A New EPMA Image Fusion Algorithm based on Contourlet-lifting Wavelet Transform and Regional Variance

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***Abstract*—Combined with image processes under microbeam analysis,and based on analyzing the feature of electron probe deeply,the paper presents an optimized method based on Contourlet-lifting wavelet transform and regional variance.firstly,to get the fused image before Contourlet fusion based on regional variance,and then the processing image and the target image will be fused under lifting wavelet transform based on regional variance,finally get the fusion result. The experiment shows that,the processed multi-source electron probe image is much more comprehensive and accurate than any other single source image,and it will facilitate further processing and analyzing images such as micro-surface target recognition and impurity extraction**

***Index Terms*—image fusion, Contourlet transform, lifting wavelet transform, regional variance, Electron probe analysis**

I. Introduction

Electron probe uses high-speed micro-electron beam to bombard the sample surface, appropriate detection system and information processing system are also used to collect and process samples excited by the X-ray、the secondary electron, backscattered electron,etc, it is not only a large precision instruments with micro-area qualitative and chemical composition as well as microstructure characteristics of all inorganic solid materials, but also can analyze samples, surface and morphology, moreover, morphology images and the corresponding element distribution images can be accessed at the same time in the micro-area, this is the so-called EPMA images,which has been widely used in geology, metallurgy, materials, environment 、ceramic、chemical, semiconductor, machinery, nuclear physics and other fields, even in the criminal investigation. In the morphological analysis, such as minerals, primarily to understand its morphology and crystallization characteristics in order to name for minerals and provide evidence for confirming minerals' structure.

At present, the electronic probe system is equipped with image processing software, mainly for single-image processing, including image histogram processing, grain-size analysis, distance measurement, binary analysis and pseudo-color processing and other functions, for other additional features such as graphics software is relatively small , Li Jing-ming, etc. has made some study on scanning electron microscope image processing, while even mentioned little for the sample morphology of multi-image fusion. Based on analyzing the characteristics of EMPA, combined with Contourlet new wavelet technology, this paper focused on multi-source image fusion method of EMPA, which has provided a new channel for broadening the application of electron probe field and optimization of the image analysis results.

II. EPMA Image Analysis

(1) What is Electron probe micro-analyzer (EPMA)

Electron probe micro-analyzer[1] is a microbeam instrument used primarily for the in situ non-destructive chemical analysis of minute solid samples. EPMA[1] is also informally called an electron microprobe, or just probe. It is fundamentally the same as an SEM, with the capability of chemical analysis. The primary importance of an EPMA is the ability to acquire precise, quantitative elemental analyses at very small "spot" sizes (as little as 1-2 microns), primarily by wavelength-dispersive spectroscopy (WDS). The spatial scale of analysis, combined with the ability to create detailed images of the sample, makes it possible to analyze geological materials in situ and to resolve complex chemical variation within single phases (in geology, mostly glasses and minerals). The electron optics of an SEM or EPMA allow much

Supported by the grant from Scientific research plan projects of JiangXi Education Department(No.2007233) and Key Laboratory of Nuclear Resources and Environment (East China Institute of Technology) of Ministry of Education of China(No. 081216).

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doi:10.4304/jsw.5.11.1200-1207

higher resolution images to be obtained than can be seen using visible-light optics, so features that are irresolvable under a light microscope can be readily imaged to study detailed microtextures or provide the fine-scale context of an individual spot analysis. A variety of detectors[1-4] can be used for:

a)imaging modes such as secondary-electron imaging (SEI), back-scattered electron imaging (BSE), and cathodoluminescence imaging (CL).

b)acquiring 2D element maps.

c)acquiring compositional information by energy-dispersive spectroscopy (EDS) and wavelength-dispersive spectroscopy (WDS).

d)analyzing crystal-lattice preferred orientations (EBSD).

(2) Fundamental Principles of Electron probe micro-analyzer

When the high-speed electron beam focused incident on the sample, incident electron interact with sample's extranuclear electron atoms. Through a series of elastic scattering and inelastic scattering, large-angle scattering or multiple small-angle scattering occurs in these electrons. When the total scattering angle is more than 90 degrees, these electrons are likely to be reflected out of the incident surface again, these reflected electron are called backscattered electrons. Broadly speaking, secondary electrons are also part of the scope of backscattered electrons ; however, backscattered electron has a higher energy, while secondary electron's energy is much lower. We usually call the electrons whose energy is higher than 50ev as the back-scattered electron ,otherwise called the secondary electron.

