Analysis of 3D linear and non-linear filtering effects based on 3D MDCT medical images

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***Abstract*—The risk of X-ray exposure will increase when applying the 3D-CT methods such as MDCT. To decrease this risk it is better to lower the dose-level of X-ray, but it reduces the resolution of obtained image and causes negative effect on imaging diagnosis. We think that 3D-filtering methods will recover the reduction. In order to obtain a better filtered result, 3D linear and non-linear filters are designed and applied to 80%, 60%, 40% and 20%-dose simulated low dose clinical MDCT images of abdomen with a tumor. Direct observation and 3D voxel value profile is extracted to evaluate the filtered results. Experimental results show both the filtering and the evaluating method perform well.**

Keywords: 3D-filtering; 3D-Medical image; MDCT; Low dose CT; Noise reduction

I. INTRODUCTION

3D multi-detector computed tomography (MDCT) images can display organs and focuses distinctly for people, but it needs rather high total exposure of X-ray which is harmful to human body. To decrease this risk it is better to lower the dose-level of X-ray, but it reduces the resolution of obtained image and causes negative effect on imaging diagnosis. There are many 2D and 3D filtering methods in the literature [1, 2, 3, 4, 5, 6, 7]. They may be classified under two broad headings, linear and non-linear filtering.

Since the intension of the correlation between voxels in connected neighborhood will decrease with the increase of the distance away from the center. Based on this, the weights of the 3D average filter can be set linearly. On the other hand, the edges can not be attenuated after filtering, therefore the smoothing should be performed at intra region and suppressed at region boundaries. The non-linear diffusion-based filtering was developed according to this. [6]

We are examining the methods to reduce the noise without the expense of blurring the texture of the little tumor referring the 3D correlation between adjacent voxels in 3D images.

This paper aims to achieve a preferable filtering result of 3D low dose MDCT images by linear and non-linear filtering, and evaluate the results through direct observation and 3D voxel value profile.

II. 3D LINEAR AND NON-LINEAR FILTERING FOR 3D-MDCT IMAGES

In order to examine whether the filtering algorithms described in this paper are effective for the low dose 3D-MDCT clinical images of abdomen with a tumor, 4 types of dose of X-ray methods were applied to create the images, i.e. 80%-dose, 60%-dose, 40%-dose and 20%-dose, as Figure 1 shows. And in order to show the tumor clearly, the liver is extracted by hand in the rectangle region and shown in Figure. 2. The 3D datasets are saved in 12 bits which the CT attenuation value of the voxel is from -1024Hu to 3071Hu, and their spacing distance among voxels along X, Y and Z axes is almost the same. And the size of the dataset is 512 × 512 × 13. Great amount of noise distributes randomly at every 2D slice of 3D-MDCT low dose images, which is different to normal dose images.

For linear filter, 3D average filter is designed according to the distance between the center and the neighbors. Let W_0, W_1, ..., W_5 as weights of the center, 1^{st}, …, 5^{th} neighbors, *A-max* is

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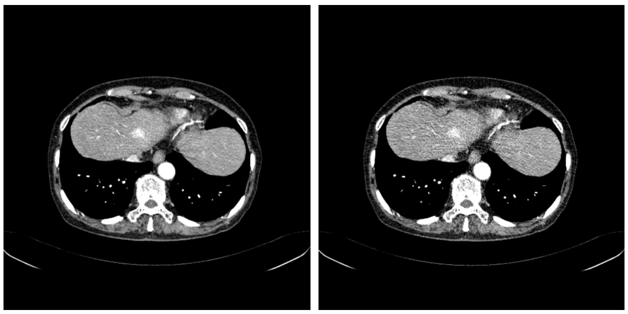
the maximum of the neighbor number. The average filter designed following rules below can obtain good results.

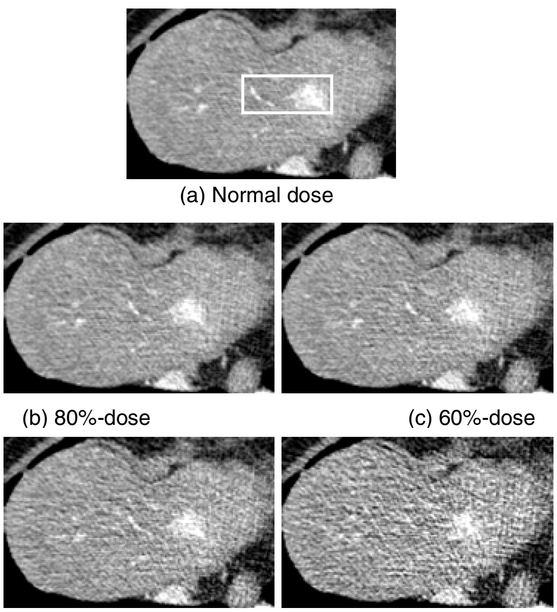
- $W_0 >> W_1 > W_2 >> W_3 > W_4 > W_5$
- $W_i > 0$, if $0 <= i <= j$, $j <= A\text{-}max$; $W_i = 0$, if $i > A\text{-}max$.

