A Novel Image Fusion Model Based on Variation Panchromatic and Multispectral

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***Abstract* — In order to improve the space quality and high-spectral quality of high fused images, this paper presents a new image fusion model. In order to ensure the convergence objective, this model introduces the three energy functional items, which are the geometry injection, spectral information maintenance and contrast enhancement to construct a total energy functional form and solve the discrete values. Experimental results show that this model can adjust and generate the corresponding fused image according to different fusion, which can be extended to any number of bands of image fusion.**

Keywords - geometry; multi-band; discrete value; computing speed

I. INTRODUCTION

Image fusion takes the image as a researching and processing object, and it makes the image obtained by the same target or scene from different sensors or the multi-image obtained by the same sensor with different ways merging into one picture according to the fusion rules. In this picture the information of multiple original images can be reflected to achieve the general description of the target and the scene [1-2].

Image fusion is as the branch of information fusion and accepts more and more attention, and its range of applications is wider and wider. Currently there are many image fusion algorithms like gray value selection method, IHS transform method, pyramid transform method, wavelet transform method and so on. Although there are many fusion algorithms, there is no perfect algorithm. Every algorithm has its own shortcomings, such as the weighted average algorithm reduces the sharpness of the image and blurs the edges and contours, the pyramid transform algorithm increases the amount of computing, the wavelet transform algorithm fuzzes the clear area of image [3-6].

Due to the restriction of a variety of observational factors like imaging systems, detector characteristics and satellite attitude, it is hard for many remote sensing satellites to get a piece of image with high partial resolution and high spectral resolution, instead it can provide a panchromatic image with high spectral resolution and several multi-spectral images with high spatial resolution. For example, IKONOS and QuickBird satellite remote sensing data contain a panchromatic band and four multispectral bands [7]. With the growing demand for the remote sensing applications with high spatial and high spectral resolution images, image fusion has become an effective solution [8].

It combines the obtained panchromatic image and multispectral images to provide a fused image with complementary information of panchromatic and multispectral images. Traditional fusion methods, such as Intensity-hue-saturation (IHS) transform proposed by Carper WJ, principal component analysis proposed by Saleta JL, Brovey exchange proposed by Laben CA et al, high-pass filter and Gram-Schmidt proposed by Zhang Y, etc . Have the problems of missing spectral information of the original images. Wavelet transform is the current mainstream method of remote sensing image fusion, but the fusion image based on wavelet transform algorithm always has the ringing phenomenon. The multi-scale geometric analysis method can more effectively represent the geometry of the image, thus it make up the defects of wavelet transform including ridgelet transform proposed by Chen T et al, curvelet transform proposed by Choi M, contourlet transfer proposed by Yang Xiao-Hui et al. However, fusion method based on multi-scale geometric analysis widely exits the problem of high complexity of computing and low efficiency [9-11].

Recently, some image fusion model based on variational method has been proposed and it shows its good convergence properties. These variational fusion models can be divided into two categories. One is the topographic map proposed by Ballester C et al. This model assumes that the topographic map of panchromatic images contains the geometry of multispectral image. However, there are some constrictions of the assumption, which may lead to spectral distortion. Moeller M et al introduced the wavelet transform into the model and extended to the hyper-spectral image fusion model. Socolinsky et al proposed the contrast model, and this model uses the gradient information of the input image to define the contrast of the target of fusion image, and then through minimizing the objective function, the fused results are obtained. Piella G et al introduced the image enhancements to further enhance the contrast of fused image. However, the contrast model does not consider the keeping of spectral information; therefore it does not suitable for the fusion of remote sensing images [12].

In this paper, a new variational model is used in panchromatic images and multi-spectral image. In order to improve the spatial resolution of multispectral image and keep its original spectral information, on the basis of

Socolinsky contrast model, an improved energy functional is constructed to research the solution closest to the gradient of panchromatic image and take it as the gradient of fused image. In order to ensure the fusion objectives, variational model also designs the energy functional items corresponding to the maintenance of spectral information and the need of enhancing the contrast. Experimental results of IKONOS and QuickBird data show that this model can generate the fused image both with high partial quality and high spectral quality.

