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Vessel Enhancement Based on Length-constrained Hessian Information

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***Abstract*—Vessel enhancement is an important pre-processing step of applications in vessel image analysis. However, most of the current methods are developed merely based on the intensity variety inside and outside vessel instead of considering the vessel path, which emphasizes the vascular structures via characterizing additional connectivity and length information. Aiming at further utilizing beneficial length information of vessels, we propose a novel method to impose length constraint on Hessian information for vessel enhancement. Specifically, Eigen analysis of multiscale Hessian matrix has been taken at each pixel for the local vesselness response and direction information. Then, vessel path is searched along each pixel's direction, as well as maintains the property of curvilinear smoothness. The proposed method is compared with three conventional vessel enhancement methods. The experiment results show that our proposed approach has the advantages of the fine response of low-contrast vessel region and less noise background. In addition, the quantity evaluation indicates that a state-of-art vessel enhancement performance could be achieved compared with other methods.**

***Keywords*—vessel enhancement; vessel path; length-constrained; Hessian information;**

I. INTRODUCTION

Vessel enhancement plays a crucial role in clinical vessel visualization and quantificational analysis. The multiscale nature of vessels, image noise and poor visibility of small vessels make it a challenging task. To tackle this problem, a variety of algorithms has been proposed. A common approach for vessel enhancement is based on the Eigen analysis of Hessian matrix. It takes advantage of the fact that the local intensity of the ideal bright vessel part has negative peaks on the second derivative across it [1]. The most famous method based on this concept was proposed by Frangi et al. [2] in 1998. They considered all eigenvalues and gave the intuitive geometrical interpretation for vessel enhancement.

Apart from the second order derivatives, the gradient information, which has less interruption from the adjacent objects, also can be utilized for the vessel enhancement. A gradient flux which attains its maximum at the centerline of the vessel is the fundamental of the method called OOF (optimally oriented flux) proposed by Law et al. [3] in 2008. Despite the success of Hessian and gradient based methods, they only use the local information of the image which may bring the problem of junction suppression and noisy background. Merveille O et al. [4] proposed the method called RORPO (Ranking the Orientation Response of Path Operators) based on non-local path opening operation and took intensity difference between inside and outside the vessel regions into consideration in 2014. This method achieved promising results in solving junction suppression by using non-local features of vessel via path operator. However, compared with local information based method, it may cause inaccurate vessel direction because of applying the path operation with pre-fixed rough curvilinear orientations. Moreover, it could suffer from the noisy interruption and poor robustness via using intensity subtraction only for enhancement.

Coping with the aforementioned challenges, we proposed a new novel method to integrate the non-local vessel path information to local vessel information. In order to preserve more details of vessels and obtain better visualization, the vessel path is searched in a way that can well present vessels' geometric shape and curvilinear smoothness. In addition, we further developed a transformation of the traditional curvature response. Finally, we proposed to use the length-constrained hessian information for vessel enhancement.

The rest of this paper is organized as follow. Section II describes the proposed vessel enhancement method. Section III presents the experimental results. Finally, section IV concludes the paper.

