Blood Vessel Enhancement by Directed Diffusion

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Abstract: In this paper, a blood vessel in an angiographic image, which plays an importance role in the diagnose diseases including in the eyes, brain and heart, is enhanced by using a directed diffusion technique. A fundamental component of the angiographic analysis is vessel segmentation that the proposed method provides a preprocessing of the image into a form suitable for human analysis, or more importantly, for machine analysis such the segmentation. Vessel enhancement is a challenging problem due to the complex nature of vascular trees and to imaging imperfections. Some parts of the inherent imperfections in angiography are the intensity inhomogeneity between the larger and smaller vessels, and another imperfection is the leakage of contrast agent into the background tissue that provides to low contrast between vessels and tissue. In the proposed scheme, the directed diffusion solves the problem by formulating a local geometric structure, which consists of direction and scale of the blood vessels. The diffusion process uses the local structure to enhance by a diffusivity tensor. The proposed algorithm can be applied to maintain sharpness and coherence-smooth the intra-regions into homogeneity better than traditional diffusion methods, which are Gaussian regulation and coherence enhancing diffusion.

Keywords: Blood Vessel, Anisotropic Diffusion, Directed Diffusion, Angiographic image.

1. INTRODUCTION

Angiography is performed to specifically image and diagnose diseases of blood vessels of a human body, including the eyes, brain and heart. Traditionally, angiography was used to diagnose pathology of these vessels such as blockage caused by plaque build up by using a cinefilm projection screen. However in recent decades, radiologists, cardiologists and vascular surgeons have used the X-ray angiography procedure to guide minimally invasive surgery of the blood vessels and arteries of the heart by using the digital images (angiographic image). In the last several years, diagnostic vascular images are often made using MR, CT and/or ultrasound and while X-ray angiography is reserved for therapy [1].

A fundamental component of the angiographic images analysis is vessel segmentation [2], which the images require to provide a preprocessing into a form suitable for human analysis, or more importantly, for machine analysis such the segmentation. Vessel enhancement is a challenging problem due to the complex nature of vascular trees and to imaging imperfections [3]. Some parts of the inherent imperfections in angiography are the intensity inhomogeneity between the larger and smaller vessels, and another imperfection is the leakage of contrast agent into the background tissue, which provides to low contrast between vessels and tissue. In the proposed scheme, the directed diffusion [4] solves the problem by formulating a local geometric structure, which consists of direction and scale of the blood vessels.

In order to enhance the blood vessels, we employ a method diffusing the local gray scale along the direction of blood vessels, which is measured by the local structures of vesselness in the form of negative ridge measures [5, 6]. To achieve the proposed method, anisotropic diffusion technique [7, 8, 9] is adapted to enhance the blood vessels with the directed diffusivity tensor [4]. The proposed algorithm can be applied to maintain sharpness and coherence-smooth the intra-regions into homogeneity better than traditional diffusion methods, which are Gaussian regulation and coherence enhancing diffusion.

The rest of this paper is organized as follows. In Section 2, a short summary of conventional anisotropic diffusion is described. Section 3 describes the vessellness measurement method, which uses to indicate the degree of blood vessels; consequently, sub-section 3.3 will illustrate the proposed algorithm. Experimentation results, which are used two types of angiographic images consisting of fluorescence [12] and X-Ray [13], are illustrated in Section 4, and final Section is conclusion.

2. DIRECTED DIFFUSION

2.1 Nonlinear diffusion

The directed diffusion is derived for nonlinear diffusion, which was first proposed and has deservedly attracted much attention in the field of image processing by Perona and Malik [7]. In their work, nonlinear diffusion was used to reduce noise while enhancing the true location of edge images, which this diffusion is introduced with a space- and time-variant diffusion coefficient, $c(x, y, t)$, as formulated by:

$$\frac{\partial f(x,y,t)}{\partial t} = div\left[c(x,y,t)\cdot\nabla f(x,y)\right], \tag{1}$$

where $f(x,y,t)$ is an image pixel at discrete time steps (t^{th} iterations, for $t = 0$ the representation is the original data: $f(x,y,0) = f(x,y)$). *div* is the divergence operator and $\nabla f(x,y)$ denotes the gradient of images.

