \end{Bmatrix} \tag{7}$$

where I(x,y) corresponds to the value of pixel and T_1 is some global threshold that finds out whether the pixel belongs to vessel or not. The value of T_2 is set by examining the vesselness outcomes for various values. Normalization between 0 and 1 is performed for the intensities generated by using equation (7).

The obtained transformed intensities using above equation (7) are normalized between 0 and 1. The converted intensities $I_t(x,y)$ and scale factor σ are combined in adaptive feature transformation function which is defined by (8),

$$T(x,y;\sigma)=\frac{\lambda_2(x,y;\sigma)}{\sigma * I_t(x,y)} \tag{8}$$

The final vesselness function is obtained by using the following equation (9).

$$V(x,y;\sigma)=\begin{cases}1-\exp\left(\dfrac{T^2(x,y;\sigma)}{c}\right), & if\,\lambda_2(x,y;\sigma)>0\\ 0, & else,\end{cases} \tag{9}$$

Where c is a constant that determines the effect of the contrast enhancement and λ_2 is eigenvalue of the original image. The final measure of the vesselness is obtained by using the vesselness function $V(x,y;\sigma)$ which gives a value in between 0 and 1. To deal with different widths of the vessels, the vesselness response function is computed along various scales to obtain accurate segmentation and finally the highest vesselness output is chosen as the optimal one using (10).

$$V(x,y)=\max(V(x,y;\sigma)), \quad \sigma_{\min}\le\sigma\le\sigma_{\max} \tag{10}$$

where σ_{min} and σ_{max} are the minimum and maximum scales, respectively.

2.3 Vesselness Function by Yanli et al

An approach is presented by the author's in[8] for finding out the feature map for the vesselness of coronary arteries. The authors in their study have utilized the association between vessel morphology and eigenvalues of Hessian matrix. In their work Hessian matrix with a large positive eigenvalue λ_2 and a small eigenvalue $\lambda_1\left(|\lambda_2|\gg|\lambda_1|\right)$ is considered for a 2D angiogram image where vessels are represented by dark curvilinear structures. For extracting the vesselness map they threshold the eigenvalue map using the following thresholding function.

$$f(p_o,\sigma)=\begin{cases}\lambda_2, & if\,\lambda_2>\dfrac{\sigma^2}{4}\\ 0, & else,\end{cases} \tag{11}$$

where p_o represents pixel value in 2D image and σ represents the scale at which vesselness is computed. The function will take the large positive eigenvalue λ_2 if the given condition, $\lambda_2>\frac{\sigma^2}{4}$, is satisfied. The final vessel feature map $f(p_o)$ is defined by the following expression.

$$f(p_o)=\max(f(p_o,\sigma)/\exp\sqrt{2\sigma}), \quad \sigma_{\min}\le\sigma\le\sigma_{\max} \tag{12}$$

where $\sigma_{\min}$ and $\sigma_{\max}$ describe the scales according to the size of smallest and largest vessel width, respectively.

2.4 Vesselness Function by Wang et al

Another feature map for vesselness of coronary arteries is described in[9] where the authors have exploited the information that the eigenvector with large absolute eigenvalue specifies the direction at that specific point and the eigenvector with smaller absolute eigenvalue specifies the direction of minimal curvature. They have obtained the vessel structures by applying the following function defined in (13) to each pixel of a 2D angiogram image. The function, $Z(x,y,\lambda_1)$, will find out the vesselness by assigning the value according to the given condition to those pixels which belong to the vascular structures.

$$Z(x,y,\lambda_1)=\begin{cases}\log\left(|\lambda_1|+1\right), & if\,\lambda_1<-8\log(\sigma)\\ 0, & otherwise\end{cases} \tag{13}$$

To enhance the coronary vessels of multiple widths, the vesselness is computed at multiple scales and the highest response is selected as the optimal one using the condition given below.

$$E(x,y)=\max(Z(x,y,\lambda_1(\sigma))), \quad \sigma=\sigma_1,\sigma_2,\ldots,\sigma_n \tag{14}$$

In their work, the range of scale value is from 1 to 9.

3. Results and Discussion

To assess the performance of different vesselness functions for enhancement, we have used real datasets for 2D angiograms. Various experiments are performed to compare the performance of the four vesselness function[6–9] and the results are shown in Figure 1, Figure 2 and Figure 3.