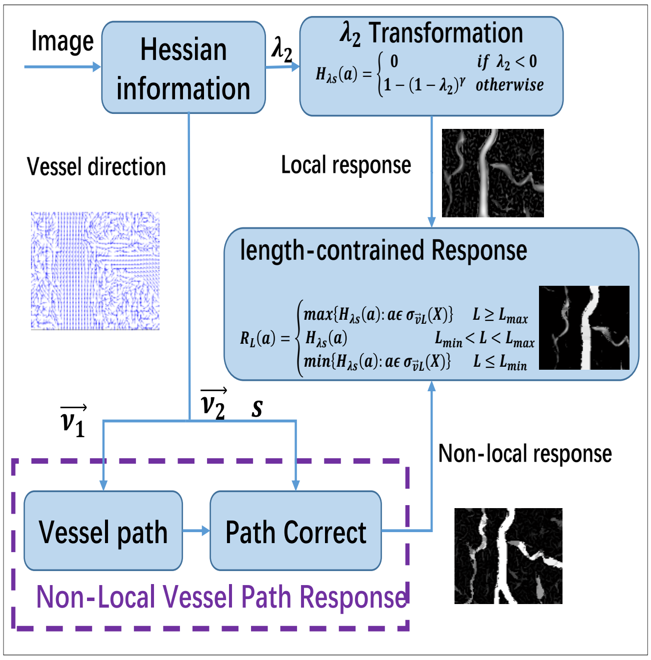
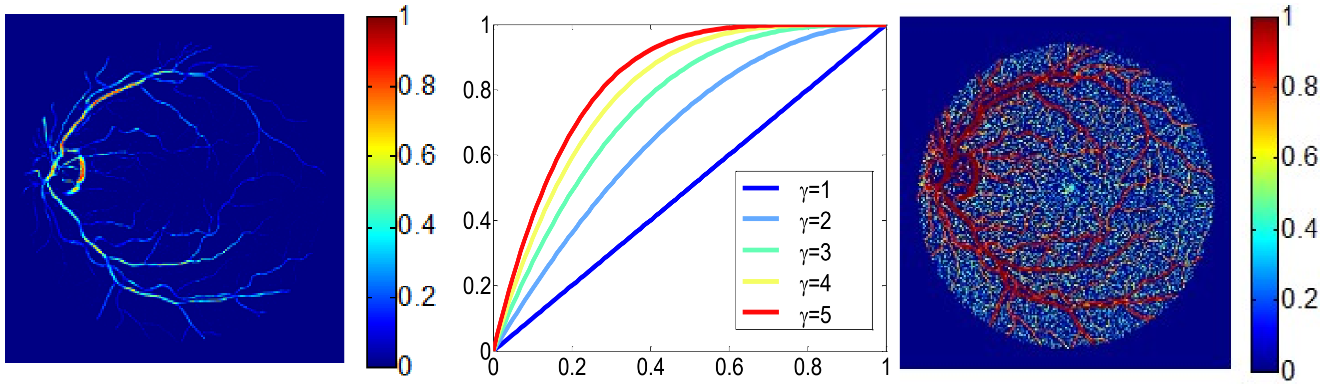


Fig.1. The flowchart of the proposed framework for the vessel enhancement.



(a) (b) (c)

Fig.2. Transformation of the traditional curvature response. (a) Original value's distribution of the λ_2 ; (b) Transformation of $H_{\lambda s}$ with different γ ; (c) Magnified value's distribution of λ_2 with γ=5;

II. Proposed Method

The proposed method is illustrated in Fig.1, where generating of the vessel path is the key step. In this method, the multiscale Hessian matrix information is first obtained. Next, we magnify the low curvature response. Meanwhile the vessel path is searched and corrected according to the local vessel directions and scales. Then the final vessel enhancement results from the adjusted curvature response combined with the non-local vessel path response.

A. Hessian information and curvature response

In order to detect vessel structure, it is common to take the Eigen analysis of the Hessian matrix that captures the second order structure of local intensity variations in the proximity of each pixel [1]. The Hessian matrix can be calculated through the convolution of the image with the second derivative of a Gaussian kernel at scale 's'. Since the vessel usually has different size, it is usual to analyze the eigenvalues of multiscale Hessian matrix. Specifically, Hessian matrix measures contrast between the region inside and outside the range (-s, s), which indicates scale 's' can represent the radius of vessel. The two eigenvalues of Hessian matrix of a 2D image are referred as λ_1 and λ_2 ($|\lambda_1| < |\lambda_2|$) and corresponding eigenvector are $\vec{v}_1$ and $\vec{v}_2$ respectively. λ_1 represents the variation of the intensity along the vessel's principal orientation ($\vec{v}_1$) and λ_2 represents variation of intensity along its perpendicular orientation ($\vec{v}_2$).

In fact, the intensity change along the principal orientation of vessel is much smaller than that along its perpendicular orientation [5]. Based on this observation, magnitude of λ_2 is a good measurement of the curvature response as well as the likelihood of vessel structures. Namely, pixels with large value of λ_2 have high probability belonging to the vessel. However, in the region of bifurcation and vessel with low contrast, the values of λ_2 are concentrated in the small numerical value parts (see Figure 2(a)) .Therefore, our target changed to enhance the vessel pixels with small value of λ_2. Here we define the new local vessel response by magnifying the small value part of λ_2 ,which is normalized by its maximum value. Then the new curvature response (for dark objects in bright background) is defined as:

$$H_{\lambda s}(\mathrm{a}) = \begin{cases} 0 & \mathit{if}\ \lambda_2 < 0. \\ 1-(1-\lambda_2)^{\gamma} & \mathit{otherwise}. \end{cases} \tag{1}$$