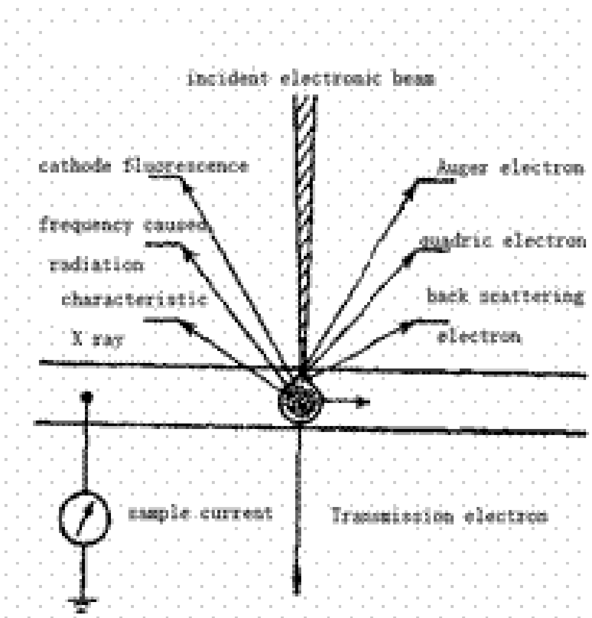


Figure 1. The main information of sample under the electronic beam bombard

(3) Image fundamental of Electron probe micro-analyzer[4]

Usually the number of backscattered electrons increases with the atomic number of samples. Therefore, under the same conditions, different substances will produce different number of backscattered electrons. Therefore, the use of backscattered electron detector can be qualitative distinction among different substances. In addition, backscattered electron is also related to electron beam incident angles and sample surface morphology. Therefore, apart from ingredients information, backscattered electron can also give the sample surface morphology information. Kimoto and Hashimoto (1969) have designed a method to separate component information and shape information. They put two electronic detectors symmetrical configuration on both sides of the incident electron beam; allow the atomic number information in both detectors that have the same size and polarity; but for the surface topography information, the value of the same size, polarity detectors are opposite. Therefore, we use electro-optical to add the information obtained by the two detectors, and then get a composition of samples (average atomic number) information, through CT Scan imaging, we can get the COMP images (back scattered electron image); If subtract the two signals, then obtained information on the sample surface morphology, through CT Scan imaging, we can get the TOPO images, which can reflect the spatial morphology of the sample information, however, there is no SEI high-resolution.

The secondary electrons are reflected back from the specimen surface, its energy is below 50eV. The formation process is like this:when the incident electron atoms interact with the sample atoms, the transfer of energy between incident electron and atom extranuclear electron (mostly valence electrons) occurs (typically a few to several tens eV), if the extranuclear electron energy is greater than the ionization energy, then the electron may be free electrons, if free electrons is very close to the sample surface, and the energy is greater than the corresponding work function, it may escape from the sample surface, and become the secondary electrons. Because the energy of secondary electron is low, only secondary electron with surface of 100 Egyptian is possible to be detected, so secondary electron image (SEI) has a high spatial resolution.

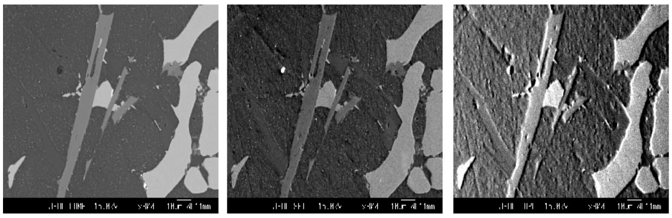


Figure 2:BSE 、SEI and TOPO image of same sample(has been registrated)

III. THE PROCESS OF EPMA FUSION WTH CONTOURLET-LIFTING WAVELET AND REGIONAL VARIANCE

A. The foundation of Contourlet transform

Contourlet[5] is a geometric transform, it will separately analyze multi-scale analysis and direction analysis,which can effectively express the contour and texture-rich images. With "long strip "structure changed by scale, it can effectively track line singularity and surface singularity of image.

Contourlet transform[5,6] uses double filter structure, first use Laplace Pyramid(LP)decomposition to multi-scale decomposite the input image in order to capture singularity points, after each LF decomposition low frequency sub band with half resolution and high frequency sub band with same resolution can be obtained,this high-frequency sub-bands are different signals after sub-sampling between the original image and low-frequency sub bands, continue to iterate using low-frequency sub-band LP decomposition transform, then the original image can be decomposed into a series of different scales of low-frequency and high frequency sub-band,subsequently, the directional filter bank(DFB) is used to carry out directional analysis for high frequency sub band after LP decomposition. The role of FB is to capture the directional high-frequency information,and integrate the singular points that distribute in the same direction into one coefficient,during calculation, use tree-structured decomposition, fan type filter (QFB) is used in each layer to segmentate frequency in the direction of fan type,followed by re-sampling operation with the appropriate combination of rotation in order to realize high frequency direction analysis.

