Applied Mechanics and Materials Vol. 103 (2012) pp 700-704
Online available since 2011/Sep/27 at www.scientific.net

doi:10.4028/www.scientific.net/AMM.103.700

An Improved Method for CT/MRI Image Fusion on Bandelets Transform Domain

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Keywords: Computed tomography, Magnetic resonance image, Wedgelets transform, Bandelets transform, Maximum local energy, Medical image processing, Social life.

Abstract. People living in the information age, are more and more attention to their own lives. It is also said, social life is more important in present and future. The social life contains three fields. In this paper, we will propose a new method for adjunctive therapy in social life. Recent years, as the bandelets transform has some benefits, many scholars are interested in this field. They proposed many methods to solve different problems in different fields. In this paper, we propose a new maximum local energy method to calculate the low coefficients of images. And then adopt the sum modified laplacian method to select the high coefficients of images. Later, we compare the results with wedgelets transform. In our experiments, we take wedgelets transform, bandelets transform, and LE-wedgelets transform for comparing the results. Beside the human vision, we also compare the results by quantitative analysis. The numerical experiments state clearly that the maximum local energy is an effect way for image fusion, which can get well performance in visual effect and quantitative analysis. During 100 clinic CT/MR fusion experiments in practice, compare with previous methods, the PSNR of our method is improved respectively 5.836, 5.337, 0.035.

Introduction

Imaging sensors are an important resource in today's world. Because of that a single sensor cannot provide a complete view of the scene in many applications. The result of fused images, if suitably obtained from a set of source sensor images, can get a better view of the sight than the view provided by any of the individual source images. In recent decades, there has been growing interest in the use of multiple sensors to increase the capabilities of intelligent machines and systems. As a result, multisensor fusion has become an area of intense research and development activity in the past few years.

A variety of image fusion techniques have been developed. Generally speaking, we can roughly divide them into two groups, multiscale decomposition based fusion methods such as pyramid algorithm [1], wavelet transform method [2], wedgelet transform [3],bandelet transform [4] etc., and nonmultiscale decomposition based fusion methods, for example, weighted average method, nonliner method, estimation theory based methods and so on.

The weighted average method is one of the most simple image fusion methods. The source images do not be transformed and decomposed and fused image directly averages the gray level of defocused images' pixels. This method is suitable for real-time processing, but will decrease the signal to noise ratio of the image. These are certified by some researchers. The pyramid method firstly constructs the input image pyramid, and then takes some feature selection approach to form the fusion value pyramid. By the inverter of the pyramid, the pyramid of image can be reconstructed, to produce fusion images. This method is relatively simple, but it also has some drawbacks. The themes of classical wavelets include terms such as compression and efficient representation. These features which play an important role in analysis of functions in two variables are dilation, translation, spatial and frequency localization and singularity orientation. However, classical wavelets have drawbacks in representing images, such as the problem of efficient representation in two dimensions. Recently, several theoretical papers have called attention to the benefits of Bandelets transform [5,6]. So this paper will introduce this method and propose a new method to apply in these transforms in CT/MRI images fusion.

We briefly introduce the structure of this paper. In Section 2, we primitively introduce the principle of Bandelets transform for image fusion. As a solution, we propose in Section 3 a new method --- Maximum Local Energy method in multi-focus images fusion. Numerical experiments are presented in Section 4 to confirm that our proposed method is useful for image fusion. At last, we conclude the paper in Section 5.

Bandelets Transform for Image Fusion

The Bandelets transform [5,7] are defined as anisotropic wavelets that are warped along the geometric flow, which is a vector field indicating the local direction of the regularity along edges. The dictionary of bandelet frames is constructed by using a dyadic square segmentation and parameterized geometric flows. The ability to exploit image geometry, makes its approximation error decay optimal asymptotically for piece-wise regular images.

For image surfaces, the geometry is not a collection of discontinuities, but rather areas of high curvature. The Bandelet transform recasts these areas of high curvature into an optimal estimation of regularity direction. Figure 1 shows an example of bandelets along the geometric flow in the direction of edges. In real applications, the geometry is estimated by searching for the regularity flow and then for a polynomial to describe that flow.

Let us suppose the image support is $S = \cup_i \Omega_i$. Ω_i is the region in depth i. In each Ω_i , the flow is either parallel horizontally or vertically. The image is devised as dynamic square regions, each region Ω_i includes only one contour. If the region does not contain any contour, the image intensity is uniformly regular and the flow is not defined.

