A united optimum images fusion based on analysis of color distortion

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In remote sensing community, IHS (intensity, hue, and saturation) transform is one of the most commonly used fusion algorithm. A study on IHS fusion indicates that the color distortion cannot be avoided. Meanwhile, wavelet decomposition has a property of frequency division in transform domain. And the statistical property of wavelet coefficient reflects those significant features. So, a united optimal fusion method, which using the statistical property of wavelet decomposition and IHS transform on pixel and feature levels, is proposed. That is, the high frequency of intensity component I is fused on feature level with multi-resolution wavelet in IHS space, and the low frequency of intensity component I is fused on pixel level with optimal weight coefficients. Spectral information and spatial resolution are two performance indexes of optimal weight coefficients. Experiment results show that it is a practical and effective method.

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Remote sensing is a continuously growing market with applications like vegetation mapping, city planning, precision farming and observation of the environment[1]. A multi-spectral remote sensing image consists of many bands and abundant spectral information, and a panchromatic image has a high spatial resolution. So various fusion methods for these two types of images focus on how to combine these two advantages to get a perfect image, such as IHS method[2], Brovey transform (BT)[3], principal component analysis (PCA)[4] and wavelet transform[4], etc. Up to now, new fusion methods based on injecting high-frequency components into resampled versions of the multi-spectral data have demonstrated a superior performance[3,5,7]. The rationale of spectrum substitution was formally developed in a multiresolution framework by employing the wavelet transform (WT)[5,8], uniform rational filterbanks[6], and the generalized laplacian pyramid (GLP)[7]. The IHS color space transform is a typical and classical method with many advantages, such as less distort of spectral and easily transform.

In this paper, a further study on IHS fusion indicates that the replaced intensity component I_{new} can be rectified to reduce the color distortion. So, a united optimal fusion method, which using the statistical property of wavelet decomposition and IHS transform on pixel and feature levels, is proposed in this paper. It is called as optimal IHS (OIHS) fusion method.

A linear transform from RGB to IHS color space is shown as[2]

$$\begin{bmatrix} I \\ v1 \\ v2 \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ -\sqrt{2}/6 & -\sqrt{2}/6 & -\sqrt{2}/6 \\ 1/\sqrt{2} & -1/\sqrt{2} & 0 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix}, \tag{1a}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & -1/\sqrt{2} & -1/\sqrt{2} \\ 1 & \sqrt{2} & 0 \end{bmatrix} \cdot \begin{bmatrix} I \\ v1 \\ v2 \end{bmatrix}. \tag{1b}$$

In the Cartesian coordinate system, variable $v1$ and $v2$ in Eqs. (1) can be considered as x and y axes while I indicates the z axis. So the hue (H) and saturation (S) can be represented by

$$H = \tan^{-1}(v2/v1), \quad S = \sqrt{v1^2 + v2^2}. \tag{2}$$

Then, the RGB cube is rotated until the horizontal plane is parallel to the Maxwell triangle and the vertical axis lies on the gray line of RGB cube. This rotating is a nonlinear transform. And this RGB-IHS conversion system can be represented as[2]

$$I = (R + G + B)/3, \tag{3a}$$

$$H = \begin{cases} \cos^{-1}(a) & \text{if } G \geq R \\ 2\pi - \cos^{-1}(a) & \text{if } G \leq R \end{cases}, \tag{3b}$$

$$S = 1 - \frac{3\min(R, G, B)}{R + G + B}. \tag{3c}$$

where $a = \frac{(2B-G-R)/2}{\sqrt{(B-G)^2+(B-R)(G-R)}}$.

A detailed study indicated that the color distortion problem arises from the change of the saturation during the fusion process. Based on these references, there are two conclusions as follows[2].

1) A generalized IHS transform can be written as

$$\begin{aligned} \begin{bmatrix} R_{\mathrm{F}} \\ G_{\mathrm{F}} \\ B_{\mathrm{F}} \end{bmatrix} &= \begin{bmatrix} 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & -1/\sqrt{2} & -1/\sqrt{2} \\ 1 & \sqrt{2} & 0 \end{bmatrix} \cdot \begin{bmatrix} I_{\mathrm{M}} + (I_{\mathrm{P}} - I_{\mathrm{M}}) \\ v1_{\mathrm{M}} \\ v2_{\mathrm{M}} \end{bmatrix} \\ &= \begin{bmatrix} R_{\mathrm{M}} + \sigma \\ G_{\mathrm{M}} + \sigma \\ B_{\mathrm{M}} + \sigma \end{bmatrix}. \end{aligned} \tag{4}$$

where $\sigma = I_{\mathrm{P}} - I_{\mathrm{M}}$ or $I_{\mathrm{P}} = I_{\mathrm{M}} + \sigma$. The low-resolution intensity component (I_{M}) of multi-spectral image should be replaced with the intensity component (I_{P}) of panchromatic image, which has higher spatial resolution. R_{M}, G_{M}, B_{M}, I_{M}, $v1_{\mathrm{M}}$ and $v2_{\mathrm{M}}$ represent the corresponding values for the resized original multi-spectral thematic mapper (TM) image. R_F, G_F and B_F are corresponding values of the fused image.