This paper mainly makes the extensive and innovative work in the following areas:

(1) In order to improve the space quality and high-spectral quality of high fused images, this paper presents a new image fusion model. This model introduces the three energy functional items, which are the geometry injection, spectral information maintenance and contrast enhancement. On the basis of Socolinsky contrast model, an improved energy functional is constructed to solve the minimization problem and find the solution closest to the panchromatic image gradient. In order to improve the spatial resolution of the multispectral image and keep its original spectrum as possible, this thesis takes the consistent item, related items between the bands and the contrast enhancements of the spectral term into the fusion model.

(2) In order to further verify the correctness and effectiveness of the new proposed image fusion model, the simulation experiment is taken. the experiment uses the IKONOS and QuickBird data to make contrast experiments. Panchromatic images and multispectral images are used to make geometrical registration. Through comparing experimental model, combined with the subjective and objective evaluation results the proposed model has a good balance between the improvement of spatial quality and maintenance of spectral information. Simulation results show that this model can generate the fused image both with high spatial quality and high spectral quality.

II. MULTI-BAND IMAGE MODEL

A. *Method Process*

Since the non-sub-sampled contourlet transform can overcome the aliasing phenomenon and it has better spectral characteristics, the basic process flow of the proposed fusion image is shown in Figure 1, and the main steps are as follows:

(1) Multi-spectral images are conducted HIS transfer, and then the brightness, hue and saturation are obtained ;

(2) Luminance component of multispectral image and panchromatic images are respectively taking non-sub-sampled contourlet transform to get its high-frequency coefficients;

(3) Low-frequency coefficients are weighted fusion; high-frequency coefficients are selected by using the pulse coupled neural network algorithm;

(4) Fused coefficients are taking NSCT reconstruction;

(5) HIS is transformed inversely, and then the final fused image is obtained.

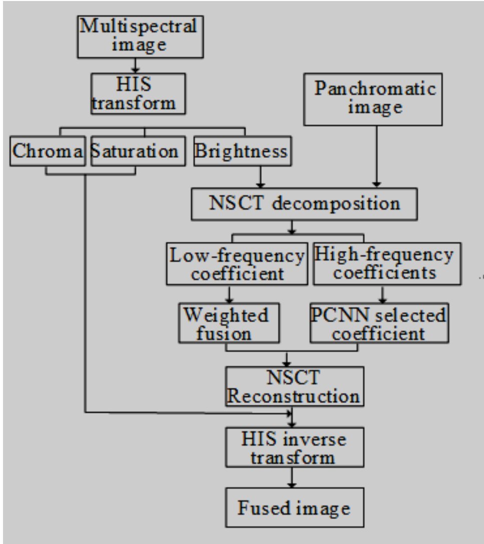


Figure 1. Process of fusion

B. *Model*

Let $I_b:\Omega\to[0,1]$ is the b_{-th} band image ($b=1,...,B$, B is the number of bands) defined in the spatial domain as $\Omega\subset R^2$. For each piece of input image I_b and each point $p=(x,y)\in\Omega$, structure tensor at the point P is defined as follows:

$$x^2(p)=\begin{bmatrix}\sum_{b=1}^{B}\left(w_b(p)\frac{\partial I_b}{\partial_x}\right)^2 & \sum_{b=1}^{B}w_b^2(p)\frac{\partial I_b}{\partial_x}\frac{\partial I_b}{\partial y_2}\\ \sum_{b=1}^{B}w_b^2(p)\frac{\partial I_b}{\partial_y}\frac{\partial I_b}{\partial_x} & \sum_{b=1}^{B}\left(w_b(p)\frac{\partial I_b}{\partial_y}\right)\end{bmatrix}\tag{1}$$

Wherein,

$$w_b(p)=\frac{\left|\nabla I_b(p)\right|}{\left(\sum_{b=1}^{B}\left|\nabla I_b(p)\right|^2\right)^{\frac{1}{2}}}\tag{2}$$

Target gradient V is defined as:

$$V(p)=\sqrt{\lambda_p}+\theta_p+\operatorname{sgn}\left(\theta_p+\cdot\sum_{b=1}^{B}\omega_b(p)\nabla I_b(p)\right)\tag{3}$$

Wherein,

$$\operatorname{sgn}(t)=\begin{Bmatrix}1, & if\ t\geq 0\\ -1, & \text{so}\end{Bmatrix}$$

λ_p^+ is the maximum eigenvalue of $x^2(p)$; θ_p^+ is the corresponding eigenvector of λ_p^+ .