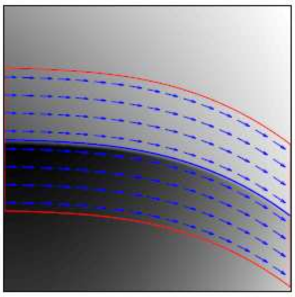

Fig. 1 An illustration of bandelets with geometric flows in the direction of the edge.

The Bandelet transform is first implement by reordering the two-dimensional Wavelet coefficients in multiscale analysis and then performing a one-dimensional wavelet transform in geometric directional analysis. In using Bandelets transform to process images, we suppose the image $f(x_1,x_2)$ is uniformly regular, C^α is α times continuously differentiable, the regions of an image are approximated in the separable wavelet basis of $L^2(\Omega)$ in

$$\begin{Bmatrix} \phi_{j,m_1}(x_1)\psi_{j,m_2}(x_2) \\ \psi_{j,m_1}(x_1)\phi_{j,m_2}(x_2) \\ \psi_{j,m_1}(x_1)\psi_{j,m_2}(x_2) \end{Bmatrix}_{(j,m_1,m_2)\in I_\Omega} \quad (1)$$

where I_Ω is an index set that depends upon the geometry of the boundary of Ω. x_1, x_2 are the location of pixel in the image. And $\phi_{j,m_1}(x_1)\psi_{j,m_2}(x_2), \psi_{j,m_1}(x_1)\phi_{j,m_2}(x_2), \psi_{j,m_1}(x_1)\psi_{j,m_2}(x_2)$ are the modified wavelets at the boundary. If a geometric flow is calculated in Ω, this suggests replacing the orthogonal family $\{\phi_{j,m_1}(x_1)\psi_{j,m_2}(x_2)\}_{j,m_1,m_2}$ by the family $\{\psi_{l,m_1}(x_1)\psi_{j,m_2}(x_2)\}_{j,l>j,m_1,m_2}$ which generates the same space. The functions $\{\psi_{l,m_1}(x_1)\psi_{j,m_2}(x_2)\}$ are called Bandelets because their support is parallel to the flow lines and is more elongated ($2^l>2^j$) in the direction of the geometric flow. The above expression (1) can be replaced by

$$\begin{Bmatrix} \psi_{l,m_1}(x_1)\psi_{j,m_2}(x_2-c(x_1)) \\ \psi_{j,m_1}(x_1)\phi_{j,m_2}(x_2-c(x_1)) \\ \psi_{j,m_1}(x_1)\psi_{j,m_2}(x_2-c(x_1)) \end{Bmatrix}_{j,l>j,m_1,m_2} \tag{2}$$

Since the flow is parallel vertically, a flow line associated to a fixed translation parameter x_2 is a set of point $(x_1, x_2+c(x_1)) \in \Omega$ for x_1 varying, with $c(x)=\int_{x_{\min}}^{x} c'(u)du$. l is the direction of geometric flow which is more elongated ($2^l>2^j$). The above function (2) is got by inserting Bandelets in the Warped Wavelet basis in

$$\begin{Bmatrix} \phi_{j,m_1}(x_1)\psi_{j,m_2}(x_2-c(x_1)) \\ \psi_{j,m_1}(x_1)\phi_{j,m_2}(x_2-c(x_1)) \\ \psi_{j,m_1}(x_1)\psi_{j,m_2}(x_2-c(x_1)) \end{Bmatrix}_{(j,m_1,m_2)\in I_{W\Omega}} \tag{3}$$

where $W\Omega$ is the warped region, $W\Omega=\{(x_1,x_2):(x_1,x_2+c(x_1))\in\Omega\}$.

Bandelets transform can adaptively track the geometric direction of the image. It also can process the different changes in different regions. It abandoned the concept of ``edge", which is not easy to define in mathematic. Instead of this, it adopted the concept of ``geometric flow" to reflect the continuous transformation in the image.

Image Fusion Algorithm

Bandelets transform based image fusion is completed primarily by the way that different type images are respectively bandelets transformed, and then according to certain criteria for selecting the appropriate low-frequency and high-frequency coefficients. And through Bandelet inverse transform, the two type images are fused as a clear, more information image. In this paper, we take the following steps; firstly, use Bandelets transform in two images to get the coefficients. After that, we process the coefficients of the low frequency and high frequency of these images, and fuse these images according to some fusion method. Finally, through inverse Bandelets transform, we get a clear image.

