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Vessel Enhancement Using Directional Features

[1]Mohammad A.U. Khan, [2]Phan Tran Ho Truc, [1]Rabya Bahadur and [1]Sara Javed
[1]Department of Electrical Engineering,
Comsats Institute of Information Technology, Abbottabad, Pakistan
[2]Department of Computer Engineering, Kyung Hee University, Suwon, South Korea

Abstract: In this study, we propose a novel framework for vessel enhancement in angiography images. The proposed approach utilize the image directional information to estimate the Hessian eigenvalues with less noise sensitivity and thus can correctly reveal more small, thin vessels. Also, the directional image decomposition helps to avoid junction suppression due to which, yields vessel tree are more continuous. Qualitative and quantitative evaluations show that the proposed filter generates better performance in comparison with conventional Hessian-based approaches.

Key words: Vessel enhancement filter, directional filter bank, medical imaging

INTRODUCTION

Medical diagnoses are based on correct assessment of blood vessels. When the information is minute, then the navigation and localization of computer guided procedures are more precise.

In order to provide relief in the problem of calculating the Hessian in a noisy environment, we have proposed a new framework for vessel enhancement filter utilizing the linear directional information present in an image. The proposed approach decomposes an input image into a set of directional images, where each image contains linear features in a narrow directional range. The idea behind this directional decomposition is that noise in each directional image will be significantly reduced compared to that of the original one due to its omni-directional nature. Next, the Hessian eigenvalue calculations are facilitated. Instead of calculating from the original image both Hessian eigenvalues and eigenvectors, which indicate the vessel directions, as done in conventional filters, the proposed framework estimate these eigenvalues in each directional image with the global vessel direction known in advance. Then, an appropriate enhancement filter is applied to enhance vessels in each directional image. Finally, these enhanced directional images are re-combined to yield an output image with enhanced vessels and suppressed noise. The experiment results show that our approach is less noise sensitive can reveal small vessel network and avoid unexpected junction suppression.

The original image is decomposed into 2n (n = 1, 2,) directional images, it is proven that noise, which is largely omni-directional in nature, in each directional image, 2^n is reduced by 2^n times compared with the original one.

VESSEL MODEL

Vessel enhancement is conventionally considered as searching for line-like or tubular structures in a given image. Specifically, the intensity image I(p), where p = (x; y), is approximated by its Taylor expansion about a point p_0 up to the second order:

$$I(p) \cong I(p_0) + \Delta p^T.\nabla I(p_0) + \frac{1}{2}\Delta p^T.H(I(p_0)).\Delta p \qquad (1)$$

where,

$$\Delta p = p - p_0$$

$\nabla I(p_0)$ and $H(I(p_0))$ are the gradient vector and the Hessian matrix at p_0 int p_0.

In order to capture vessels with various sizes, we should compute the gradient and the Hessian at multiple scales σ in a certain range. In this case, the only way to ensure the well-posed properties such as linearity, translation invariance, rotation invariance and re-scaling invariance is the use of linear scale space theory (Florack *et al*., 1992; Lindeberg *et al*., 1994), in which differentiation is calculated by a convolution with derivatives of a Gaussian:

$$I_x = \sigma^\gamma G_{x,\sigma} * I;\ I_y = \sigma^\gamma G_{x,\sigma} * I \qquad (2)$$

Corresponding Author: Rabya Bahadur, Department of Electrical Engineering, Comsats Institute of Information Technology, Abbottabad, Pakistan

Where I_x, I_y, $G_{x,\sigma}$ and $G_{y,\sigma}$ are, respectively the spatial derivatives in x- and y- direction of the image I (x,y) and a Gaussian with standard deviation σ:

