33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

A Multi-Scale Non-linear Vessel Enhancement Technique

Behnaz Abdollahi, Ayman El-Baz, and Amir A. Amini, IEEE Fellow

Abstract— **We present an enhancement method based on non-linear diffusion filter and statistical intensity approaches for smoothing and extracting 3-D vascular system from Magnetic Resonance Angiography (MRA) data. Our method distinguishes and enhances the vessels from the other embedded tissues. The Expectation Maximization (EM) technique is employed with non-linear diffusion in order to find the optimal contrast for enhancing vessels; therefore, smoothing while dimming the embedded tissues around the vessels and brightening the vessels. The non-linear diffusion filter smooths the homogeneous regions while preserving edges. The EM technique finds the optimal statistical parameters based on the probability distribution of the classes to discriminate the tissues in the image. Our enhancement technique has been applied to 4 3-D MRA-TOF datasets consisting of around 300 images and has been compared to the regularized Perona and Malik filter. Our experimental results show that the proposed method enhances the image, keeping only the vessels while eliminating the signal from other tissues. In comparison, the conventional non-linear diffusion filter keeps unwanted tissues in addition to the vessels.**

I. INTRODUCTION

Vascular diseases are among the most significant causes of death in the world. An enhanced three dimensional visualization of blood vessels could help in diagnosing the disease and choosing appropriate treatment. The parameters that make extraction of blood vessels challenging include anatomical variability of the vasculature, surrounding tissues, image contrast, resolution, and noise. In many approaches to analysis, the preprocessing step enhances the vessels and improves its visualization; assisting the task of segmentation and centerline extraction.

Scale space theory can be utilized for smoothing and enhancing medical images. In scale space theory a set of smooth images are generated by employing the diffusion equation; the original image is the initial condition of the function. The diffusion function is specified either as scalar or tensor based. The original idea of image diffusion for image filtering was proposed by Perona and Malik and was based on a scalar function; it was proposed as a solution to edge detection [1]. Weickert added orientation to enhance small vessels and coherence structure [5], [11]. Subsequent methods to conventional diffusion filtering replaced the diffusion tensor by the Hessian. Multi-scale vessel enhancing methods based on eigenvalues of the Hessian matrix typically determine the vesselness of a pixel. Different geometric interpretation extracted by the eigenvalue system of the Hessian matrix is used to measure the vesselness [4], [8], [9], [10], [15]. For review of anisotropic diffusion, please refer to [3], [7], [13]. For implementation review of tensor based diffusion filters in ITK we refer the reader to [17]. Catte [2] and Yu and Accton [14] applied a new filter as an edge detection method on Ultrasound images, only considering speckle noise in the image. Frangi [10] proposed the multi-scale enhancing method based on Hessian and tensor structure. Weickert [11] defined the coherence-enhancing diffusion which improves the tensor based diffusion to find divided regions and to connect them. Krissian [12] and Manniesing [16] proposed anisotropic diffusion filters to segment vessels in 3-D, based on a tensor structure filter. Fischl proposed a new method to indicate the best kernel function that matches the image [6]. For further review on vessel analysis we refer the reader to [18]. Our method uses the scalar diffusion function, and is mainly based on the conventional Perona and Malik nonlinear diffusion filter.

Vessels constitute a small area within each slice. They are surrounded by other tissues and are thin and small. Non-linear diffusion filtering enhances the regions while preserving the edges, but it cannot distinguish the homogenous vessel region from other tissues. We propose a new method to enhance the vessel structure which employs the conventional Perona and Malik non-linear diffusion filter while making use of the Expectation Maximization (EM) algorithm [19]. EM is an optimization method estimating statistical parameters. It is an iterative method and discriminates the classes which are defined based on their probability density function (PDF).