Principle of Low Frequency Fusion

This paper uses the maximum local energy (LE) [8,9] as a measurement in low frequency domain. Select the maximum energy of two source images as output. Due to the partial human visual perception characteristics and the relationship of decomposition about local correlation coefficients, the statistical characteristics of neighbor should be considered. Therefore, the statistic algorithm is based on the 3X3 window. The algorithm is described as follows:

$$\mathrm{LE}_\xi(i,j)=\sum_{i'\in M, j'\in N} p(i+i',j+j')\bullet f_\xi^{(0)2}(i+i',j+j') \quad . \tag{4}$$

where p is the local filtering operator. M, N is the scope of local window. $\xi\in A$ or B (A, B is the window for scanning two images) . $f_\xi^{(0)}(i,j)$ is low frequency coefficients.

Local bandelets energy (LBE) is

$$LBE_\xi^{l,k}(i,j)=E_1 * f_\xi^{(0)2}(i,j)+E_2 * f_\xi^{(0)2}(i,j)+\cdots+E_K * f_\xi^{(0)2}(i,j). \tag{5}$$

where $E_1,E_2,\ldots, E_{K-1}$ and E_K are the filter operators in K different directions.

Principle of High Frequency Fusion

Under the assumption that image details are contained in the high-frequency subbands in Multi-scale domain, the typical fusion rule is maximum-based rule, which selects high-frequency coefficients with maximum absolute value. Recently, there are many measurements, such as energy of gradient (EOG), spatial frequency (SF), Tenengrad, energy of laplace (EOL) and sum modified laplacian (SML). In this paper, we use SML for choosing the high frequency coefficients.

At the same time, a focus measure is defined in a maximum for the focused image. Therefore, for multifocus image fusion, the focused image areas of the source images must produce maximum focus measures. Set $f(x,y)$ be the gray level intensity of pixel (x,y). Defined modified Laplacian (ML) [9] [11] is

$$\begin{aligned}\nabla^2_{\mathrm{ML}} f(x,y) = &\left|2f(x,y) - f(x-\mathrm{step},y) - f(x+\mathrm{step},y)\right| \\ &+ \left|2f(x,y) - f(x,y-\mathrm{step}) - f(x,y+\mathrm{step})\right|\end{aligned} \tag{8}$$

In this paper "step" always equals to 1.

$$SML_x^{l,k}(i,j) = \sum_{i=-M}^{M}\sum_{j=-N}^{N} \nabla^2_{ML} f(i+p, j+q) \qquad for \ \ \nabla^2_{ML} f(i,j) \ge T \tag{9}$$

where, l, k respectively the scale and the direction of transform. $x \in A$ or B is respectively the source images. T is a discrimination threshold value. M,N determine the window with size of $(2M+1)\times(2N+1)$.

Suppose $C_A^{l,k}(i,j)$, $C_B^{l,k}(i,j)$ and $C_F^{l,k}(i,j)$ denote the coefficients of source images and fused images. The proposed SML-based fusion rule can be described as follows:

$$C_F^{l,k}(i,j) = \begin{cases} C_A^{l,k}(i,j), if: SML_A^{l,k}(i,j) \ge SML_B^{l,k}(i,j) \\ C_B^{l,k}(i,j), if: SML_A^{l,k}(i,j) < SML_B^{l,k}(i,j) \end{cases}. \tag{10}$$

Experimental Results and Discussion

In this section, we compare the LE-Bandelets transform with other methods. From the visual analysis, we can find that, the proposed method is better than other methods. Beside visual analysis, we compare the results in numerical analysis. The quantitative analysis result is shown in Table 1. We use the evaluation functions in [10,11] to measure our results.