To make the diffusion process prefer intra-region to inter-region smoothing and thus preserve edges, the region boundaries need to identify. Obviously, this information is not available a priori, the best way to estimate the boundary locations by edge detector. Perona and Malik claim that the simplest gradient of images at time t ($\nabla f(x,y,t)$) works excellently; consequently, the diffusion coefficient, $c(x, y, t)$, is given by:

$$c(x,y,t) = g\left(\left|\nabla f(x,y,t)\right|\right). \tag{2}$$

The diffusivity function $g\left(\left|\nabla f(x,y,t)\right|\right)$ is provided to enhance the edges of objects in an image by smoothing the original images while preserving brightness discontinuities. In

this function, Perona and Malik defines by:

$$g\left(\nabla f(x,y,t)\right) = \left(1 + \frac{\|\nabla f(x,y,t)\|^2}{K^2}\right)^{-1},$$

where K denotes a parameter controlling the diffusion strength. The enhancing process is obtained by gradient magnitude $|\nabla f(x,y,t)|$: if $|\nabla f(x,y,t)|$ is large, then the diffusion will be low to preserve the edges. If $|\nabla f(x,y,t)|$ is small, then the diffusion will tend to smooth the pixel $f(x, y)$.

Catté et al. [8] used a Gaussian function (G_σ) with a small variance for convolution with the gradient magnitude term by replacing $g\left(|\nabla f(x,y,t)|\right)$ with $g\left(|G_\sigma * \nabla f(x,y,t)|\right)$. The regulation of Catté et al. provides edge sharpening and is more stable than the Perona and Malik method. For a theoretical problem of Perona and Malik, Weickert and Benhamouda [10] studied in more detail about the discrete implementations, a regularization factor.

2.2 Diffusion tensor

A technique to develop the directed diffusion by using the local geometric structures is adapted from coherence enhancing diffusion (CED), which was proposed by J. Weickert in 1997 [4]. He suggested many useful properties of the nonlinear diffusion under some general assumptions about the input images and some conditions imposed on the diffusion tensor, D, which was used to replace the diffusion coefficient, $c(x, y, t)$. Therefore, a formulation of CED equation is expressed by:

$$\frac{\partial f(x,y,t)}{\partial t} = div\left[D \cdot \nabla f(x,y)\right] \tag{3}$$

The diffusivity tensor is a function of image gradient, which D is defined in a matrix framework as following:

$$D = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}. \tag{4}$$

This matrix is constructed the smoothing perpendicular of image gradient and a integration scale ρ by using the convolution of an image $f(x, y)$ with a Gaussian kernel G_σ to obtain a smoothed version of the image, $f_\sigma(x,y) = G_\sigma * f(x,y)$. Accordingly, the diffusivity tensor can be attained by a componentwise convolution of the terms $\nabla f_\sigma(x,y)\left(\nabla f_\sigma(x,y)\right)^T$ and a Gaussian G_ρ that is given as:

$$S_\rho\left(\nabla f_\sigma(x,y)\right) = G_\rho * \left(\nabla f_\sigma(x,y)\left(\nabla f_\sigma(x,y)\right)^T\right) \tag{5}$$

The structure tensor, S_ρ, is symmetric and positive semi-definite.

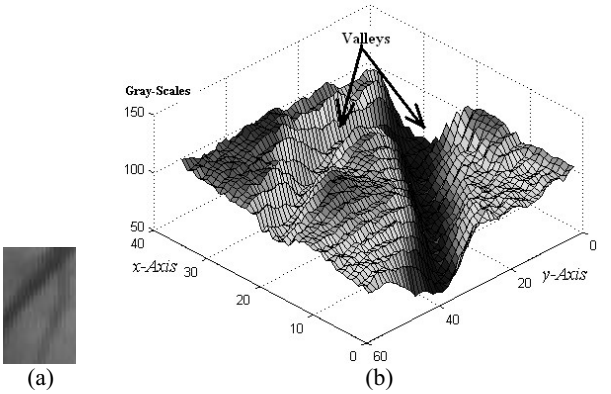
$$S_\rho = \begin{bmatrix} s_{11} & s_{12} \\ s_{21} & s_{22} \end{bmatrix} \tag{6}$$

In the CED, the integration scale ρ takes on positive values; the diffusion along coherent structures based on the construction of a diffusion tensor whose eigen-directions coincide with the eigenvectors of the structure tensor whereas have different eigenvalues; namely,

$$\begin{aligned} \lambda_1 &= \alpha \\ \lambda_2 &= \alpha + (1-\alpha)e^{\left(\frac{-C}{(\mu_1-\mu_2)^{2m}}\right)} \end{aligned} \tag{7}$$

where μ_1 and μ_2 are the eigenvalues of the structure tensor and C, m, and α are parameters controlling the exponential shape.