$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3}$$

The parameter γ was proposed by Lindeberg *et al.* (1994) and Lindeberg (1996) to normalize the derivatives of the image. This normalization is necessary for comparison of the response of differentiations at multiple scales because the intensity and its derivatives are decreasing functions of scale. In vessel enhancement application, where no scale is preferred, γ is usually set to one. Line-like structures can be extracted based on the analysis of principal curvatures, which are normally obtained as the eigenvalues of the Hessian matrix (Frangi *et al.*, 1998). Because a vessel in medical images, especially MRA images, is bright over darker background and the brightness is decreased from its center toward its boundaries, it is supposed that a vessel is modeled as a tube with a Gaussian profile across its axis, which is identical to the x-axis:

$$I_0(x,y) = \frac{C}{2\pi\sigma^2} e^{-\frac{y^2}{2\sigma_0^2}} \tag{4}$$

The first and second derivatives are:

$$\frac{\partial I_0}{\partial x} = 0; \frac{\partial I_0}{\partial y} = -\frac{y}{\sigma_0^2} I_0$$
$$\frac{\partial^2 I_0}{\partial x^2} = 0; \frac{\partial^2 I_0}{\partial x \partial y} = 0; \frac{\partial^2 I_0}{\partial y^2} = \frac{y^2 - \sigma_0}{\sigma_0^4} I_0$$

Therefore, the Hessian can be expressed as:

$$H = \begin{bmatrix} \frac{\partial^2 I_0}{\partial x^2} & \frac{\partial^2 I_0}{\partial x \partial y} \\ \frac{\partial^2 I_0}{\partial x \partial y} & \frac{\partial^2 I_0}{\partial y^2} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & \frac{y^2 - \sigma^2}{\sigma_0^4} I_0 \end{bmatrix} \tag{5}$$

and its eigenvalues and eigenvectors:

$$\left.\begin{matrix} \lambda_1 = 0 \\ \vec{v} = (1,0) \end{matrix}\right| \lambda_2 = \frac{y^2 - \sigma_0^2}{\sigma_0^2} I_0 \tag{6}$$
$$\vec{v_2} = (0,1)$$

When applying multiscale analysis, the model is convolved with a Gaussian of standard deviation σ. The above derivations are still correct except that σ_0 is replaced with $\sqrt{\sigma_0^2 + \sigma^2}$. We can see from the above result that at pixels inside the vessel ($y^2 < \sigma^2$), we have one negative eigenvalue corresponding to the eigenvector orthogonal to the axis of the vessel. The other eigenvalue is zero with the associated eigenvector in the same direction of the vessel axis. Note that in this case, where the vessel direction ($\vec{v}$) is aligned with the ***x***-axis, eigenvalues of the Hessian are same as its diagonal values. This fact has been exploited in this research study. The directional images are aligned with the x-axis and eigenvalues are picked as diagonal entries in the Hessian matrix. The formal calculation of eigenvalues for a given Hessian matrix is entirely avoided.

DFB-BASED VESSEL ENHANCEMENT FILTER

Our approach consists of the following steps, as shown in Fig. 2, 1) construction of directional images; 2) vessel axis aligning; 3) vessel enhancement and 4) reconstruction of enhanced images.

Construction of directional images: An angiography image, which consists of piece-wise linear segments, could be an appropriate candidate for the decomposition thanks to the Decimation-free Directional Filter Bank (DDFB), whose structure is shown in Fig. 1. Specifically, the input image is decomposed to 2n (n = 1; 2; :::) directional images T_i. The motivation here is to detect thin and low contrast vessels (which are largely directional in nature) while avoiding false detection of non-vascular structures. Directional segregation property of decimation-free directional filter bank is helpful in eliminating randomly oriented noise patterns and non-vascular structures which normally yield similar amplitudes in all directional images.

The angiography image often has non-uniform illumination. Therefore, a bank of homomorphic filters (Stockham, 1972), where each one is applied to one directional image, is used to remove the annoying non-uniform illumination.

