Trilateral Filtering: A Non-linear Noise Reduction Technique for MRI

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INTRODUCTION

Filtering is a preliminary process in many medical image processing applications, which is aimed at restoring a noise-corrupted image to its noiseless counterpart. Post-processing tasks, e.g., visualization, segmentation and quantification, may benefit from the reduction of noise. Diffusion equations with scalar-valued and tensor-valued diffusivities [1] and non-linear filters [2] have been used to perform smoothing in medical images. In this paper, we present a novel filtering method, integrating geometric, photometric and local structural similarities, to achieve edge-preserving smoothing in medical images. It is simple to implement and is applicable to multi-dimensional signals. The experimental results have shown that this new technique provides greater noise reduction than other denoising techniques. Our method uses a narrow spatial window[1] (3 pixels in each dimension) and takes only a few iterations (3 iterations in the experiments in this work) in the smoothing process.

METHODS

Bilateral filtering (BF) [3] is a simple, non-iterative and local approach to edge-preserving smoothing. A filtered image is obtained by replacing the intensity value of each pixel with an average value weighted by the geometric and photometric similarities between neighboring pixels within a spatial window. The novel filtering method proposed in this paper, namely trilateral filtering (TF), works along the same lines as BF; it takes the geometric, photometric and local structural similarities to smooth the images with a narrow spatial window while preserving the edges. Local structural information is used to determine inhomogeneity in the images and influence the smoothing process with orientation information. On one hand, low-pass filtering is performed in the homogeneous regions. On the other hand, smoothing along edges is achieved by considering the three similarities between neighborhoods in the inhomogeneous regions. We found that this new approach provides greater noise reduction than that of BF with a 3-pixel-width spatial window. TF is expressed as follows:

$$\mathbf{I}^{(t+1)}(\mathbf{x}) = \frac{1}{k(\mathbf{x})} \sum_{\mathbf{z}\in N(\mathbf{x})} \mathbf{I}^{(t)}(\mathbf{z}) \left\{ (1-a(\mathbf{x}))\cdot c(\mathbf{z},\mathbf{x}) + a(\mathbf{x})\cdot c(\mathbf{z},\mathbf{x})\cdot s\left(\mathbf{I}^{(t)}(\mathbf{z}),\mathbf{I}^{(t)}(\mathbf{x})\right)\cdot \sum_{i=1}^{D-1} d_i(\mathbf{z},\mathbf{x}) \right\}, \quad (1)$$

where

$$d_i(\mathbf{z},\mathbf{x}) = \exp\left(-\frac{\delta^2(\mathbf{z}-\mathbf{x},\hat{e}_i)}{2\sigma^2}\right), \quad (2)$$

$$a(\mathbf{x}) = \frac{\left(\hat{A}(\mathbf{x})\cdot(1-p)\right)^q}{\left(\hat{A}(\mathbf{x})\cdot(1-p)\right)^q + \left((1-\hat{A}(\mathbf{x}))\cdot p\right)^q} \quad (3)$$

and

$$\delta(\mathbf{u},\mathbf{v}) = 1 - |\hat{u}\cdot\hat{v}|. \quad (4)$$

$\mathbf{I}$ represents an image, t is a time variable, $\mathbf{x}$ and $\mathbf{z}$ are spatial coordinates, $k(\cdot)$ is the normalization constant, $N(\cdot)$ denotes the narrow spatial window, $c(\cdot)$ and $s(\cdot)$ measure the geometric and photometric similarities between neighborhoods in $N(\cdot)$ as defined in [3]. $\hat{A}(\cdot)$ is the normalized Frobenius norm of the orientation tensor described in [4], p and q are positive constants, p=0.1 and q=4 in this work; $a(\cdot)\to 0$ in homogeneous regions and $a(\cdot)\to 1$ in regions that contain discontinuities, therefore, $a(\cdot)$ is used to determine inhomogeneity in the image. D is the dimensionality of $\mathbf{I}$, $\delta(\cdot)$ quantifies the angular differences between $\mathbf{u}$ and $\mathbf{v}$, σ controls the sensitivity of $\delta(\cdot)$ in $d_i(\cdot)$. For 3D images, $\hat{e}_1$ and $\hat{e}_2$ are the first and second smallest eigenvalues of the orientation tensor [4]; $d_i(\cdot)$ measures the local structural orientation similarities between $\mathbf{x}$ and $\mathbf{z}$.