The CED method based on the structure tensor provides a local description of the anisotropy of the images. However, from our observation, this method has two important properties: (*i*) it may be broken linear structures at the same time of enhancing, (*ii*) an undesirable effect of this diffusion process is that valley junctions may be destroyed and nonlinear structures are deformed. In this paper, the CED method is adapted to enhance the blood vessels in the poor contrast. The adaptation diffusion process is based on diffusion tensors, which includes the differential structure of the image around valleys in order to enhance them while globally smoothing the image and preserving blood vessel junctions. This tensor is called "vesselness tensor" that provides a local coarse measure of blood vessels and their direction.



(a) (b)

Fig. 1 (a) blood vessel, (b) considered the blood vessel in (a) as the valleys with 3-D surface.

3. BLOOD VESSEL ENHANCEMENT

In our approach, vessel enhancement is conceived as a filtering process that searches for geometrical structures, which can be regarded as a valley in Fig. 1. Since vessels appear in different sizes it is important to introduce a measurement scale, which varies within a certain range.

3.1 Vesselness measurement

The vesselness is measured by a negative ridge [5], which has a structure such a valley. To define the vesselness corresponding with the CED, the diffusivity tensor in Eq. (4) is given by:

$$D = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} = \begin{bmatrix} v_1 & v_2 \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \tag{8}$$

where the parameters: λ_1, λ_2 are eigenvalues and v_1, v_2 denote eigenvectors. These parameters are calculated by second-order derivative in the neighborhood of coordinate pixel (x, y). In the proposed scheme, the eigenvalue parameters are used to control the direction and contrast of the filters and the eigenvector parameters are provided to represent the scale of the blood vessels, which these parameters are captured from Hessian tensor (H_σ) [11] as defined in the following:

$$H_\sigma = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial^2 f_\sigma(x,y)}{\partial x^2} & \dfrac{\partial^2 f_\sigma(x,y)}{\partial x \partial y} \\ \dfrac{\partial^2 f_\sigma(x,y)}{\partial x \partial y} & \dfrac{\partial^2 f_\sigma(x,y)}{\partial y^2} \end{bmatrix} \quad (9)$$

where $f_\sigma(x,y)$ is the initial image $f(x, y)$ convolved by a Gaussian kernel of the scale σ (standard deviation).

The Hessian tensor has an intuitive justification in the context of vessel detection. The second derivative of a Gaussian kernel at scale σ generates a probe kernel, which measures the contrast between the regions inside and outside the range $(-\sigma, \sigma)$ in the direction of the derivative. Therefore, the local direction filter that corresponds with the structure tensor in Eq. (6) is defined as:

$$\begin{aligned} \mu_1 &= 0.5(h_{11} + h_{22} - \alpha) \\ \mu_2 &= 0.5(h_{11} + h_{22} + \alpha), \qquad \alpha = \sqrt{(h_{11} - h_{22})^2 + 4h_{12}^4} \end{aligned} . \quad (10)$$

The idea behind eigenvalue analysis of the Hessian is to extract the principal directions in which the local second order structure of the image can be decomposed. Since this directly gives the direction of smallest curvature (along the vessel) application of several filters in multiple orientations is avoided. In this case, we select the eigenvector v_1 corresponding to the highest eigenvalue in absolute value $(\tilde{\mu}_1 = |\mu_1|)$ and the eigenvector v_2 corresponds to the lowest eigenvalue $(\tilde{\mu}_2 = |\mu_2|)$. Therefore, the eigenvalue parameters, λ_1, λ_2, are given by:

$$\begin{aligned} \lambda_1 &= 0.01, \\ \lambda_2 &= \frac{\tilde{\mu}_2 - \tilde{\mu}_1}{\tilde{\mu}_1 + \tilde{\mu}_2}, \end{aligned} \quad (11)$$

where λ_2 indicates to the degree of vesselness if $\mu_1 \geq 0$.