Vessel class is discriminated further in each iteration, and the difference between the contrast of the vessel and the other tissues is increased in every iteration of the smoothing process. The smoothing changes are adaptive because the contrast of the image is changed adaptively. Our experimental results demonstrate that the proposed method improves vessel enhancement when compared to the conventional non-linear diffusion filter. In addition, our method is a new technique that finds the constant gradient threshold of the diffusion function adaptively. In section II and III we introduce the Perona and Malik diffusion filter and the EM algorithm, respectively. In section IV we describe the proposed method and show experimental results. Finally conclusions are given in section V.

Manuscript received April 15, 2011

Behnaz Abdollahi is with University of Louisville. Louisville, KY 40292 USA. Phone: 502-852-3400; fax:502-852-1577. email: b0abdo02@louisville.edu

Ayman El-Baz is with University of Louisville. Louisville, KY 40292 USA. email: aselba01@louisville.edu

A. A. Amini is Professor and Endowed Chair in Bioimaging at University of Louisville. Louisville, KY 40292 USA. email: amir.amini@louisville.edu

II. Non-Linear Diffusion Filter

Foremost, Perona and Malik [1] proposed the idea of the non-linear diffusion filter. Their proposed diffusion functions are mainly based on the gradient operator to limit smoothing across edges and regions. The generic definition of the diffusion function is indicated as:

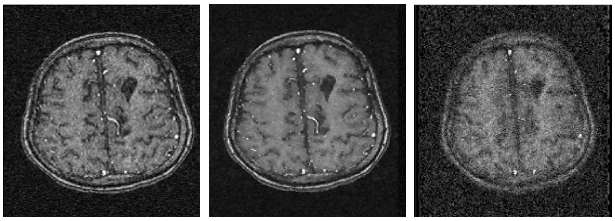
$$\frac{\partial I}{\partial t} = \text{div}\left[c\left(\|\nabla I\|\right).\nabla I\right] \tag{1}$$

I is the image, ∇I is the Gradient of the image, $c\left(\|\nabla I\|\right)$ is the diffusion function which controls the smoothness of homogeneous regions and preserves the edges of the regions. c is one in the interior of the regions and zero on the boundaries. $c.\nabla I$ is called the flow function, the greatest flow happens when the gradient magnitude is close to the threshold. Two diffusion equations were proposed in [1]:

$$c\left(\|\nabla I\|\right) = \frac{1}{1+\left(\frac{\|\nabla I\|}{\kappa}\right)^2} \tag{2}$$

$$c\left(\|\nabla I\|\right) = \exp\left[-\left(\frac{\|\nabla I\|}{\kappa^2}\right)\right] \tag{3}$$

if $\|\nabla I\| \gg \kappa$ then $\mathrm{c}\left(\|\nabla I\|\right) = 0$, if $\|\nabla I\| \ll \kappa$ then $c\left(\|\nabla\|\right) = 1$. The parameter κ is a constant and is a threshold for choosing the smoothing value. If κ is chosen to be a large number then the homogeneous regions are smoothed to a greater extent. There is still no automatic solution to finding the κ, on the other hand choosing an appropriate κ is critical to implementation results. The effect of different κ's is shown on one slice of the MRA images in Fig. 1.



(a) (b) (c)

Fig. 1. The results of Perona and Malik non-linear diffusion filter after 10 iterations a) Original Image b) *k =10 c) k=30.*

As shown in Fig. 1 the chosen κ should not be very small or very large in our dataset, when the κ is chosen 10; the regions are smoothed and the edges are kept; however, Fig. 1c shows a noisy image which is the result for $\kappa = 30$. Therefore, the gradient threshold is vital to implementation results; in our proposed approach, we substitute it with the best threshold that we calculate from the EM algorithm. We do not need to test different thresholds on a dataset in order to find the best setting.

III. Probabilistic model for MRA-TOF

Statistical approaches play an important role in extracting regions of the image. We define three classes: vessels, the background and the other tissues. The total probability distribution of our Gaussian mixture model is:

$$\begin{aligned} p =& w_1.P(q|vessel) + w2.P(q|background) \\ &+ w_3.P(q|othertissue) \end{aligned} \tag{4}$$

where q is our data or intensity level and $P(q|anyclass)$ is the probability density function for each class. Fig. 3 and Fig. 4 shows the Gaussian mixture model for the classes. w_s are the proportion of each class in the image and their summation should be one.