Energy functional of contrast model is as follows:

$$E_G(F)=\int_\Omega\left|\nabla F(P)-V(p)\right|^2dp\tag{4}$$

Wherein, F represents the fusion image and $0\leq F\leq 1$. Practically, the functional $E_G(F)$ in formula (4) can be regarded as the fusion image structure. Local variations of

(F) is the energy term of the degree of the changing matching in the structure of the target image (V).

III. IMAGE FUSION MODEL BASED ON VARIATIONAL PANCHROMATIC AND MULTISPECTRAL

Image fusion's target of panchromatic and multi-spectral is to produce a fused image with complementary information of panchromatic image and multi-spectral image, which improves the spatial resolution of multispectral image and maintains its original spectral information at the same time. However, the intention of designing contrast model by Socolinsky is to obtain the optimal grayscale image from the image with arbitrary number of band. Therefore, it is necessary to improve the contrast model to be applicable to remote sensing image fusion.

Functional approach allows the combination of a number of different types of algorithms simultaneously in a variational framework, such as Wang et al for multi-focus image and de-noising and de-fusion at the same time. In order to ensure the fusion target, this article introduces the geometry injection, spectral information maintenance and energy term of contrast enhancement into the variational model.

C. Geometry Injection Items

The spatial resolution of panchromatic image is high and the multispectral image with the improvement of spatial resolution should contain the geometry of panchromatic image, so this paper takes the gradient (PAN) of the panchromatic image as the target gradient V of the fusion image. In order to control the influence of the gradient in panchromatic image to spatial resolution in fusion image, the normal number ζ is introduced, and functional form is defined as follows:

$$\mathrm{E}_G^*\left(H_b\right)=\alpha\int_\Omega\left|\nabla H_b\left(p\right)-\zeta\nabla PAN\left(p\right)\right|^2 dp \tag{5}$$

Wherein, H_b is the first b_{-th} band image of the fusion image, which means the gradient operator.

Since the gradient operator in the formula (5) is sensitive to noise, in order to ensure the smoothness of the solution the total variation is added into the functional items, and then the new injection energy term with geometry is defined as:

$$\mathrm{E}_G\left(H_b\right)=\alpha\int_\Omega\left|\nabla H_b\left(p\right)-\zeta\nabla PAN\left(p\right)\right|^2+\beta\int_\Omega\left|\nabla F_b\left(p\right)\right|dp \tag{6}$$

What need to be noted is that the second term in formula (6) can also be used to remove image noise.

D. Maintenance Item of Spectral Information

Spectral information of each pixel in the multi-spectral image is very essential to the target identification, classification and so on; therefore how to keep the spectral information in original multispectral image is critical. This article uses the spectral angle mapping proposed by Yuhas RH (SAM) to analyze the spectral changes.

Let $v=\left(v_1,v_2,...,v_B\right)$ and $\hat{v}=\left(\hat{v}_{1,}\hat{v}_{2,...,}\hat{v}_B\right)$ are respectively the pixel value vector at some points in multispectral images and fusion images, so the absolute value of spectral angle between two vectors can be expressed by SAM as follows:

$$SAM\left(v,\hat{v}\right)=\arccos\left(\frac{\langle v,\hat{v}\rangle}{\|v\|_2\|\hat{v}\|_2}\right) \tag{7}$$

Wherein, $\|\cdot\|_2$ represents the norm of L_2.

When v and $\hat{v}$ are parallel, there is:

$$\frac{v_b}{\hat{v}_b}=\frac{v_{b'}}{\hat{v}_{b'}},\ 1\le b,b'\le B \tag{8}$$

In order to ensure correlation of the spectral fusion and the original multispectral image, the item maintaining the energy of spectral information is defined as:

$$\mathrm{E}_S\left(H_b\right)=\gamma\int_\Omega\left(F_b\right)^2 dp+\eta\sum_{b'=1,b'\ne b}^{B}\int_\Omega\left(H_bMS_{b'}-H_{b'}MS_b\right)^2 dp \tag{9}$$

Wherein, MS_b represents the b_{-th} band image of multispectral image corresponding to the fusion image H_b. The first item is used to keep the spectral relation of the fusion image and the original multispectral image, and the second item is used to maintain the spectral relation of different bands in the multispectral image.