2) It can be proven the hue H for the fused image using Eq. (3b) is unchanged because of

$$\begin{aligned} a' &= [2(B_M+\sigma)-(G_M+\sigma)-(R_M+\sigma)] \\ &\quad /2\{[(B_M+\sigma)-(G_M+\sigma)]^2 \\ &\quad +[(B_M+\sigma)-(R_M+\sigma)] \\ &\quad \cdot[(G_M+\sigma)-(R_M+\sigma))]\}^{1/2} \\ &= \frac{(2B-G-R)/2}{\sqrt{(B-G)^2+(B-R)(G-R)}} = a_0. \end{aligned} \tag{5}$$

In contrast, the saturation value S_M for the resized original multi-spectral TM image can be given by Eq. (6) when the new saturation value S' for the fused image as Eq. (7). So the difference between these two saturation values can be written as Eq. (8) when $I_M \neq I_P$.

$$\begin{aligned} S_M &= 1-\frac{3X_M}{R_M+G_M+B_M} = \frac{3I_M-3X_M}{R_M+G_M+B_M} \\ &= \frac{I_M-X_M}{I_M}, \end{aligned} \tag{6}$$

$$\begin{aligned} S' &= 1-\frac{3\min(R_M+\sigma, G_M+\sigma, B_M+\sigma)}{R_M+G_M+B_M+3\sigma} \\ &= \frac{I_M-X_M}{I_{new}}, \end{aligned} \tag{7}$$

$$\Delta S = S' - S_M = (X_M - I_M)\frac{\sigma}{I_{new}\times I_M}, \tag{8}$$

where X_M denotes the minimum value among R_M, G_M, and B_M. According to Eq. (8), σ is crucial in the color distortion problem. Because I_P rarely equals to I_M, σ is not generally equal to zero. Therefore, the color distortion problem appears. The analysis of color distortion is written in detail in Ref. [8].

Based on the two conclusions above, we propose an optimal IHS fusion method. Following Eq. (4), a computationally efficient IHS method without the coordinate transform indicates that the I_M component is crucial to the fusion result because of the difference between I_M and I_P, i.e., the color distortion can be reduced by diminishing σ value. With this viewpoint, a new intensity component can be adopted. It is defined as

$$I_{new} = k_{opt}I_P + (1-k_{opt})I_M, \tag{9}$$

Where k_{opt} and $(1-k_{opt})$ are weight coefficients corresponding to I_P and I_M, respectively. In other words, the optimal coefficient k_{opt} is crucial to adjust color distortion. The bigger the k_{opt} is, the less the color distortion is, because the fused image keeps much more original multi-spectral information. The poor result is that the spatial resolution of fused image cannot be improved enough. With a viewpoint of synthetically quality evaluation for fused image, an optimal fused result can be obtain with a calculated optimal coefficient k_{opt}.

The mean and variance of sub-band coefficients on each scale can be calculated when a image is decomposed with wavelet multi-resolution decomposition. The results show that the mean of sub-band is approximate to zero except the mean of base band. The greater the decomposition scale is, the bigger the variance is. In fact, the main difference of remote sensing images, which have same ground object, is the high frequency in spatial frequency domain rather not the low frequency. In other words, there is greater difference between the high frequency sub-bands after wavelet decomposition.

And at the same time, serial sub-band coefficients are approximate equal to zero except the base band coefficient after wavelet decomposition. The amplitudes of coefficients are corresponding to those notable features, such as edge, line and region. These notable features are mutational gray values. So the fused rule can be defined as the optimal selection for these statistical characteristic from the registered two remote sensing images on each sub-band after wavelet decomposition.The fused result keeps the feature information of high frequency sub-band in frequency transform domain. So a multi-spectral image and a panchromatic image can be fused after wavelet reconstruction.

As the analysis above, OIHS fusion method based on the statistical properties of wavelet decomposition is proposed. This method combines the advantages of IHS method and WT frequency division character.

The flowchart of OIHS method, which using the statistical property of wavelet decomposition and IHS transform on pixel and feature levels, is shown in Fig. 1.

The steps of this fusion method are described in detail as follows.

1) A panchromatic image A, which has high spatial resolution, is registered with a multi-spectral image B.