EXPERIMENTAL RESULTS & DISCUSSION

The novel non-linear filtering technique TF has been applied to a 3D T1 MRI dataset obtained from BrainWeb[2] (of voxel size $1\times1\times1$ mm^3, 5% noise and 0% RF). Noise reduction experiments have been conducted together with other denoising techniques, viz. Gaussian filtering (GF), BF and edge-enhancing anisotropic diffusion (EED) [1][3], for performance comparisons. The dataset is partitioned into regions of five different classes based on intensity values in reference to a noiseless counterpart. The five classes are: (1) air and bone (Air+B), (2) cerebrospinal fluid and skin (CSF+S), (3) gray matter and fat (GM+F), (4) white matter and fat (WM+F), and (5) high density fat (HDF). Figure 1(a) shows a portion of a slice image from the dataset and Figure 1(b) indicates the regions of the five classes in different colors. We have compared the increases in sample mean ("mean") and standard deviation (SD) of each class after the application of different denoising methods. Increases are measured in dB according to this formula: $20\times\log_{10}$(New Value/Old Value).

Figures 2(a) and 2(b) show the increases in mean and SD respectively. It is noted that mean values do not change significantly after smoothing. Maximum increase is given by EED (< 0.6 dB, i.e., < 7%), whereas maximum decrease is given by GF (< 0.4 dB, i.e., < 5%). TF produces the greatest reduction in SD for the classes Air+B, GM+F and WM+F. It gives a comparable decrease in SD as BF for the class CSF+S, as opposed to GF and EED which increase the SD. Both BF and TF do not reduce the noise in the image regions of the class HDF, as reflected by the close-to-zero changes in the mean and SD. This may relate to the fact that the HDF regions are not corrupted by the noise severely. These experimental results suggest that TF provides the greatest noise reduction amongst the other denoising methods. Figures 1(c)–(f) show the smoothed images obtained with TF, GF, EED and BF respectively. It is evident that TF is capable to smooth the MRI image while preserving the edges. It provides a more than satisfactory image restoration as compared to other noise reduction methods.

REFERENCES

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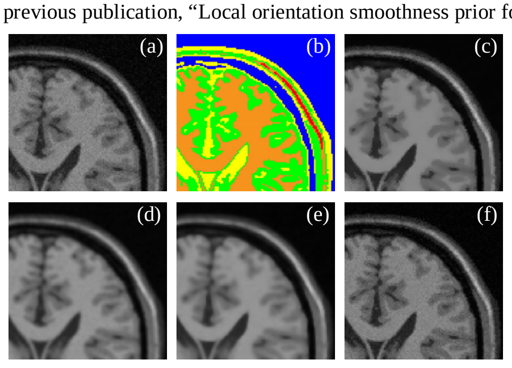
Fig. 1. T1 MRI dataset. (a) A portion of a slice image; (b) the five classes in different colors: Air+B in blue, CSF+S in yellow, GM+F in green, WM+F in orange and HDF in red; smooth images obtained with (c) TF, (d) GF, (e) EED and (f) BF



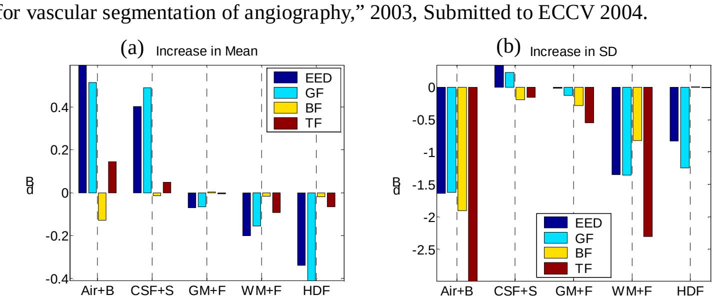


Fig. 2. Performance comparisons. Increases in sample (a) mean and (b) standard deviation (SD) for the five classes. Increases are measured in dB

[1] The use of narrow spatial window makes spatial-domain operation(s) in a smoothing process computationally efficient.
[2] A simulated brain database from Montréal Neurological Institute, McGill University (www.bic.mni.mcgill.ca/brainweb).
[3] BF and EED noise reduction methods smooth images with edge-preserving capability.