E. Contrast Enhancement Item

The most common method to improve the image contrast is adjusting the pixel value of the images. This thesis introduces the contrast enhancement item to further improve the visual quality of the fused image, which is defined as follows:

$$O_C\left(H_b\right)=\mu\left\{\frac{1}{2}\int_\Omega\left(F_b\left(p\right)-\frac{1}{2}\right)^2 dp-\frac{1}{4|\Omega|}\int_\Omega\int_\Omega\left|H_b\left(p\right)-H_b\left(q\right)\right|dpdq\right\} \tag{10}$$

Wherein, $|\Omega|$ represents the area of the image. The first item of the energy term makes the mean of H_b closing to the mid-value of the grayscale, and the second item defines the measure of the contrast in the whole image. Therefore, the minimum O_C is equivalent to equalization process to image H_b, and the contrast in the whole image is maximized at the same time.

*F. **Solution of model***

Combined the geometry injection function (6), spectral information maintenance function (9) and contrast enhancement function (10) to obtain the total energy functional form as follows:

$$\begin{aligned}
\mathrm{E}(F_b) &= \mathrm{E}_G + \mathrm{E}_S + \mathrm{E}_C = \\
&\alpha \int_\Omega |\nabla F_b - \zeta \nabla PAN|^2 dp + \beta \int_\Omega |\nabla F_b| dp + \\
&\gamma \int_\Omega (F_b - MS_b)^2 dp + \\
&\eta \sum_{b'=1, b' \neq b}^{B} \int_\Omega (F_b MS_{b'} - F_{b'} MS_b)^2 dp + \\
&\mu \left\{ \frac{1}{2} \int_\Omega \left(F_b(p) - \frac{1}{2} \right)^2 dp - \frac{1}{4|\Omega|} \int_\Omega \int_\Omega |F_b(p) - F_b(q)| dp dq \right\}
\end{aligned} \tag{11}$$

And 0 ≤Fb ≤ 1. What need to be noted is that the minus of the last item in formula (11) is non-convex for resulting $E(F_b)$. However, the function E exist a minimum value 1.

For the b_{-th} band image, the first order variations of the energy term are calculated as follows:

$$\frac{\delta E_G}{\delta F_b} = 2\alpha\left(\zeta div\left(\nabla PAN(p)\right) - \Delta F_b(p)\right) - \beta \nabla \cdot \frac{\nabla F_b(p)}{|\nabla F_b(p)|} \tag{12}$$

$$\begin{aligned}
\frac{\delta E_S}{\delta F_b} &= 2\gamma\left(F_b(p) - MS_b(p)\right) + \\
&2\eta X \sum_{b'=1, b' \neq b}^{B} \left(F_b(p) MS_{b'}(p) - F_{b'}(p) MS_b(p)\right) MS_{b'}(p)
\end{aligned} \tag{13}$$

$$\frac{\delta E_C}{\delta F_b} = \mu \left\{ F_b(p) - \frac{1}{|\Omega|} A\left(q : F_b(q) \prec F_b(p)\right) \right\} \tag{14}$$

Wherein, $A(\cdot)$ represents the number of pixels satisfying the condition, α , β , γ , η and μ are positive weighting parameters, which are used to balance the contribution of energy terms to the fused image.

In order to minimize the energy function, the time variable t is introduced, and then it is solved based on the gradient descent flow method:

$$\frac{\partial F_b}{\partial t} = -\frac{\delta E(F_b)}{\delta F_b} \tag{15}$$

The formula (15) can be solved by discrete quantizing as following:

$$\begin{aligned}
&\frac{F_b^{k+1}(p) - F_b^k(p)}{\Delta t} = \\
&2\alpha\left(\Delta F_b^k(p) - \zeta div\left(\nabla PAN(p)\right)\right) + \\
&\beta \nabla \cdot \frac{\nabla F_b^k(p)}{|\nabla F_b^k(p)|} + 2\gamma\left(MS_b(p) - F_b^k(p)\right) - \\
&2\eta \sum_{b'=1, b' \neq b}^{B} \left(F_b^k(p) MS_{b'}(p) - F_{b'}^k(p) MS_b(p)\right) MS_{b'}(p) + \\
&\mu \left\{ \frac{1}{|\Omega|} A\left(q : F_b^k(p) \prec F_b^k(p)\right) - F_b^k(p) \right\}
\end{aligned} \tag{16}$$