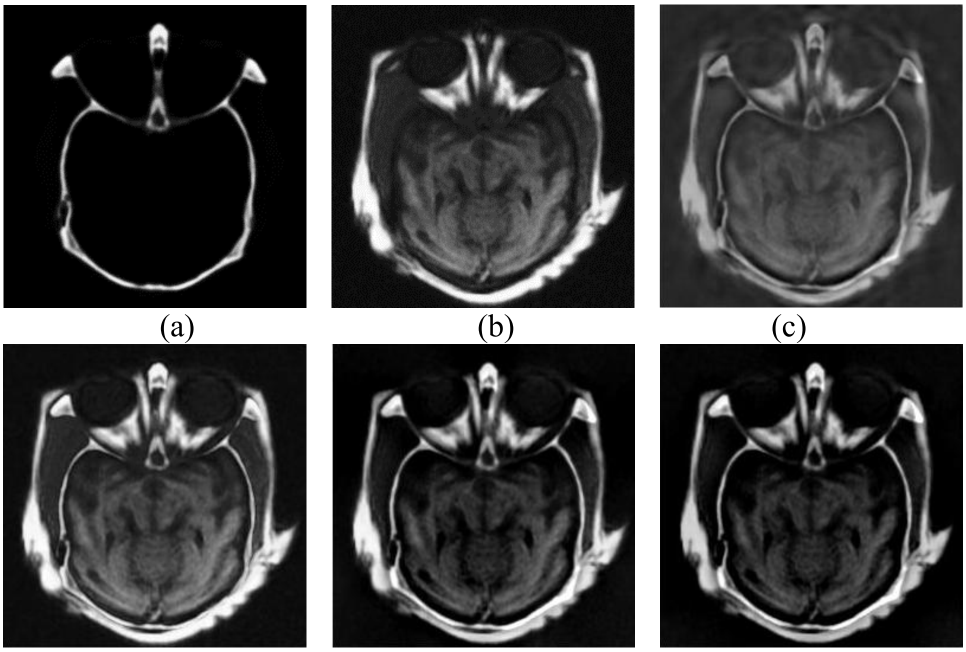

Fig.2 (a) CT image. (b) MR image. (c) Wedgelet transform fused image. (d) LE-Wedgelet transform fused image. (e) Bandelet transform fused image. (f) LE-Bandelet transform fused image.

Table 1 Quantitative analysis

Methods	Wedgelets	Bandelets	LE-Wedgelets	LE-Bandelets
PSNR	17.703	18.229	23.531	**23.566**
Q	0.8132	0.8876	0.9149	**0.9256**
Q_W	0.7903	0.8890	0.8789	**0.9187**
Q_E	0.5201	0.5303	0.6788	**0.6953**
SSIM	0.7015	0.6563	**0.8364**	0.5870
MS-SSIM	0.8237	0.9105	0.8398	**0.9406**

Conclusion

In this paper, we present Local Bandelets Energy fusion method, a new algorithm that gives the number of benefits for image fusion. From the above table, we can see that, in these experiments, maximum Local Energy (LE) improved the results of traditional methods. Meanwhile, LBE fusion method gives a best performance. We can conclude that LBE perform a better result. It is useful for medical image fusion.

There are several areas in which our method can be improved or extended. We currently consider improving the *LBE* method. In addition, we also plan to apply it in other beyond wavelet transforms in future.

References

[1] Z. M. Yu, F. Gao, Laplacian Pyramid and Contrast Pyramid Based Image Fusion and Their Performance Comparison, Application Research of Computers, vol.21, no.10, (2004) pp.96-98

[2] G. Pajares, J. M. Cruz, A Wavelet-based Image Fusion Tutorial, Pattern Recognition, vol.37, no,9, (2004) pp.1855-1872

[3] Donoho D. L, Huo X.M. Wedgelets: nearly-minimax estimation of edges, Annals of Statics, vol.27, no.3, (1999) pp.857-897

[4] E. Le Pennec and S. Mallat, Bandelet Image Approximation and Compression, IEEE Trans. Image Processing, vol.14, no.4, (2005) pp.423-438

[5] X. Qu, J. Yan, A Novel Image Fusion Algorithm based on Bandelet Transform, Chinese Optics Letters, vol.5, no.10, (2007) pp.569-572

[6] A. Maalouf, P. Carre, B. Augereau, Bandelet-based Anisotropic Diffusion, IEEE International Conference on Image Processing, San Antonio, TX (2007) pp.(I)289-292

[7] H. Biao, Z. Xia, J. Licheng, Second Generation Bandelet-domain Hidden Markov Tree-3S Model for SAR Image Segmentation, Journal of Infrared Millin Waves, vol.29, no.2, (2010) pp.145-149

[8] H. Lu, L. Zhang, S. Serikawa etc., Local Energy based Image Fusion in Sharp Frequency Localized Contourlet Transform, Journal of Computational Information Systems, vol.6, no.12, (2010) pp.3997-4005

[9] H. Lu, Y. Li, S. Serikawa etc., Local Energy based Multi-focus Image Fusion Method on Curvelet Transforms, IEEE 10th International Symposium on Communications and Information Technologies, (2010) pp.1154-1157

[10] P. Gemma, H. Heijmans, A New Quality Metric for Image Fusion, International Conference on Image Processing, vol.2, (2003) pp.(III)173-176

[11] Z. Wang, Q. Li, Information Content Weighting for Perceptual Image Quality Assessment, IEEE Trans. on Image Processing, accepted

Advances in Precision Instrumentation and Measurement
doi:10.4028/www.scientific.net/AMM.103

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doi:10.4028/www.scientific.net/AMM.103.700