

Integration of Curvelet and Bi-Gaussian for Extraction of Vascular Structures

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Abstract: In medical imaging, the detection of tubular structures like blood vessels or airways is a prior step for quantification of diseases and evaluation of treatment progress. An enhanced algorithm for extraction of blood vessels is described in this paper to improve the detection of low contrast blood vessels and avoid undesired merging of adjacent objects because of the intrinsic usage of low level Gaussian Kernel. The proposed method uses curvelet based contrast enhancement and a bi-Gaussian function with Vessel Enhancement diffusion filter. The bi-Gaussian kernel replaces the low level Gaussian kernel by allowing independent selection of scales in foreground and back ground. The proposed method reduces interference from adjacent object by selecting a narrow neighborhood for foreground and background. In this approach an integrated framework of the conventional vesselness function and a reformulated gradient flux are used. Experiments and results of the proposed methods delivers accurate and stable tubular structures and outperforms several conventional derivative filters in separating closely located adjacent objects as well as image noise.

Key words: Vessel Enhancement • Tubular structure detection • Hessian matrix • Gradient models
• Gaussian Kernel

INTRODUCTION

Detecting tubular structure in digital images is an important low level operation of computer vision and has many applications such as treatment of vascular diseases. On the other hand, manual segmentation of blood vessels is a time consuming task. Advances in the computation power of modern computers automated segmentation methods are capable of producing segmentation results in a quite short period of time than manual segmentation. Therefore advanced vessel extraction techniques are receiving significant attention. Vascular structures in the medical images are commonly separated from its background prior to clinical evaluation. This is because the extracted vascular structures are analyzed directly and surgical planning can be prepared. In such a way extracting and separating blood vessels from non-vessel structures in medical image play a vital role. A technique is used to extract the blood vessel by optimizing the

central axis of blood vessels based on the resampling of slices that are orthogonal to the estimated blood vessel axis is described in [1-10]. In this the resampled slice contours that form the surface of blood vessels, are detected using gradient information and used iteratively to refine the medial axis of the vessels. Although this method can produce accurate medial axes, it requires user interaction to specify the initial location of blood vessels.

A stochastic vessel tracking approach based on tubular models proposed in [9] attempts to find the parameters of a tubular model that best matches the local features of the data. An extension of this idea is described in [11-27], in which a deformable tubular model is used. Unlike a traditional cylindrical coordinate system, the tubular coordinate system accommodates curved axes and can generate smooth and accurate surfaces of blood vessels. This method requires user interaction for the specification of curved axes and occurrence of problems at the bifurcations of blood vessels.

In medical imaging, tubular structures are used for detection, classification and quantification of abnormalities and for treatment planning [21]. There are many techniques used for detecting the vascular structures and a recent survey can be found in [14]. From the literature survey in [14] it is found that derivative filters have put on much attention. The image derivatives were often used to detect the boundaries or centerlines of tubular structures [11]. The boundaries are considered as antisymmetry structures and first order gray level derivatives were used to detect the boundaries. As an application, in the context of automatic lung nodule detection in thoracic CT scans [2, 3], blood vessels and nodules may share similar characteristics locally, global constraints inherent in the data such as the continuity of blood vessels may be used to discriminate between them. Thus the segmented blood vessels can be used to resolve local ambiguities based on global considerations. Experimental results have shown that by using extracted blood vessels it is possible to eliminate approximately 38% of the false positives generated by an existing automated nodule detection system [3]. On the other hand, centerlines are typically even or symmetric structures and should be detected with the second-order derivatives. The structure tensor method was implemented to determine the local boundary direction and strength [1]. Hessian Line filters are used for center line extraction [7, 17, 20]. A hybrid method known as medialness tube filter which based on Hessian and boundary gradient are used to determine the axial directions and local diameters [12]. Normalization scheme is used in account of size variation. In this method the filters identify the objects at different scales and combine all the results into a single output response [15]. All these methods employ Gaussian kernel to calculate the spatial intensity derivatives.