This article sets initial image F_b^0 as the corresponding band of the original multispectral image. Gradient operator is approximated to the forward difference, and the divergence term $div(\nabla pAN)$ is approximated to the backward difference. Laplace operator method is approximated with 5-points method:

$$\begin{aligned}
\Delta F_b^k(x,y) &= F_b^k(x+1,y) + F_b^k(x,y+1) + \\
&F_b^k(x-1,y) + F_b^k(x,y-1) - 4F_b^k(x,y)
\end{aligned} \tag{17}$$

For borders, the symmetrical expansion method is used.

To improve the computing speed of contrast enhancement item, before each iteration the F_b^k is mapped to $[0, L]$ and the number of pixels of each gradation level is stored in the array for calculating $A(\cdot)$. After each iteration the value of F_b^k must maintain between 0 and 1. For the part out of range, it takes the truncation processing.

Formula (16) shows that the proposed model can handle all the bands at the same time, and the complexity of the first iteration is as $O(N)$; N is the total number of pixels of the image.

IV. EXPERIMENTAL SIMULATION AND ANALYSIS

A. Experimental Environment and Setup

To validate the effectiveness of the model, IKONOS and QuickBird are used to make comparative experiments. Panchromatic and multi-spectral image pairs have been made geometric registration. Table 1 shows the related information of experimental data.

TABLE I EXPERIMENTAL DATA DESCRIPTION

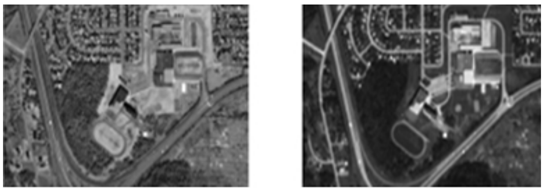
	Ik1	Ik2	Qb
Location	England	Japan	Newsland
Size of multispectral image	160×280	125×125	514×514
Size of panchromatic image	690×1209	514×514	2123×2123

Multi-spectral image uses the double cubic interpolation to sample the size of panchromatic image. Experimental images are shown in Figure 2.

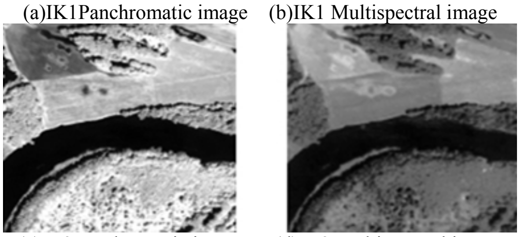
In the variational framework, the selection of the f parameters has an important impact to the fusion results. According to the physical meaning of the various energy terms, the parameters α , ζ , μ are associated with the spatial resolution, and the parameters γ and η are related to the spectral resolution, while the parameter β is used in keeping smoothness of the solution. Depending on the application goals (improving spatial resolution or maintaining spectral information) the corresponding weight parameters can be adjusted to determine the influence of each energy items in energy function. In the practical application, it needs a appropriate balance between the spatial resolution and spectral resolution. The parameters in experiment are set as follows: $\alpha = 0.3$, $\zeta = 0.4$, $\beta = 0.002$, $\gamma = 0.6$, $\eta = 0.5$, $\mu = 0.4$; the time step is as Δt=0.20 . The convergence conditions are set as the mean square deviation between the adjacent two iterations is less than 0.6%.

To verify the validity of the parameter setting, firstly the fusion performances of different parameter combinations are compared. Table 2 shows the five sets of parameters collection used in comparative experiment.

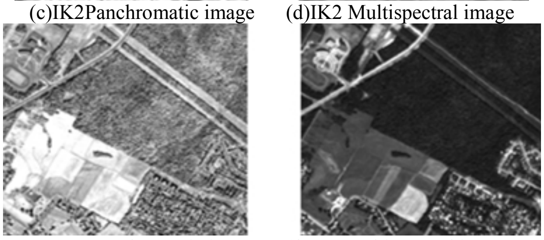
What need to be noted is that the parameter set H and parameter set I are respectively corresponding to functional L_G and $L_C 3$. The parameter set J is used to obtain the fusion image with high spatial quality; the parameter set K is used to obtain the fusion image with high- spectral quality; the parameter set L is used to obtain the fusion image with high spectral quality but low spatial quality.



