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MEDICAL IMAGE DENOISE METHOD BASED ON CURVELET TRANSFORM: AN APPROACH FOR EDGE PRESERVATION

T. Janardhan Reddy
Department of ECE, G.Pulla Reddy Engineering College, Kurnool, India.

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ABSTRACT

In medical images noise and artifacts are presented due to the measurement techniques and instrumentation. Because of the noise present in the medical images, physicians are unable to obtain required information from the images. The paper proposes a noise reduction method for both computed tomography (CT) and magnetic resonance imaging (MRI) which fuses the Curvelet transform based method. The performance is analysed by computing Peak Signal to Noise Ratio (PSNR).The results show the proposed method can obtain enhanced visual and de-noise effect.

KEYWORDS: Curvelet Transform, Medical Image de-noise, PSNR.

INTRODUCTION

Medical images are often exposed to various noise interferences in the process of generation, transmission and recording. Image denoising by an appropriate method is veryimportant before the high-level process of edge detection, image segmentation, featureextraction, pattern recognition and on. The image denoising method can be divided intotwo categories: one is the spatial domain methods, in which image smoothed by convolutionof smoothing template and, in order to suppress or eliminating noise. Theother is frequency domain methods, in which the image is filtered by a suitable frequency band-pass filter after transformation of the image, and then gets the de-noisedimage by the inverse transform. Spatial domain methods includes mean filtering, medianfiltering, adaptive noise filtering and morphological filtering, frequency filterincludes Fourier transform and image de-noising using wavelet and ultra-wavelet.

In recent years, wavelet theory has developed rapidly, and because of its capability of good time-frequency localization and multi-resolution analysis, it has a very wide range of applications in various fields of image processing. In the field de-noising, wavelet theory is attached any importance by many scholars, who denoised signals using wavelet transform, and obtained very good results [1] [2]. Because of advantages and potential in denoising, wavelet analysis has been a research focus, and get some achievements. At present, the wavelet denoising method can be broadly classified into three categories. The first method proposed by Mallat is wavelet transform modulus maxima denoising. The second category is correlation denoising method based on wavelet transform and the third method is threshold method proposed by Donoho [3] [4] [5] [6].Reconstruction filter of modulus maximum is to reconstruct the signal by using themodulus maxima of wavelet coefficients at all scales of the signal. The modulusmaximum of wavelet coefficients of signal contains the peak variability and singularity.If these signals can be reconstructed from the maximum value, and the singularity ofsignal can be changed by dealing with the modulus maxima of wavelet coefficients, sothe corresponding singularity can be removed by inhabiting the certain maxima ofcoefficients, above is the basic idea of modulus maximareconstruction filter. Modulusmaxima reconstruction filter is based on signal and noise presented various propertiesin wavelet transform with the different scale, it has a good theoretical basis and morestable filtering performance, it is less depend on noise and do not need to know thenoise variance, so it has superiority especially for low SNR when the signal filtering.However, it has a fundamental drawback, that is, there is a problem comes from thereconstruction of wavelet coefficients by modulus maxima in filtering process, whichmakes the calculation of this method is greatly increased, while the actual filteringeffect is not very satisfactory.

Wavelet denoising based on signal correlation and noise is constructing the corresponding rules on different expression of wavelet transform at different scales, then the wavelet coefficients of signal and noise are processed, as well as the substance is completely removed the reduced coefficient of the noise , maximize the effective signal to retain the wavelet coefficients at the same time. After the wavelet transform of thesignal, the wavelet coefficients of signal at each scale have obvious correlation, particularly near the edge of the signal, the relevance is more obvious, but the wavelet coefficients corresponding to scale of noise is no such obvious correlation.Wavelet threshold denoising method is able to concentrate signal energy to a smallnumber of wavelet coefficients, while the transformations of white noise in any orthogonal basis is still the white noise, and have the same magnitude. In contrast, the wavelet coefficients magnitude of signal are inevitable larger than those of noise whose energy scattered and smaller. To select an appropriate threshold and remove the wavelet coefficients of the noise by thresholding can achieved the purpose of retaining useful signals.For the defects of Wavelet transform, Candes andDonoho proposed Curvelet that more suitable for analysing signals in the high singularity.

Curvelet transform has a good selection and identification of the direction toeffectively approximate the image details of the edge of and texture, Curvelet transformin the field of image fusion can better describe the characteristics of the original image,thereby improving the quality of fusion, now the second generation of Curvelet transformis mainly used for image processing [10] [11].