EM is an optimization method for estimating parameters. All we have is the probabilistic model of our incomplete data. In our domain the observed data is the intensity of the image. Labels, indicating whether the pixels belong to the vessel or the background, are unobserved information. Mean and variance of the Gaussian distribution are the statistical parameters EM estimates. The EM algorithm definition is as follows: Let X be the incomplete data, Y the complete data, and θ the parameter vector. At the initialization state, θ is assumed to have a value not very far from the final answer; the algorithm updates θ vector until changes are very small; argmaxQ can be any mathematical method that finds the maximum of Q. In our paper we utilize the maximum likelihood to maximize the parameters. The Expectation and Maximization steps make the changes and updates the feature vector.

$$\text{Expectation-Step: } \mathrm{Q}\left(\theta/\theta\left(\mathrm{k}\right)\right) = \mathrm{E}\left[\ln \mathrm{P}((\mathrm{Y}/\theta)/\mathrm{Y},\theta\left(k\right)\right] \tag{5}$$

$$\text{Maximization-Step: } \theta\left(k+1\right) = \text{argmaxQ}\left(\theta/\theta\left(k\right)\right) \tag{6}$$

$\theta\left(k\right)$ is the parameter vector in kth iteration. $\mathrm{P}(Y/\theta)$ is the probability density function of classes. Our chosen parameter vector is the mean and variance of each class in the image. Our application has three classes, so we use the mixture model and we assume that all the classes are independent variables.

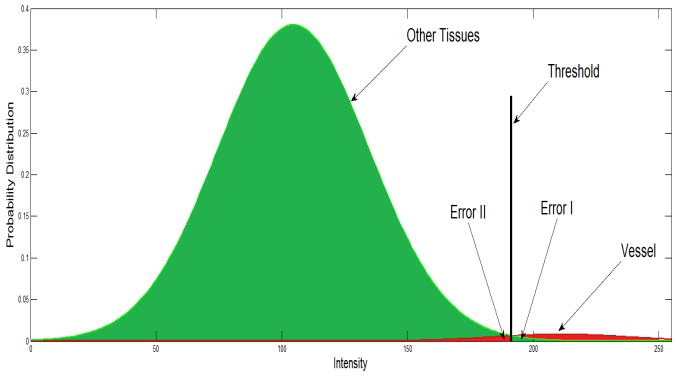


Fig. 2. The probability distribution of two classes, ErrorI and ErrorII are the error regions between two classes.

IV. Proposed Method - Combination of Non-linear Diffusion Filter and EM Algorithm

Vessels are thin, have weak edges, and are surrounded by the other tissues. Conventional non-linear diffusion filter smooths different regions; however cannot enhance vessels from other organs. Hence, we utilize a combination of the non-linear diffusion filter and the EM algorithm. We designate three classes for our dataset: vessel, background, and other tissues. Our iterative framework smooths every image slice while EM pulls out the optimized separated distribution of the three classes. We find the error area from the overlapping regions of the vessel class and the other classes.

The inverse of this value is the adaptive contrast, which is added to the vessel regions and subtracted from other regions, to intensify vessels in the background in each iteration. We calculate the risk function between the vessel class and the other two classes in order to find the adaptive contrast. Fig. 2 shows the risk area between two different classes. The area of ErrorI and ErrorII is the overlap error area between the two classes. We indicate an adaptive contrast based on risk function:

$$\Im = \frac{1}{error1 + error2} \tag{7}$$

error1 and *error2* are the error areas between the vessels' and the other classes' distribution in 3-D dataset. $\Im$ is the adaptive contrast which we extract based on the risk function, and we utilize it to enhance the images. The adaptive contrast is extracted from all the slices of the dataset; and the non-linear diffusion filter is applied on each slice individually while using the 3-D neighborhood information to smooth the regions. The non-linear diffusion filter and image enhancement are applied simultaneously on each slice. After each iteration, the intensity level of all the images are changed. In the next iteration, the EM has to find the optimized threshold for updated images.

