HYBRID DIFFUSION COMPARED WITH EXISTING DIFFUSION SCHEMES ON SIMULATED LOW DOSE CT SCANS

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ABSTRACT

Because of the growing interest in low dose Computed Tomography (CT) scanning, noise has become a major issue in CT imaging. Diffusion filtering is a well-known technique for filtering noise from images. We propose a hybrid diffusion model, which combines edge-enhancing diffusion (EED) and coherence-enhancing diffusion (CED) in a continuous manner. This diffusion model is compared with five existing diffusion schemes. Quantitative experimental results are presented on clinical CT chest scans, using high dose and simulated low dose scans.

1. INTRODUCTION

Clinical scans are inherently noisy. This is especially true for Computed Tomography (CT) scans, for which the radiation dose is kept as low as possible, to minimize the risk of inducing cancer to a patient. Low dose scanning is therefore being used widely, especially for screening and follow-up examinations. However, lowering the dose increases image noise and decreases contrast. Reducing image noise by automated methods has accordingly become an important topic in medical image analysis. Diffusion methods [1] have been widely used for this purpose, and tested on phantom data [2], but their actual performance in filtering noise from patient CT data has not received much attention yet.

In this paper a hybrid diffusion model is proposed, which combines edge- and coherence-enhancing diffusion [3] in a continuous manner. Quantitative experimental results are presented on clinical CT chest scans obtained with standard clinical dose. From these scans, low dose scans were simulated using a model for adding physically realistic noise to the raw scanner data before reconstruction [4]. Our hybrid diffusion model is, together with several existing diffusion schemes, applied to these simulated low dose scans and the result is compared with the original CT chest scan.

2. DIFFUSION FILTERING

Diffusion can be regarded as a physical process that equilibrates concentration differences without creating or destroying mass. In image processing the intensity value of a pixel can be regarded as the concentration, which diffuses over a neighborhood around that pixel. In this paper six diffusion schemes are compared. The first scheme is isotropic homogeneous diffusion. This simplest form of diffusion boils down to convolving the image with an isotropic Gaussian kernel with scale σ. The second scheme is isotropic inhomogeneous diffusion, originally due to Perona and Malik [5] and improved by Catté et al. [6]. This scheme is called regularized Perona-Malik diffusion (RPM) and is implemented as described in [2]. RPM requires a scale σ, a contrast parameter λ, a time step size τ and a number of iterations *noi*. The third scheme is an anisotropic inhomogeneous diffusion scheme called edge-enhancing diffusion (EED) [3], which we implemented as described in [2]. It has the same parameters as the RPM scheme. The three other diffusion schemes are hybrid diffusion models that combine edge-enhancing diffusion (EED) and coherence-enhancing diffusion (CED) [3]. EED is a noise filtering technique, which preserves edges by filtering along an edge in 2D [3], and along a plane in 3D [2]. CED is specifically designed to enhance elongated flow-like structures in 2D [3] and can be designed to enhance tube-like structures (such as blood vessels) in 3D [8]. Combining EED and CED is especially interesting for volumetric clinical data, such as CT chest scans (which contain blood vessels and other small structures). Both EED and CED use a diffusion tensor to steer the diffusion. The eigenvectors of the diffusion tensor determine the directions of filtering at every pixel in the image and their orientation is equal to that of the eigenvectors of the structure tensor [7]. The strength of filtering is determined by setting the eigenvalues λ_i of the diffusion tensor and depends on the filtering method used (EED [2] or CED [8]). Ideally, diffusion should be performed ($\lambda_i \rightarrow 1$) if the eigenvalue of the structure tensor (μ_i) is small; if μ_i is large there should be little diffusion ($\lambda_i \rightarrow 0$). The three hybrid diffusion models are described below. To address the differences between these models, the behavior of their diffusion tensor for several situations is illustrated in Figure 1.

2.1. Hybrid diffusion model by Frangakis and Hegerl

The hybrid diffusion model was first proposed by Frangakis and Hegerl [9]. Their model (HFH) uses the difference between the largest (μ_1) and the smallest (μ_3) eigenvalue of the structure tensor as a discrete switch (with a threshold t_{ec}) to decide whether the diffusion tensor of CED or EED should be used. Figure 1(b) illustrates the behavior of the diffusion tensor of this model. In case 1 EED is used, because there is no structure present. This results in isotropic filtering. Case 2 represents a plane, but in this case CED is used. Here, actually EED would be preferred, as it would filter along the plane and therefore enhance it. CED is also used in cases 3 and 4. In the former it is rightly used to enhance the tube-like structure. In the latter, however, it would have been desirable to have a little more smoothing in the direction of the second eigenvector. Finally, in case 5 EED is used and diffusion will take place in the direction of the third eigenvector. This hybrid diffusion model requires a scale σ, contrast parameters λ_c for CED [8] and λ_e for EED [2], an integration scale ρ [8], a small positive parameter α for CED [8], a threshold t_{ec}, a time step size τ and a number of iterations *noi* [1].