On the other hand, the procedure of non-linear diffusion-based filtering can be defined in Eq.1 and Eq.2. [6]



(a) Normal dose image. (b) 40%-dose image.

Figure 1. Original images. (Slice 7)



(a) Normal dose

(b) 80%-dose (c) 60%-dose

(d) 40%-dose (e) 20%-dose

Figure 2. Cut experiment objects

In Eq.1 and Eq.2, I is the input data, t indicates the iteration step, λ is a contrast parameter that takes a value in the range $0<\lambda<0.16$ as suggested in [6]; κ is the diffusion parameter and ∇ is the gradient operator that can be defined in a voxel connected neighborhood represented by $A\text{-}max$; n is the number of cell within $A\text{-}max$ except the center; $I_{x,y,z}(k)$ is the adjacent voxel value of $I_{x,y,z}$. In Eq. 2, when $A\text{-}max$ is set to 2, There are18 voxels in this connected neighborhood.

The 4 parameters of the diffusion filtering can be divided into 2 types: the first is influencing the filtered effect by controlling the summary of the gradient within the neighborhood, i.e. κ and λ. Secondly t and n influence the filtering by making larger neighborhood. These parameters influence the filtering effect dependently.

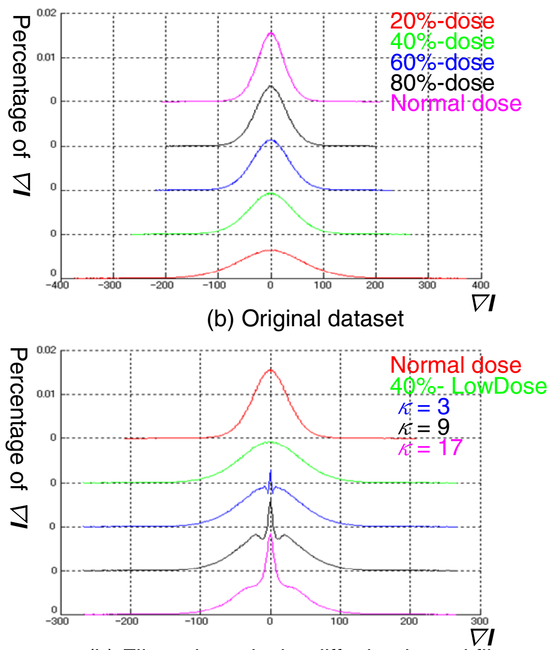


Figure 3. Percentage histogram of ∇I.

$$I^{t+1}_{x,y,z} = I^{t}_{x,y,z} + \lambda \sum_{n} \left(e^{-\left(\frac{\nabla_n I^t}{\kappa}\right)^2} \nabla_n I^t \right) \tag{1}$$

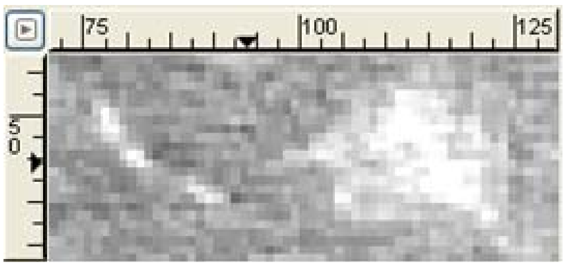
$$\nabla_k I_{x,y,z} = I_{x,y,z}(k) - I_{x,y,z}, k = 1 \sim n \tag{2}$$

Reference to Eq. 1, κ plays the most direct and distinct filtering effect; the larger value of κ, the smoothing will be more pronounced for the noise with small ∇I. But the noise with large ∇I almost remains unchanged, shown in Figure 3. Simultaneously the capability of lowering the noise level of the average filter is effective. Therefore we can combine the diffusion-based filtering and the average filter with a large center weight to smooth the low dose clinical images. This filtering is called combination filtering in this paper.