Finally, the eigenvectors of the diffusivity tensor, D in Eq. (8), can be calculated with each component as the following:

$$\begin{aligned} d_{11} &= 0.5\left(\lambda_1 + \lambda_2 + (\lambda_2 - \lambda_1)(s_{11} - s_{12})/\alpha\right) \\ d_{22} &= 0.5\left(\lambda_1 + \lambda_2 - (\lambda_2 - \lambda_1)(s_{11} - s_{12})/\alpha\right) \\ d_{12} &= d_{21} = s_{12}(\lambda_2 - \lambda_1)/\alpha \end{aligned} \quad (12)$$

3.2 Identify the proper scale

To detect the blood vessel in different sizes, it is not sufficient to evaluate the diffusivity matrix D by using only one scale through the process; thus, for each pixel we will identify the proper scale by using the matching filter [14]. In the proposed algorithm, a set of the scale $\sigma = \{1.5,\ 2.2,\ 3.5\}$ is used to search the optimal scale for each object in the neighborhood pixel (x, y) with 15×15 Gaussian kernel (G_σ) that the scale is given as:

$$f_\sigma(x,y) = \max_{\sigma=\{1.5,2.2,3.5\}} G_\sigma * f(x,y). \quad (13)$$

The convolved image with Gaussian kernel, $f_\sigma(x,y)$, was provided with the optimal scale to enhance the blood vessels; thus, each pixel has a proper scale; thereby in each image, multi-scale Gaussian filters are employed to formulate the Hessian matrix of Eq. (9), which both the direction and scale are provided to define the diffusivity tensor.

3.3 Vessel enhancement algorithm

Fig. 2 illustrates the proposed algorithm. In this algorithm, the blood vessel images are read and kept in a buffer $f(x, y)$, which has size M×N, x = 0, 1, 2 ,…, M-1 and y = 0, 1, 2 ,…, N-1. Each pixel in the buffer $f(x, y)$ is searched a proper scale from the set of standard deviation $\sigma = \{1.5,\ 2.2,\ 3.5\}$; therefore, the pixel on coordinate (x, y) is identified with the scale σ in the form $f_\sigma(x,y)$. Before taking into the loop of directed diffusion, variables that are used in the diffusivity process are set; hence, K=0.2, *diffusivity parameter,* L = 0.25 and *number of iterations,* NI = 30.

In each time of the loop of directed diffusion, the equations (9)-(12) are respectively calculated to obtain the diffusivity matrix D.

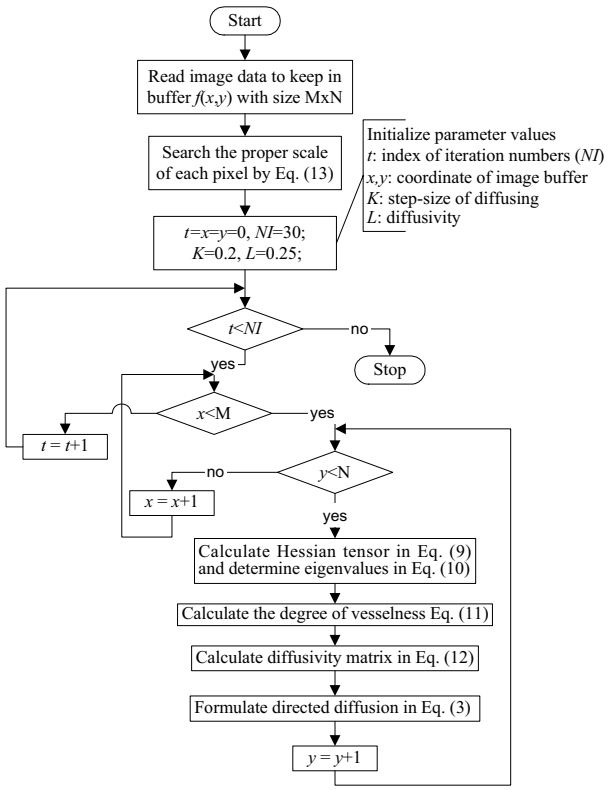


Fig. 2 The algorithm of directed diffusion.