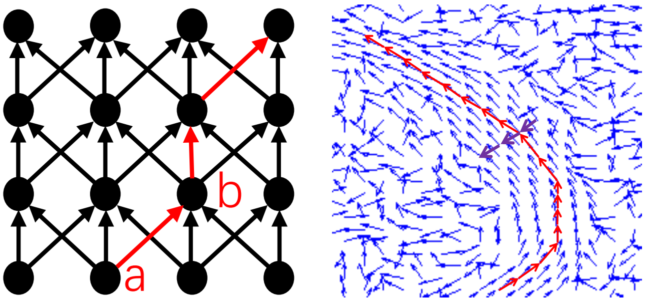
where γ is manually set constant indicating the degree of amplification and 'a' is an image point. Transformation made by equation (1) with different γ , can present the region of small value of λ_2 while not change their own monotonicity (see Figure 2(b)). Then, we select the largest response among multiple scales of Hessian matrix to represent the local vessel measurement.

B. Vessel path response

$H_{\lambda s}$ can enhance regions of bifurcation and low-contrast vessel that have small values of λ_2, as well as the noise background (see figure 2 (c)). In order to solve this problem, we introduce the non-local vessel path feature to distinguish vessel from noise.

1) Adjacency and paths: Morphological path operator was proposed in [6], which is used to filter the curved lines via specified orientations. Supposing the discrete image points set as E, which can be equipped with a binary adjacency links '→'. Specifically, '$a \rightarrow b$' means that there is a path going from point 'a' to point 'b' in E by a specified orientation (see Figure3 (a)). Using the adjacency relationship we can define the path of length L that is constituted of L points successively adjacent of E. Practically, the L-tuple $X = (a_1, a_2, \ldots, a_L)$ is called a path of length L. We denote it by $\boldsymbol{\sigma}_L(X)$.

2) Vessel path searching: Inspired by the morphological path operator, we introduce the direction information from Hessian matrix to form the vessel path. From the Eigen analysis of the Hessian matrix, we can get the eigenvector $\vec{v}_1$ and $\vec{v}_2$ indicating the direction along vessel and its radial direction respectively [7]. Therefore, we can incorporate points in the direction of $\vec{v}_1$ and its opposite direction in each point to forming the vessel path. The path searches the nearest points



(a) (b)

Fig.3. (a) A path going form ‘a’ to ‘b’ by specified orientation ; (b) The vessel path along the $\vec{v}_1$ direction in red and radial path along the $\vec{v}_2$ direction in purple.

based on the current point’s direction and takes a pointwise step (see figure 3 (a)).We denote the path formed by vessel direction information with length of L by $\boldsymbol{\sigma}_{\vec{v}L}$:

$$\boldsymbol{\sigma}_{\vec{v}L}(\mathrm{X}) = (a_{\vec{v}1}, a_{\vec{v}2}, \dots, a_{\vec{v}L}) \quad (2)$$

where $a_{\vec{v}i} \to a_{\vec{v}i+1}$, $i\epsilon(1,2,\dots,L-1)$ and X contains elements of the path. It is vital to make stop criterion for path searching when it may go out of the vessel. The most obvious indicator for whether path crosses the border is the local vessel response $H_{\lambda s}$. What is more, all vessel paths are expected to be locally smooth, which can be enforced by limiting the direction change between two consecutive points in the path. For these reasons, the condition for keeping vessel path’s searching is when the following expression is fulfilled:

$$\{|\vec{v}_i{}^T\vec{v}_{i+1}| < \theta_{path}\} \wedge \{H_{\lambda s}(a) > 0 : a \,\epsilon\, \boldsymbol{\sigma}_{\vec{v}L}\} \quad (3)$$

where $\vec{v}_i$ denote the corresponding direction from Hessian matrix for the point in path. The first term in Equation (3) enforces smoothness of path and the second term ensures the local curvature response. Based on analysis of vessel path, the threshold of smoothness constraint is empirically chosen as $\theta_{path} = \cos\left(\frac{\pi}{6}\right)$.