2.2. Hybrid diffusion model by Fernández and Li

Fernández and Li [10] recently proposed another version of the hybrid diffusion model (HFL). Instead of setting the second eigenvalue of the CED diffusion tensor to α, they use the function $h(\mu_1\text{-}\mu_2)$ [10] to set this value. The advantage of this change is that CED now enhances plane-like structures. Another difference in comparison to the HFH model is that they define an extra threshold t_g. When the intensity of a pixel is below t_g, it is regarded as background and homogeneous Gaussian smoothing is applied, otherwise the discrete switch [9] is evaluated. Figure 1(c) illustrates the behavior of the diffusion tensor of this hybrid diffusion model (all pixels evaluated in Figure 1 have intensity values above t_g). In cases 1, 3 and 5 this model behaves similar to the HFH model. In case 2, however, the plane-like structure is enhanced by CED, due to the change in eigenvalue settings of the CED diffusion tensor. Although this improves the result, the use of EED in this case would have required no change in the CED eigenvalue settings. Case 4 also benefits from the adjustment in the CED eigenvalue settings. This model has the same parameters as the HFH model, except for the additional threshold t_g.

2.3. Our hybrid diffusion model

A problem with the above mentioned models is that only μ_1 and μ_3 are used to construct a discrete switch. The difference between these two eigenvalues does not contain enough information to discriminate between situations in which CED is preferred and situations in which EED is appropriate. This is illustrated in Figure 1, where for example in both cases 2 and 3 the difference between μ_1 and μ_3 is large, but in case 2 EED is preferred (because EED is designed to enhance planes) and in case 3 CED is preferred (because CED is designed to enhance tube-like structures). We propose a hybrid diffusion model (OH), which preserves the settings of the eigenvalues of the EED and CED diffusion tensors [2,8] and combines these by using a continuous switch. This is achieved by setting an EED fraction (ε) as follows:

$$\varepsilon = e^{\frac{\mu_2}{\lambda_{h1}^2}\cdot\left(\frac{\mu_1}{\mu_2}-\frac{\mu_2}{\mu_3}\right)} - e^{-\frac{\lambda_{h2}}{\mu_3}} \tag{2.1}$$

where ε is clipped to the range [0,1]. Here λ_{h1} and λ_{h2} are user-defined contrast parameters. The EED fraction is used to set the eigenvalues λ_i (i = 1, 2 or 3) of the hybrid diffusion tensor as a combination of the CED and EED diffusion tensor:

$$\lambda_i = (1-\varepsilon)\cdot\lambda_{ci} + \varepsilon\cdot\lambda_{ei} \tag{2.2}$$

with λ_{ci} representing the eigenvalues of the CED diffusion tensor [8], and λ_{ei} representing the eigenvalues of the EED diffusion tensor [2]. Figure 1(d) illustrates the behavior of the diffusion tensor of this hybrid diffusion model. In all cases, the behavior of the diffusion tensor is equal to or better than the diffusion tensors of the other two hybrid models. The parameters for this model are identical to the parameters of the HFH model, with the difference that there is no threshold (t_{ec}) and two additional contrast parameters λ_{h1} and λ_{h2}.

3. RESULTS

To evaluate the performance of our hybrid diffusion model, all six presented diffusion schemes were applied to four patient CT chest scans. A high dose CT chest scan was acquired with either 150 mAs or 130 mAs. For each high dose scan an ultra low dose (15 mAs) scan was simulated using a model for adding physically realistic noise to the raw scanner data before reconstruction [4]. The advantage of this approach is that we can investigate precisely to which extent the low dose scan resembles the high dose scan, after filtering. In all scans several (58 in total) non-overlapping volumes of interest (VOI) were indicated, in either the lung or the mediastinum/abdomen. The simulated low dose scans were filtered using the parameter settings in Table 1.

3.1. Quantitative evaluation

To be able to quantitatively evaluate the performance of the various diffusion schemes, a voxel based comparison of the filtered simulated low dose and the original high dose scan is performed.