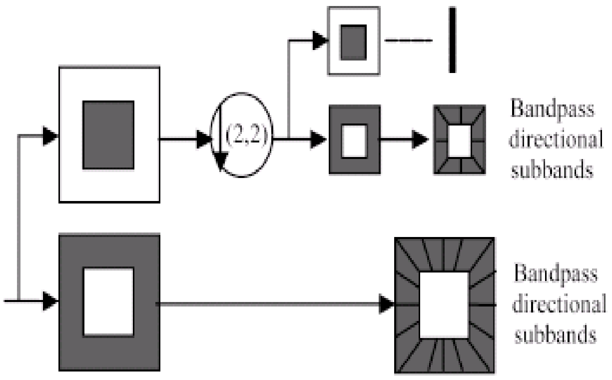


Figure 3. Contourlet decomposition schematic diagram

Contourlet is an image geometry transformation, the multi-scale decomposition and the directional decomposition are two independent processes which will effectively express the contours and texture-rich of images. They have "long strip" structure that aspect ratios have changed with the scale in the elongated supports, Contourlet can effectively track the characteristics of linear discontinuities and area discontinuities in the image. Compared with wavelet, contourlet has a rich basic function which can describe the smooth edges using less transform coefficients, and can turn the point discontinuities which have the same direction together into a linear or area discontinuities.(see Figure 4)

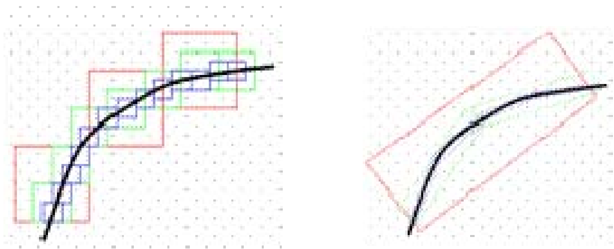


Figure.4 The comparison schematic of basic function

Compared with wavelet, Contourlet has better characteristics as follows[12,16]:

(1) more flexible multi-scale description. Its uniqueness is to use direction filter groups to decomposite bandpass image after LP transform into specific numbers of direction sub-bands, which can extract the distribution of the direction of the image texture . The direction sub band after Contourlet can more specifically reflect the the contour and marginal distribution, compared with wavelet transform sub-band ,the texture direction and distribution are clearly defined. Meanwhile, in the Contourlet transform sub-band , the singular points in the sub band also represent the important characteristics of the image. The image texture features and important factors after Contourlet transform can be extracted.

(2) After Contourlet decomposition, the coefficients are approximately correlation. Energy is concentrated in the direction of the various scales of the texture and edge sub-band,meanwhile coefficients variation is associated with large coefficients. So the distribution of sub-band coefficients of Contourlet is non-linear.

B. The foundation of lifting wavelet transform

In 1995, Swedens[15] proposed a spatial-based wavelet constructor --- lifting scheme, which not only maintains the original features of wavelet, but also overcomes limits cased by translational invariance . Wavelet lifting scheme can realize rapid wavelet algorithm which can be transformed in the current location.

Lifting wavelet decomposition process[15] is divided into split, predict and update:

(1) split: Split the original signal sj into two disjoint subsets which is sj-1, and dj-1 , usually sj-1 is low-frequency approximation component, while dj-1 is the high-frequency details of components. Generally the signal sequence is divided into even and odd sequences, namely: split (sj) = (sj-1, dj-1);

(2) prediction: Based on original data correlation, use even-numbered sequence sj-1 to predict (or interpolation) odd-numbered sequence dj-1, that is, filter p after process even-numbered signals, the residual signal can be obtained by subtracting odd signal's pratical value and predit value. Actually the subset dj-1 can not be accurately predicted from subset sj-1, but P (sj-1) may be very close to dj-1, so you can use the difference of P (sj-1) and dj-1 to replace the original dj-1, it would result in the present dj-1 is less than the original dj-1, so be dj-1 = dj-1 - P (sj-1). Here,we can already use a smaller subset of sj-1 and dj-1 to replace the original signal set sj. Repeat the

process of decomposition and prediction, after n steps the original signal set can be represented by (sn, dn, ··· , s1, d1);

(3) Update: Some of overall nature (such as mean) and the raw data of subset sj-1 after decomposition steps is not same as before , so an update process is needed. a better sub-data sets sj-1 is generated through the operator U, so as to maintain the original data set sj. The update process expression is like this: sj-1 = sj-1 + U (dj-1).

