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# Detection of Narrowed Coronary Arteries in X-ray Angiographic Images using Contour processing of Segmented Heart Vessels based on Hessian Vesselness Filter and Wavelet based Image Fusion

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## ABSTRACT
In this paper a method for Detection of narrowed coronary arteries in X-ray Angiographic images is addressed. For this purpose firstly coronary arteries are segmented base on some probability masks which indicates the membership function of being a vessel for each pixel in the image. In order to build the membership functions whole of angiographic frames in the sequence are utilized. To this aim, angiographic sequence is filtered by the Hessian based vesselness filter to increase discrimination between the vascular structures and the background. Next, a 2D discrete wavelet transform is employed for fusion of the angiographic frames and their filtered versions. In the next step, the heart vessels are detected by applying the fused image with a couple of constant values as threshold coefficients. The coefficients are employed to adjust the effect of threshold. As a consequence, two images containing the detected vessels are yielded. After that, in order to mask out the redundant particles in the result morphological operations are employed. In order to find narrowed vessels their contours are obtained and the thickness of vessels is measured. A predefined threshold is employed to find the abrupt decrease in the vessel thickness. Experiments demonstrate the efficiency of the proposed method in order to detect the narrowed heart vessels in X-ray angiographic frames.

## Keywords
Vessel segmentation, X-ray angiographic image, wavelet based image fusion, contour analysis, thickness measurement

## 1. INTRODUCTION
In recent decades, medical imaging techniques including X-ray angiography and computed tomography angiography (CTA) have provided a remarkable aided the diagnosis of atherosclerosis. In this way, vessel analysis in medical images and videos is one of the most significant research fields because it is appropriate in diagnostic and intervention planning purposes. For various visualization applications such as multiplanar reformats or endovascular views, extraction of vessel centerline can be employed to generate particular visualization information. In addition, for some of other applications including quantification, e.g. for determining the dimension of stents or stenosis grading, vessel segmentation can play an important role. In most of methods, proposed in literature, for vessel analysis, images enhancement is the first step to improve vascular structures. It helps vessel visualization, e.g. in maximum intensity projections or volume rendering techniques. For vessel segmentation, in case of coronary arteries in angiographic images, digital post-processing operations are essential to isolate vessels from background. In many of techniques the knowledge that vessels are tubular structures is employed to describe vessels by their central axes and width.

Central vessel axis (CVA) segmentation is presented in [1, 2], in which for recognizing the type of local structure in image (e.g., tubular-like), information from 2nd-order derivatives at multiple scales is extracted. To obtain this information, the main mode of variation in Hessian matrix is inspected. Hessian-based vessel enhancement filters (HBVF) have been proposed by Lorenz et al. [3], Sato et al. [4], and Frangi et al. [5]. HBVF is a powerful method for enhancing vascular structures in variety of imaging tasks including DSA [3, 5], CTA [4], and 3D MRA [1, 4, and 5]. To improve visualization and diagnostic purposes, in [6], vessel enhancement is accomplished using vessel enhancing diffusion (VED).

In this method, vessel segmentation in X-ray angiographic frame is realized using some experts which are in tandem. Firstly Hessian based vessel enhancement filter (HBVF) is applied to the angiographic frame to be segmented for enhancement of vessel structures. Meanwhile, the filter is applied to other frames in the angiographic sequence. Afterward, angiographic frames in the sequence and their vesselness filtered versions are fused using 2-D wavelet transform to make an image which is used as a threshold for detecting the vessels. Next, for detecting the vascular structures the fused image accompanying with a couple of thresholds is applied to the vesselness filtered frame to be segmented. Finally, in order to find the narrowed coronary arteries, vessel contours processing is employed for the measurement of the vessel thickness. The remainder of the paper proceeds as follows: In section 2 vesselness filter for enhancing the tubular structures in image is introduced. In Section 3, 2-D discrete wavelet transform and its application in image fusion are reviewed. Section 4 focuses on the proposed vessel segmentation method, followed by vessel contour processing for detection of narrowed vessels in section 5, experimental results in section 6 and conclusion in section 7.