2) The multi-spectral image B is decomposed with IHS transform. In IHS color space, I is the intensity component, S is the saturation component, and H is the hue component. Then, I is decomposed to 2^j level with wavelet function.

3) The gray histogram of panchromatic image A is normalized corresponding to the intensity component of image B. In succession, the normalized image A$'$ is decomposed to 2^j level with wavelet function too. Here, the decomposed scale j should be equal to the decomposition level mentioned above.

4) Images on each decomposition level are fused based on fusion rule. Then, the new intensity component I' is reconstructed by wavelet inverse transform.

5) The fused image C is obtained after IHS inverse transform with I', H and S components.

6) The weight coefficient k_{opt} should be modified according to the evaluated indexes for fused image, i.e.,

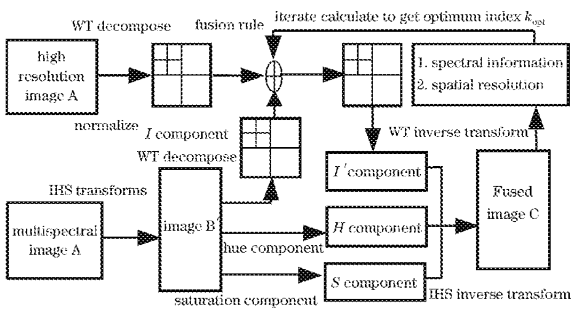

Fig. 1. An optimal IHS fusion method of pixel and feature for remote sensing images based on the statistical properties of wavelet decomposition.

the weight coefficients, k_1 and k_2 of base-band are modified because of $k_{\rm opt} = k_1 = 1 - k_2$. Then step 4) to step 6) should be repeated to calculate the weight coefficients.

7) The resulting weight coefficient must satisfy objective function. That is, the result $k_{\rm opt}$ is the optimal coefficient.

As the analysis of color distortion above, the intensities component $I_{\rm M}$ of multi-spectral image B and the panchromatic image A are fused with OIHS method based on the statistical properties of wavelet decomposition. The fusion rule is described as follows.

1) A window (3×3 pixels) is designed in frequency domain.

2) On 2^j resolution level, the mean and variance of sub-band wavelet coefficient are calculated in that window. The mean is written as $u(2^j)$. And the variance is written as $D(2^j)$.

3) The sub-band high frequency coefficient is decided on feature level fusion by

$$W^k(2^j,x,y) = \begin{cases} W_{\rm A}^k(2^j,x,y), & D_{\rm A}^k > D_{\rm B}^k \\ W_{\rm B}^k(2^j,x,y), & D_{\rm A}^k < D_{\rm B}^k \end{cases}. \quad (10)$$

In Eq. (10), $W(2^j,x,y)$ is the fused result of high frequency coefficient corresponding to 2^j resolution level. $W_{\rm A}(2^j,x,y)$ and $W_{\rm B}(2^j,x,y)$ are high frequency coefficients of image A and I', respectively. $D_{\rm A}$ and $D_{\rm B}$ are variances of 3×3 pixels frequency windows. The center pixel of that window is (x,y).

4) The sub-band low frequency coefficient is decided on pixel level fusion by

$$A(2^j,x,y) = k_{\rm opt}A_{\rm A}(2^j,x,y) + (1-k_{\rm opt})A_{\rm B}(2^j,x,y). \quad (11)$$

Where $A_{\rm A}(2^j,x,y)$and $A_{\rm B}(2^j,x,y)$ are low frequency based-band coefficients of image A and intensity component $I_{\rm M}$ of multi-spectral image B corresponding to 2^j resolution, respectively. $k_{\rm opt}$ is decided by iterated calculation. It must satisfy objective function at the end of iterated calculation.

Then, the performance indexes of optimal weight coefficients are defined as follows.

Let f be the fused image, and $f_{\rm M}$ be the multi-spectral image. The performance index on spectral information $E_{\rm SP}$ is defined as

$$E_{\rm SP} = Corr(f, f_{\rm M}) = \frac{\sum\limits_{j=1}^{npix}(f_j-\bar{f})(f_{{\rm M}_j}-\bar{f}_{\rm M})}{\sqrt{\sum\limits_{j=1}^{npix}(f_j-\bar{f})^2(f_{{\rm M}_j}-\bar{f}_{\rm M})^2}}, \quad (12)$$

where $npix$ is the pixel number of this fused image, $\bar{f}$ and $\bar{f}_{\rm M}$ denote the gray mean of image, respectively. So this index $E_{\rm SP}$ reflects the similarity between the fused image and the multi-spectral image.