3) Length correct: Practically, the vessel’s radius are usually changing along the vessel and especially in bifurcations. Hence, the length of vessel path could be longer in the center and decays toward the boundaries after path searching based on the direction $\vec{v}_1$. However, we can correct the length of these points by searching another ‘path’ along the radial direction $\vec{v}_2$ from border to center (see figure 3(b)). For the sake of simplicity, we use the same criterion present in (3) and add the radial length constraint as the follows:

$$\{|\vec{v}_i{}^T\vec{v}_{i+1}| < \theta_{path}\} \wedge \{H_{\lambda s}(a) > 0 : a \,\epsilon\, \boldsymbol{\sigma}_{\vec{v}L}\} \wedge \{L < 2s\} \quad (4)$$

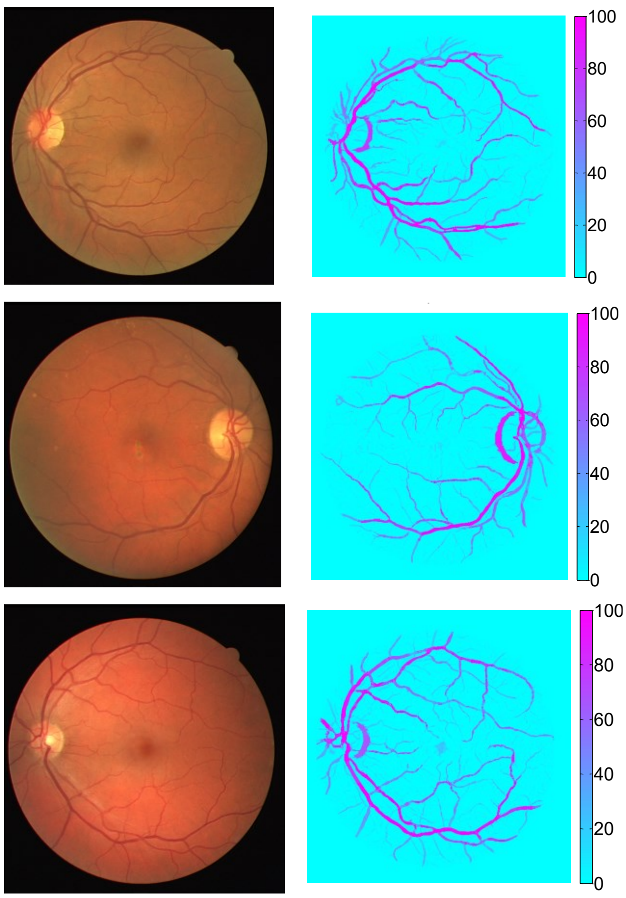
The third term in (4) ensures the searching path cross through center point of the vessel. Then we selected the longest length in this path as the final length for the points that in the same cross-section of the vessel. There are three examples presented in Fig.4, where the maximum length is set as100.

C. Length-constrained vessel response

We proposed the Length-constrained vessel enhancement as the follows:

$$R_L(a) = \begin{cases} max\{H_{\lambda s}(a) : a\epsilon\ \sigma_{\vec{v}L}(X)\} & L \geq L_{max} \\ H_{\lambda s}(a) & L_{min} < L < L_{max} \\ min\{H_{\lambda s}(a) : a\epsilon\ \sigma_{\vec{v}L}(X)\} & L \leq L_{min} \end{cases} \quad (5)$$

where, L_{max} is manually set constant means the certain minimum length for vessel and L_{min} means the certain maximum length for non-vessel objects. The basic idea of $R_L(a)$ is to choose the proper response for all the points in the same vessel path. Hence, it can enhance the response of points with longer path and suppress the response of points with shorter path at the same time.



(a) (b)

Fig.4. Three examples of vessel path length map. (a) The origianl images; (b) The vessel length map of the input images.