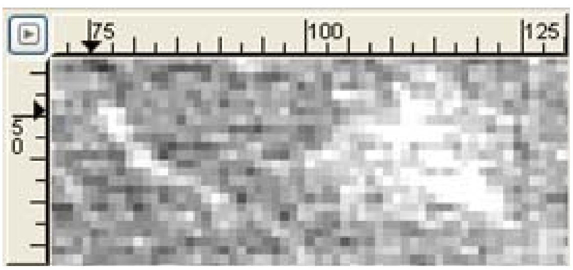
III. FILTERING EXPERIMENTS

The aim of filtering experiments is to obtain a filtering with better performance for 3D MDCT clinical images.

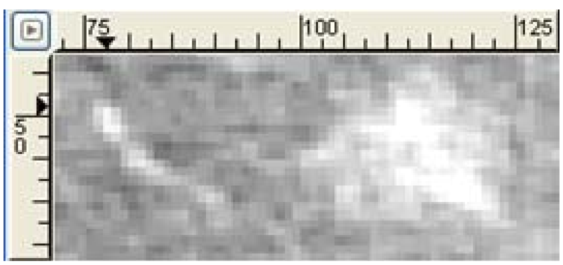
For linear filtering, 3D average filer is designed based on section 2. After several trials, we set W_0, to W_3 as 0.2917, 0.0625, 0.02083 and 0.01042 for beginning, denotes this filter as F_0. In order to obtain a preferable filtering result by 3D average filter, we make W_1 as constant, change W_0 and the rest weights as follow: denote weights of F_0 as W_0', W_1', W_2' and W_3'; weights to be designed is W_0^d, W_1^d, W_2^d and W_3^d; set $W_0^d = r_2 * W_1'$, $r_2 = r_1 + \triangle r$, $\triangle r$ = -1, 0, 1, … , 5, $r_1 = W_0' / W_1' \approx 4.67$; keep W_1^d equal to W_1' as constant; $W_2^d / W_3^d = W_2' / W_3' = 2$.



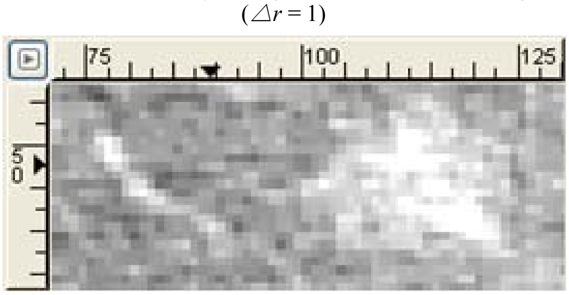
(a) Normal dose



(b) 40%-dose



(c) Filtered result by average filter for 40%-dose image. ($\triangle r = 1$)



(d) Filtered result by combination filter for 40%-dose image. ($\kappa = 17$, $\triangle r = 5$)

Figure 4. Filtered results.

For the diffusion-based filter, our goal of filtering is to enhance the low dose images to distinguish the small tumor with the size around 2mm. Therefore, the range of the connected neighborhood should not be too large. We think that t is around **3** iterations and *A-max* is about **2** may be preferable. λ is set to the middle value of the range from 0 to 0.16 [6], i.e., $\lambda = 0.08$. Then we can fix t, *A-max* and λ, change κ step by step.

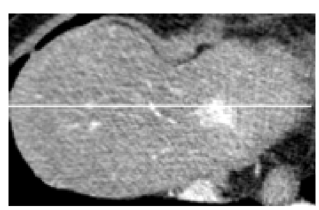
Moreover in order to obtain more preferable filtering result, the average filter and the non-linear diffusion-based filter are combined to enhance the 3D MDCT datasets. The non-linear filter whose κ = 17 is applied firstly, then the average filter whose $\triangle r$ = 5 is taken into account. To observe the detail information clearly, the region with blood vessel and tumor (see the white rectangle in Figure 2(a)) is cut and enlarged, as Figure 4 shows.

IV. Evaluate the Filtered Results

In this section, we will present the results evaluated both by direct observation and 3D voxel value profile. The goal is to obtain an optimal 3D filter.

For 40%-dose dataset, according filtered results by average filter, much noise has been reduced after different filtering. Among them, the filter when $\triangle r$ equals to 1 can reduce the noise level while preserve the detail of the structure content well relative to other average setting; while for the diffusion-based filter, that κ is about 17 is better relatively. But after comparing to the normal dose image, the combination filter performs best relative to the average and diffusion-based filter, reference to Figure 4.

Additionally the 3D voxel value profile is extracted from the 3D dataset along certain line which passing through tumor (see Figure 5) to show the filtered effect in detail, reference to Figure 6. There are many visual peaks in the profile from the low dose image, whereas the peaks have been reduced after filtering. After comparing these profiles, we think the profile from the dataset smoothed by the combination filter is closest to the one from the normal dose image than the others. For other dose datasets, similar results can be obtained.