## 2. VESSELNESS FILTER

Detection of vascular structures is the main purpose of this filter. To this aim, the eigensystem of the Hessian matrix is analyzed by the filter to determine the curvature direction of image which is necessity for detection of vascular structures. Curvature direction in each point is the direction according to eigenvector of Hessian matrix in which the second order of image information is extremum. Eq(1) presents Hessian matrix which determines the second order information of 2D image.

$$\mathrm{I(x, y)} \Rightarrow H = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix}$$

Where H and I denote Hessian matrix and original image and $I_{xx}, I_{xy}, I_{yx}$ and $I_{yy}$ denote second derivative of image information, respectively. To obtain $\partial I / \partial x$ and $\partial I / \partial y$ original image can be filtered using $I$=[−1 2 −1]and $I$= [−1 2 −1]$^T$ vectors. After computing eigenvalue and eigenvector for Hessian matrix of each image pixel, following conditions are possible:

For bright vascular structures on a dark background if the ordering of eigenvalues are $\lambda_1 \le \lambda_2$, $v_1$ indicates the direction along the vessel when $\lambda_1 \approx 0$ and $\lambda_1 \le \lambda_2$. Based on eigenvalues of Hessian matrix, numerous vesselness filter are proposed in literature [3],[4],[5],[7]. In this work, we use the definition of vesselness function that proposed in Frangi et. al. work [5]. The formulation of vesselness measurement, proposed in [5], is given as follows:

For 2D images:

$$f(\lambda) = \begin{cases} 0 & \lambda_2 > 0 \\ e^{-\frac{R_B^2}{2\beta^2}} . (1 - e^{-\frac{S^2}{2c^2}}) & otherwise \end{cases}$$

$$R_A = \frac{\lambda_1}{\lambda_2}$$

Where $R_A$ make distinction between plate and line like structures, $R_B$ investigates deviation from a blob like structure, and S differentiates between vessels and background. The parameters β, c adjust the influence of $R_A$, $R_B$ and S. To determine vesselness response, Hessian with Gaussian derivatives at multiple scales is computed and the highest response is considered as the output of the filter.

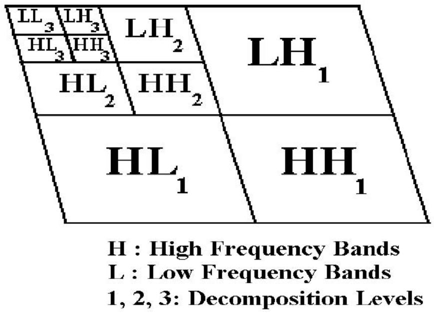


**Fig. 1: The structures of 2-D DWT whit 3 decomposition levels**

## 3. DISCRETE WAVELET TRANSFORMS (DWT)

The wavelet transform is an effective tool for multiresolution image analysis. It decomposes image into lower resolution sub-spaces for analysis. To construct a wavelet decomposition of signal, the sequence of FIR filters $g_i$ and $h_i$ can be employed. To this aim, the discrete scaling function and the discrete wavelet function are defined as follow:

$$\varphi_{i,j}(k) = 2^{i/2} h_i^{(k-2^i j)}$$
$$\psi_{i,j}(k) = 2^{i/2} g_i^{(k-2^i j)} \quad (4)$$

Therefore, we obtain a wavelet orthonormal basis:

$$S^{DWT} = \{\varphi_{N,j}, \psi_{1,j}, \psi_{2,j}, ..., \psi_{N,j}\} \quad j \in z$$

Consequently, a discrete signal x can be expressed using these scaling function and wavelet function:

$$x(k) = \sum s_{(N)}(j) \varphi_{N,j}(k) + \sum_{i=1}^{N} \sum_{j \in z} d_{(i)}(j) \psi_{i,j}(k) \quad (5)$$

### 3.1 2-D DWT

For 2-D signals such as images, 2-D wavelet transforms are employed. Figure 1 presents the structures of 2-D DWT with 3 decomposition levels. After one level of decomposition, four frequency bands are obtained including Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). The next level decomposition is just applied to the LL band of the current decomposition stage, which forms a recursive decomposition process. As a consequence, N-level decomposition will finally have 3N+1 different frequency bands, including 3N high frequency bands and just one LL frequency band. The 2-D DWT will have a pyramid structure shown in figure 1.