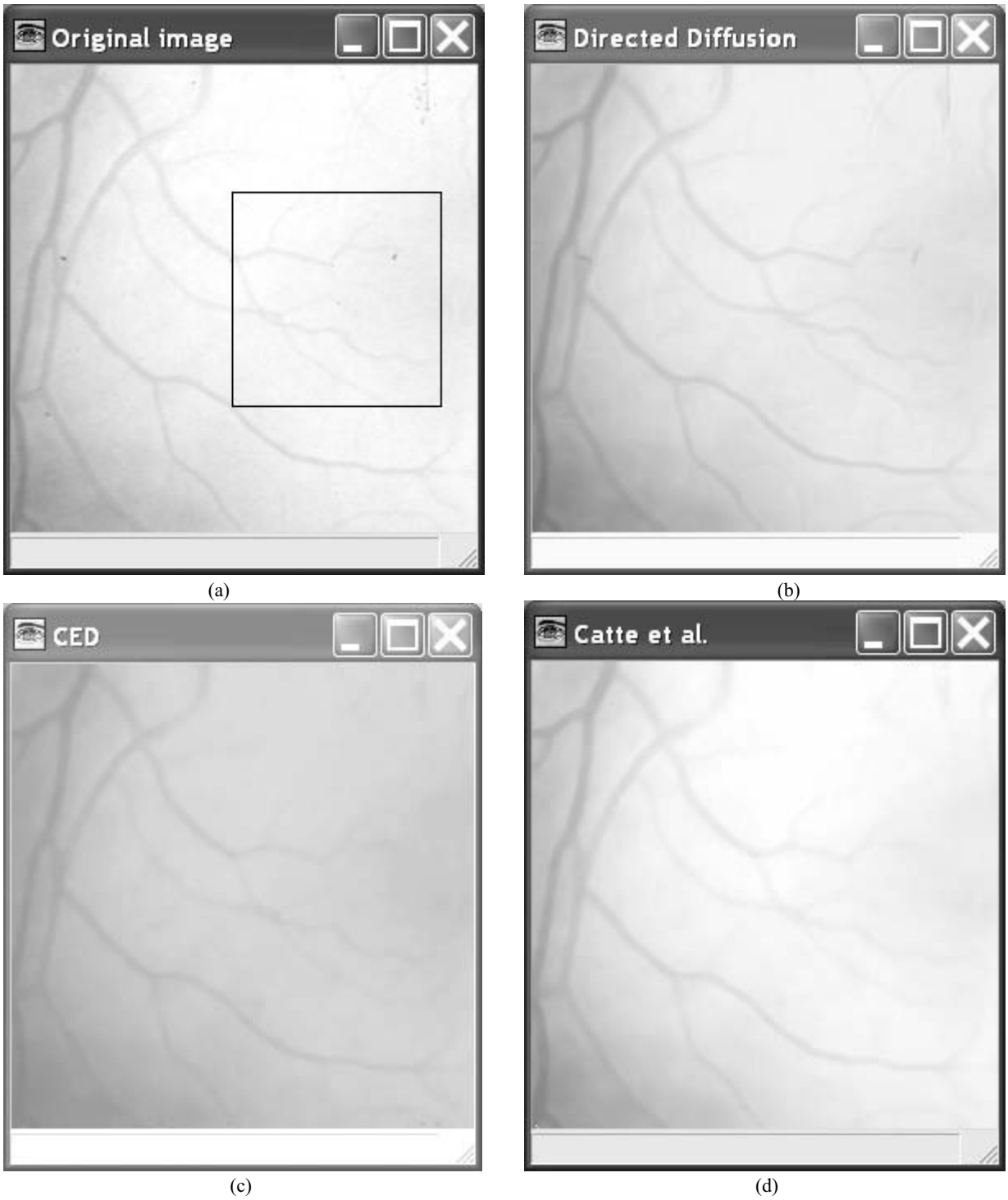
4. EXPERIMENTATAL RESULTS

In experimentations, some examples of angiographic images are used to illustrate the performance of the proposed scheme, which is compared with CED [4] and a regulation of Catté et al [8]. The images that used to test the algorithms have two different types of the angiographic images. Fig. 3(a) is a fluorescence angiographic image of blood vessels in eye. Fig. 4(a) is an X-ray angiographic image of coronary arteries.

Figure 3 and 4 are shown the experimental results by comparing with the CED and the Gaussian regulation diffusion of Catté et al. Fig. 3(a) and 4(a) are the original images that Fig. 3(a) has rectangle use to notice the quality of the enhancement methods. In the comparisons, the diffusion parameters of each method are declared with the same values

that consist of K=0.2, *diffusivity* = 0.25 and *number of iterations* = 30.

The effectiveness of the proposed method is shown through visual comparison with two the other diffusion methods. For the blood vessel enhancement algorithm, the directed diffusion can smooth the data better in homogeneous regions. The superior performance of the proposed method over the CED and the method of Catté et al. is in maintaining sharpness, booting up the magnitude and preserving the location of the blood vessels in the different sizes and orientations.



(a) (b)

(c) (d)

Fig. 3 (a) original image, and enhanced results: (b) the proposed method, (c) CED, and (d) Catté et al.

