A Maximum Local Energy Method for Multispectral Image Fusion in A Remote Sensing Management System

Lifeng Zhang, Yujie Li, *Huimin Lu, Akira Yamawaki, Shiyuan Yang and Seiichi Serikawa

Abstract

This paper presents an image fusion method suitable for Multispectral remote sensing image fusion, based on multi-resolution analysis in a remote sensing system. This method dedicates to fuse multispectral low-resolution remotely sensed images with a more highly resolved panchromatic image. The high-resolution regions of each remotely sensed image coefficients are extracted by beyond wavelet transform (BWT). BWT is a multi-resolution analysis, whose basis functions are directional edges with progressively increasing resolution. The advantage of BWT is well adapted to cured-singularities and point-singularities. There are two obvious virtues of this method. Firstly, directional detail coefficients matching image edges, which is better than that obtained in a separable wavelet domain. Secondly, selection strategy of maximum local energy (MLE) between low-frequency coefficients is more effective. Experiments are proved that the MLE is a new way for remotely sensed image fusion, which can get good performance. Fusion results in beyond wavelet transform are also compared.

*Corresponding Author: Huimin Lu
(E-mail: luhuimin@ieee.org)
[1]Dept. of Electrical Electronics and Engineering Kyushu Institute of Technology Kitakyushu, Japan

Keywords: Beyond wavelet transform; Maximum local energy; Image fusion; Contourlet transform; Curvelet transform; Bandelet transform; Wedgelet transform; Satellite remote sensing; Sum modified Laplacian

1. Introduction

3S technology is an important part in the science and technology of surveying engineering, and 3S technology is the GPS, GIS, and RS technology[1,2]. Remote sensing fusion methods are discussed in detail in this paper. Remote sensing methods [3] are usually used for processing the disaster management.

For the remote sensing system, due to the limited scope of imaging devices, it is difficult to display all of the goals clearly. This problem can be solved by an image fusion technology. That is, the same imaging lens are used on the targets twice or more, and imaging the clear part of these is fused into a new image in order to facilitate human observation or computer processing. 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, wavelet transform method et. al., and nonmultiscale decomposition based fusion methods,for example, weighted average method, nonliner method, estimation theory based methods and so on.

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. The pyramid method is relatively simple, but it also has some drawbacks. The themes of classical wavelets include terms such as compression and efficient representation. Using wavelet transform method, the image can be decomposed into a series of sub-band images with different resolution, frequency and direction characteristics. 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 beyond wavelets.

In this paper will introduce the above methods and propose a new method applied in these transforms in the “3S” technology systems. In Section II, we primitively introduce the principles of beyond transforms. As a solution, in Section III, we propose a new method, called The Maximum Local Energy method, for remote sensed image fusion. Numerical experiments are presented in Section IV to confirm the effectiveness of our proposed method for image fusion. Finally, our conclusion is presented in Section V.

2. Background of Beyond Wavelets

The themes of classical wavelets are compression and efficient representation. The important features in the analysis of functions in two variables are dilation, translation, spatial and frequency localization, and singularity orientation. Important singularities in one dimension are simply points. One-dimensional singularities are important in two-dimensional signal or higher. Smooth singularities in two-dimensional images often occur as boundaries of physical objects. Efficient representation in two dimensions is a hard problem. Therefore, we introduce beyond wavelets transform for solving these problems.

2.1 Wedgelet Transform

The multiscale wedgelet transform [4,5] is the first step towards explicitly capturing the geometric structure of images. There are two parts in the multiscale wedgelet framework: decomposition and representation. Each wedgelet by itself simply and succinctly represents a straight edge within a certain region of the image. Wedgelets can take a good approximation of singularities and simultaneously maintain the edge feature and smoothing of the homogeneous region.

2.2 Bandelet Transform

The bandelets transform [6–8] is defined as anisotropic wavelets that are warped along the geometric flow, which is a vector field indicating the local direction of the regularity along the edges. The dictionary of bandelet frames is constructed using dyadic square segmentation and parameterized geometric flows. The ability to exploit image geometry makes its approximation error decay optimal asymptotically for piecewise regular images. In image surfaces, the geometry is not a collection of discontinuities but areas of high curvature. The bandelet transform recasts these areas of high curvature into an optimal estimation of regularity direction. In real applications, the geometry is estimated by searching for the regularity flow and then for a polynomial to describe as flows.