### 3.2 Image fusion using wavelet transform

Image fusion is one of the most important applications of wavelet transform. Figure 2 presents the block diagram of a generic wavelet-based image fusion scheme. For image fusion using wavelet, firstly wavelet transform is performed on each source images to be fused, afterward based on a set of fusion rules; a fusion decision map is generated.

According to the fusion decision map, the fused wavelet coefficient map can be constructed using wavelet coefficients of the source images. Finally to make the fused image, inverse wavelet transform is accomplished.

As the diagram indicates, the fusion rules are playing a very important role during the fusion process. Pixel-based and window-based fusion rules are two frequently used methods in literature [8], [9]. In the former method, to make decision on one of the coefficients of the fused image, the corresponding coefficients in the source images are considered, while in the latter, not only the corresponding coefficients, but also their close neighbors are considered. In this approach we use a pixel based fusion rule for fusing the angiographic frames.

## 4. VESSEL SEGMENTATION

After applying the vesselness filter to the angiographic frame, the structures like vessels become more visible. Note however that, in the background there are some particles such as ribs that take a great value due to applying the vesselness filter. As a result of applying the filter to such structures, the vessel segmentation algorithm results in error. As a remedy, in this approach we use information obtained from different angiographic frames to filter out the non-vessel structures. Figure 3(a) presents a sample of angiographic frame to be segmented by the algorithm and the result of applying vesselness filter on the frame (Figure 3 (b)). As it is shown in Figure 3 the vessel pixels take low intensity levels in the angiographic frame while their intensity levels in the filtered image are higher than the background. Consequently, for detecting the vessels a threshold can be applied to the vesselness filtered image. As discussed above, before applying the threshold, some of non-vessel structures in the background should be removed.

For this purpose, according to the intensity level of the vessel structures in the angiographic frame and its filtered version, two images in which the level of each pixel presents the probability that a pixel belongs to the vessels are computed.

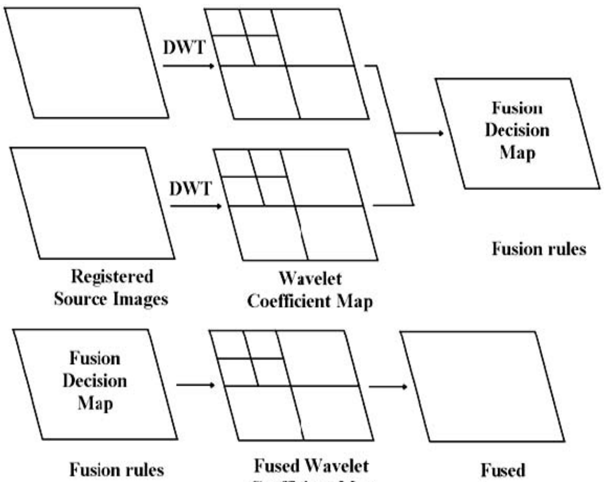


**Fig. 2: Wavelet based image fusion scheme**

To obtain such images following formula is utilized in which each pixel between the whole frames in an angiographic movie is considered.

$$I_m[x_i, y_i] = \min(I[x_i, y_i, t]), \qquad t = 1,...,L$$
$$I_{mf}[x_i, y_i] = \max(I_f[x_i, y_i, t]) \quad i:1,...,M \quad j:1,...,N \qquad (6)$$

Where I , M , N and L denote the angiographic sequence to be segmented and the number of rows, columns and frames of its matrix, respectively. In $I_m$ most of dark pixels belong to the vessels; while in $I_{mf}$ bright pixels have a more probability to belong to the vessels (See Figure. 3(a, b)) to make $I_{mf}$ similar to $I_m$ (in which the dark pixels belong to the vessels) we use negative version of $I$ and name it $I_m^{inv}$. For discriminating the vessels in the filtered image $I_{mf}$ and $I_m^{inv}$ are used to make a threshold for applying to the filtered image. In this approach we use an image as the threshold which is obtained by fusing $I_{mf}$ and $I_m^{inv}$ using wavelet theory. In the previous section we made a review about wavelet based image fusion. Here, for fusing two images after decomposition step, we use pixel based fusion rule in which the coefficient of the fused image is obtained by averaging the corresponding Haar wavelet coefficient in $I_{mf}$ and $I_m^{inv}$. These coefficients are computed using 5-level decomposition. We can summarize above discussions as follow:

$$I_{mf}, I_m^{inv} \xrightarrow{\text{Wavelet Based Image Fusion}} I_{FUS} \qquad (7)$$