Distinct homomorphic filters are employed matched with their corresponding directional images because the direct application of one homomorphic filter upon the original image is unsatisfactory in eliminating non-uniform illumination and may even enhance background noise (Fig. 3). Besides, application of homomorphic filtering on outputs of DDFB provides us a better control on the parameters of homomorphic filter. This arrangement has made possible by the joint optimization of directional filters with homomorphic filters, which is referred to as Directional Homomorphic Filter Bank (DHFB). The structure of DHFB has been depicted in Fig. 4.

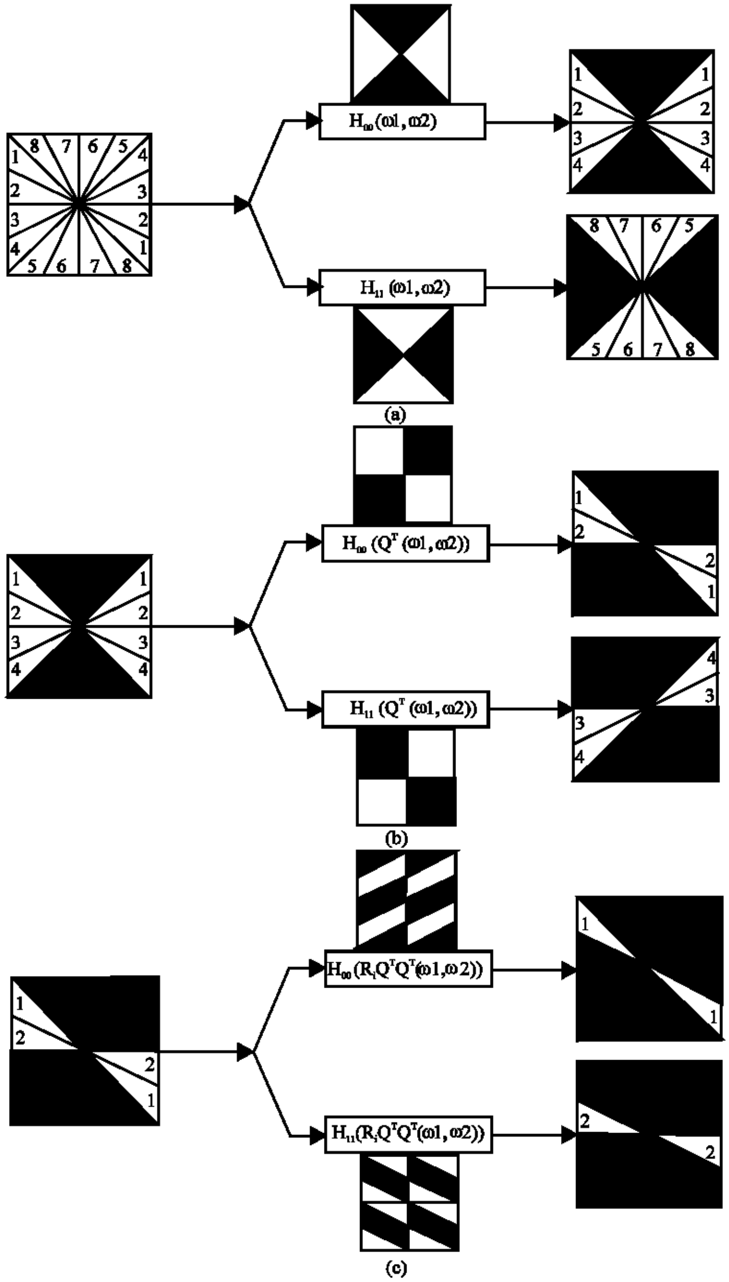

Fig. 1: DDFB structure a) First stage b) Second stage c) Third stage

Vessel axis aligning: Many vessel enhancement approaches (Frangi *et al*., 1998; Sato *et al*., 1998; Lorenz *et al*., 1997; Shikata *et al*., 2004), utilize the semi-local information gained from the Hessian matrix of the image. There are two main reasons to use the second order derivatives of the Hessian method instead of the first order derivatives of the gradient method (Carmona and Zhong, 1998). One is, the line like structures are characterized by oscillations and thus yield large second-order derivatives but do not generate large first order derivatives.