An adaptive multi local medialness function is used to improve the centerline detection [18]. In this method instead of using the Gaussian linear scale a first derivative of bivariate Gaussian is used to measure the boundaries. To extend the gradient around the boundaries into tube centers a Gradient based vector flow is adopted [26]. Optimally oriented flux is used to determine the orientation difference in curvilinear structures [13]. This method works well against the disturbances created by close objects and is employed for vessel segmentation. A recent review literature on Vessel segmentation and tree construction is presented. The vessel tree is reconstruction based on a fuzzy shape representation of the data which is obtained by using regulated morphological operations [1].

In the proposed work, a filtering kernel is used for detecting closely located structures. First, a curvelet transform is used for contrast enhancement. Second, a bi-Gaussian kernel is used to minimize the adjacent disturbances. Third, a vessel enhancement diffusion filter is used to improve the extraction of adjacent tubular objects.

The paper is organized as follows: In section 2, a review on the conventional filters is described. Section 3 describes the proposed work Curvelet based bi Gaussian for vascular structure detection. Finally, in section 4 we conclude with a discussion on the experimental results and present directions for future work and conclusion in Section 5.

Review on Conventional Filters: In this section a review of several conventional line filters and tube filters are discussed. To understand the drawbacks of the existing method, consider the perspective of the differential convolution [10]. Consider a low pass filter $f(\sigma, x) = I(x) * h(\sigma, x)$ where h represents the smoothing kernel, σ represents the scale and $I(x)$ represent the input image. Then the i -th order derivative in the direction \vec{r} can be obtained by

$$\frac{\partial^i f(\sigma, x)}{\partial \vec{r}^i} = I(x) * \frac{\partial^i h(\sigma, x)}{\partial \vec{r}^i} \quad (1)$$

The second order derivative operator applied to detect structures of 2D or 3D images can be divided into Laplacian and Hessian, which usually combine the one dimensional derivatives. To describe the objects with different sizes, the filters are merged with a multi scale framework.

The subsequent section describes the conventional filters used for the detection of tubular structures. This paper focuses on the kernel $h(\sigma, x)$ and its derivatives.

Vesselness Models: The vesselness models are the conventional Gaussian Line filters. These filters depend on the orientational difference and anisotropic distribution of the second-order directional derivatives. In this the tube shape is measured as equation (2)

$$\frac{\partial^2 I_\sigma}{\partial \vec{r}^2} = \vec{r}^T H_\sigma(x) \vec{r} \quad (2)$$

where \vec{r} represent the unit vector and H_σ represent the Hessian at scale σ . The directional Derivative of Gaussian [22] can be obtained as equation (3)

$$\frac{\partial^2 I_\sigma}{\partial r^2} = I(x) * \frac{\partial^2 G(\sigma, x)}{\partial r^2} \quad (3)$$

Isotropic kernel [8] is defined by radially rotating the Derivative of Gaussian and developed a medialness filter for the extraction of anatomic objects in medical images. Laplacian of Gaussian [6] is developed by neglecting the orientational difference. In both the filters the scale normalization factor $NF(\sigma)$ is σ^2 . The drawback of using Gaussian kernel is that the object boundaries are smoothed so that the closely located structures tend to merge together.

Flux based Filter: Vasilevskiy et.al introduced a flux based tube filters for vessel segmentation [21]. The gradient flux of an image is the can be represented as equation (4)

$$Flux(\sigma, x) = \sigma I(x) * \Delta \bar{R}(\sigma, \sigma_b, x) \quad (4)$$

where σ represents the spherical radius and $\bar{R}(\sigma, \sigma_b, x) = G(\sigma_b, x) * \bar{R}(\sigma, x)$ represents the smoothed rectangular function. Optimal oriented flux model is an improved flux filter which is defined as a second order derivative and is defined in equation (5)

$$Q_{\sigma, x}^{i, j} = \sigma I(x) * \frac{\partial^2 \bar{R}(\sigma, \sigma_b, x)}{\partial x_i \partial x_j} \quad (5)$$

The advantage of flux based filters compared to Gaussian Line filters is the better performance in separating adjacent objects.

Medialness Filter: Medialness filter estimates the likelihood of a point belongs to the medial axis of the object. An adaptive medialness model is developed for three dimensional vessel segmentation [12]. In this method the orientation of the filter kernel is defined by Eigen vector. The medialness function is defined as in equation (6)

$$M(\sigma, \sigma_b, x) = \sigma^{\gamma+1} . I(x) * \Delta \bar{R}^c(\sigma, \sigma_b, x) \quad (6)$$

where \bar{R}^c represents the smoothed two dimensional rectangular kernel. The advantage of medialness is that it detects the vessel boundaries more accurately. The drawback of medialness is that the intra region discontinuities are wrongly detected.