2.3 Curvelet Transform

In the single scale ridgelet or local ridgelet transform [9], curvelets can be constructed to describe the singularity of the boundary with curved objects. Curvelet transform combines the beneficial abilities of ridgelet transform, which is good at expressing the line characteristic and wavelet transform, and has the advantage of expressing point features. In fact, this method is the multi-scale transformation of local ridgelet transform. Curvelet transform has the advantage of direction. Curvelet transform also has the exact reconstruction property and gives stable reconstruction under perturbations of the coefficients.

2.4 Contourlet Transform

Recently, Do and Vetterli [10,11] proposed an efficient directional multi-resolution image representation called contourlet transform. Contourlet is a “true” two-dimensional transform that can capture the intrinsic geometrical structure, and has been applied to several tasks in image processing. Contourlet transform better represents the salient features of the image such as, edges, lines, curves, and contours, than wavelet transform because of its anisotropy and directionality. Two steps are involved in contourlet transform, subband decomposition and the directional transform. Contourlet transform uses the Laplacian pyramid (LP) transform to decompose the image in multiscale form before adopting the directional filter banks (DFB) to decompose the high frequency coefficients and obtain details with different directions of the directional subband. Contourlet transform accurately expresses directions. However, because of the non-subsampled process in LP and DFB, it causes frequency aliasing, which creates larger changes in decomposition coefficient distribution with a small shift in the input image. However, if we fuse the decomposition coefficients, the process results in edge aliasing or the pseudo-Gibbs phenomena. Therefore, non-subsampled contourlet transform (NSCT) was created simply by turning the down sampler units in the subsampled contourlet by considering some aliasing issues [12].

3. Remote Sensed Image Fusion Rules

This paper demonstrates maximum local energy (MLE) [11,13,14] to measure a low frequency domain. The maximum energy of two source images was selected as an 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 statistical algorithm is based on the 3×3 window. The algorithm is described as follows:

$$\mathrm{LE}_{\xi}(i,j)=\sum_{i'\in M,\, j'\in N} p(i+i',j+j')\bullet f_{\xi}^{(0)2}(i+i',j+j') \qquad (1)$$

Where p is the local filtering operator. M and N are the scope of the local window. $\xi \in A$ or B (A and B are the window for scanning two images). $f_{\xi}^{(0)}(i,j)$ are the low frequency coefficients. Local beyond wavelet energy (LBE) is expressed as

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

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

$$E_1 = \begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix}, E_2 = \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix}, E_3 = \begin{bmatrix} -1 & 0 & -1 \\ 0 & 4 & 0 \\ -1 & 0 & -1 \end{bmatrix} \quad (3)$$

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

$$I_F^{l,k}(i,j) = \begin{cases} I_A^{l,k}(i,j), if : LCE_A^{l,k}(i,j) \geq LCE_B^{l,k}(i,j) \\ I_B^{l,k}(i,j), if : LCE_A^{l,k}(i,j) < LCE_B^{l,k}(i,j) \end{cases} \quad (4)$$

Assuming that the image details are contained in the high-frequency subbands in the multi-scale domain, the typical fusion rule is a maximum-based rule, which selects high-frequency coefficients with the maximum absolute value. Recently, measurements such as energy of gradient (EOG), spatial frequency (SF), Tenengrad, energy of Laplace (EOL), and sum modified Laplacian (SML) have been used. In this paper, and we use SML to choose the high frequency coefficients.

A focus measure is defined in a maximum for the focused image. Therefore, for multifocal image fusion, the focused image areas of the source images must produce maximum focus measures. Set $f(x,y)$ as the gray level intensity of pixel (x,y). Modified Laplacian (ML) [8] is defined as follows:

$$\nabla_{ML}^2 f(x,y) = |2f(x,y) - f(x-step,y) - f(x+step,y)| + |2f(x,y) - f(x,y-step) - f(x,y+step)|. \quad (5)$$

In this paper, “step” is always equals to 1.

$$SML_x^{l,k}(i,j) = \sum_{i=-M}^{M} \sum_{j=-N}^{N} \nabla_{ML}^2 f(i+p, j+q), \quad for\, \nabla_{ML}^2 f(i,j) \geq T \quad (6)$$

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

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

$$C_F^{l,k}(i,j) = \begin{cases} C_A^{l,k}(i,j), if : SML_A^{l,k}(i,j) \geq SML_B^{l,k}(i,j) \\ C_B^{l,k}(i,j), if : SML_A^{l,k}(i,j) < SML_B^{l,k}(i,j) \end{cases} \quad (7)$$

4. Experiments and Discussions

The proposed modified sharp frequency localized energy beyond wavelet transform-based fusion has been assessed on the high-resolution image datasets collected by IKONOS. The second data set is the urban of Nakornprathom by IKONOS-2 satellite, in Thailand. The Multi-spectral of sensor in the satellite are: blue (455-520µm), green (510-600µm), red (630-700µm), NIR (760-850µm). The pixel resolution of MS image is 4 m, and pixel resolution of Pan image is 1 m.