Vessels or vascular structures are detected when the ratio between the minimal and the maximal second-order directional derivatives, which are respectively the smaller and the larger eigenvalues of the Hessian, is low. And the direction having the larger eigenvalues is considered to be the direction along the vessel. However, the estimation of the vessel direction using the Hessian becomes less accurate in real medical images because the second-order derivatives are highly sensitive to noise. In the proposed approach, the global directional information of the

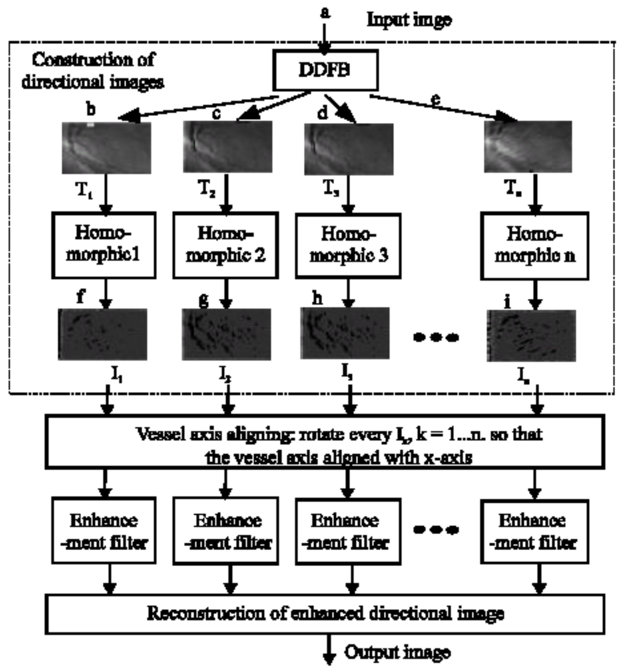

Fig. 2: Block diagram of the proposed enhancement framework. There are four main steps: Construction of directional images, vessel axis aligning, vessel enhancement and reconstruction

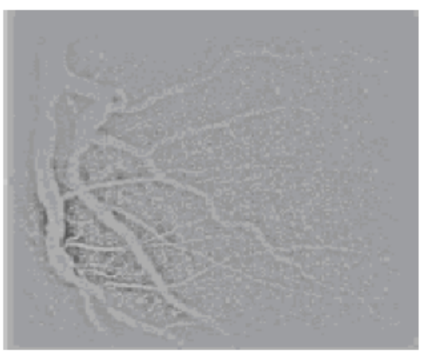

Fig. 3: Result obtained with direct application of homomorphic filter to original image in Fig. 4 a. Note that the background noise has been unexpectedly amplified

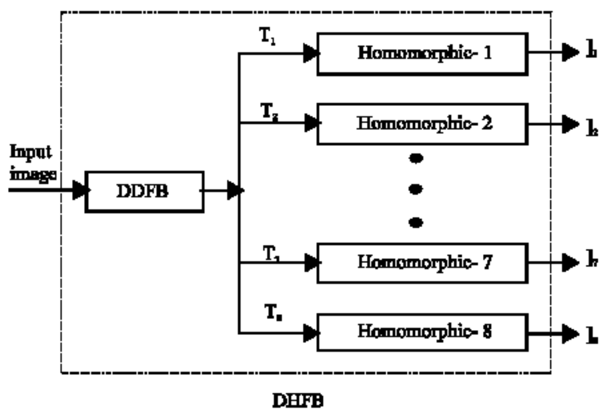

Fig. 4: DHFB structure. The output directional images I_1, I_2, I_3 become uniform illuminated

vessels, which are obtained from the directional images, is incorporated in calculating the minimal and maximal second-order derivatives to reduce noise sensitiveness. It means that we, as proven in Eq. 5 and 6, can use the Hessians diagonal values to replace its eigenvalues if the axis direction is identical the x-axis. Therefore, in this step, the above resulting directional images are rotated such that the vessel axis is aligned with the x-axis. Suppose the directional image I_i corresponds to orientation range from α^i_{min} to α^i_{min} (trigonometrical angle).