Table 1: Summary of the derivative filter for detection of tubular structures

Method	Filtering Kernel	Derivative operator	NF(σ)
LoG [8]	Gaussian	Laplacian	$\sigma^{2\gamma}$
Vesselness[7][17]	Gaussian	Hessian	$\sigma^{2\gamma}$
Flux[22]	Rectangle	Laplacian	σ^γ
OOF[13]	Rectangle	Hessian	σ^γ
BG[4]	Gaussian & Rectangle	Hessian	$\sigma^{2\gamma}$
Proposed Work	Bi Gaussian	Hessian	$\sigma^{2\gamma}$

Proposed System: This section describes the proposed vessel segmentation algorithm in which first the image is enhanced using curvelet transform followed by a bi-Gaussian with vesselness enhanced diffusion filtering of the enhanced image.

Contrast Enhancement using Curvelet Transform: Curvelet Transform deals with edge discontinuities and is used for edge enhancement in the image. Curvelet coefficient [19] is modified to enhance the edges in the image. The function k_c is defined to modify the values of the curvelet coefficient. The value of k_c is defined in equation (7).

$$k_c = \begin{cases} 10 & ; \quad x < c\rho \\ 2 \left(\frac{x - c\rho}{c\rho} \left(\frac{m}{\rho} \right)^p + \frac{2c\rho - x}{c\rho} \right) & ; \quad c\rho \leq x < 2c\rho \\ 5 \left(\frac{m}{x} \right)^p & ; \quad 2c\rho \leq x < m \\ 10 \left(\frac{m}{x} \right)^s & ; \quad m \leq x \end{cases} \quad (7)$$

where ρ represents the noise standard deviation, p represents the degree of non-linearity, c represents the normalization parameter, s represents the dynamic range compression and m represent the value under which the coefficients are amplified. The value of m can be derived from $m = M_c$ with the value of $l < 1$, where M_c represent the Maximum curvelet coefficient. The following are the steps for curvelet enhancement in the image.

- Estimate the noise standard deviation ρ in the input image I .
- Calculate the curvelet transform for the input image. This results in a set of bands D_i . Each band i contains N_i coefficients which defines the given level of resolution.
- Calculate the noise standard deviation ρ_i for each band i of the curvelet transform.

- For each band i calculate the following
- Maximum M_i of the band
- Multiply each curvelet $D_{i,k}$ coefficient by $\gamma_c(|D_{i,k}|, \rho_i)$
- The image is enhanced and is reconstructed using the modified curvelet coefficients.

Bi Gaussian Kernel: Bi Gaussian is obtained by merging two Gaussians with different parameters. Bi Gaussian Kernel allows selection of independent scales in the background and the foreground [4]. This leads to noise suppression and reduce the disturbances caused by adjacent objects. The conventional Gaussian kernel $G(\sigma, x)$ suffers from the disturbances of adjacent structures because of the use of single scale for the foreground and background. Consequently, interference is introduced and hence the neighborhood will be sampled. On the other hand the rectangular kernels $R(\sigma, \sigma_b, x)$ has the advantage of separating adjacent structures but suffers from contrast computation due to the smaller gradient scale σ_b . In this paper, the bi Gaussian is implemented by combining the merits of Gaussian kernels and rectangular kernels. A second order of the Gaussian kernel is used to shift at the boundaries $x = \pm\sigma$, where σ represents the scale. A second order bi Gaussian is defined by the equation (8)

$$BG(\sigma, \sigma_b, x) = \begin{cases} k.G''(\sigma_b, x - \sigma_b + \sigma) & ; \quad x \leq -\sigma \\ G''(\sigma, x) & ; \quad x < \sigma \\ k.G''(\sigma_b, x + \sigma_b - \sigma) & ; \quad x \geq \sigma \end{cases} \quad (8)$$

where k is used to balance the positive and negative weights. K can be defined as in equation (9)

$$k = - \frac{\int_0^\sigma G''(\sigma, x) dx}{\int_\sigma^\infty G''(\sigma_b, x + \sigma_b - \sigma) dx} \quad (9)$$

where σ represent the scale on the foreground and σ_b represent the scale on the background and N dimensional $G(\sigma, x)$ are defined as in equation (10)

$$G(\sigma, x) = \frac{1}{(\sqrt{2\pi}\sigma)^N} e^{-\frac{|x|^2}{2\sigma^2}} \quad (10)$$

Combining the advantages of the Gaussian and Rectangular kernels the adjacent objects are clearly separated. In this paper some prior assumptions are adopted which is by other authors [16][19].