From the above we can see that lifting scheme can realize situ operations, that is, the algorithm does not require data except enhancing steps, therefore,the new data streams can replace old data streams. When situ upgrading filter group is reused, obtained the intertwined wavelet coefficients are obtained.

Reconstruction is the reverse process of of analysis, the whole process of lifting wavelet are as follows:

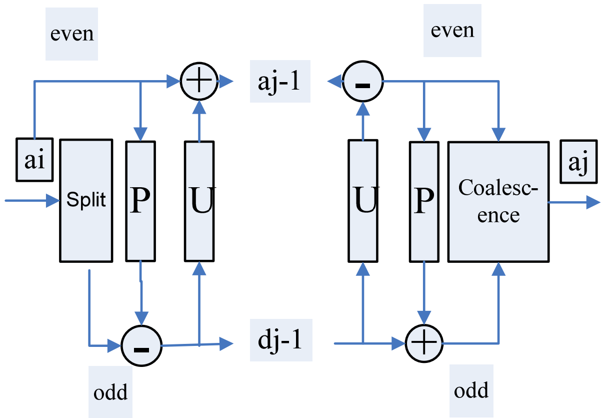


Figure 4.Construction and decomposition of lifting wavelet transform

Contourlet[5-11] inherited the multi-resolution and time-frequency localization properties of wavelet , as well as both good direction and anisotropy and more sparse for the natural images, brought Contourlet into image fusion, which can better extract the geometric features of the original image, provide more information for fusion images, while the lifting wavelet image fusion has advantage in raising the standard deviation, but Contourlet transform has better effect in enhancing information entropy, which can make the image fusion retain more information, because of this, this paper presents Contourlet transform algorithm, the realization of these statements is as follows:

(1) Contourlet decomposition[7]: Contourlet transform for the source image A and B that has registrated accurately in order to get the correlated Contourlet coefficients set, make 3 or 4 decomposition steps.

(2) image fusion: As for the low frequency and high frequency sub-band after decomposition, utilize regional variance-based fusion rule to distinguish in order to get Contourlet coefficients of multi-scale.

(3)Contourlet reconstruction[7]: Reconstruction is the reverse process of of decomposition, make reverse transform for the coefficients after fusion to get fusion image, which can contain more information of source images.

(4) Lifting wavelet decomposition[15]: We have to set image C as the clearer and contains more information of source image A and B, one-dimensional transformation of C along the row direction after Contourlet reconstruction to get approximation coefficient matrix and the details of the coefficient matrix; and then one-dimensional lifting transformation along the column direction respectively after decomposition of the approximation and details of the coefficient matrix to get three high-frequency coefficient matrix and a low-frequency coefficient matrix, so that complete a layer of the image wavelet decomposition. Repeat the decomposition process of low-frequency coefficient matrix, five levels of wavelet decomposite for image.

(5) image fusion: fusion for each decomposition level, utilize regional variance-based fusion rule to process different frequency component.

(6)lifting wavelet reconstruction[15]: reverse transform for the coefficients matrix to get output image.

The specific fusion algorithm frame is as follows:

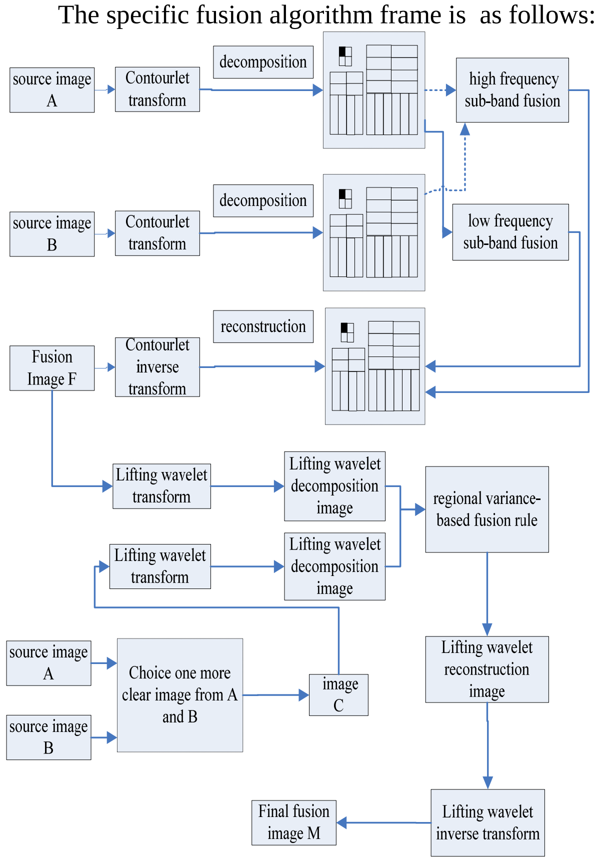


Figure 5.The frame of Contourlet-lifting wavelet transform and regional variance

C. the design of fusion rule

Concerning fusion rules, regional-based fusion rules is used[17]. For the high-frequency sub-band coefficients, under the maximum decomposition scale L, using local inner product to fuse ; For the decomposition of L other than the high-frequency coefficients of scale L-1 layer, according to Gauss-Laplace edge detection operator to calculate the edge information as a partial fusion rules and fuse the high frequency sub-band based on the similarity of two complementary images