It will be rotated by an amount as large as the mean value m^i_α:

$$m^i_\alpha = \frac{\alpha^i_{min} + \alpha^i_{max}}{2} \quad (7)$$

Let I'_i denote the aligned directional images.

$$I'_i = \mathrm{rotate}(I_i, m^i_\alpha) \quad (8)$$

Where i = 1,2,3,….,n and n is the total number of directional images.

Two demonstrating rotated directional images I_i' can be seen in Fig. 5.

Then, the Hessian is computed on top of each aligned directional image. The minimal and the maximal second-order derivatives in one image can be gained as its Hessian diagonal values. These values are used to build up the corresponding enhancement filter described in the following step.

Vessel enhancement: In this step, each aligned directional image is filtered by an appropriate vessel enhancement filter. The proposed filter is inspired by the work of Frangi *et al*. (1998), who utilizes the eigen-values of the Hessian. Vessel enhancement is considered to be searching for linelike structures, where the ratio between the smaller and the larger eigenvalues is low. Different from (Frangi *et al*. (1998), we compute the diagonal values of the Hessian of each aligned directional image. As shown in Eq. 6, those values are

$$h_{11} = 0; h_{22} = \frac{y^2 - (\sigma_0^2 + \sigma^2)}{(\sigma_0^2 + \sigma^2)^2} I_0(x,y) \tag{9}$$

Where σ selected in a range S is the standard deviation of the Gaussian kernel used in multiscale analysis.

Inside the vessel, $|y| < \sqrt{\sigma_0^2 + \sigma^2}$ and h_{22} is negative. Practically, the vessel axis is not in general identical to the x-axis. So h_{11}~0. Vessel pixels are declared when $h_{11} < 0$ and $\frac{h_{11}}{h_{22}} << 1$.

To distinguish background pixels which have random noise fluctuation, we define a structureness measurement which is similar to the second-order structureness defined in Frangi *et al*. (1998)

$$C = \sqrt{h_{11}^2 + h_{22}^2} \tag{10}$$

Because background has no structure and small derivative magnitude, this structureness C should be low. Based on the above observations, the vessel filter output can be defined as:

$$\phi_\sigma(p) = \eta(h_{22}) \exp\left(-\frac{R^2}{2\beta^2}\right)\left[1 - \exp\left(\frac{C^2}{2\gamma^2}\right)\right] \tag{11}$$

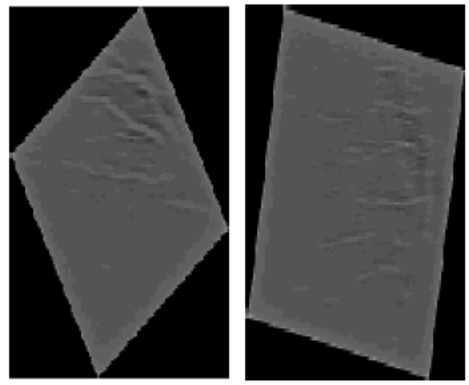

Fig. 5: Two demonstrating rotated directional images. The vessel orientations are aligned with the x-axis

$$\text{where} \quad p = (x,y), R = \frac{h_{11}}{h_{22}} \text{ and} \\ \eta(z) = \begin{cases} 0 & \text{if } z \geq 0; \\ 1 & \text{if } z < 0. \end{cases} \tag{12}$$

The filter is analyzed at different scales σ in a range S. When the scale matches the size of the vessel, the filter response will be maximum. Therefore, the final vessel filter response is:

$$\Phi(p) = \max_{\sigma \in S} \phi_\sigma(p) \tag{13}$$

One filter (13) is applied to one directional image to enhance vessel structures in it. Then all enhanced directional images are re-combined to generate the final result as follows.