- The zero order kernel $h(\sigma, x)$ should be a decreasing function of σ to restrict weighted average between adjacent objects.
- The zero order kernel $h(\sigma, x)$ should be an even function, i.e $h(x) = h(-x)$, which responds to rotational invariance.
- The first order kernel $h'(\sigma, x)$ should be an odd function, i.e $h(x) = -h(-x)$ and its integral $\int_{-\alpha}^{\alpha} h'(\sigma, x) dx = 0$, which responds to asymmetric objects.
- The second order kernel $h''(\sigma, x)$ should be an even function and its integral $\int_{-\alpha}^{\alpha} h''(\sigma, x) dx = 0$ which responds to the detection of symmetric objects.

Deduction of Bi Gaussian Kernels: The deduction of bi Gaussian is necessary to exploit the capability of Hessian matrix in orientation and structure discrimination. This is done by integrating equation (8). According to the prior condition iv, i.e $\int_{-\alpha}^{\alpha} G''(\sigma, \sigma_b, x) dx = 0$, we get $k = \frac{\sigma_b^2}{\sigma}$

The first order bi Gaussian kernel is derived from the prior condition iii $BG'(\sigma, \sigma_b, 0) = 0$, $BG'(x)$ can be defined as follows.

$$BG'(\sigma, \sigma_b, x) = \int_0^x BG''(\sigma, \sigma_b, x) dx + B'(\sigma, \sigma_b, 0) = \begin{cases} k.G'(\sigma_b, x - \sigma_b + \sigma) & ; \quad x \leq -\sigma \\ G'(\sigma, x) & ; \quad x < \sigma \\ k.G'(\sigma_b, x + \sigma_b - \sigma) & ; \quad x \geq \sigma \end{cases} \quad (11)$$

Finally, the zeroth order bi Gaussian kernel is derived as follows:

$$BG(\sigma, \sigma_b, x) = \int_0^x BG'(\sigma, \sigma_b, x) dx + B(\sigma, \sigma_b, 0) = \begin{cases} k.G(\sigma_b, x - \sigma_b + \sigma) + c_1 & ; \quad x \leq -\sigma \\ G(\sigma, x) + c_0 & ; \quad x < \sigma \\ k.G(\sigma_b, x + \sigma_b - \sigma) + c_1 & ; \quad x \geq \sigma \end{cases} \quad (12)$$

where c_0 and c_1 are constants and are defined in equation (13) and (14)

$$c_0 = k.G(\sigma_b, \sigma_b) - G(\sigma, \sigma) = \frac{e^{1/2}}{\sqrt{2}} \left(\frac{\sigma_b}{\sigma} - 1 \right) \frac{1}{\sigma} \quad (13)$$

$$c_1 = k.G(\sigma_b, \sigma_b) - G(\sigma, \sigma) + c_0 = 0 \quad (14)$$

Normalization: The criteria for normalization are as follows:

- I. $A_0^h = \int_{-\alpha}^{\alpha} h(\sigma, x) dx = 1$ represent the constant conservation
- ii. $A_1^h = \int_{-\alpha}^{\alpha} h'(\sigma, x) dx = -\int_0^{\alpha} h'(\sigma, x) dx$ remains unchanged with σ represents the step conservation.
- iii. $A_2^h = 2 \int_{-\alpha}^{\alpha} h''(\sigma, x) dx = -\int_{-\sigma}^{\sigma} h''(\sigma, x) dx$ should be kept constant and it represents the bar conservation.

Based on the normalization criteria, the normalization co-efficient for the second order bi Gaussian kernel $N_2^{BG}(\sigma)$ is chosen to be σ^2 .