Table 1 reports the 1m IKONOS-2 Pan image and 4m IKONOS-2 MS image fusion qualities. For h/l=1/4 IKONOS-2 Pan image and IKONOS-2 MS image fusion, WT and CT, yield better average CCs than that of other methods. However, CCs between fused MS and reference originals may be valid detectors of fusion artifacts; the parameters with global distortion of pixel vectors also adopted in this work, such as Q4, ERGAS, MS-SSIM, will give a more comprehensive measure of quality. From Table 1 we can see that the Q4, SSIM, and MS-SSIM values of MLE-SML-Contourlet Transform and MLE-SML-Bandelet Transform are higher than the others. In multi-resolution analysis, the ERGAS value of both are higher than MLE-SML-Wedgelet Transform and MLE-SML-Curvelet Transform. From the Figure 1, the details of the MLE-SML-Contourlet Transform and MLE-SML-Bandelet Transform fused images are obvious clearly than the other methods.

In Reference [15], a multi-scale SSIM method for image quality assessment is proposed. Input to signal A and B, and let μ_A, σ_A and σ_{AB} respectively as the mean of A, the variance of A, the covariance of A and B. The parameters of relative importance α, β, γ are equal to 1. The SSIM is given as follow:

$$SSIM(\mathrm{x},\mathrm{y}) = \frac{(2\mu_A\mu_B + C_1)(2\sigma_{AB} + C_2)}{(\mu_A^2 + \mu_B^2 + C_1)(\mu_A^2 + \mu_B^2 + C_2)} \tag{8}$$

Where C_1, C_2 are small constants. The overall multi-scale SSIM (MS-SSIM) evaluation at the *j-th* scale with Scale M is obtained by

$$\text{MS-SSIM}(A,\mathrm{B}) = [l_M(A,B)]^{\alpha M} \cdot \prod_{j=1}^{M} [c_j(A,B)]^{\beta j} [s_j(A,B)]^{\gamma j} \tag{9}$$

Where $l(A,B)$, $c(A,B)$, $s(A,B)$ are the luminance, contrast and structure comparison measures, respectively.

An image quality index for MS images having four spectral bands was proposed [16] for assessing Pan-sharpening methods. The quality index Q4 is a generalization to 4-band images of the Q index. The Q4 is defined as

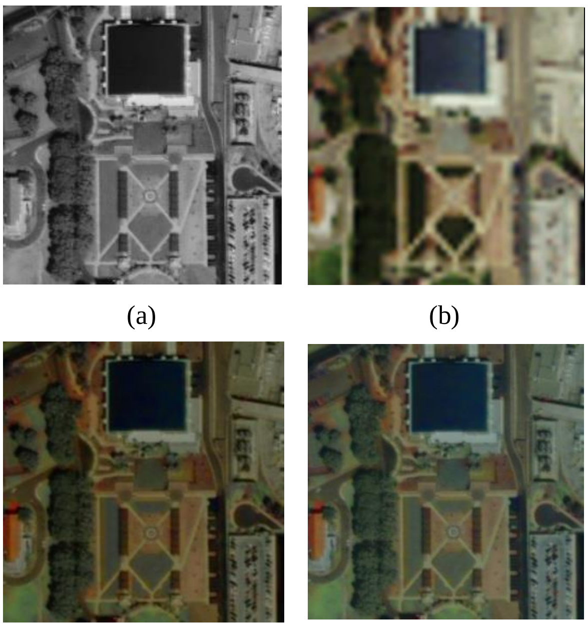
$$Q4_N = \left\{ \frac{\sigma_{AB}}{\sigma_A \cdot \sigma_B} \cdot \frac{2\sigma_A \cdot \sigma_B}{\sigma_A^2 + \sigma_B^2} \cdot \frac{2|\bar{A}| \cdot |\bar{B}|}{|\bar{A}|^2 + |\bar{B}|^2} \right\}_{N \times N} \tag{10}$$

Where, the first term is the modulus of the hyper complex correlation coefficients (CCs) between the two spectral pixel vectors, and is sensitive both to loss of correlation and to spectral distortion between the two MS data sets. The second and third terms respectively measure contrast changes and mean bias on all bands simultaneously. All statistics are calculated as averages on $N \times N$ blocks, here, $N = 32$. The highest value of Q4, attained if and only if the test MS image is equal to the reference, is 1; the lowest value is 0.