Reconstruction of enhanced images: Each directional image now contains enhanced vessels in its directional range and is called the enhanced directional image.

Denote Φ_i (p), I = 1..n, as the enhanced directional images. Those images need rotating back to their original orientations.

$$\Phi_i'(p) = \text{rotate}(\Phi_i(p), -m_\alpha^i) \tag{14}$$

where m_α^i is given in (7).

The output enhanced image F (p) can be obtained by either

$$F(p) = \max_{i=1..n} \Phi_i'(p) \tag{15}$$

or

$$F(p) = \sum_{i=1}^{n} \Phi_i'(p) \qquad (16)$$

In our implementation, the latter is used for its simplicity.

EXPERIMENTAL RESULTS

Experiments are employed with both synthetic images and real medical images to verify the performance of the proposed DFB-based enhancement filter in comparison with the filters introduced by Frangi *et al.* (1998) and Shikata *et al.* (2004). In all experiments using our proposed filter, the input image is decomposed to sixteen directional images (n = 4) as a trade-off between performance and execution time. The scale range $S=\{1,\sqrt{2},2,2\sqrt{2},4\}$ is used for all three models.

For qualitative comparison, we applied the three filters to a synthetic image and couples of angiography images. Our proposed approach provides improved results in the sense that it avoids unexpected junction suppression and is able to reveal more small vessels. To obtain quantitative performance evaluation, a series of phantom images characterizing most of the common challenges to vessel detection are constructed and a goodness measurement is used to evaluate the results obtained by employing each filter to those phantoms. It is shown that our proposed filter outperforms the others.

Junction suppression: Figure 6 shows the results of an synthetic image on which the three filter models are employed. The suppressed junctions make vessels discontinuous. Although this error may be small, it can cause the splitting of a single vessel, which in turn can have a critical effect on the vessel tree reconstruction accuracy. It is the use of directional image decomposition that makes the proposed model work. Normally, a vessel has one principal direction, which is mathematically indicated by a small ratio between the smaller and the larger eigenvalue of the Hessian. Meanwhile, at a junction, where a vessel branches off, there are more than two principal directions and thus the ratio of two eigenvalues is no longer small. As a result, the conventional enhancement filters (Frangi *et al.*, 1998; Shikata *et al.*, 2004) consider those points as noise and then suppress them. Our proposed approach, on the other hand, decomposes the input image to various directional images, each of which contains vessels with similar orientations. During the re-combination of enhanced directional images, junctions are re-constructed at those points which have vessel values in more than two directional images. Therefore, junctions are not only preserved but also enhanced in the final output image.

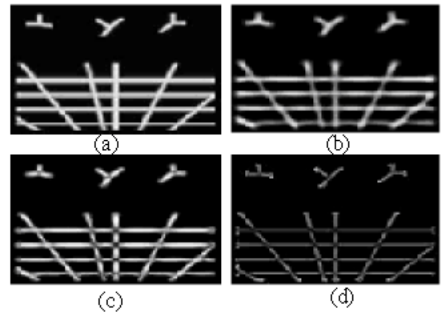

Fig. 6: Vessel enhancement results. (a) The original synthetic image (b) Enhanced image by our approach (c) by Frangi method and (d) by Shikata method. The Frangi and Shikata models unexpectedly suppress the junctions while ours does not

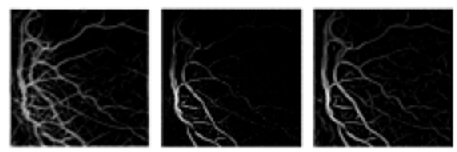

Fig. 7: Vessel enhancement in actual medical images shown in Fig. 1. LEFT columm: Enhanced images by our approach method, MIDDLE columm: By Frangi method and RIGHT column: by Shikata method. The Frangi and Shikata models fail to correctly enhance small vessels but our approach succeeds

Small vessel enhancement: Figure 7 shows our approach enhancement results (left column) compared to results acquired using Frangi (middle) and Shikata (right column) filters. The dataset used here are angiography images with typical challenges to exact vessel reconstruction aboveI and shown in Fig. 1. As can be observed, Frangi filter gives good results with large vessels but fails to detect small ones while Shikata model is able to enhance small vessels but unfortunately enhances background noise also. Conversely, our proposed filter can enhance small vessels with more continuous appearances.