Where $I_{FUS}$ is the fused image. For making the threshold for vessel detection we use $I_{FUS}$ as follow:

$$V = I[x, y, t] > I_{FUS}.Th \qquad (8)$$

Where *V* and *Th* denote the vessels and the coefficient for adjusting the effect of threshold. Adjusting the threshold parameter (TH) for detection of vessels is a critical task because applying a high threshold value can remove some of vessel structures while a low threshold value cannot filter out non-vessels. Figure 3(c, d) presents the response of vesselness filter after applying threshold. Effects of applying high and low amounts of threshold on the filtered image by vesselness filter conform above discussion. It is worth noting that although some parts of vessels are removed due to applying a high amount of threshold, the direction of remaining parts is obtainable; accordingly, whole of vessels can be recovered according to these directions. In this approach, to cope with the problem of vessel segmentation, firstly a high level threshold is applied to the image to remove most of non-vessels from image.

**Fig. 3: Original image (a) and the response of the vesselness filter (b). Applying a low (c) and a high (d) level threshold on the vesselness filtered image (For th = 0.7 (d) some part of vessels are removed, and for th = 0.2 (c) some of ribs are shown as vessels in error).**

Subsequently, the remaining vessels are detected and their directions are obtained for recovering the removed parts. Afterward, according to the obtained direction structure element for dilation operator is constructed (as a binary matrix) and it is employed to expand the remaining vessels as a recovering step (see Figure 4 (d)). This yields some false positives in the detected vessels. To reduce the false positives in the yielded image, a low level threshold is applied on the vesselness filtered image. Finally product of two images is considered as the result of the approach.

$$I_r(x,y) = I_{thl}(x,y).I_D(x,y)$$

Where $I_{thl}$ , $I_D$ and $I_r$ denote vesselness filtered image after applying low level threshold, the dilated image and the result image, respectively. According to eq.9 since $I_{thl}$ and $I_D$ are binary images, $I_r$ is result of applying and operator between $I_{thl}$ and $I_D$ .

As a final point, according to the fact that some of diagnostic applications only need main vessels, removing fine particles of image could yield a more clear result. For this purpose, firstly labeling operation is accomplished in the result image.

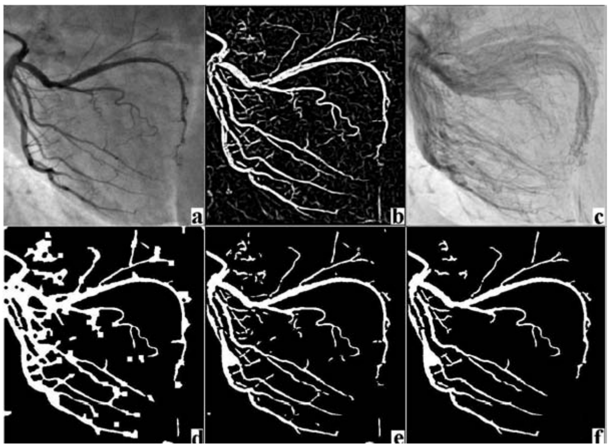

**Fig. 4: Other example of X-ray angiographic frame (a) its vesselness filtered version (b) the fused image to be used as threshold (c) recovered vessels after applying the high level threshold ( $I_D$ ) (d) the result image ( $I_r$ ) before (e) and after (f) particle removal.**

Afterward, the size of each label is considered and the labels smaller than a predefined size are removed. Adjusting the size threshold for removing the particle is critical issue in segmentation of vascular structure. It depends on the minimum size of vessels to be detected. Figure 4 presents other example of X-ray angiographic image and the result after performing each part of the proposed algorithm.