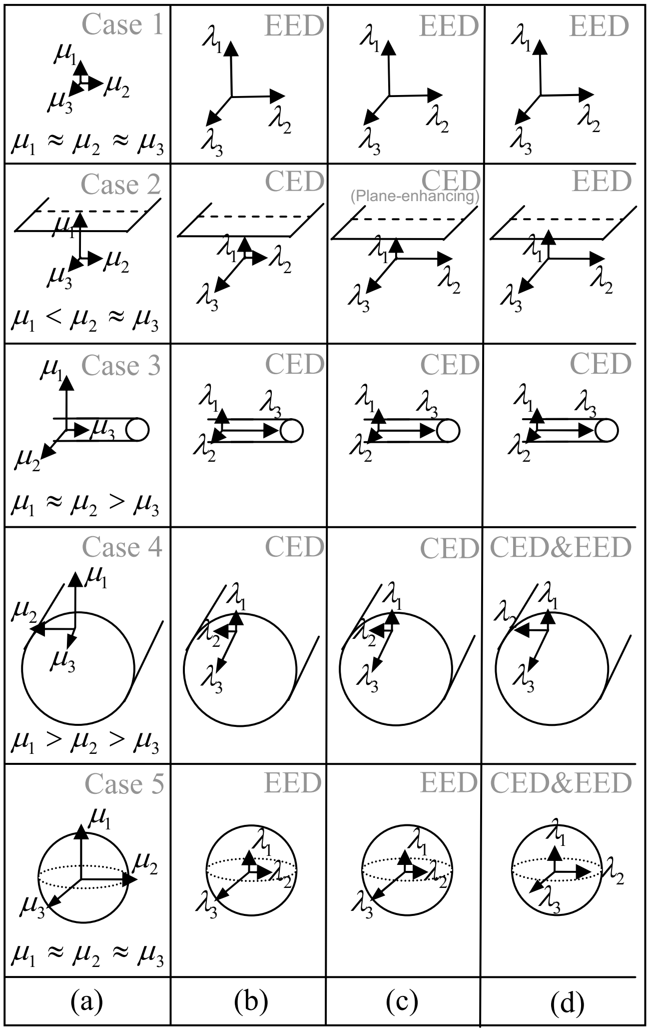

Figure 1 (a) Various scenarios (cases 1-5) represented by the structure tensor. (b,c,d) The eigenvectors of the diffusion tensor of the HFH Model, the HFL Model and the OH Model, respectively.

Diffusion scheme	Parameter settings
Gaussian Smoothing (GS)	$\sigma = 1$
RPM [2]	$\sigma = 1$, $\lambda = 50$, $\tau = 0.15$, $noi = 5$
EED [2]	$\sigma = 1$, $\lambda = 20$, $\tau = 0.15$, $noi = 3$
HFH Model [9]	$\sigma = 1$, $\lambda_e = 20$, $\lambda_c = 20$, $\rho = 1$, $\alpha = 0.001$, $t_{ec} = 500$ $\tau = 0.15$, $noi = 5$
HFL Model [10]	$\sigma = 1$, $\lambda_e = 20$, $\lambda_c = 20$, $\rho = 1$, $t_{ec} = 500$, $t_g = -900$, $\tau = 0.15$, $noi = 3$
OH Model	$\sigma = 1$, $\lambda_e = 20$, $\lambda_c = 15$, $\lambda_{h1} = 100$, $\lambda_{h2} = 1000$, $\rho = 1$, $\alpha = 0.001$, $\tau = 0.15$, $noi = 3$

Table 1 Parameter settings of the diffusion schemes.

Diffusion scheme	Average abs. mean diff. over all VOIs	Std. dev.
No filtering	37.38	14.06
GS	24.22	7.34
RPM	19.93	6.61
HFL	19.66	7.00
EED	19.61	6.71
HFH	19.54	7.12
OH	18.94	6.57

Table 2 Average absolute mean difference over all VOIs, with the standard deviation for every diffusion scheme.

	GS	RPM	HFL	**EED**	**HFH**	**OH**
GS	x	$2.5 \cdot 10^{-16}$	$3.0 \cdot 10^{-14}$	$3.8 \cdot 10^{-18}$	$7.5 \cdot 10^{-14}$	$4.1 \cdot 10^{-17}$
RPM	$2.5 \cdot 10^{-16}$	x	$2.1 \cdot 10^{-1}$	$4.9 \cdot 10^{-2}$	$2.1 \cdot 10^{-2}$	$6.2 \cdot 10^{-7}$
HFL	$3.0 \cdot 10^{-14}$	$2{,}1 \cdot 10^{-1}$	x	$6.8 \cdot 10^{-1}$	$3.9 \cdot 10^{-1}$	$1.1 \cdot 10^{-10}$
EED	$3.8 \cdot 10^{-18}$	$4.9 \cdot 10^{-2}$	$6.8 \cdot 10^{-1}$	x	$6.5 \cdot 10^{-1}$	$5.4 \cdot 10^{-9}$
HFH	$7.5 \cdot 10^{-14}$	$2.1 \cdot 10^{-2}$	$3.9 \cdot 10^{-1}$	$6.5 \cdot 10^{-1}$	X	$3.1 \cdot 10^{-4}$
OH	$4.1 \cdot 10^{-17}$	$6.2 \cdot 10^{-7}$	$1.1 \cdot 10^{-10}$	$5.4 \cdot 10^{-9}$	$3.1 \cdot 10^{-4}$	x