Quantitative evaluation: A series of testing data were generated from the original phantom by adding various levels of white noise, having variance of 5 to 80%. The noise variance is calculated as a percentage of the 8-bit dynamic range of the image (0-255). The 80%-variance data was selected to explore the enhancement performance for the worst case. It means that, to our experience, this data represents the most possibly challenging situation, which is well beyond any worst case of real clinical images.

CONCLUSIONS

We have presented in this study a novel approach to vessel enhancement in angiography images. The proposed DFB-based filter overcomes limitations of conventional Hessianbased methods such as noise sensitivity, junction suppression and limited small vessel enhancement. The qualitative comparisons and quantitative evaluation performed on both synthetic and real medical images showed these improvements.

Our proposed approach utilizes the image directional information obtained by the Decimation-free Directional Filter Bank (DDFB) to provide a relief in Hessian analysis in noisy environment. During the directional image decomposition, noise in each resulting directional image is reduced compared with that in the original one. Then, instead of calculating both Hessian eigenvalues and eigenvectors, which indicate the vessel directions, as done in conventional filters, our framework estimates these eigenvalues in each directional image with the global vessel directions known a priori. Consequently, the Hessian analysis in the proposed frame work is more noise robust and thus our filter can enhance small vessels with less noise sensitivity. In addition, the fact that enhancement filters are applied on not the original image but the directional ones, which contains vessels in similar orientations, helps to avoid the unexpected junction suppression. In conclusion, although the proposed DFB-based filter is computationally costly, we consider it a suitable candidate for a pre-processing step in an accurate vessel-tree reconstruction in clinical tasks because of its good performance.

REFERENCES

Carmona, R.A. and S. Zhong, 1998. Adaptive smoothing respecting feature directions. IEEE Trans. Imag. Proc., 7: 353-358.

Florack, L.M., B.M.H. Romeny, J.J. Koenderink and M.A. Viergever, 1992. Scale and the differential structure of images. Image and Vision Computing, 10: 376-388.

Frangi, A.F., W.J. Niessen, K.L. Vincken and M.A. Viergever, 1998. Multiscale vessel enhancement filtering. Proc. Int. Conf. Medical Image Computing Computer-Assisted Intervention Lect. Notes Comp. Sci., 1496: 130-137.

Lindeberg, T., 1994. Scale-Space Theory in Computer Vision. Kluwer Academic.

Lindeberg, T., 1996. Edge Detection and Ridge Detection With Automatic Scale Selection. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), San Francisco, pp: 465-470

Lorenz, C., I.C. Carlsen, T.M. Buzug, C. Fassnacht and J. Weese, 1997. A multi-scale line lter with automatic scale selection based on the hessian matrix for medical image segmentation. In: Proc. Scale-Space Theories in Computer Vision. Lect. Notes Comp. Sci., 1252: 152-163.

Sato, Y., S. Nakajima, N. Shiraga, H. Atsumi, S. Yoshida, T. Koller, G. Gerig and R. Kikinis, 1998. Three-dimensional multi-scale line filter for segmentation and visualization of curvilinear structures in medical images. Medical Image Analysis, 2: 143-168.

Shikata, H., E.A. Hoffman and M. Sonka, 2004. Automated Segmentation of Pulmonary Vascular Tree from 3 dct Images. In: Proc. SPIE Int. Symp. Medical Imaging, San Diego, CA, 2004.

Stockham, T.G., 1972. Image processing in the context of a visual model. Proc. of IEEE, pp: 828-842.