CURVELET TRANSFORM

Continuous Curvelet Transform

Continuous Curvelet transform signal represent as inner product of basis functions and signal function (or function) to denote the sparse representation [7] [8] [9], expressed as:

$$C(j,l,k) = \left\langle f, \varphi_{j,l,k} \right\rangle \tag{1}$$

where $\varphi_{j,l,k}$ is Curvelet function, j, l, k, respectively, is scale, orientation, location parameters. Curvelet transform implements in the frequency domain. To define a window function W (r), r ∈ (1 / 2, 2):and a angle function V (t), t ∈ [1,1].

$$\sum_{j=-\infty}^{\infty} W^2(2^j r) = 1, r \in (3/4, 3/2) \tag{2}$$

$$\sum_{l=-\infty}^{\infty} V^2(\mathrm{t}-1) = 1, \mathrm{t} \in (-1/2, 1/2) \tag{3}$$

$$U_j(r,\theta) = 2^{-3j/4} W(2^{-j} r) \mathrm{V}\left(\frac{2^{(j/2)}\theta}{2\pi}\right) \tag{4}$$

where [j/2] is an integer part of j/2. The support area Uj is a wedge shaped area come from support area W and V.

To define the curvelet at scale 2^{-j} the direction θ_l, translation parameter (k1, k2) is

$$\varphi_{j,\mathrm{l},\mathrm{k}}(x) = \varphi_j(R_{\theta_l}(x - x_k^{(j,k)})) \tag{5}$$

$$x_k(j,l) = R_{\theta_l}^{-1}(k_1.2^{-j}, k_2.2^{-j/2}) \tag{6}$$

Curvevelet transform can be expressed as:

$$c(j,l,k) = \left\langle f, \varphi_{j,l,k} \right\rangle = \int R^{2f(x)} \overline{\varphi}_{j,l,k}(x) dx \tag{7}$$

Discrete Curvelet Transform

The input is f [t1, t2] (0 ≤ t1, t2 ≤n) in the Cartesian coordinates corresponding to the local window, the discrete form of Curvelet transform is

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$$c^D(j,l,k) = \sum_{0 \le t_1, t_2 \le n} f[t_1, t_2]\bar{\varphi}^D_{j,l,k}[t_1, t_2] \tag{8}$$

Aided by a band pass function

$$\psi(\omega_1) = \sqrt{(\omega_1/2)^2 - (\omega_1)^2} \tag{9}$$

to define $\psi_j(\omega_1) = \psi(2^{-j}\omega_1)$ (10)

where $s_{\theta_l} = \begin{pmatrix} 1 & 0 \\ -\tan\theta_1 & 1 \end{pmatrix}$ (11)

It is not equally spaced, but the slope is equal intervals.Define

$$\tilde{U}_j(\omega) = \psi_j(\omega_1)V_j(\omega) \tag{12}$$

$$\tilde{U}_j(\omega) = \psi_j(\omega_1)V_j(\mathrm{s}_{\theta_l}\,\omega) = \tilde{U}_j(\mathrm{s}_{\theta_l}\,\omega) \tag{13}$$

PROPOSED METHOD

The following are steps of image denoise using Curvelet generally:

Step 1: preprocessing the image.
Step 2: Curvelet transform the image.
Step 3: calculate the threshold of transform coefficients for each offspring, deal with coefficient.
Step 4: To do Curvelet inverse transform to obtain denoised image.

The following are steps of CT image and MRI denoise using Curvelet:
Step 1: CT and MRI images with noise decomposed into low frequency coefficients and high frequency coefficients at each scale by Curvelet transform.
Step 2: To estimate the noise variance using Monte-Carlo method with the scale of sub-band , and then process high-frequency coefficients at all scales , the hard threshold function is defined as

$$T(x) = \begin{cases} x, f\,|x| > \lambda \\ 0, f\,|x| \le \lambda \end{cases}$$

where $\lambda = 3\sigma$
Step 3: Apply IFFT to high-frequency coefficients and low-frequency coefficients, get the thedenoised image.

RESULTS AND DISCUSSION

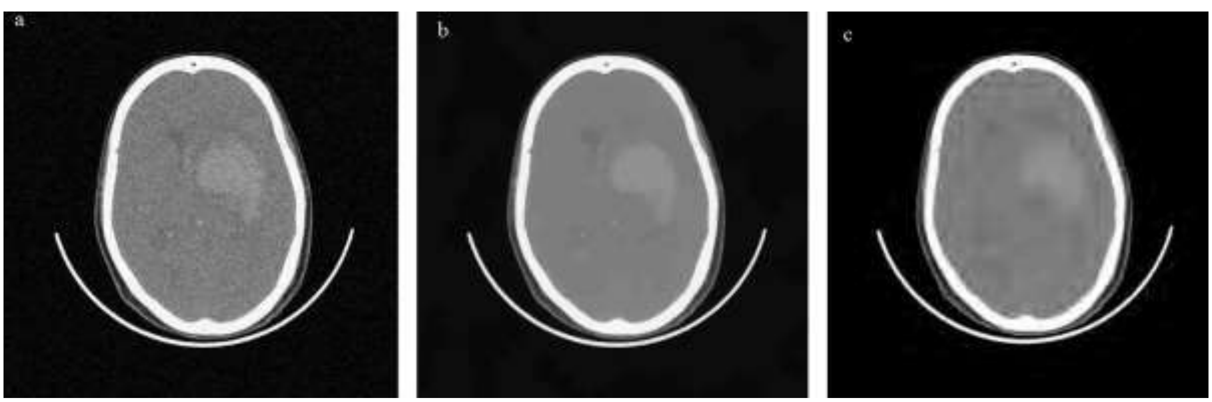

Fig.1 (a) Noisy CT brain image with PSNR = 20.3dB (b) Wavelet de-noising with PSNR= 42.5 and (c) Curvelet de-noising with PSNR = 46.3 dB.