Fig. 3 shows the probability distribution function of the three classes in the first iteration for one 3-D MRA-TOF dataset. The right most marginal Gaussian distribution belongs to the vessel class whose intensity level is high and it constitutes only a small part of the whole image. Adding a threshold to the vessels in each iteration causes increased contrast and further difference between the vessels and the other tissues. The distribution and its parameters are computed in 3-D so we only have one figure for all the slices. The initialization is based on manual sampling of each class. The background is so dark and the vessels are the most bright regions in each slice and other tissues have the intensity between the two above classes. The initial probability for each class is chosen equal at the initialization step.

Fig. 4 shows the distribution of the classes after applying the proposed technique; the intensity level of the surrounded tissues is decreased. Consequently, the whole image is darkens while the vessels are distinguished and enlightened in the background. The diffusion function is calculated for each pixel utilizing the 3-D neighbors. Hence, we define a cubic grid for the pixels' neighbors. We use 3-D weighted

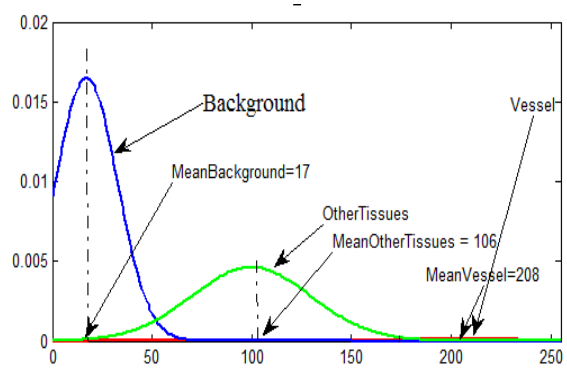


Fig. 3. The initial Probability Density Function of the three classes (Background, Vessel and Other Tissues).

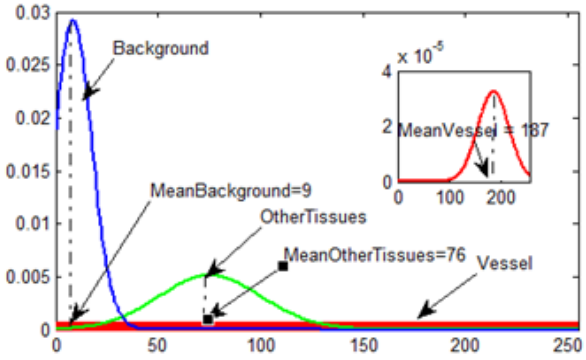


Fig. 4. The final Probability Density Function of the three classes, vessels are brightened while the mean of the other two tissues in the left are darkened.

neighborhood pixel's intensity in the non-linear diffusion function. The new intensity level for each pixel is indicated as:

$$\begin{aligned} Inew(i,j) = & Iold(i,j) + \lambda * [\\ & Cn.\nabla In(i,j) + \\ & Ctn.\nabla It(i,j) + \\ & Cbn.\nabla Ib(i,j)] \end{aligned} \tag{8}$$

Inew(i,j) is the updated intensity of the pixel in i,j coordinate. Cn, Ctn and Cbn are diffusion equations applied to the pixels' neighbor in the current slice, the top slice, and the bottom slice respectively and (3) is chosen as the diffusion equation. ∇In is the difference between the intensity level applied to the pixel in the i,j coordination with its neighbors in the current slice and the ∇It and ∇Ib are the difference between the intensity level applied to the pixel in the i,j coordination with its neighbors in top and bottom slices respectively. $Iold(i,j)$ is intensity of the pixel in i,j coordinate of the previous image. λ is a constant usually defined between zero and one. For updating the image intensity level, if each pixel in each slice has an intensity level greater than our adaptive threshold then it belongs to the vessel, so we add an adaptive constant to contrast its region with other neighbors. If it is smaller than the threshold it might not belongs to vessel regions, so we reduce the intensity weight of it and all of its neighbours. The neighborhood pixels is a