(a)IK1Panchromatic image (b)IK1 Multispectral image



(c)IK2Panchromatic image (d)IK2 Multispectral image



(e)IK2Panchromatic image (f)IK2 Multispectral image

Figure 2. Experimental images

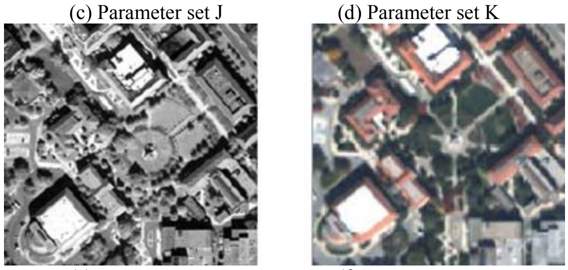
TABLE II SELECTION OF PARAMETER SETS

	α	ζ	μ	γ	η
H	0.3	3	0.002	0	0
I	0	1	0	0	0.3
J	0.6	6	0.02	2	0.5
K	0.1	2	0.002	0	0.2
L	0.2	1	0.002	05	0.1

Figure 3 shows the fusion results of each parameter sets with the IKONOS data Ik1. Data Ik1 has the urban features (such as buildings and highways), and it has the natural features as well (such as trees).

(a) Parameter set H (b) Parameter set I

(c) Parameter set J (d) Parameter set K



(e) Parameter set L (f) Parameter set M

Figure 3. Results of each parameter sets with the data IK1

B. Results Analysis

In order to evaluate the fusion effect, the average gradient (AG), correlation coefficient, error relative global dimension syntheses (ERGAS) and universal image quality index (UIQI) are used as evaluation criteria [18].

BB are used to evaluate the correlation of fusion image and the original multi-spectral image, which is defined as follows:

$$BB_b = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}\left(F_b(x,y)-\hat{\mu}_b\right)\left(MS_b(x,y)-\hat{\mu}_b\right)}{\sqrt{\sum_{x=1}^{M}\sum_{y=1}^{N}\left(F_b(x,y)-\hat{\mu}_b\right)^2 \sum_{x=1}^{M}\sum_{y=1}^{N}\left(MS_b(x,y)-\hat{\mu}_b\right)^2}} \tag{18}$$

Wherein, μ_b and b are respectively denotes the mean of multispectral image MS_b and fusion image F_b. The Ideal value of BB is 1.

ERGAS reflects the overall situation of the spectral quality changes, which is defined as follows [19]:

$$ERGAS = 100\frac{d_h}{d_1}\sqrt{\frac{1}{B}\sum_{b=1}^{B}\left(\frac{RMSE\left(F_b \cdot MS_b\right)}{\mu_b}\right)^2} \tag{19}$$

Wherein, d_h / d_1 is the ratio of spatial resolution of the panchromatic image and the original multi-spectral image; the ideal value of ERGAS is 0.

UIQI is used to evaluate the degree of structural distortion of the fusion image and the original multi-spectral image, which is defined as follows:

$$UIQI_b = \frac{\sigma F_b M_{\delta_b}}{\sigma F_b \sigma MS_b}\cdot\frac{2\hat{\mu}\mu_b}{\hat{\mu}_b^2+\mu_b^2}\cdot\frac{2\sigma F_b \sigma MS_b}{\sigma_{F_b}^2+\sigma_{MS_b}^2} \tag{20}$$

If two images are identical, UIQI reaches the maximum value 1.

The quantitative evaluation results of each parameter sets' fusion results in Figure 3 are shown in Table 3; wherein, $\overline{AG}$, $\overline{BB}$ and $\overline{UIQI}$ respectively represent the mean of the AG, BB and UIQI indicators of all the bands in multispectral images.