Vesselness Measure: The vesselness measure is based on the vessel enhancement diffusion filter which uses the eigen values of the Hessian along with bi Gaussian. To analyze the behavior of an image I, the expansion of the Taylor series in the neighborhood of a point x_0 , is defined in equation (15)

$$I(\sigma, x_0 + \delta x_0) \approx I(\sigma, x_0) + \delta x_0^T \Delta_{\sigma,0} + \delta x_0^T H_{\sigma,0} \delta x_0 \quad (15)$$

where $\Delta_{\sigma,0}$ represents the gradient vector and $H_{\sigma,0}$ represents the Hessian matrix of the image computed at x_0 at scale σ . The Taylor series expansion on an image I approximates the structure of the image upto second order. The differential operators used are the second order derivatives of bi Gaussian kernels defined in equation (16).

$$I(\sigma, x) = \sigma^y I(x).BG''(\sigma, \sigma_b, x) \quad (16)$$

where y is the normalized scale chosen from differential operators and is chosen as 2.

The principal directions along which the second order derivative of the image is decomposed is extracted using the eigen values of the Hessian. The direction along the vessel can be computed directly using the equation (16).

$$H_{\sigma,0} u_{\sigma,k}^T u_{\sigma,k} = \lambda_{\sigma,k} u_{\sigma,k} \quad (16)$$

where $\lambda_{\sigma,k}$ represents the eigen value corresponding the k -th normalized eigen vector $u_{\sigma,k}$ of the Hessian $H_{\sigma,0}$.

When mapped with Hessian matrix, the eigen values extracts three ortho-normal direction which are invariant upto a scaling factor. Assuming the eigen values λ_i in sorted order ($i=1,2,3$) then $|\lambda_3| \geq |\lambda_2| > |\lambda_1|$, a bright tubular structure will have $\lambda_i=0$ with its eigen vectors corresponding to the axial directions and $\lambda_3 \approx \lambda_2 < 0$ with the eigen vectors corresponding to the cross section of the plane. The second order structureness will be low in the background since no structures are present and the eigen value will be very small. For the region with high contrast than the background the normalization scale will be larger due to the existence of atleast one large eigen value. Therefore the vesselness function $v_0(x)$ can be defined as equation (18)

$$v_0(x) = \begin{cases} 0 & \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ \left(1 - e^{-\frac{R_A^2}{2\alpha^2}} \right) \left(e^{-\frac{R_B^2}{2\beta^2}} \right) \left(1 - e^{-\frac{S_c^2}{2c^2}} \right) & \text{otherwise} \end{cases} \quad (17)$$

where α , β and c represents the thresholds that controls the sensitivity of the filters to measure R_A , R_B and S which are defined in the following equations (18) – (20)

$$R_A = \frac{\text{LargestCrossSectionArea} / \pi}{\text{LargestAxisSemiLength}^2} = \frac{|\lambda_2|}{|\lambda_3|} \quad (18)$$

$$R_B = \frac{\text{Volume} / (4\pi/3)}{\left(\text{LargestCrossSectionArea} / \pi \right)^2} = \frac{|\lambda_1|}{\sqrt{|\lambda_2 \lambda_3|}} \quad (19)$$

$$S = \sqrt{\sum_{i \leq D} \lambda_i^2} \quad (20)$$

For two dimensional images the vesselness measure can be obtained using equation (21)

$$v_0(x) = \begin{cases} 0 & \text{if } \lambda_2 > 0 \\ \left(e^{-\frac{R_B^2}{2\beta^2}} \right) \left(1 - e^{-\frac{S_c^2}{2c^2}} \right) & \text{otherwise} \end{cases} \quad (21)$$

To account for the variety of tubular sizes, the final estimation of the vesselness measure is obtained by multiscale integration which is defined in equation (22).

$$v_0(x) = \max \{v(\sigma, x), \sigma_{\min} \leq \sigma \leq \sigma_{\max}\} \quad (22) \quad f(x) = \text{FFT}^{-1}(\text{FFT}[I(x)] \cdot \text{FFT}[BG(x)])$$

where σ_{\min} and σ_{\max} represents the minimum and maximum scales.

Experimental Results: In this section the curvelet based bi Gaussian technique is compared with the traditional methods using real images as well as the bi Gaussian kernel is compared with the conventional Gaussian kernel and Rectangular kernel on synthesized signal, since the proposed work uses the bi Gaussian kernel with combines the merits of Gaussian and Rectangular kernel.