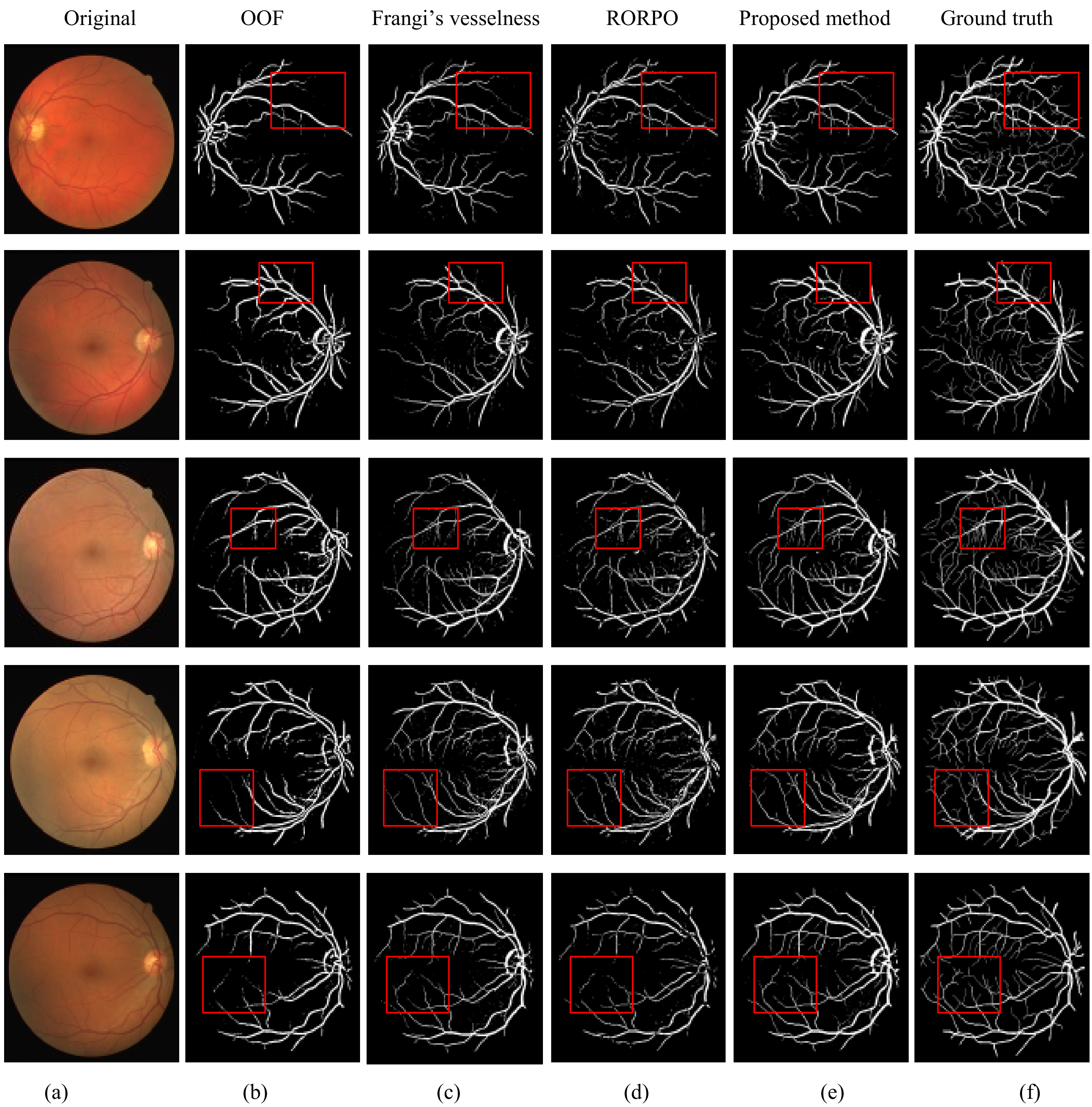


Fig.4. Five examples randomly chosen from the DRIVE dataset. They are enhanced with four different methods and segmented using global thresholds. (a) Input images; (b) The results of the OOF method; (c) The results of Frangi's method; (d) The results of the RORPO; (e) The results of the proposed method; (f) The ground truth images.

III. EXPERIMENTAL RESULTS

In order to assess the performance of the proposed length-constrained vessel enhancement, the proposed method is compared with three other state-of-the-art methods, called Frangi's vesselness [2], OOF (optimally oriented flux) [3] and RORPO (Ranking the Orientation Response of Path Operators) [4]. Frangi's method and OOF are two classical methods that based on the local vessel information. RORPO is a recently proposed curvilinear filter that based on the non-local vessel information and achieves the promising results.