In all these figures, the original 2D angiogram image is shown by Figures 1(a), Figure 2(a) and Figure 3(a). The first row of Figures 1, Figure 2 and Figure 3 show the results of applying all four filters described in[6–9], respectively. Whereas, the second row exhibits their respective segmentation results as a largest connected component.

It is observed in Figure 1 that the vesselness measure in[7,9] shown in Figure 1(c) and Figure 1(e), respectively, have produced quite comparable results. Moreover, it is noticed that the vesselness function presented in [6]shown in Figure 1(b) has problem of branch disconnection in the area of the junction marked by the white box. On the other hand, the vesselness defined in[8] has produced some discontinuities in the vesselness as depicted by white box in Figure 1(d).

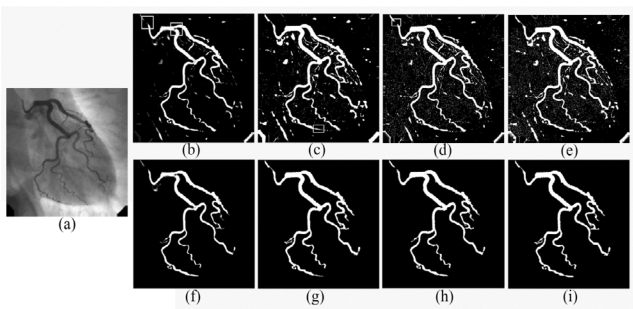

Figure 1. Vesselness measures and segmentation of Angiogram-1.

A 2D angiogram for right coronary artery is shown in Figure 2 which shows the obtained results after applying all the four filters for finding out the vesselness measure. As can be observed, Frangi's filter[6] shown in Figure 2(b) has over smoothed the portion marked by white box. Whereas, the remaining three filters give almost same performance but with increased background noise and unsmooth edges as shown in Figures 2(c), 2(d), and 2(e).

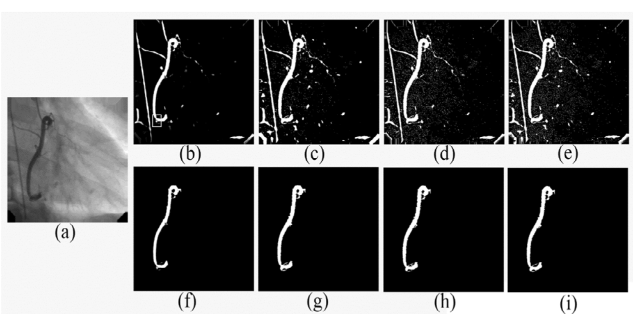

Figure 2. Vesselness measures and segmentation of Angiogram-2.

Another 2D angiogram image containing left coronary artery is shown in Figure 3. The results of Figure 3 reveal that the response of the filter functions in[7–9] shown in Figures 3(c), Figure 3(d) and Figure 3(e), respectively are quite comparable in our experiments. Moreover, they do not produce disconnect branches as produced by Frangi filter[6] whose vesselness response is shown in Figure 3(b). The vesselness functions described in[8,9] produce more background noise as compared to the ones described in[6,7]. The Frangi's function[6] shows better performance in suppressing background noise. Although vesselness functions in [7]gives better performance in reducing the background noise as compared to the functions in[9,8], however it suffers from non-smooth edges.

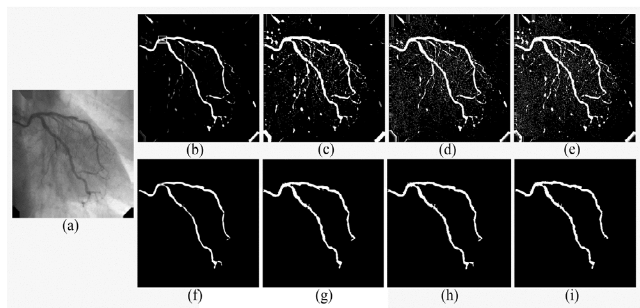

Figure 3. Vesselness measures and segmentation of Angiogram-3.