Algorithm Implementation: In this paper the image is Fourier transformed and is multiplied with the bi Gaussian kernel and is transformed back using inverse Fourier transform. To speed up the computational process, Fast Fourier Transforms(FFT) are used. The response of the filter is calculated as follows:

The codes are implemented in matlab and is embedded with the FFT library. The codes for curvelet are downloaded from the internet and the coefficients are modified to fit the application.

RESULTS AND DISCUSSIONS

The conventional derivative filters have several scale space parameter which include σ_{\max} , that represent the maximum scale and σ_{\min} that represent the minimum scale and γ the normalizing coefficient. σ_{\max} and γ are sensitive parameters and are chosen carefully. Experiments were conducted on synthesized signal to validate the influence of γ to various filters. The second order derivatives of the Gaussian, Rectangular and bi Gaussian are convoluted with the synthesized signal[4]. The results are showed in Fig.1. From the results it is clear that $\gamma > 1$ provides smoother results and $\gamma < 1$ separates adjacent objects.

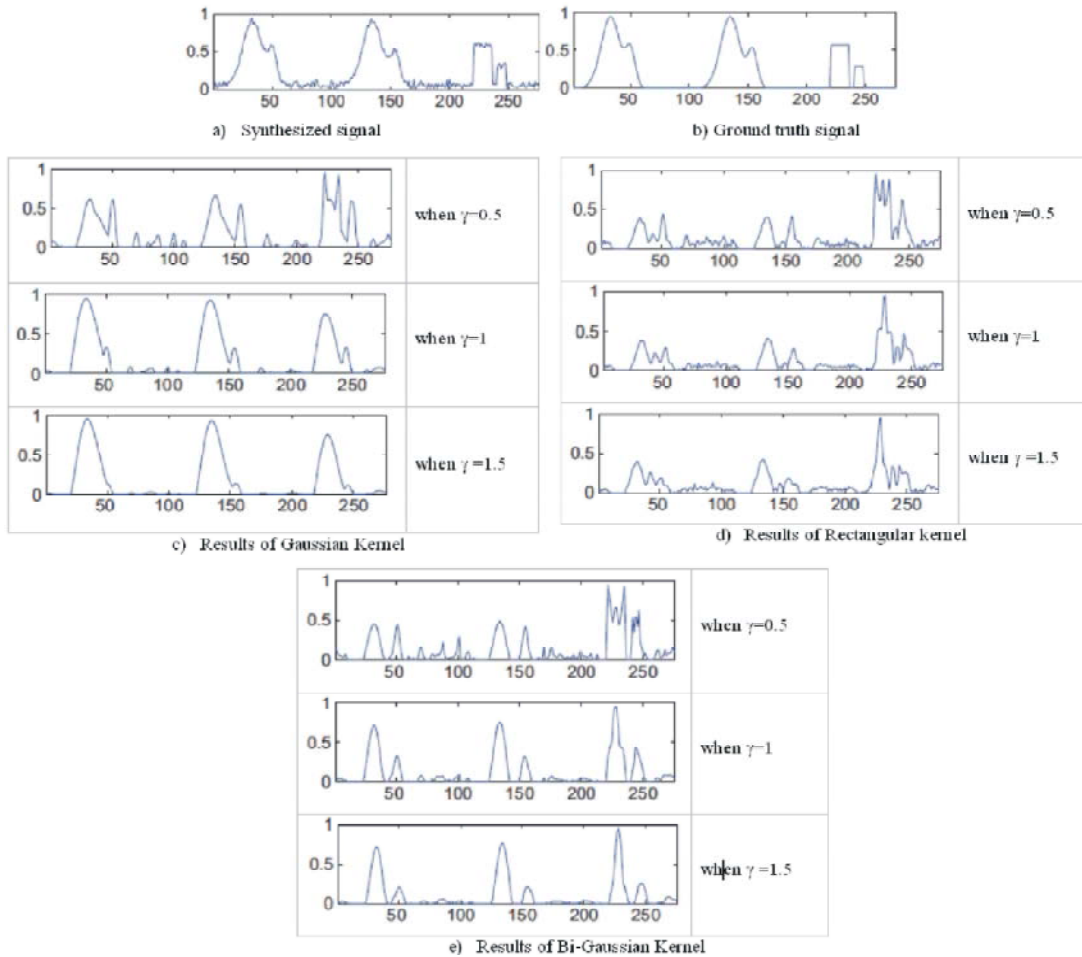


Fig. 1: Testing the synthesized signal with the parameter γ in various kernels

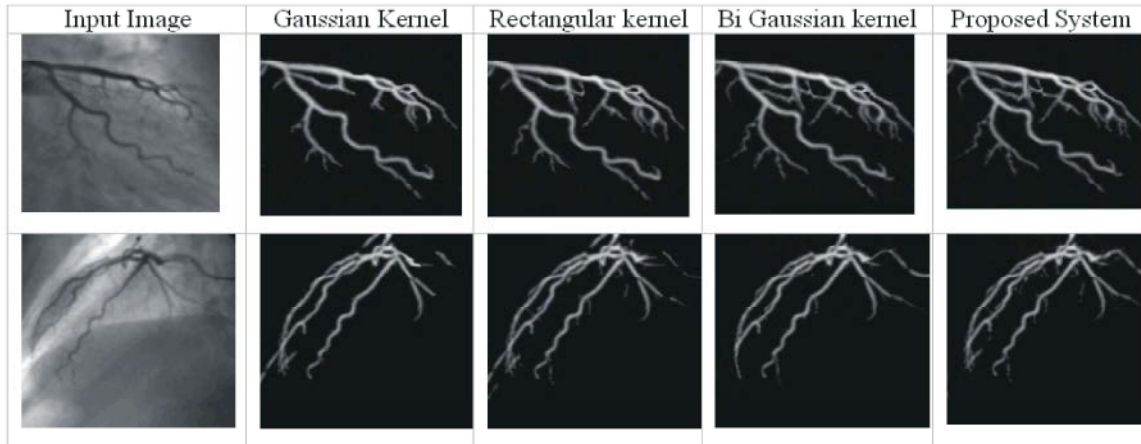


Fig. 2: Results on 2-D input data using the various filtering kernels

Testing the real input images with the proposed system and the various kernels are shown in Fig 2. The results show that the Bi- Gaussian applied to the images smoothed using curvelet transform provide better results in vascular extraction than the traditional kernel filters. By using curvelet transform the image is smoothed and vessel is enhanced and choosing a scale in foreground and background makes the vessels appear clear.

Analysis of Experimental Results: The performance assessment of the vessel extraction is done by comparing the results obtained by the various conventional filters with the proposed system. The efficiency of the filtering kernels is evaluated based on the vessel separation. Sensitivity, Specificity, Accuracy, F1 measure and false discovery rate are considered to evaluate the efficiency of the proposed system compared to the conventional filtering kernels and are given in equations (23) – (27).

$$Sensitivity = \frac{TruePositive}{TruePositive + FalseNegative} \quad (23)$$

$$Specificity = \frac{TruePositive}{TruePositive + FalsePositive} \quad (24)$$

$$F1measure = \frac{2TruePositive}{2TruePositive + FalsePositive + FalseNegative} \quad (25)$$

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative} \quad (26)$$

$$FalseDiscoveryRate = \frac{FalsePositive}{TruePositive + FalsePositive} \quad (27)$$

