Denoising 3D Computed Tomography Images using New Modified Coherence Enhancing Diffusion Model

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Abstract: The denoising step for Computed Tomography (CT) images is an important challenge in the medical image processing. These images are degraded by low resolution and noise. In this paper, we propose a new method for 3D CT denoising based on Coherence Enhancing Diffusion model. Quantitative measures such as PSNR, SSIM and RMSE are computed to a phantom CT image in order to improve the efficiently of our proposed model, compared to a number of denoising algorithms. Furthermore, experimental results on a real 3D CT data show that this approach is effective and promising in removing noise and preserving details.

1 INTRODUCTION

Computed Tomography (CT scan) is a diagnostic medical test which consists in measuring the X-ray absorption by the tissue in order to reconstruct 2D images or 3D anatomical structures. The quality of CT images depends on the amount of the X-ray radiation, so the low-dose lead to increase the noise in image, and the large radiation increase the risk of cancer. That's why the noise filtering while reducing radiation dose is a challenge task of almost studies in denoising CT images. Several removal noise methods for 3D CT data have been proposed in literature. Among these methods, the anisotropic diffusion was widely used for denoising medical data (Romdhane et al., 2014); (Mendrik et al., 2009); (Perona and Malik, 1990); (Kroon et al., 2010); (Weickert, 1998); (Weickert, 1999). It's based on the use of Partial Differential Equations (PDE) making a strong diffusion in homogeneous zones and low diffusion across boundaries. It allows eliminating the noise while preserving the image discontinuities. Weickert (Weickert, 1999) used a nonlinear PDE based on a diffusion tensor in order to describe local variation present in images by applying the smoothing process according to the directional information. He proposed a Coherence Enhancing Diffusion (CED) model, it is able enhancing the structural elements and for medical applications it's applied successfully and leads to facilitate the analysis. Many regularisation used in the anisotropic diffusion such as (Frangakis and Hegerl, 2001), (Meijering et al., 2002), (Tschumperlé, 2006), (Pop et al., 2007), (Mendrik et al., 2009) and (Magnier et al., 2013).

This paper shows a modified 3D Coherence Enhancing Diffusion model applied for denoising 3D CT data. The paper is organized as follows: section 2 introduces the anisotropic diffusion tensor, section 3 describes the proposed model, section 4 presents results in terms of denoising quality and section 5 concludes the work.

2 ANISOTROPIC DIFFUSION TENSOR

Perona and Malik (Perona and Malik, 1990) were proposed the first nonlinear anisotropic diffusion model developed for image enhancement. The nonlinear PDE equation is given by:

$$\partial I_t = div\,(c.\nabla I) \tag{1}$$

Where I is 3D image, div denotes the divergence operator, ∇ is the gradient operator, t is the diffusion time and $c(.)$ is the diffusivity function that weights the gradient to control the diffusion process. Among the diffusivity function, Perona and Malik used the following equation:

$$c(|\nabla I|) = \exp\left(-\left(\frac{|\nabla I|}{k}\right)^2\right) \tag{2}$$

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Weickert (Weickert, 1999) used a tensor in the nonlinear partial differential equation (PDE) of Perona and Malik, taking into account the orientation of the gradient and the flow towards the orientation of interesting features among the diffusion.

$$\partial I_t = div\,(\,D \cdot \nabla I\,) \qquad (3)$$

Where $D(.)$ is the diffusion tensor constructed from the eigenvectors v_1, v_2 and v_3 ($v_1 = [v_{11}, v_{12}, v_{13}]$) and the eigenvalues μ_1, μ_2 and μ_3 of the structure tensor J_ρ defined as follow:

$$J_\rho = K_\rho * (\nabla I_\sigma \cdot \nabla I_\sigma^T) \qquad (4)$$

Where: ∇I_σ is the gradient of the smoothed image at scale σ and K_ρ is a Gaussian kernel with standard deviation ρ. The tensor *D(.)* is given by:

$$D = \begin{bmatrix} a & d & e \\ d & b & f \\ e & f & c \end{bmatrix} \quad with\; D(i,j) = \sum_{n=1..3} \lambda_n \cdot v_{ni} \cdot v_{nj} \qquad (5)$$

Weickert proposed two models to construct the tensor: the first one is using the Coherence Enhancing Diffusion (CED) function and the other is the Edge Enhancing Diffusion (EED). In this paper we focus only in the CED model which preserves small structures and enhances tubular structures. The 3D extension was developed on (Weickert, 1999) where author proposed the following diffusion functions:

$$\begin{aligned} &\lambda_1 = \alpha \\ &\lambda_2 = \alpha \\ &\lambda_3 = \begin{cases} 1 & if\ \mu_2 = 0\ or\ \mu_3 = 0 \\ \alpha + (1-\alpha)\cdot e^{-\frac{\ln(2)\cdot \lambda_c^2}{k}}, & else \end{cases} \end{aligned} \qquad (6)$$

Where $k = (\mu_2 / (\alpha + \mu_3))^2$, α is a small parameter $\alpha \in (0,1)$ which keeps the tensor D uniformly positive definite and λ_c is the CED contrast parameter. These definitions replay an only smooth in one orientation of space v_3 using the ratio between the second and the third eigenvalues of the structure tensor.