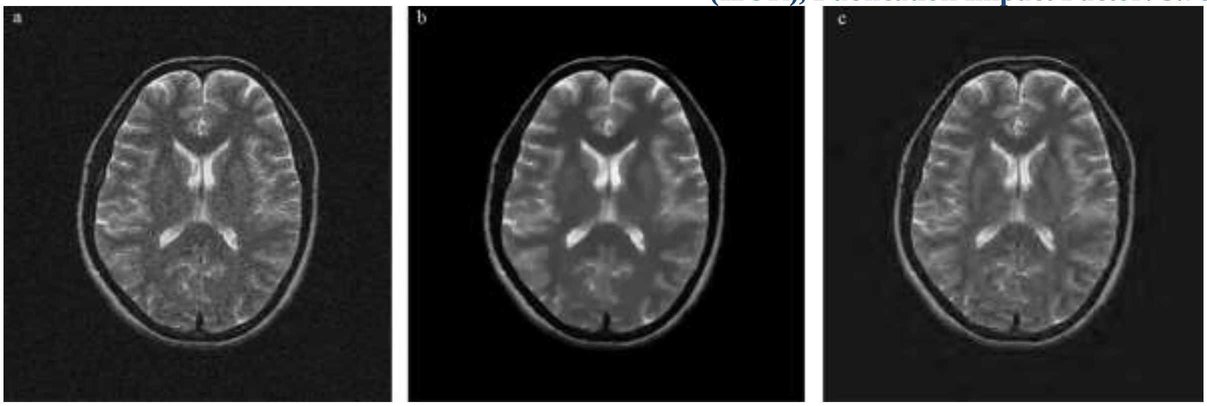

Fig.2 (a) Noisy MRI brain image with PSNR = 23.22dB (b) Wavelet de-noising with PSNR= 46.7dB and (c) Curvelet de-noising with PSNR = 49.5 dB.

According to the above results, curvelet de-noising promises better visual effect than wavelet de-noising method.

CONCLUSION

In this paper, the proposed method of image denoising with Curvelet transform brought better denoising effect and visual effects than that of method using Wavelet. Curvelet transform can accurately express very little edge using very less non-zero coefficient to guarantee the better ability of image representation than wavelet does on lower mean square error in the noisy environment.

REFERENCES

[1] Fourati W, Kammoun, F., Bouhlel, M.S.,“Medical image denoising using wavelet thresholding”, in Journal Of Testing And Evaluation, vol. 33, no. 5, 2005.
[2] Mulcahy C, “Image compression using the Haar wavelet transform, in Spelman Science And Mathematics Journal, vol. 1, pp.22-31,1997.
[3] Daubechies I,“Wavelet transforms and orthonormal wavelet bases, Different Perspectives on Wavelets”, in Proceedings of Symposia in Applied Mathematics, San Antonio, Tex, vol. 47, pp. 1–33. American Mathematical Society, Providence ,1993.
[4] Mallat S,“A theory for multiresolution signal decomposition: the wavelet representation”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 11, no.7, pp. 674–693, 1989.
[5] Rajpoot K., Rajpoot N,“Hyperspectral colon tissue cell classiffication, in Proceedings of the SPIE Medical Imaging”, 2004.
[6] Uzun I., Amira, A,“Design and FPGA Implementation of Finite Ridgelet Transform”, IEEE International Symposium on Circuits and Systems (ISCAS), vol. 6, pp. 5826–5829 ,2005.
[7] Alzu’bi, S, Amira A,“3D Medical Volume Segmentation Using Hybrid Multiresolution Statistical Approache”s.Advances in Artificial Intelligence, 2010, http://www.hindawi.com/journals/aai/2010/520427.html (accessed Online on: October 8, 2010).
[8] Boubchir L, Fadili JM,“Multivariate statistical modelling of images with the curvelettransform”, in Image processing group, GREYC UMR CNRS 6072, France, pp. 747–750 ,2005.
[9] CandesE, Demanet, L, Donoho D, Ying L,“Fast Discrete Curvelet Transform”, in Applied and Computational Mathematics, Caltech, Pasadena, CA, Department of Statistics, Stanford University, Stanford, CA , 2006.
[10] Do M.N., Vetterli M, “The finite ridgelet transform for image representation”, IEEE Transactions on. Image Processingvol.12, pp.16-28, 2003.
[11] Do M., Vetterli, M.,“Image denoising using orthonormal finite ridgelet transform”,in Proceedings of SPIE: Wavelet Applications in Signal and Image Processing, vol. 4119, pp. 831–842, 2003.