Table 3 Paired two-tailed T-test over all VOIs per diff. scheme

For every VOI the absolute mean difference between the original and filtered scan was computed. Ideally this difference should be close to zero, if a noise filter would recover the exact high dose scan from the low dose scan. In practice, however, this will never happen. One of the reasons for this is that the high dose scan also contains noise (although much less), whereas the noise in the low dose scan is blurred (due to filtering). The parameter settings in Table 1 were selected to have the average lowest absolute mean difference over all VOIs. Table 2 shows the average absolute mean differences for every diffusion scheme. Examining Table 2 results in the observation that the OH model has the lowest average absolute mean difference over all VOIs. Although the difference in comparison to the other diffusion schemes seems relatively small, Table 3 shows that the difference is nevertheless significant. For almost every VOI, the OH model performs better than the other diffusion schemes.

3.2. Qualitative evaluation

In addition to the quantitative evaluation, we have inspected the results of the various diffusion schemes visually. A quantitative evaluation is useful, but not sufficient to assess the performance of the diffusion schemes. Figure 2 shows a subimage of the results of the diffusion schemes applied to one of the patient CT chest scans.

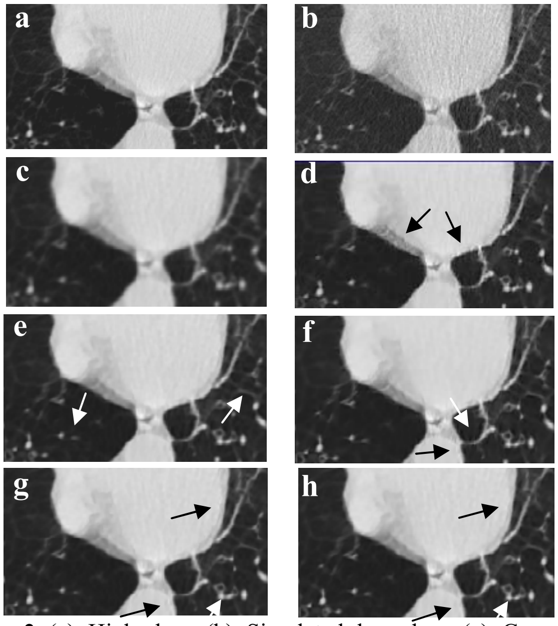

Figure 2 (a) High dose (b) Simulated low dose (c) Gaussian smoothing (edges are blurred) (d) RPM (noise is preserved at the edges, see arrows) (e) EED (structures in the lung are smoothed, see arrows) (f) HFH model (edge-artifacts due to the use of CED, see arrows) (g) HFL model compared with (h) OH model (OH preserves structures better (white arrow) and performs better at edges (black arrows).

The arrows in image 2d indicate that, when using RPM, the noise at the edges remains. EED (2e) performs better, but structures in the lungs are somewhat blurred (arrows). Image 2f shows the artifacts of the HFH model near the edges, indicated by the arrows. Finally, when comparing the result of the HFL model (2g) with the result of the OH model (2h), the OH model seems to perform better near the edges (black arrows) and small structures are preserved better (white arrow).

4. DISCUSSION AND CONCLUSION

We have proposed a hybrid diffusion model, which combines edge-enhancing diffusion and coherence-enhancing diffusion in a continuous manner. The idea of combining EED and CED is very nice. One of the largest drawbacks of the first version of the hybrid diffusion model (HFH), however, is that the result shows some artifacts (see Figure 2f). These artifacts are undesirable, especially in medical data. The HFL model solves these artifacts, but changes the settings of CED in the process. The OH model adjusts the switch between CED and EED, to be able to fully exploit the advantages of CED and EED. The qualitative results show that the OH and the HFL model both perform very well on CT chest data. The OH model, however, performs better at the edges and small structures.

The quantitative results (absolute mean difference and paired T-test) show that the proposed new hybrid diffusion model performs best in comparison to the other diffusion schemes.

In conclusion, the new hybrid diffusion model is a promising alternative to EED, the HFH and the HFL model, for filtering noise while preserving structures, and is especially useful for filtering low dose patient CT scans.

5. REFERENCES

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