3 NEW PROPOSED CED MODEL

Several regularizations were proposed for CED model in 3D-domain. The most interesting regularization was the one which force the diffusion process along both the second and third eigenvectors (Pop et al., 2007). Our proposed model is inspired from the model of Sorin Pop (Pop et al., 2007) while using the notion of dimensionality of structures defined by Van Kempen (Van Kempen et al., 1999).

Plane-like and line-like structures are two available linear structures in the 3D-case, that's why Bakker (Bakker et al., 2001) defined two measures to estimate the semblance of seismic fault:

$$C_{plane} = \frac{\mu_1 - \mu_2}{\mu_1 + \mu_2}\ ,\ C_{line} = \frac{\mu_2 - \mu_3}{\mu_2 + \mu_3} \qquad (7)$$

Considering the similarity between faults in seismic imagery and edges in 3D imagery, the authors in (Pop et al., 2007) proposed the edge indicator using the measures defined previously as follow:

$$C_{edge} = C_{line}\,(1 - C_{plane}) \qquad (8)$$

And their CED proposed model is called CED-τD defined by the following equation:

$$\begin{aligned} &\lambda_1 = \alpha \\ &\lambda_2 = \lambda_3 - (\lambda_3 - \lambda_1) h_r (C_{edge}) \\ &\lambda_3 = \begin{cases} \alpha & if\ K = 0 \\ \alpha + (1-\alpha)\cdot e^{-\frac{C}{K}}, & else \end{cases} \end{aligned} \qquad (9)$$

Where $h_r(s)$ is a sigmoid function which plays the role of a fuzzy corner and edge detector through the value of two parameters the threshold $\tau \in [0,1]$ and the slope γ, defined by:

$$h_r(s) = \frac{\tanh[\gamma(s-\tau)] + 1}{\tanh[\gamma(1-\tau)] + 1} \qquad (10)$$

As shown in equation (9), the eigenvalue λ_2 takes values between λ_1 and λ_3, with regularization by the sigmoid function h_r.

Using the confidence measure described in (8), we propose the new model as follow:

$$\begin{aligned} &\lambda_1 = \alpha \\ &\lambda_2 = \begin{cases} \alpha & if\ K = 0 \\ \left|\tanh\left(\frac{C_{edge}}{K}\right)\right| & , else \end{cases} \\ &\lambda_3 = \begin{cases} \alpha & if\ K = 0 \\ \alpha + (1-\alpha)\cdot e^{-\frac{C}{K}}, & else \end{cases} \end{aligned} \qquad (11)$$

Where k is the measure of coherence defined as:

$$K = (\mu_1 - \mu_2)^2 + (\mu_1 - \mu_3)^2 + (\mu_2 - \mu_3)^2 \qquad (12)$$

Our model allows guaranteeing the diffusion along the second and the third direction with respect to the nature of the linear structures according to the confidence measure C_{edge} . Moreover, the hyperbolic tangent function is used to represent a transition phenomenon between two states (i.e. in our 3D case the line and plane-like structures), so it supports the role of the edge indicator. The absolute value guarantees that the tensor remains always with positive eigenvalues. The coherence measure K acts as a diffusion barrier; for $K \gg C$, the diffusion is along the two directions v_3 and v_2 and when K tends to 0 the diffusion seems to be isotropic and doesn't exceed α value. The next section present experiment results for denoising synthetic and real CT images compared to other CED models.

4 RESULTS

4.1 Synthetic Data

In this section, we first simulate we first test a 3D Shepp-Logan Phantom image with volume size ($128 \times 128 \times 102$) to improve the performance of the proposed denoising algorithm compared to other denoising model such as: the original CED proposed by Weickert (Weickert, 1999), the total variation model (TV), bilateral model and CED-τD (Pop et al., 2007). As quantitative measures, we use the Peak Signal-to-Noise Ratio (PSNR), the root mean square error (RMSE) and the Structural Similarity Index (SSIM) (Wang et al., 2004). The phantom dataset is corrupted with 3% and 5% additive Gaussian white noise (Figure 2-b and Figure 3-b successively). The parameters for our model and for the two others are fixed to: $\sigma = 1$, $\alpha = 0.01$, $\rho = 2$, $\partial t = 0.15$ and $C = 0.01$.