As an application, centerlines of coronary arteries are used for measurement of vessel diameters, and also for calculation of lesion symmetry. Therefore, in this paper, we have also compared the centerlines extracted for all four methods[6-9] by using simple morphological operations. The extracted centerlines for an angiogram shown in Figure 1(a) are presented in Figure 4. The skeletons obtained for the vesselness function in[6–9] are shown in Figure 4(a), Figure 4(b), Figure 4(c) and Figure 4(d), respectively. As far as centerlines are considered, a significant difference can be observed. It can be seen clearly that the centerlines shown in Figure 4 are not smooth and contains many spurs. However, skeleton obtained for the vesselness described in[7] as shown in Figure 4(b) is better as compared to other vesselness functions but not promising. A clear view of the portions specified by the white boxes in Figure 4(a), Figure 4(b), Figure 4(c) and Figure 4(d) are shown in the second row by Figure 4(e), Figure 4(f), Figure 4(g) and Figure 4(h), respectively.

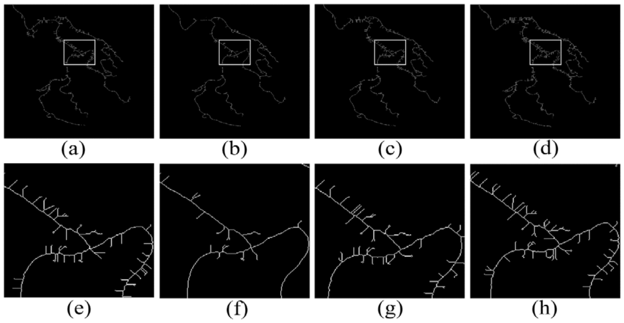

Figure 4. Extracted centerlines of Angiogram-1.

Another example for centerlines comparison is shown in Figure 5 which is the skeleton obtained for an image shown in Figure 3(a). A similar behavior is observed in Figure 5. In this case also almost all the centerlines obtained for all four vesselness function[6–9] are not smoothed as shown in Figure 5(a), Figure 5(b), Figure 5(c), and Figure 5(d), respectively. As a result these centerlines cannot be used directly for further analysis of lesions and other applications. A clear view of the area enclosed by the white boxes in first row is shown in Figure 5(e), Figure 5(f), Figure 5(g) and Figure 5(h), respectively.

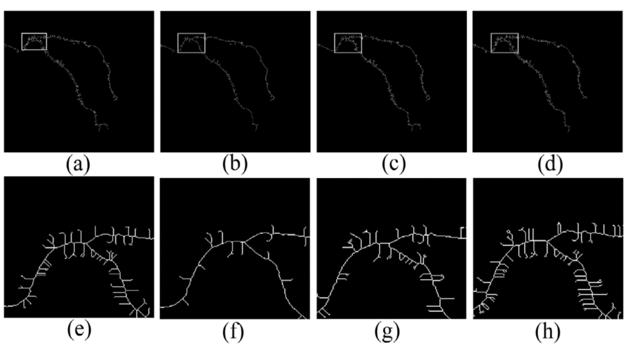

Figure 5. Extracted centerlines of Angiogram-2.

By looking at Figure 1, Figure 2 and Figure 3, it can be analyzed that the obtained segmentations are not accurate which leads to erroneous skeleton of coronary arteries as shown in Figure 4 and Figure 5. Therefore in order to obtain the accurate segmentation of coronary vessels, after extracting the largest connected component from the vesselness measure, we have applied simple region growing method to achieve refined segmentation of coronary arteries. Vessel segmentation based on the good feature map may lead to accurate centerline extraction. The region growing algorithm that we have used in our paper is the one proposed by[11] global region based active contour. The vesselness measure is applied as an input to the region growing process. The algorithm requires an initial mask from where it starts to grow in nearby regions. For a fair comparison we have kept the position of initial masks same for every filtered image obtained from the four different filters[6–9]. Further, median filtering is applied on the resultant images obtained after region growing process to make the edges smoother. The result for the segmentation of the left coronary artery is shown in Figure 6, where input to the region growing algorithm is the filtered image produced by using vesselness filter function in[7] followed by median filtering.

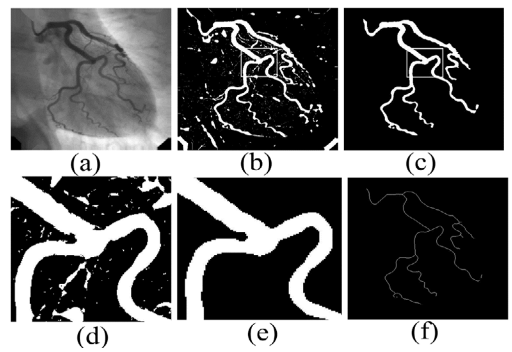

Figure 6. The results of Appling region growing and median filtering on Ying's vesselness.