(1) the fusion algorithm based on regional edge information in high frequency sub-band is as follows:

①calculate the matching parameters $m_{j,AB}^{\lambda}$ of two source image A and B:

$$m_{j,AB}^{\lambda}(m,n)=\frac{2\sum_{m'=-2}^{2}\sum_{n'=-2}^{2}d_{j,A}^{\lambda}(m+m',n+n')d_{j,B}^{\lambda}(m+m',n+n')}{\sum_{m'=-2}^{2}\sum_{n'=-2}^{2}d_{j,A}^{\lambda}((m+m',n+n'))^{2}d_{j,B}^{\lambda}(m+m',n+n'))^{2}}$$

$d_{j,F}^{\lambda}$

Where $\lambda = 1,2,3, d_{j,A}^{\lambda}(m+m',n+n')$ $d_{j,B}^{\lambda}(m+m',n+n')$ are the coefficient amplitudes of 3 high frequency sub-bands of two source images in 5×5 neighborhood of (m,n) when the resolution is 2j.

② Fusion operator determination. First define a matching threshold β,if $m_{j,AB}^{\lambda}<\beta$,it means the source image A and B are not all that similar, then the high frequency coefficients amplitude $d_{j,F}^{\lambda}$ are as follows:

$d_{j.F}^{\lambda} = d_{j.A}^{\lambda}$, if $E_{j.A}^{\lambda} \geq E_{j.B}^{\lambda}$

$d_{j.F}^{\lambda} = d_{i.B}^{\lambda}$, if $E_{j.A}^{\lambda} < E_{j.B}^{\lambda}$

Where E_j^{λ} is 3 Gause-Laplacian edgecoefficients under scale j, that is:

$$E_j^{\lambda} = \sum_{m'=-2}^{2}\sum_{n'=-2}^{2} W(m',n')d_j^{\lambda}(m+m',n+n')$$

Where $W(m',n')$ is Gause-Laplacian template coefficient, the template is 5×5 matrix:

$$W(m',n')=\begin{bmatrix} -2 & -4 & -4 & -4 & -2 \\ -4 & 0 & 8 & 0 & -4 \\ -4 & 8 & 24 & 8 & -4 \\ -4 & 0 & 8 & 0 & -4 \\ -2 & -4 & -4 & -4 & -2 \end{bmatrix}$$

If $m_{j,AB}^{\lambda} \geqslant \beta$, It means the similarity of A and B is high, then the high frequency coefficients amplitude $d_{j,F}^{\lambda}$ are as follows:

$$\left.\begin{array}{l} d_{j.F}^{\lambda} = \phi_{j.\max}^{\lambda} d_{j.A}^{\lambda} + \phi_{j.\min}^{\lambda} d_{j.B}^{\lambda}, \text{当 } E_{j.A}^{\lambda} \geqslant E_{j.B}^{\lambda}, \\ d_{j.F}^{\lambda} = \phi_{j.\min}^{\lambda} d_{j.A}^{\lambda} + \phi_{j.\max}^{\lambda} d_{j.B}^{\lambda}, \text{当 } E_{j.A}^{\lambda} < E_{j.B}^{\lambda}. \end{array}\right\}$$

$$\phi_{j.\min}^{\lambda} = \frac{1}{2} - \frac{1}{2}\left(\frac{1-m_{j.AB}^{\lambda}}{1-\beta}\right),$$

$$\phi_{j.\max}^{\lambda} = 1 - \phi_{j.\min}^{\lambda}, \lambda = 1,2,3.$$

(2) Low frequency sub band fusion rule

The image's low-frequency components contains more energy that determines the outline of the image. Concerning the selection of low-frequency sub-band coefficients, generally use the average method that can effectively suppress noise, but also reduce the contrast of the image to a certain extent, so that some useful information is lost. In order to select appropriate low-frequency sub-band coefficients, and inhibit the impact of noise on the convergence, this paper presents a regional variance-based coefficient scheme.