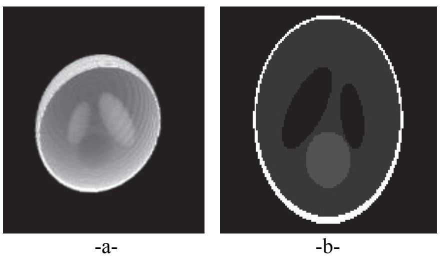

Figure 1: -a- 3D view of 3D Shepp-Logan Phantom, -b- Transversal Slice of 3D Shepp-Logan Phantom.

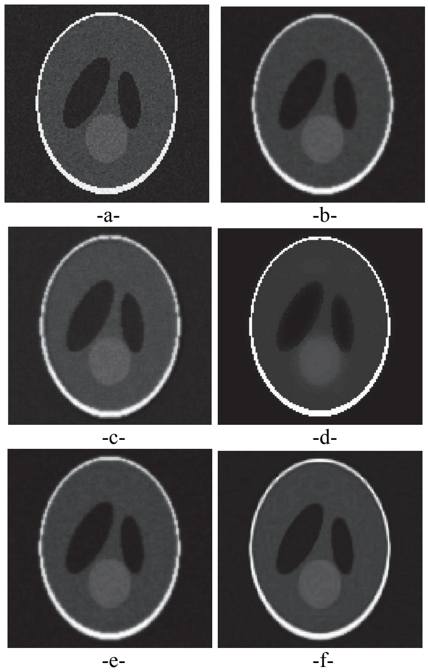

Figure 2: Performance of the diffusion methods of 4 iterations: -a- 3% Gaussian white noisy image, -b- CED_Weickert model , -c- Total Variation model (TV), -d- Bilateral model, -e- CED_τD model, -f- CED_proposed model.

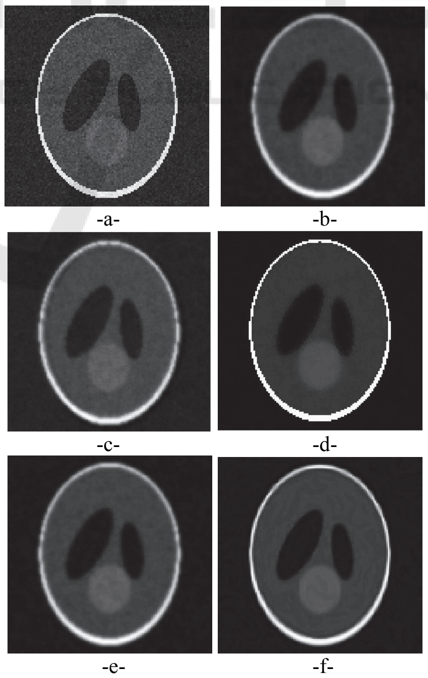

Figure 3: Performance of the diffusion methods for 4 iterations: -a- 5% Gaussian white noisy image, -b- CED_Weickert model, -c- Total Variation model (TV), -d- Bilateral model, -e- CED_τD model, -f- CED_proposed model.

As shown in the figures (Fig. 2 and Fig. 3), our model reduces noise significantly more than the others, moreover it preserves well the edges and enhances the homogenous areas. In term of visual quality, the two behaviours of the original CED and CED-τD modes are very similar and the quantitative measures in table1 confirm the results. The TV and bilateral models succeeded in removing noise but they lead to blur the data.

Table 1: Quantitative measures for denoising 3% and 5% additive white Gaussian noise in image.

	Model	PSNR	SSIM	RMSE
3% of Gaussian noise	**CED_Weickert**	22.51	0.878	0.075
	Total Variation (TV)	21.92	0.819	0.080
	Bilateral	17.91	0.428	0.127
	CED_τD	22.31	0.875	0.077
	CED_proposed	**24.31**	**0.919**	**0.060**
5% of Gaussian noise	**CED_Weickert**	20.18	0.813	0.098
	Total Variation (TV)	20.61	0.731	0.093
	Bilateral	15.54	0.405	0.167
	CED_τD	20.09	0.810	0.099
	CED_proposed	**22.95**	**0.880**	**0.071**