Wald et al. [17] proposed the relative dimensionless global error in synthesis (ERGAS) in 1997. It is given by

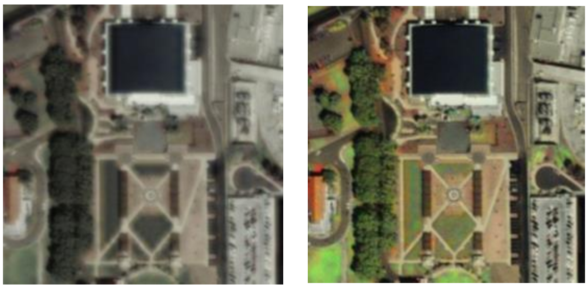
$$ERGAS = 100\frac{h}{l}\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\frac{RMSE(k)}{\mu(k)}\right)} \tag{11}$$

Where h/l is the high/low resolution images ratio (here, is the ratio between pixel sizes of Pan and MS). $\mu(k)$ is the mean (average) of the *k-th* band, and K is the number of bands.



(a) (b)

(c) (d)



(e) (f)

Figure 1: Detail of fused IKONOS-2 Pan image (512×512) and MS image (512×512). (a) Pan image. (b) Resampled MS image. (c) SML-Wedgelet Transform fusion. (d) MLE-SML-Bandelet Transform fusion. (e) MLE-SML-Curvelet Transform fusion. (f) MLE-SML-Contourlet Transform fusion.

5. Conclusions

Remote sensing data and analysis techniques are now providing detailed information for detecting and monitoring changes in natural environment and climate. In this paper, we firstly considered the maximum local energy (MLE) method for remote sensed multispectral image fusion in a remote sensing management system. The fused images are best processed through MLE-SML-Contourlet Transform and MLE-SML-Bandelet Transform for remote sensing images. Therefore, MLE-SML-Contourlet Transform and MLE-SML-Bandelet Transform are superior for processing remote sensed images.

Table 1: The Average Quality Assessments of IKONOS-2 Pan Image and MS Image Fusion

	Methods			
	MLE-SML-WT	***MLE-SML-BT***	***MLE-SML-CT***	***MLE-SML-CoT***
CCs	0.7817	0.9011	0.8591	0.8295
Q4	0.7918	0.8839	0.8517	0.8991
ERGAS	6.6639	9.0645	7.4278	9.1848
SSIM	0.6827	0.6582	0.6246	0.6641
MS-SSIM	0.7596	0.7914	0.7543	0.7800

The value in the above table is average value.

References

[1]. Z.J. Wang, D. Ziou, C. Armenakis, D. Li, Q.Q. Li, A Comparative Analysis of Image Fusion Methods, IEEE Trans. on Geoscience and Remote Sensing[J], 2005, vol.43(6), pp 1391-1402.

[2]. J. Nunez, X. Otazu, O. Fors, A. Prades, V. Pala, R. Arbiol, Multiresolution-based Image Fusion With Additive Wavelet Decomposition, IEEE Trans. on Geoscience and Remote Sensing[J], 1999, vol.37(3), pp 1204-1211.

[3]. Q. Weng, Advances in Environmental Remote Sensing:Sensors, Algorithms, and Applications[M], CRC Press, USA, 2011.

[4]. D.L. Donoho, X.M Huo, Wedgelets: nearly-minimax estimation of edges, Annals of Statistics [J], 1999, vol.27(4), pp 857-897.

[5]. L. Demaret, F. Friedrich and H. Fuehr, A Quick guide to wedgelets, GSF Research Center for Environment and Health, 2005.

[6]. E. Le Pennec and S. Mallat, Bandelet Image Approximation and Compression, Multiscale Modeling & Simulation [J], 2005, vol.4(3), pp 992-1039.

[7]. E. Le Pennec and S. Mallat, Sparse Geometric Image Representations with Bandelets, IEEE Trans. Image Processing [J], 2005.4, vol.4, pp 423-438.