Suppose C(X) represents for coefficients matrix of low-frequency components of image X, p = (m, n) is low-frequency coefficients of spatial location, then C (X, p) is the value of low-frequency component coefficient matrix labeled (m, n) element, first use weighted variance with a point p as the center of the small area within Q to indicate regional variance, u (X, p) is the average value of low-frequency coefficient matrix of image X with p as the center point of the region Q, if, G (X, p) indicates that regional variance of low-frequency coefficient matrix of X with p as the center point of the region Q, then

$$G(X,p)=\sum_{q\in Q} w(q)\left|C(X,q)-\bar{u}(X,p)\right|^2$$

Where w (q) is weight value, which is nearer from p, the greater is the weight. G (A, p) and G (B, p) are regional significance representation of low-frequency variance coefficient matrix of A and B. In addition, M2 (p) is the definition of A and B's low-frequency coefficient matrix 's regional varience matching in p:

$$M_2(p)=\frac{2\sum_{q\in Q} w(q)\left|C(A,q)-\bar{u}(A,p)\right|\left|C(B,q)-\bar{u}(B,p)\right|}{G(A,p)+G(B,p)}$$

M2 (p) varies between 0 and 1, the smaller is the value, the coefficient matrix correlation is lower.

Set T2 is matching threshold,generally is （0.5-1）.

$$C(F,p)=\begin{cases} C(A,p), & G(A,p)\geq G(B,p) \\ C(B,p), & G(A,p)<G(B,p) \end{cases}$$

$$C(F,p)=\begin{cases} W_{\max}C(A,p)+W_{\min}C(B,p), & G(A,p)\geq G(B,p) \\ W_{\min}C(A,p)+W_{\max}C(B,p), & G(A,p)<G(B,p) \end{cases}$$

$$W_{\min}=0.5-0.5\left(\frac{1-M_2(p)}{1-T_2}\right),\quad W_{\max}=1-W_{\min}$$

When M2(p)<T2,use elective fusion strategy:

$$C(F,p)=\begin{cases} C(A,p), & G(A,p)\geq G(B,p) \\ C(B,p), & G(A,p)<G(B,p) \end{cases}$$

When M2(p)>T2,use average fusion strategy:

$$C(F,p)=\begin{cases} W_{\max}C(A,p)+W_{\min}C(B,p), & G(A,p)\geq G(B,p) \\ W_{\min}C(A,p)+W_{\max}C(B,p), & G(A,p)<G(B,p) \end{cases}$$

$$W_{\min}=0.5-0.5\left(\frac{1-M_2(p)}{1-T_2}\right),\quad W_{\max}=1-W_{\min}$$

Based on correlation of neighbor pixels and regional varience, this strategy can effectively retain details and edge, therefore, the fusion image is clearer and the details are rich.

IV. THE RESULTS OF FUSION EVALUATION

The quality assessment of fusion image includes a subjective evaluation and objective evaluation. The image analysis, recognition, understanding and evaluation were done by people is called subjective evaluation. In this case, the image is no longer just the distribution of physical quantities, but also includes human visual psychological factors. Therefore, the results of subjective assessment of the image are more comprehensive and are consistent with the actual observation of the image quality, however, the results of this evaluation will be affected by many factors, such as different observers, image type and observing environment. What's more, the human visual degree of psychological factors are difficult to measure by physical , leading to evaluation results not precise enough. An objective evaluation is mainly carried out by numerical calculation quantitative evaluation, so it is strictly, objective and scientific. This paper will use the following indicators to measure the effect of the fused image.

(1) Entropy[22,23]: The image's entropy is a measure of how much it contains the average amount of information, which is defined as:

$$H = -\sum_{i=0}^{L-1} p(i)\log_2 p(i)$$

in the top formula, p(i) is the distribution probability of gray-scale i, the range of [0,1,…..L-1]. Fused image entropy reflects the size of the image that contains the amount of the amount of information.

(2) Standard deviation [22,23]: The standard deviation of the image reflects the distribution of discrete gray-level image. High-contrast images correspond to a large standard deviation, and vice versa. Suppose an image of gray-scale distribute as: P= {p (0), p (1) …p (L-1)}, L is the sum of gray series of a picture, p (i) is probability of a first-order histogram. The image average gray-scale is:

$$\bar{i} = \sum_{i=0}^{L-1} ip(i)$$

Then the image standard deviation of gray-scale as follows:

$$\sigma = \sqrt{\sum_{i=0}^{L-1}(i-\bar{i})^2\, p(i)}$$

(3) The average gradient [23]: The size of the fused images F are known to M * N, M, N are the number of image's row and column respectively. The average gradient of the image is defined as:

$$G = \frac{1}{(M-1)*(N-1)}\sum_{i=1}^{M-1}\sum_{J=1}^{N-1}\sqrt{(\Delta I_x{}^2 + \Delta I_y^2)/2}$$

In which, △Ix and △Iy are the first-order differential in direction of the image x and y . In general, the greater is the average gradient, then more abundant and higher is the image level and definition.