## 5. Detection of narrowed coronary arteries in the angiographic frames

As a most important aim of this study, in this section a method is proposed to detect the narrowed heart vessels in angiographic frames. Reducing the medical mistakes, arises from the sight error, is the most motivation of scientists beyond conducting such researches. In other words by integration of decision support by means of medical image analysis into clinical practice it is expected to reduce the human error in diagnosis purposes. In this section we focus on detecting narrowed vessels in X-ray angiographic frames. The block diagram of the proposed algorithm is presented in Figure 5. In this method vessel contours are employed to measure the vessel thickness. In computer vision, contours are known as the outlines of image regions. To obtain the contours of vessels, boundary detection is used in this algorithm in particular, a morphological dilation of segmented vessels, followed by subtracting from the vessels results in the boundary of the vessels. Subsequently, tracing of the yielded boundary using the connected component analysis provides the contours.

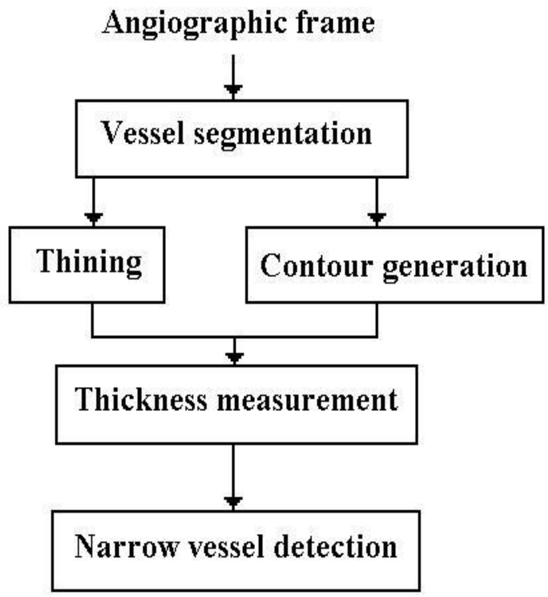


**Fig 5: The block diagram of the proposed method**

Figure 6 shows the angiographic frame including the vessels and their contours. In order to measure the thickness of vessels, the distance between each point of the vessel contours, and its corresponding point in other side of vessel should be computed. For this purpose, firstly the centerline of the vessels is obtained using a thinning algorithm. The centerline is used as a reference for the thickness measurement. Figure 7 presents the idea employed to obtain the thickness of the vessels.

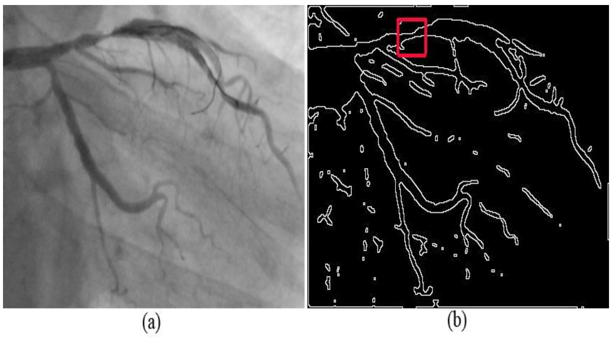


**Fig 6: angiographic frame including the heart vessels and their contours**

**Fig 7: Measuring the vessel thickness**

As previously mentioned, the centerline is utilized as a reference for the measurement. Consequently, the two sides of vessels contours (the red points in the Figure 7) should be obtained. For this purpose, firstly the direction of the vessel in the point the reference point (the blue point in the Figure 7) is computed. Afterward a line segment, perpendicular to the vessel centerline, is generated. Coincidence of the line segment and the vessel contours (boundaries) are considered to obtain the thickness.

After obtaining the vessel thickness in whole of the image, they are investigated for the observation abrupt decrease which can results in detection of narrowed vessels. Figure 8 presents a narrowed vessel and its thickness plot, computed by the proposed algorithm. As Figure 8 Shows, the median of the thickness plot falls suddenly in the narrowing part of the vessel. In addition, in the smoothed version of the thickness plot, a local minimum is observed.

## 6. EXPERIMENTAL RESULTS

In this section for benchmarking the proposed algorithm it is applied to some of X-ray angiographic frames for vessel segmentation.