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TABLE III TATIVE EVALUATION RESULTS OF EACH SET OF PARAMETERS IN FIGURE 3

Parameters Set	$\overline{AG}$	$\overline{BB}$	$\overline{UIQI}$	ERGAS
H	0.0512	0.7881	0.9863	0.0156
I	0.0311	0.9701	0.9121	0.0178
J	0.0218	0.2504	0.7451	0.0463
K	0.0140	0.9900	0.9984	0.0071
L	0.0511	0.9112	0.9945	0.0121

From Figure 3 and Table 3, it can be found that if $\overline{AG}$ in parameter set J is the maximum, the spectral quality is the worst (see Figure 3 (c)). Figure 3 (b) indicates that the parameter set I will cause a small amount of spectral distortion. $\overline{BB}$, $\overline{UIQI}$ and ERGAS indicate that parameter set K maintain the best spectral information; However, just as shown in Figure 3 (d), the fusion results of spatial quality is not ideal. Figure 3 (a), Figure 3 (e) and Figure 3 (f) indicate that the parameter set H, L can obtain a better spatial quality, but from $\overline{BB}$, $UIQI$ and $ERGAS$, the maintenance of spectral information of parameter set H is not good as parameter sets L. Compared with the fusion results of parameter sets L, it can be seen that the parameter set L can maintain more spectral information, while the parameter set L's fusion results with higher spatial resolution, which indicate that the proposed variational model can adjust the weight parameters to produce fused image meeting different application needs.

To further evaluate the fusion performance of the model, this thesis makes comparative experiment based on fusion methods like PCA, discrete wavelet transform (DWT) and non-subsampled Contourlet Transform (NSCT). All the methods are realized under Matlab; experimental environment is completed with Dell desktop; processor is Intel Core i7; dominant frequency is at 3.4GHz; RAM is 3GB. DWT uses symmetrical spline wavelet function DBSS of Daubechies (2, 2); decomposition levels are 3 layers. The low-pass filter of NSCT is maxflat; directional filter is as dmaxflat; decomposition level are three layers; from low to high, the high-frequency is respectively decomposed as 1, 2 and 8 directional sub-band. The fusion strategy of DWT and NSCT select the multi- spectral low-frequency coefficients with corresponding bands for low-frequency coefficients, and the high-frequency coefficient selects the maximum absolute value of the corresponding sub-band.

The article also compares the contrast model and the contrast enhancement model Piella. Contrast model set the initial image as weighted combination of the panchromatic images and multispectral image:

$$F_b^0 = \omega_b'(p) MS_b(p) + \left(1 - \omega_b'(p)\right) PAN(p)$$

Fusion results of each method in data Ik1 are shown in Figure 3.

From Figure 4 can be found that in addition to Figure 4 (g), the features of buildings and highways in the entire remaining fused image are clearer than the original multispectral image. To better evaluate the fusion results, in Figure 5, the playground area shown in Figure 4 is locally enlarged.

From Figure 5 (b), Figure 5 (e) and Figure 4 (f) it can be found that PCA method, contrast model and Piella model A produced the significant spectral distortion. DWT method exhibits a small amount of spectrum distortion along the playground profile (see in Figure 5 (c)). In Figure 5 (g), Piella model B maintains the spectral information of the original multispectral images, but it not significantly enhances the spatial quality. This also shows that the proposed program of target gradient and initial image selection does not apply to the Piella model. Just as shown in Figure 5 (d) and Figure 5 (h), the visual quality of the fusion results of NSCT method and the proposed method are similar, but the fusion image of the proposed model remains more details, such as the forest area in the lower left corner.

(a)PCA methods (b)DWT methods (c)NSCT methods

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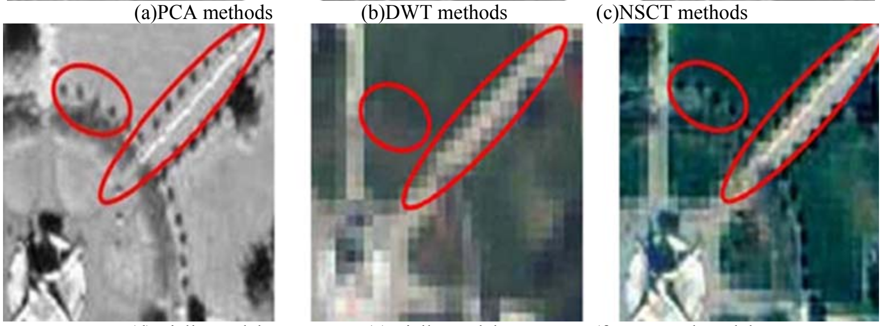
(d) Piella model H (e) Piella model I (f) Proposed model