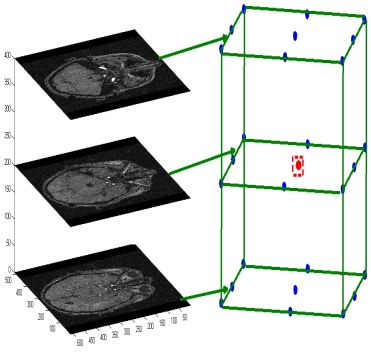


Fig. 5. The 3-D neighborhood of each pixel has 26 pixels which are shown for one pixel.

3-D grid, each pixel in 3-D has 26 neighbors, which affects in updating the intensity. Fig. 5 shows the 3-D neighborhood of each slice of every pixel. Our implementation process has the following steps:

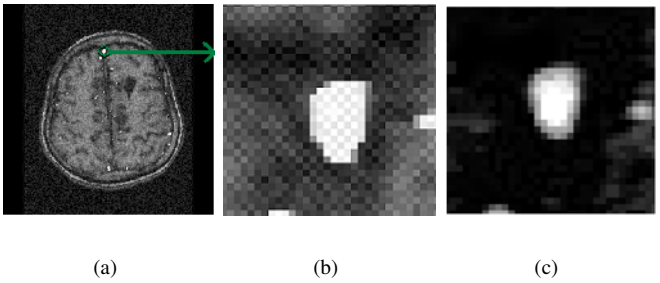
1) 3-D filtering utilizing the non-linear diffusion filter.
2) Applying the EM classifier and computing three dimensional Probability Density Function.
3) Finding the adaptive contrast threshold.
4) The result of step 3 is added to the vessels regions and subtracted from other regions in all the slices.
5) If the changes between the updated image and the previous image is smaller than a threshold then stops, else repeat the process from step 1.

A. Experimental Results

We have applied our method on 4-datasets consisting of around 300 MRA-TOF image slices. Our classifier uses all the slices and computes the adaptive contrast threshold based on all the image slices. The smoothness and intensity of the entire dataset affects each slice. We compare our results with conventional non-linear diffusion filter. Fig. 6 shows the results of our method and conventional non-linear diffusion function. The zoom and scaled version of only one slice of the image which contains vessel shows that our method successfully excludes the vessel from its neighbours region. Fig. 7 shows the output of our method and the non-linear diffusion filter and the binary image of ground truth on one slice.

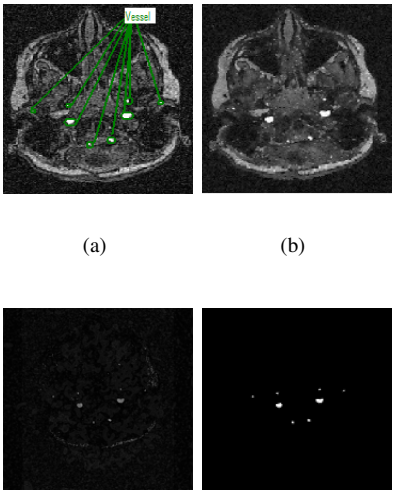
The manual segmentation for all the slices is also available to us. Comparing to the binarized image of the ground truth, it is clear that the final enhanced image for the proposed is very similar to the ground truth; the non-linear diffusion filter however keeps more tissues and the vessels are not enhanced and segmented clearly.

Fig. 8 shows the implementation results on 3 slices from a dataset with 93 slices. The first row contains three slices of one of the datasets before applying our method which the vessels are embedded in surrounded tissues. The second row shows the enhanced images, so our proposed method preserves the vessels and darkens other tissues.