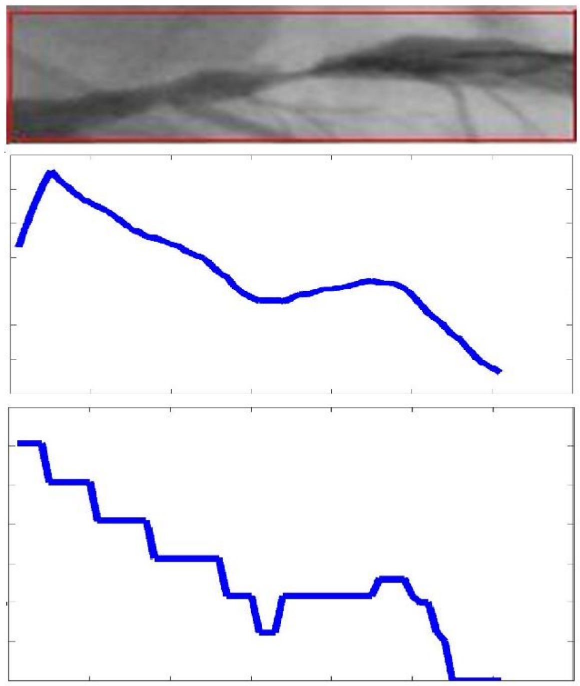

**Fig 8: the detected narrowed vessel (up), the median of the vessel thickness measured by the proposed algorithm (middle) and the smoothed version of the thickness**

### 6.1 Results of vessel segmentation algorithm

To evaluate the efficiency of the algorithm, 19 angiographic frames are used. Three parameters are employed as threshold including high and low level threshold for detecting vessels and the particle removal threshold which filters out fine particle in the result image. The amounts of high and low level thresholds for vessel discrimination are 0.7 and 0.2, respectively and the particle removal threshold is 3000 pixels. The block diagram of the approach is presented in Figure 9. As discussed in the previous section, the novelty of the proposed algorithm is using a fused image, obtained from the frames of angiographic sequence, as a threshold for detecting the vessels in the vesselness filtered image. For fusing the angiographic frames and their filtered version, a pixel based rule is utilized in which in $I_{mf}$ and $I_m^{inv}$ images the coefficients, provided after five level decompositions, are combined by obtaining their average.

As an assessment of algorithm efficiency, it is compared to vessel segmentation by a method [10] in which the thresholds for vessel segmentation are only two constant values (not two

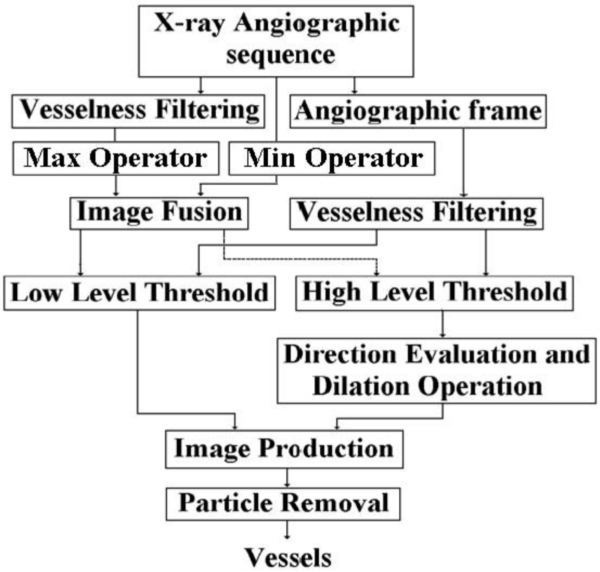


**Fig. 9: Block diagram of the proposed vessel detection method**

images). After applying the algorithm on the angiographic frames the result is compared with a version of frame in which the vessels are manually labeled. To determine the amount of parameters indicating the accuracy of the method some parameters are computed. These parameters are false positive (FP), false negative (FN) and true positive (TP). False positive presents number of non-vessel pixels which are erroneously classified as vessels. While false negative means the number of pixels which are vessels but the algorithm could not detect them, finally true positives are the number of pixels which are classified correctly as vessels. Since some mistakes are made while manual labeling of vessels, true positives are counted as following way. For every pixel in the known vessels if there is a marked pixel as vessel, its 3×3 neighborhood is also counted as a true positive. Figure 10 presents the comparison of efficiency of the proposed method and the method proposed in [10] which uses two constant values as threshold. Efficiency of the methods is computed using following formula:

$$Accuracy = {Tp}\Big/{Tp + Fn + Fp} \qquad (10)$$

In the former method, the high level threshold and the low level threshold are 0.7 and 0.2, respectively and the threshold of particle removal step is equal to 3000 pixels, while in the latter, the high and low level threshold are 0.8 and 0.2, respectively. Due to using the fused image, non-vessel particles of image are effectively filtered out because the fused image takes greater values in the non-vessel regions. Consequently, as Figure 10 shows, the proposed method outperforms the other method accuracy.