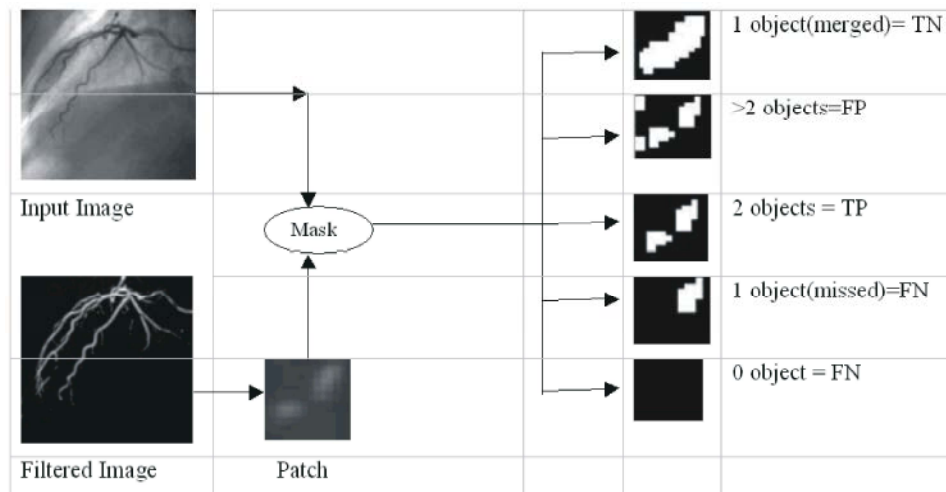


Fig. 3: Flow chart of evaluation of vessel separation in 2D images

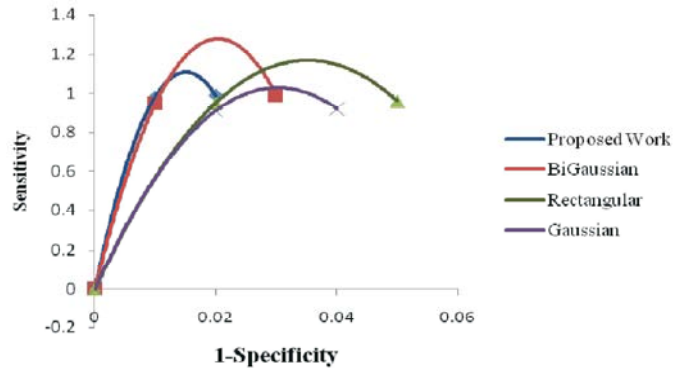


Fig. 4: Evaluation based on Sensitivity and 1-specificity

Table 2: Performance evaluation of filtering of 2D vessel on input images

Test Image	Performance metric	Gaussian Kernel	Rectangular Kernel	Bi-Gaussian Kernel	Proposed Work
T1	Accuracy	98.6	99.1	99.6	99.8
	F1 measure	94.8	96.7	98.6	99.4
T2	Accuracy	99	99.2	99.6	99.9
	F1 measure	94.4	96	97.7	99.2
T3	Accuracy	90.6	94	96.8	98.4
	F1 measure	93.2	95.3	96.8	99
T4	Accuracy	97	98	99.3	99.2
	F1 measure	95.6	88.3	99.1	99.4
T5	Accuracy	98.5	98.07	99.1	99.6
	F1 measure	93.2	92.1	98.2	98.8
T6	Accuracy	95.4	94.9	99.4	99.7
	F1 measure	98.2	98.7	98.8	99.2
T7	Accuracy	97.8	97.9	97.4	97.6
	F1 measure	98.2	98.4	98.2	98.4
T8	Accuracy	90.6	89.7	96.5	99.3
	F1 measure	92.2	90.9	97.3	98.9
T9	Accuracy	96	95.78	98.3	99.8
	F1 measure	94.8	94.1	98.3	99.2
T10	Accuracy	94.7	93.8	99.1	99.2
	F1 measure	92.6	91.2	99.2	99.4

where the True Positive, True Negative, False Positive and False Negative values are calculated based on the extracted vessel shown in Fig.3, which represents the flowchart to evaluate the vessel separation. Table 2 represents the performance evaluation of the proposed system with the traditional filtering methods based on accuracy and F1 measure and Fig 4 represents evaluation results of filtering methods based on Sensitivity and 1-specificity. The false disclosure rate of the proposed system is 2.6%.

The results performance evaluation of filtering of 2Dvessels is shown in Table 2. From the results it is clear the proposed system clearly identifies the vessels when compared to the conventional filters.

CONCLUSION

In this paper, a multi scale derivative filter is used to detect the tubular structures with the aim of separating adjacent objects in the tubular structures. First, enhancing the vessel using curvelet transform makes it efficient to select scales to separate the foreground and the background. Based on this idea, a bi Gaussian kernel is selected which merge the merits of the Gaussian and Rectangular kernel to efficiently detect the tube-like structures. The performance of the method is demonstrated in real input images. From the analysis it is clear that the proposed system outperforms the traditional filtering kernels. Compared with the conventional Gaussian kernel, the proposed method curvelet with bi Gaussian reduces the adjacent disturbances very effectively. The use of the proposed system is to extract the reliable information from closely located structures.

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