(4) The edge similarity QAB|F: According to the feature of human vision sensitive to the local changes, the edge similarity of source image and fusion results is proposed to measure the fusion method's capability of keeping important information.

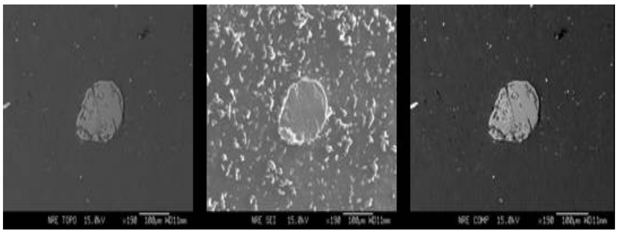
$$Q(A,B,F) = \lambda_A Q_0(A,F) + \lambda_B Q_0(B,F)$$

In which $\lambda_A(w) = \frac{s(A|\omega)}{s(A|\omega)+s(B|\omega)}$, $\lambda_B(w) = 1-\lambda_A(w)$ are the special feature of image windows.

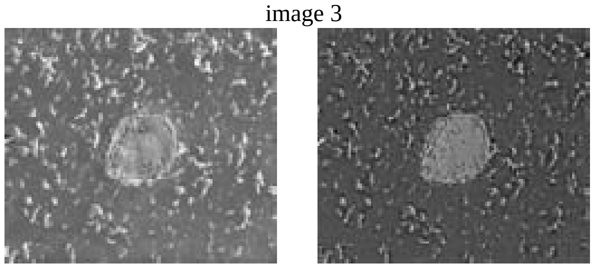
V. ANALYSE THE SIMULATION RESULT

In this paper, a strict alignment of the two groups EPMA images are used in Matlab platform, first fuse samples of BSE and the TOPO image data directly; use classification method for the BSE, TOPO and SEI sample image data in group 2, fuse the first two images, and then fuse them with the third image, finally get the fusion image.

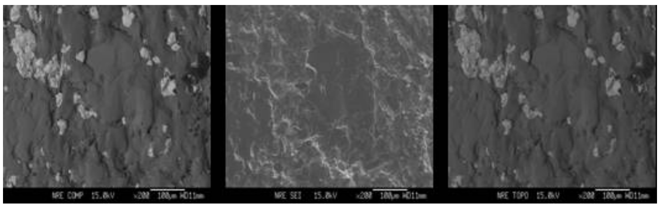
In the experiment, we use strict alignment of the two groups EPMA image to simulate.



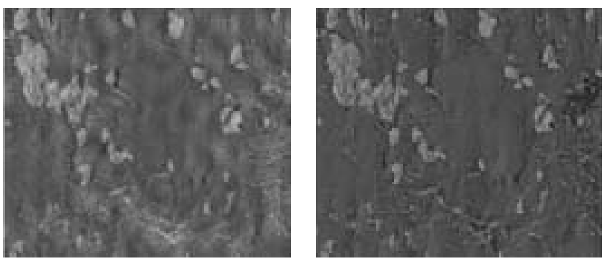
(a1) Source image1 (b1) Source image 2 (c1) Source image 3



(d1)the fusion result in this paper (e1) the fusion result based on wavelet transform



(a2) Source image 1 (b2) Source image 2 (c2) Source image 3



(d2) the fusion result based on contourlet transform (e2) the fusion result based on wavelet transform

Figure 5.the experiment result

In order to compare the performance of the algorithm, information entropy, standard deviation, average gradient, sharpness is used as an objective measure in this paper, Table 1 shows the above-mentioned information entropy, standard deviation, average gradient, image deviation.

	Fusion method	Entropy	standard deviation	average gradient
First group	this paper Algorithm	4.7867	32.782	6.2533
	wavelet Algorithm	3.9101	29.285	6.3243
Second group	this paper Algorithm	6.6162	43.759	10.18
	wavelet Algorithm	5.972	36.146	10.687

Table 1 objective evaluation of EPMA image fusion

.From a subjective analysis and objective evaluation of the data in Table 1, we can see that contourlet-lifting wavelet transform fusion method is effective. The value of information entropy and standard deviation of fusion algorithms used in this paper is higher than other fusion methods, and contain more information, it can be proved that contourlet-lifting wavelet transform is more suitable for EPMA image fusion.