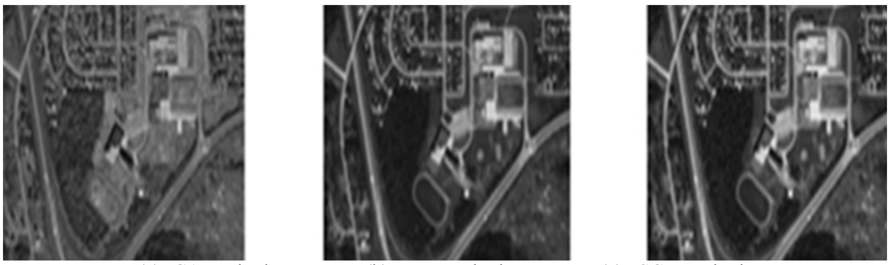
Figure 4. Fusion results of each method on data ik1

(a)PCA methods (b)DWT methods (c)NSCT methods

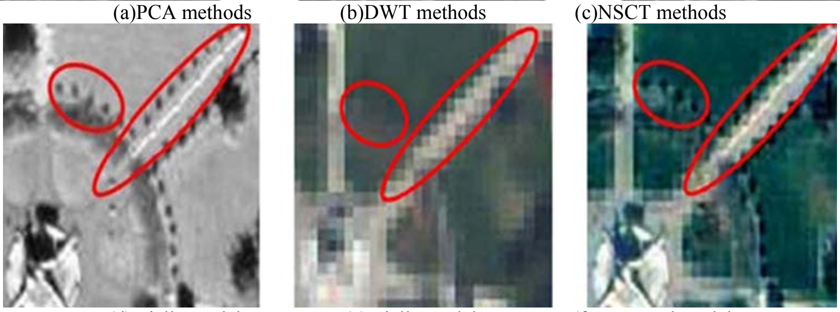


(d) Piella model H (e) Piella model I (f) Proposed model

Figure 5. Partial enlarged pictures of playground area



(a)PCA methods (b)DWT methods (c)NSCT methods



(d) Piella model H (e) Piella model I (f) Proposed model

Figure 6. Fusion results of various methods on data ik2

This article also makes the corresponding experiment on another set of IKONOS data Ik2. The characteristics of data Ik2 are mostly water and forests. Figure 6 shows the fusion results of each method on Ik2.

In Figure 6, except the fusion results of Piella Model B (shown in Figure 6 (g)), the other methods' spatial resolution in fusion image fusion have been significantly improved. in Figure 6 (b), Figure 6 (e) and 6 (f), the fusion results of PCA method, contrast model and Piella model A still exist clear distortion of the spectrum. In Figure 6 (c) there are ringing effects around the edge along the river area.

Table 4 lists the quantitative evaluation results and the running rime of each fusion method on each data. In order to evaluate the efficiency of running in remote sensing images with large size of various methods, the quantitative evaluation results of Qb on QuickBird data are also listed.

From Figure 6, the fusion targets $\overline{AG}$ and $\overline{UIQI}$ of the proposed model are the highest, which indicate that its ability to enhance the spatial information is the strongest. Indicators $\overline{BB}$ and $ERGAS$ show the maintenance of the spectral information of Piella model B is the best, but $\overline{AG}$ shows that the improvement of spatial quality is the worst. The quality of NSCT method similar is similar to the results of the proposed model, but its computational efficiency is low and the running time is slower about 39 times than the proposed model. Combined with the results of subjective and objective evaluation, the proposed model offers a better balance for the improvement of spatial quality and the maintenance of spectral information.

This paper is a one-hour lecture on the topic of fault current limiter presented to engineering students. The lecture has started with the causes and effects of fault on power systems. The traditional ways of fixing fault current have been described. The detailed analysis of two types of fault current limiters: based on magnetic materials and high temperature superconductor materials have been presented. With some modification (elimination of mathematical part) the lecture can be presented to general public.

V. CONCLUSIONS CONFLICT OF INTEREST ACKNOWLEDGMENT

This paper presents new variational model for the fusion of panchromatic images and multispectral image. In order to ensure the fusion objective, this model introduces the geometry injection, maintenance of spectral information and enhancement of. Fusion experimental results on IKONOS and QuickBird data verify the validity of this model.

VI. CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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