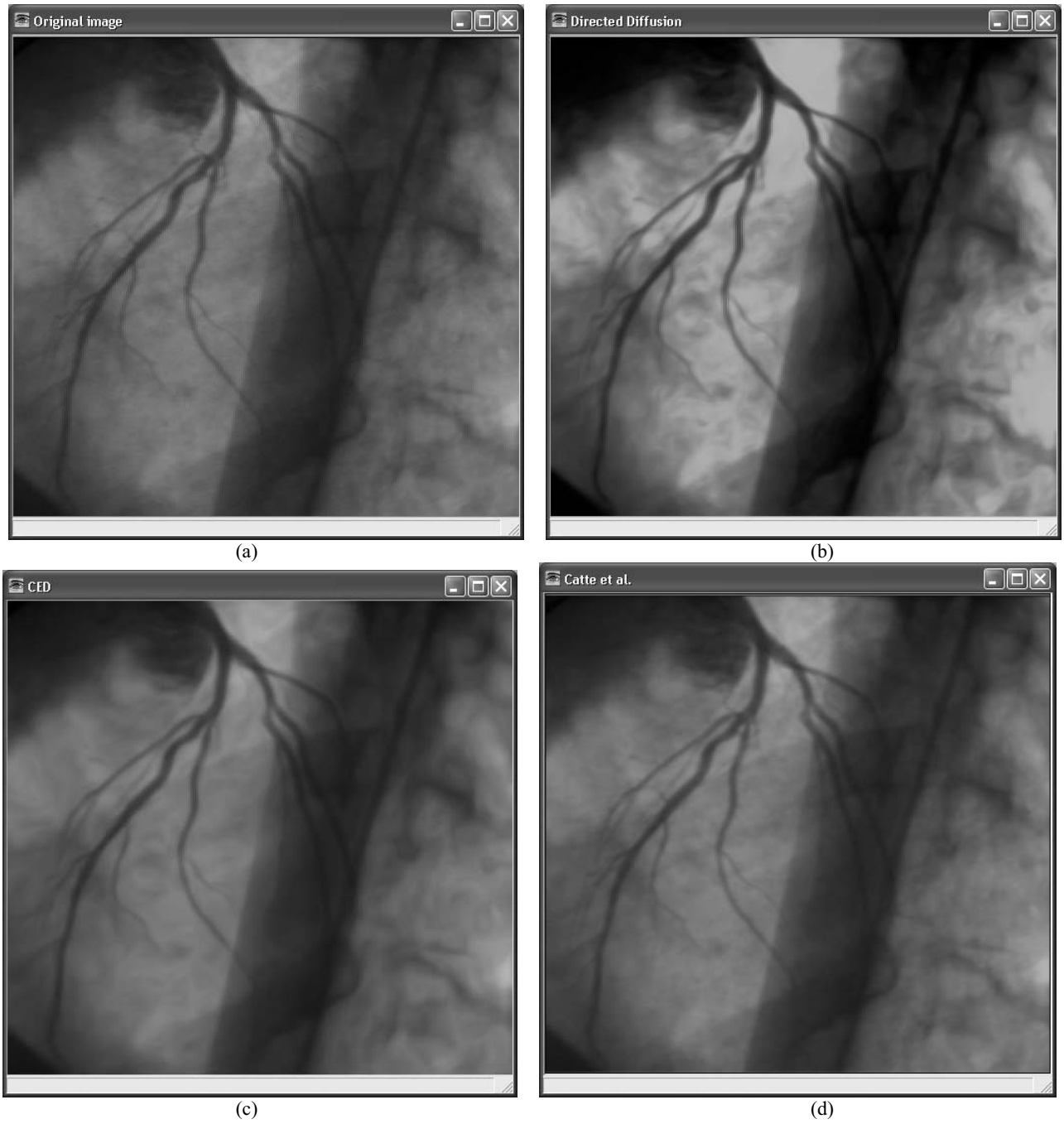


Fig. 4 (a) original image, and enhanced results: (b) the proposed method, (c) CED, and (d) Catté et al.

5. CONCLUSIONS

The effectiveness of the proposed method is shown through visual comparisons with two other anisotropic diffusion methods. For the image enhancement algorithm, the directed diffusion can smooth the data better in homogeneous regions. The superior performance of the proposed method over the CED and the regulation of Catté et al is in maintaining edge sharpness, booting up the edge magnitude, which this performance comes from the using multi-scale to define the optimal scale for each size of blood vessels. On the other hand, the algorithm can smooth the intra-region better than the traditional CED and the regulation of Catté et al in the same value of the diffusion parameters.

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