(a) (b) (c)

Fig. 6. Scaled image of one part of the vessels in one slice, comparison of conventional non-linear diffusion filter and our method. Our method completely enhances the vessel with respect to the surrounding tissues. a) Original image, shows the vessel in a green circle. b) Scaled image, conventional non-linear diffusion filter result. c) Scaled image, our method's result.



(a) (b)

(c) (d)

Fig. 7. The final result of vessel regions on one slice. a) Original Image b) Non-linear diffusion filter c) Our method d) Binary ground truth

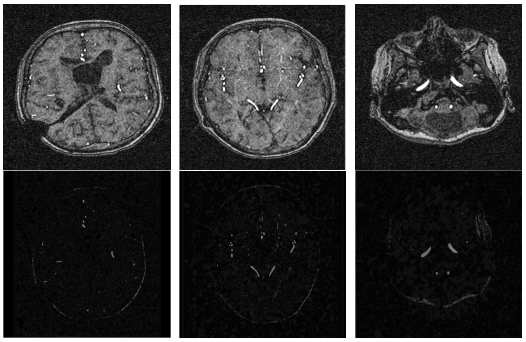


Fig. 8. Original and enhanced images of a dataset containing 93 slices. First row shows images before applying our method. Second row shows enhanced images based on our proposed method. From left to right are: slice 22, slice 44 and slice 90.

B. Evaluation Metric

The metric that we use for evaluation is a criterion defined in [15]:

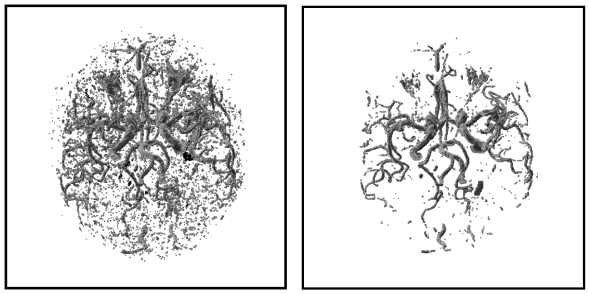
$$\tau = (V_{Ground} \cap V_{ourmethod})^2 / (V_{Ground} * V_{ourmethod}) \quad (9)$$

V_{Ground} is the volume of the vessel from the ground truth and $V_{ourmethod}$ is the volume of vessel obtained with our method. τ is between zero and one. A τ of one indicates perfect segmentation. Table I shows the τ that is calculated for our proposed method and conventional non-linear diffusion filter. τ for our method is higher than the τ for the conventional non-linear diffusion filter.

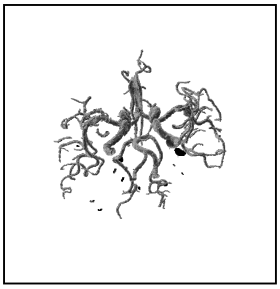
TABLE I
EVALUATION CRITERION

Measure	Nonlinear Diffusion Filter	Proposed Method
τ	0.4432	0.7217

Finally, we binarizing each slice of the image and then we visualize the final result of all the slices in 3-D. Fig. 9 shows the final result of 3-D visualization of our method. Fig. 9a is the 3-D visualization of non-linear diffusion filter segmentation output; and it detects other objects as vessel. Fig. 9b is the 3-D segmentation of our method and it shows that our proposed technique distinguishes the vessels and extract them from the surrounded tissues.



(a) (b)



(c)

Fig. 9. The 3-D final result of nonlinear diffusion filter, our method and ground truth. a) 3-D visualization of Nonlinear-diffusion filter b)3-D visualization of our proposed method c) is the ground truth 3-D result

V. CONCLUSION

In this paper we presented a new vessel enhancement technique for MRA-TOF images. Our technique uses the strengths of the non-linear diffusion filter in finding homogeneous regions. Combining the filter with EM algorithm enhances the vessels and brightens them in a black background. Since the proposed method is an image enhancement and preprocessing technique, it may be useful for combining it with other segmentation techniques. The presented results illustrate that our technique performs better in comparison to the non-linear diffusion filter.