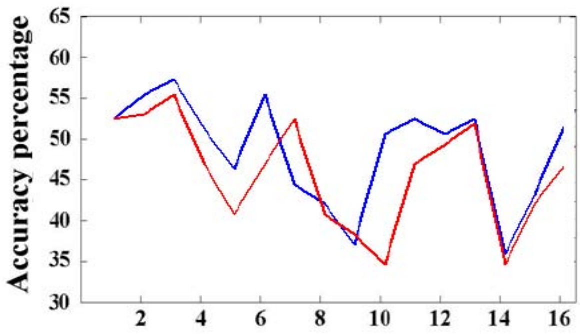


**Fig. 10: Comparison of two method accuracies for 16 angiographic frames including the proposed method (blue line) and the method which used two constant values as threshold for detecting the vessels (red line).**

## 6.2 Results of narrowed vessel detection and vessel thickness measurement

Figure 11 presents the median and the smoothed version of the thickness of a typical narrowed vessel. An abrupt change in the narrowed part of the median of the thickness and a local minimum in the smoothed version of the thickness plot are observable. The plots indicate the efficiency of the proposed method for to measure the vessels.

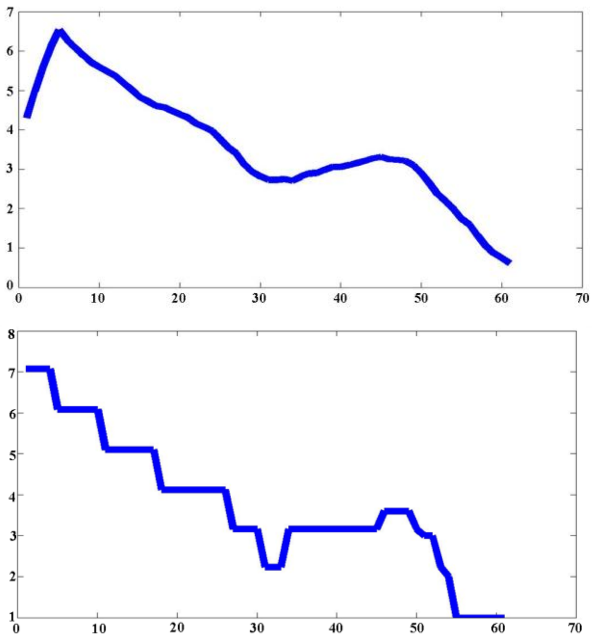

**Fig 11: plots including median (up) and the smoothed version (down) of the thickness of a typical narrowed vessel computed by the proposed algorithm**

However, the detected narrowed vessels depend on the results of the vessel segmentation stage. If the segmentation stage fails to detect a narrowed part of vessel, the measurement stage cannot detect it. Moreover, some of the detected narrowed vessels are not abnormal vessels. In other words, the side is important to observe an abnormal narrowing of vessel. As a result, investigation of an operator is still essential in order to make the final decision of observing an abnormal vessel.

## 7. CONCLUSION

In this paper a method for segmentation of vessels in X-ray angiographic frames and detection of narrowed vessels is proposed. In this method firstly Hessian based vesselness filter is applied to the angiographic frames to enhance the vessels. Afterward, a couple of threshold including high level and low level threshold, obtained by fusing the whole of frames in the angiographic sequence, is applied to the vesselness filtered image for detecting the vessels. Due to applying the high level threshold some of thin vessels are removed. To recover such vessels, morphological operations is utilized. Subsequently, the two yielded images are combined by obtaining their product; finally the particle removal is accomplished to reduce the amount of false positive. To detect the narrowed vessels the vessel contours are analyzed and measured. After applying the algorithm on the X-ray angiographic frames, most of vessels were effectively detected.

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