The original 2D angiogram image is shown in Figure 6(a). The segmentation is carried out by using vesselness feature map of vesselness function in[7] as the guidance for the region growing algorithm. It can be seen in Figure 6(b), the edges of coronary artery are not smooth and uneven as shown in Figure 4(b), which may produce unsmoothed centerline. For a more clear understanding a closed view of image in Figure 6(b) is shown in Figure 6(d). These unsmoothed edges can be corrected by providing vesselness map as guidance to region growing algorithm which is a forceful and adjustable method for segmenting medical images. Segmentation of medical images would be difficult using conventional segmentation methods i.e. thresholding or gradient based approaches. Therefore we have adopted an active contour model which is basically an energy minimization problem and can be embedded in the level set formulation, leading to an easier way to resolve the problem of topological changes. The result of applying region growing algorithm followed by median filtering is shown in Figure 6(c) which shows quite smooth edges as compared to the original vesselness defined in [7]as shown in Figure 6(b). The magnified view of the portion enclosed by white box in Figure 6(c) is shown in Figure 6(e).

The active contour model followed by median filtering has produced more satisfactory results. It can be observed in Figure 6(f), the centerline obtained after applying energy model is quite smooth with less or no spurs and hence can be used for further processing such as for measuring the diameters and finding out the lesions.

The same energy model is applied on the remaining vesselness functions with the initial mask given on the same position as initialized for obtaining Figure 6(c). The segmentation results for the remaining vesselness measure presented in[6,8–9] are shown in Figure 7. However, it can be seen in Figure 7, the segmentation of the left coronary artery is incomplete. This is due to the complex background and also because of the reason that globalized region based active contour does not favor these vesselness[6,8–9] and hence unable to detect the whole vessels in complex environments that exhibits non-uniform distribution of intensities.

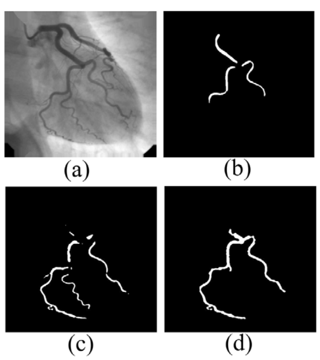

Figure 7. The results of appling region growing and median filtering on Frangi's, Yanli's and Wang's vesselness.

In case of vesselness defined in[7], the energy model exhibits good performance comparatively in extracting the complete left coronary artery and suppressing noise because their vesselness function can distinguish between vessel and the non-vessel points correctly.

Table 1 summarizes all the discussed vesselness filters with respect to performance measures including noise suppression, edge smoothness, branch disconnection and centerline smoothness. The average execution time taken by all four vesselness measure is shown in Table 2. The minimum time is taken by vesselness measure described in [9]whereas the rest of others require almost similar time.

Table 2. Average execution time

S.No.	Vesselness Measure	Average Time (Sec)
1	6	3.04
2	5	3.18
3	8	3.28
4	9	1.85

4. Conclusion

The presented work has made a performance comparison of four different vesselness measures[6–9] by keeping in mind the segmentation and centerline extraction of coronary arteries. Surprisingly, the approaches in[8,9] behave quite similar in our experiments. Whereas the Frangi's function in[6] has its strong point in eliminating the background noise and separation of neighboring vessels, however, vessels are likely to get cut off at bifurcations or junctions. It is more beneficial to have continued and connected branches, which can be obtained by using either of the vesselness filter defined in[7–9]. We have also performed segmentation of the filtered outputs using globalized region based active contour followed by median filtering to improve the artifacts such as unsmoothed edges. Use of this approach eventually leads to the extraction of a smooth centerline that can be used for the applications including detection of lesions and other CADs. Future work comprises of the expansion of our experiments to add more vesselness functions for three-dimensional (3D) Coronary Computed Tomography Angiography (CCTA).

Table 1. Summary of vesselness measures

Vesselness Measure	Noise Suppression	Edge Smoothness	Branch Disconnection	Centerline Smoothness
6	Yes	Over-smooth	yes	Lots of spurs
5	Yes	Less-Smooth	No	Less spurs
9	No	No	No	Lots of spurs
8	No	No	Yes	Lots of spurs

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