[8]. A. Maalouf, P. Carre, B. Augereau etc, Bandeletbased Anisotropic Diffusion, IEEE Inter. Conf. on Imag. Proc.[C], 2007, PP:(I)289-292.

[9]. E.J. Candes and D.L. Donoho, Curvelets: A surprisingly effective nonadaptive representation for objects with edges, Curve and Surface Fitting, TN: Vanderbilt Univ. Press, 1999.

[10]. M.N.Do and M.Vetterli, The contourlet transform: an efficient directional multiresolution image representation, IEEE Trans. Image Processing [J], 2005.12, vol.14(12), pp 1-16.

[11]. H.M. Lu, X.L. Hu, L.F. Zhang, S.Y. Yang, S. Serikawa, Local Energy based Image Fusion in Sharp Frequency Localized Contourlet Transform, Jourl. of Comp. Infor. Sys. [J], 2010, vol.6(12), pp 3997-4005.

[12]. R.G. Baraniuk, N. Kingsbury and I.W.Selesnick, The dual-tree complex wavelet transform- a coherent framework for multiscale signal and image processing, IEEE S.P. Mag. [J],2005, pp 123-151.

[13]. X.L. Hu, H.M. Lu, L.F. Zhang, S. Serikawa. A new type of multi-focus image fusion method based on curvelet transform. ICECE2010[C], 2010, pp 172-175.

[14]. H.M. Lu, Y.J. Li, and S. Serikawa et. al, An Improved Method for CT/MRI Image Fusion on Bandelets Transform Domain, Applied Mechanics and Materials [J],vol.103, 2012, pp 700-704.

[15]. Z. Wang, Q. Li, Information Content Weighting for Perceptual Image Quality Assessment, IEEE Trans. on Image Processing[J], vol.20, no.5, 2011, pp 1185-1198.

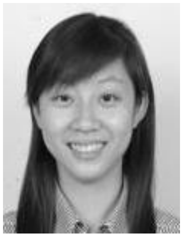
[16]. L. Alparone, S. Baronti, A. Nencini, A Global Quality Measurement of Pan-Sharpened Multispectral Imagery, IEEE Trans on Geo & Remote Sensing Letters[J], vol.1. 2004, pp 313-317.

[17]. L. Wald, T. Ranchin, M. Mangolini, Fusion of Satellite Images of Different Spatial Resolutions: Assessing the Quality of Resulting Images, Photogramm. Eng. Remote Sensing[J], vol.63, 1997, pp 691-699.

[18]. H. Y. Hwang, S-W. Cheong, P. G. Radaelli, M. Marezio, and B. Batlogg, “Lattice effects on the magnetoresistance in doped LaMnO3,” Physical Review B, vol. 33, pp. 914-917, July 1995.

[19]. J. M. De Teresa, K. Dörr, K. H. Müller, L. Schultz, and R. I. Chakalova, “Strong influence of the Mn3+ content on the binding energy of the lattice polarons in manganese perovskites,” Physical Review B, vol. 76, pp. R59928, September 1998.

Huimin Lu received the B.S. degree in Electronics Information Science and Technology from Yangzhou University, China, in 2008. And he received M.S. degrees in Electrical Engineering from Kyushu Institute of Technology and Yangzhou University in 2011, respectively. Recently, he is a Ph.D student in Kyushu Institute of Technology. His current research interests include computer vision, image fusion, deep-sea signal processing.



Yujie Li received the B.S. degree in Computer Science and Technology from Yangzhou University in 2009. And she currently is a double M.S. degrees student in Electrical Engineering in Kyushu Institute of Technology and Yangzhou University. Her research interests include computer vision, data mining, and image segmentation.

Lifeng Zhang received the B.S. degree in Electronic Engineering from Southeast University, China, in 1994. And he received M.S. and Ph.D. degrees in Electrical Engineering from Kyushu Institute of Technology, in 1999 and 2001, respectively. Recently, he is an assistant Professor in Kyushu Institute of Technology. His current research interests include computer vision, image processing, and communication.

Seiichi Serikawa received the B.S. and M.S. degrees in Electronic Engineering from Kumamoto University, Japan in 1984 and 1986. He received the Ph.D. degree in Electronic Engineering from Kyushu Institute of Technology, in 1994. Science 2004, he has been a Professor at the Kyushu Institute of Technology. Recently, he is a Vice President of School of Engineering in Kyushu Institute of Technology. His current research interests include computer vision, sensors, and robotics