REFERENCES

[1] Perona, P., Malik, J., "Scale space and edge detection using anisotropic diffusion", *in IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 12, no. 7, pp. 629639, 1990.

[2] Catt, F., Lions, P., Morel, J., Coll, T., "Image selective smoothing and edge detection by nonlinear diffusion", *in SIAM Journal on Numerical Analysis*, vol. 29, no. 1, pp. 182-193, 1992.

[3] ter Haar Romeny, B., *Geometry-Driven diffusion in Computer Vision*, Kluwer Academic Publisher, Dordretch/Boston/London, 2010.

[4] Koller, T., Gerig, G., Szekely, G., Dettwiler, D., "Multi-scale detection of curvilinear structures in 2-D and 3-D image data", *in IEEE International Conference of Computer Vision*, pp. 864-869, 1995.

[5] Weickert, J., "Anisotropic diffusion in Image Processing", PhD thesis, University of Kaiserslautern, 1996.

[6] Fischl, B., Schwartz E.L.,"Learned adaptive nonlinear filtering for anisotropic diffusion approximation in image processing", *in 13th International Conference on Pattern Recognition*, vol. 4, 1996.

[7] Weickert, J., "A review of nonlinear diffusion filtering", *in Scale Space theory in Computer vision, Lecture Notes in Computer Science*, vol. 1252, pp. 3-28, Springer, 1997.

[8] Lorenz, C., Carlsen, I., Buzug, T., Fassnacht, C., Weese, J., "Multi-scale line segmentation with automatic estimation of width, contrast and tangential direction in 2-D and 3-D medical images", *in Lecture notes in Computer Science*, vol. 1205, pp. 233-242, 1997.

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

[10] Frangi, A.F., Niessen, W.J., Koen, L.V., Viergever, M.A., "Multi-scale vessel enhancement filtering", *in Medical Image Computing and Computer-Assisted Intervention*, vol. 1496, pp. 130-137, 1998.

[11] Weickert, J., "Coherence-enhancing diffusion filtering", *in International Journal of Computer Vision*, vol. 31, no. 2-3, pp. 111-127, 1999.

[12] Krissian, K., Malandain, G., Ayache, N., Vaillant, R., Trousset, Y., "Model based detection of tabular structures in 3-D images", *in Computer Vision and Image Understanding*, vol. 18, pp. 130-171, 2000.

[13] Esedoglu, S., "An analysis of the Perona-Malik scheme", *in Journal of Communications on Pure and Applied Mathematics*, vol. 54, pp. 1442-1487, 2001.

[14] Yu, Y., Acton, S.T., "Speckle reducing anisotropic diffusion", *in IEEE Transaction on Image Processing*, vol. 11, no. 11, pp. 1260-1270, 2002.

[15] Chen, J., Amini, A.A., "Quantifying 3-D vascular structures in MRA images using hybrid PDE and geometric deformable models", *in IEEE Transaction on Medical Imaging*, vol. 23, no. 10, 2004.

[16] Manniesing, R., Viergever, M.A., Niessen, W.J., "Vessel enhancing diffusion: A scale space representation of vessel structures", *in Journal of Medical Image Analysis*, vol. 10, pp. 815-825, 2006.

[17] Enquobahrie, A., Ibanez, L., Bullitt, E., Alyward, S., "Vessel enhancing diffusion filter", *in a Technical Report in CASILAB, University of North Carolina*, 2007.

[18] Lesage, D., Angelini, E.D., Bloch, I., Funka-Lea, G., "A Review of 3-D vessel lumen segmentation techniques: Models, features and extraction schemes", *Medical Image Analysis*, vol. 13, no. 4, pp. 819-845, 2009.

[19] Dempster, A.P., Laird, N.M., Rubin, D.B., "Maximum likelihood from incomplete data via the EM algorithm" *in Journal of the Royal Statistical Society*, vol. 39, no. 1, pp. 1-22, 1977.