We tested the four methods on forty retinal images in the DRIVE database [8]. We optimized each method's parameters to achieve the results. For a better comparison and quantitative analysis, we took a segmentation with a global threshold value on all the enhancement results. We choose the best results among all the global thresholds as the final comparing results for each method. The manual segmentation masks in the dataset were used as the ground truth. Besides, in order to reduce the influence of the border, we took an erosion operation on the border mask in the database with radius of 12 pixels. Finally, we used the mean square error (MSE) and Dice coefficient for quantitatively analysis.

In MSE, the sum of square intensity differences of the corresponding pixels is divided by the size of the ground truth [9]. The smaller MSE represents the less difference between the ground truth and segmented results. Dice Coefficient is defined as:

$$\text{Dice} = \frac{2TP}{2TP+FN+FP} \tag{6}$$

A bigger Dice value indicates a better segmentation of the vessel part.

The parameters of our methods in the experiments were: the scales related to Hessian matrix was set from 0.5 to 5 with step length of 0.5, and the degree of amplification was set as $\gamma = 3$; the minimum vessel length is set as $L_{max} = 100$; the maximum length of non-vessel objects is set as $L_{min} = 9$; Other modalities or vessels most likely require different parameters.

Fig.4 shows five examples randomly chosen from the segmented results. We marked some parts of the vessel in the image to present the preservation of the vessel features. Some of the tiny and thin vessels are lost or discontinuous in the three other method, which may result from the ununiformed and low intensity distribution along these vessels. However, the proposed vessel path can still searched under this condition and obtained the accurate vessel length. Hence, these vessels can be better preserved in proposed method via length constraint with continuity. In addition, the proposed method could have better enhancement result in the junction region and clearer background compare to other methods. The better performance of the proposed method is due to the length constraint derived from the vessel path that can overcome the suppression in the bifurcations and reduce the noise in the background. From these examples, it shows that our method can achieve promising results.

Furthermore, the quantitative results presented in Fig.6, Fig. 7 and Table I. As can be seen, the proposed method can reach the best performance in average mean square error (MSE) and Dice coefficient. In addition, the proposed method could achieve consistently outstanding vessel enhancement for all the evaluated images.

TABLE I. MSE AND DICE VALUE FOR FOUR METHODS

Methods	OOF	Frangi's	RORPO	Proposed
Average MSE %	4.93	4.21	4.34	4.00
Dice Coefficient	0.692	0.717	0.705	0.738

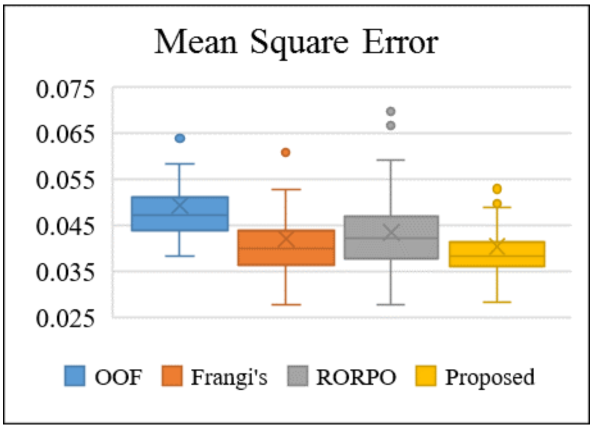


Fig.6. Mean square error of all images in datasets for four method is shown as box plots.

Fig.7. Dice coefficient of all images in datasets for four method is shown as box plots.

IV. CONCLUSION

In this paper, we propose a new approach for the vessel enhancement in 2D image, which integrates the non-local vessel path information to local vessel information. In order to obtain good enhancement visualization and preserve more features of vessel, we have proposed to make a transformation of the traditional curvature response and searching the vessel path.

The proposed method mainly consists of two steps: (1) getting the multiscale Hessian information from 2D vessel image and (2) calculating the vessel path's length. Then the final vessel response is obtained from length-constrained curvature response. The preliminary experiment shows that the proposed method is promising and achieves the state-of-the-art enhancement results. The future work will focus on the extensive testing on other modalities or vessels. Furthermore, our ambition is in the extension of the proposed method for 3D images and vessel segmentation.

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