4.2 Real Data

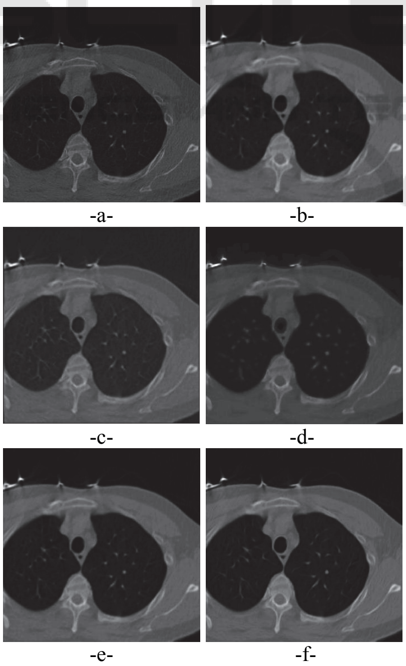

Figure 4: Performance of the diffusion methods on Transverse Slice of CT data: -a- Original data, -b- CED_Weickert model (15 iterations), -c- Total Variation model (15 iterations), -d- Bilateral model, -e- CED_τD model (15 iterations), -f- CED_proposed model (5 iterations).

We evaluate a Cardiac CT coronary angiography test bolus data for an adult with volume size ($512 \times 512 \times 193$). To perform the effectiveness of our proposed model and other methods, we use a cross-section for original data and for the results of denoising model in order to illustrate the behaviour of filtering methods. The parameters for our model and for the two others are fixed to: $\sigma = 1, \alpha = 0.1$, $\rho = 5$, $\partial t = 0.15$ and $C = 1$.

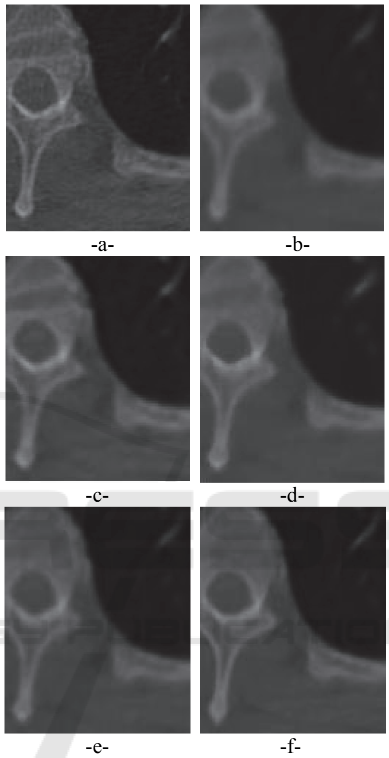

Figure 5: Detail zoom: -a- Original data, -b- CED_Weickert model, -c- Total Variation model (TV), -d- Bilateral model, -e- CED_τD model, -f- CED_proposed model.

We realize in figures (Fig. 4, Fig. 5 and Fig. 6), that the original and the CED-τD model reduced well the noise and blurred the edges but our proposed model is effective in preserving edges and removing noise. Moreover, our model has reduced the number of iterations, while maintaining the image quality (5 iterations for our model against 15 iterations for the other models), so we can have better results using less number of iterations which represent a benefit of saving time.

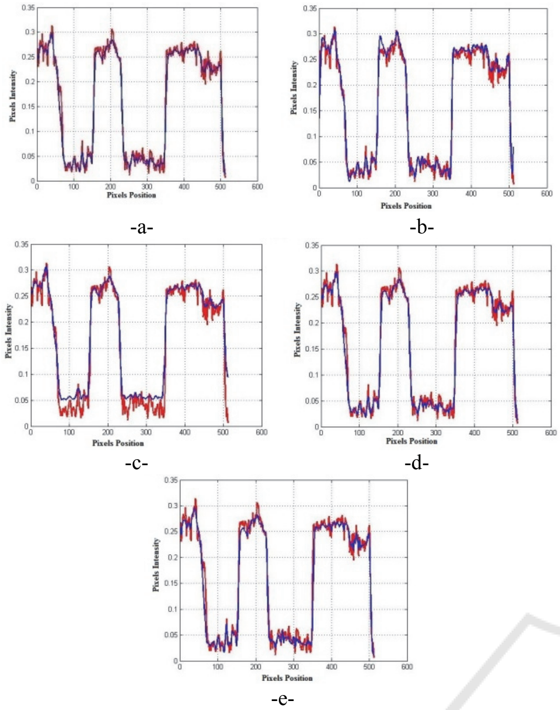

Figure 6: Cross-sectional analysis for the data (red: original data, blue: denoising method): -a- CED_Weickert model, -b- Total Variation model (TV), -c- Bilateral model, -d- CED_τD model, -e- CED_proposed model.

5 CONCLUSIONS

In this paper, a new CED model has been proposed for denoising 3D CT scan data. This new model was very promising in reducing noise and preserving edges. Quantitative measures was evaluated in order to improve the efficiently of the proposed model compared to other models. In the future work, we will look forward to generate model for denoising other kind of 3D medical image such as MRI and ultrasound data.

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