(a) XY plane

(b) YZ plane

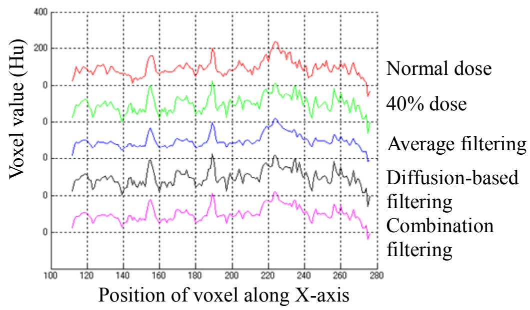
(c) XZ plane

Figure 5. Extracting position of voxel value profile in the three-biew images, as the white or black lines show.

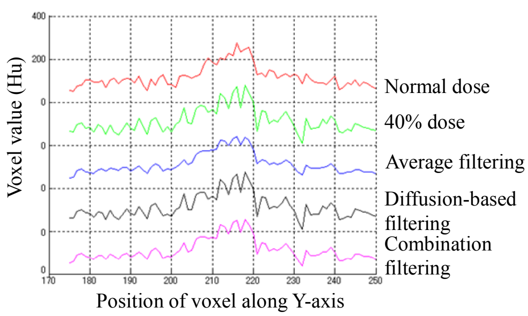
V. Discussions

Both the linear and non-linear filters make use of the information in certain neighborhood to reduce the noise. The difference of them is the linear filter calculates the filtered value linearly whereas the non-linear one does non-linearly.

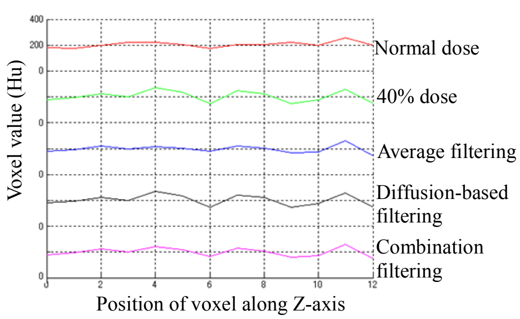
In this paper, since the weights of the 3D average filter are designed in order to distinguish the little tumor, the noise level has been lowered down effectively while the tumor and the blood vessels can be recognized well, specially for the case when $\triangle r = 1$. Therefore the average filter is effective to reduce the noise of low dose 3D MDCT clinical images. But the average filtering smoothes all the voxels with the same setting of weights, therefore in order to reduce a good quantity of noise, the region boundaries have to be attenuated to some degree.



(a) Voxel value profile of XY plane (Z = 6, Y = 227).



(b) Voxel value profile of YZ plane (X = 211, Z = 6).



(c) Voxel value profile of XZ plane (X = 211, Y = 227).

Figure 6. Voxel value profiles from three-view images. (For the average filtering, $\triangle r = 1$); for the diffusion-based filtering, $K = 17$; for the combining filtering, $K = 17$, $\triangle r = 5$.)

For the non-linear filter, the 3D median filter is also checked. But filtered results by different size of 3D median filter appear blurry. We think the 3D median filter does not fit to enhance our low dose clinical images.

For the non-linear diffusion-based filtering, it uses the exponent as the non-linear function to reduce the noise according to the gradient inside the connected neighborhood. The smoothing can be performed at intra regions and suppressed at region boundaries. Therefore, the noise at intra region can be reduced well, but region boundaries almost remain unchanged, as Figure 3(b) shows.

Based on above, we can design the combination filter which exhibits both advantages of non-linear diffusion-based filter and average filter. Firstly, the non-linear diffusion-based filter is applied to reduce the noise at intra region, then the average filter with a large value of center weight is used to lower the noise level in region boundaries mainly. In Figure 4, after comparing to the original normal and low dose images (Figure 4(a, b)), the combination filtering (Figure 4(c)) performs well in the trade-off between smoothing efficiency and the feature preservation. Moreover, the visual peaks become less and the shape of the profile is closest to the one of the normal dose image both for the voxel profile extracted from the filtered result by combination filtering, as Figure 6 shows. Therefore, the combination filtering is preferable for the low dose 3D MDCT clinical dataset.

Though good results have been obtained with the 3D filter and evaluating method, there still remain more researches to be done: research on quantitative methods making use of the correlation of the connected neighborhood to evaluate the filtered results, such as mutual information [8]; and research on 3D adaptive diffusion-based filtering.

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