VI CONCLUSION

In short, as an important tool for detection and analysis of samples , the electron microprobe is playing an increasingly important role in the modern sample analysis and detection of micro-surface material, the fusion of electron microprobe image processing make up the deficiencies of electron probe image analysis.

In this paper, combined with the practical application of electron probe, an improved fusion method of Contourlet-lifting wavelet is proposed, and experimental results of Contourlet fusion in Matlab platform is given, providing a new approach and methods for comprehensive process of electron probe image.

REFERENCES

[1] John Goodge, “Electron probe micro-analyzer (EPMA)”, http://serc.carleton.edu/research_education/geochemsheets/techniques/EPMA.html.

[2] Rick S.Blum, “Principles of Image fusion”, in Proceeding of the International Colloquium on Information Fusion ,2007

[3] DanLing Chen,Yong Sun,Liang Liu,AnDa Zhang,CiLuan Lin. In situ LA-ICP-MS zircon U-Pb age of ultrahigh-pressure eclogites in the Yukahe area, northern Qaidam Basin[J]. Science in China Series D: Earth Sciences, 2007,50(2) :322~330.

[4] Xu W L,Hergt J M,Gao S,et al. Interaction of adakitic melt-peridotite:Implications for the high-Mg#signature of Mesozoic adakitic rocks in the eastern North China Craton .Earth Planet Sci Lett, 2008, 265 :123—137

[5] Zhang Yong-an,Song Jian-SHE,”False color fusion formulti-band SAR image Based on Contourlet transform” Acta Automatica Sinica,April,2007

[6] Yanjun Yan,Lisa Osadciw,”Contourlet Based image recovery and De-noising Throuth Wireless Fading Channels” in 2005 conference on information science and systems,March 16-18,2005

[7] Minh N.Do and Martin Vetterli,Fellow,”The Contourlet Transform:An Efficient Directional Multiresolution image Representation” IEEE Transactions on image processing,VOL 14,NO,12,December 2005

[8] Zheng Y A, Zhu C S, Song J S, Zhao X H. “Fusion of multi-band SAR images based on contourlet transform”. In: Pro-ceedings of the 2006 IEEE International Conference on In-formation Acquisition..

[9] DO M N,VETTERLI M. The contourlet transform:an efficient directional multiresolution image representation[J] .IEEE Transaction on Image Processing, 2005, 14 (12) :2091-2106 .

[10] Cunha A L,Zhou J P,Do M N. The nonsubsampled contourlet transform;Theory,design,and applications[J] .IEEE Transactions on Image Processing, 2006, 15 (10) :3089～3101

[11] Arthur L da Cunha,Jiangping zhou,Minh N Do. The Nonsubsampled Contourlet Transform:Theo-ry,Design,and Applications[J] .IEEE Trans.onImage Processing, 2006, 15 (10) :3089-3101 .

[12] Bin Yang,Shutao LI,”Multi-focus image fusion using watershed region segmentation and morphological wavelet transform” in:Proceeding of the International collequium on information fusion,2007

[13] Li Wei,ect. The assessment of second generation wavelet image fusion method,Journal of automation,2008,7.

[14] Chen Hao,Liu YanYing.The research on infrared image fusion based on wavelet transform[J],Infrared and Laser,2009,1(39).97-100.

[15] Sweldens W. The Lifting Scheme:A construction of second generation wavelets .USA: University of South Carolina, 1995,

[16] Quan Haiying , Yang Yuan , Zhang Yi et al . . An image fusion approach based on second generation wavelet t ransform[J] . Systems Engineering and Elect ronics , 2001 , 23 (5) : 74 ,75 ,79

[17] Piella G. Combining Seminorms in Adaptive Lifting Schemes and Applications to Image Analysis and compression [C].J Math Imaging Vis25(2006):203-226.

[18] Jiao Lichen,Hou biao,Wang suan,Liu fang, “Image Multiscale Geometric Analysis:Theory and Application”, Publishing house of Xi’an electronic and technolony,2008,360-389

[19] Liu Wen Yao,image coding and special VLSI design. Beijing electronic industry press,2006,p42-49.

[20] Jiang Zhiguo,Han Dongbing,Xie Fengying,etc.,The research on new technology of automatic microscope image,Chinese stereology and image analysis.

[21] Wang Daneng,Chen Yong,Sui Senying,etc.,The new development of electron microscopy in structural biology.2003,22(5):449-456. 2004.9(1):31~36..

[22] Hu Chun Hai,Ding Zhi Xiu.The assessment of image fusion[J].Journal of Sensor,2007(04).

[23] Zhao L Y,Yin J.The assessment of image fusion effects[J].Information of Remote Sensing,2005(04).

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