Based on calculating correlation between high frequency component of fused image and high resolution panchromatic image, the performance index on spatial resolution $E_{\rm HF}$ can be defined as

$$E_{\rm HF} = \frac{Corr(f^h, f_{\rm H}^h) + Corr(f^v, f_{\rm H}^v) + Corr(f^d, f_{\rm H}^d)}{3}. \quad (13)$$

where $f_{\rm H}$ is the high resolution panchromatic image. f^a, f^h, f^v, and f^d are the components of fused image after wavelet decomposition. They represent the low frequency component, horizontal high frequency component, vertical high frequency component and diagonal high frequency component, respectively. In the same way, $f_{\rm H}^a$, $f_{\rm H}^h$, $f_{\rm H}^v$, and $f_{\rm H}^d$ are components of high resolution image after wavelet decomposition. The index $E_{\rm HF}$ is the arithmetic mean of correlation on high frequency component.

The optimal objective function for low frequency base-band is defined as

$$F(k_{\rm opt}) = \max\{E_{\rm SP}(k_{\rm opt}), E_{\rm HF}(k_{\rm opt})\},$$
$$\text{Domain}: \quad 0 \le k_{\rm opt} \le 1, \quad k_{\rm opt} \in D \in R, \quad (14)$$

which is corresponding to Eq. (11). Here the optimal coefficient $k_{\rm opt}$ is the fusion weight of panchromatic image A and multi-spectral image B on pixel level. This fusion calculation is carried on low frequency based-band coefficients of image A and intensity component $I_{\rm M}$ of image B. Here, $k_{\rm opt}$ lets two performance indexes, $E_{\rm SP}$ and $E_{\rm HF}$, arrive to maximum values at the same time.

In Eq. (11), the spatial resolution evaluated indexes $E_{\rm HF}$ is rising while $k_{\rm opt}$, weight of low frequency based-band coefficients of high resolution image A, is enhanced. At the same time, the spectral information evaluated index $E_{\rm SP}$ is reducing and vise verse. In conclusion, the optimal coefficient $k_{\rm opt}$ lets objective function $F(k_{\rm opt})$ reach maximum value. In other words, $E_{\rm SP}$ and $E_{\rm HF}$ should reach maximum values with optimal $k_{\rm opt}$.

The experiment image data is a part remote sensing image of suburb, Shanghai, China, obtained at June 2002 with Quickbird, a satellite remote sensing imaging sensor. The original images multi-spectral image is 2.44-m spatial resolution. It is resampled with 4-time ratios. The result is 512 × 512 pixels, showing in Fig. 2(a). Figure 2(b) is panchromatic image with 0.61-m spatial resolution. They are registered each other. The fused result with classical IHS method is shown in Fig. 2(c).

By contrast, the fused result with OIHS method is

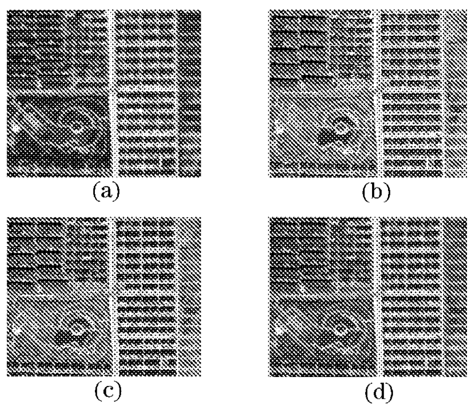

Fig. 2. The original remote sensing images and the fused results.

shown in Fig. 2(d). Here, the optimal weight coefficient of low frequency based-band coefficients is equal to 0.622, that is, the index of panchromatic image A is equal to 0.622.

In the range of $[0, 1]$, k_{opt} is increased from 0 to 1 with an iterated step that is here defined as 0.001. With the increase of k_{opt}, E_{HF} increases, while E_{SP} decreases at the same time. These two indexes are normalized according to

$$E(i) = \frac{E(i) - \min E(i)}{\max[E(i) - \min(E(i)]}, \tag{15}$$

where $E(i)$ is represent the valuated index, such as E_{HF} and E_{SP}. The iterated step is defined as i. As a result, these indexes can be drawn as curves showing in Fig. 3. In this figure, it is obvious to find that the normalized E_{HF} and E_{SP} are all nonlinear. And the cross point of E_{HF} and E_{SP} is the optimal point, i.e., the value of this point is k_{opt}, when the spectral information evaluated index E_{SP} is decreasing. That is, the cross point $k_{\text{opt1}} = 0.622$ in this figure. The convergent precision is $\sigma \leq 0.001$. As the theory analysis mentioned above, the fused image has the maximum spatial resolution while the color distortion keeps least with the optimal k_{opt}.

The correlation coefficient (CORR) and average grad (AG) are defined for quantitative evaluated index using in the fused images. The quantitative result of IHS and OIHS fusion method are listed in Table 1.

Here, the wavelet decomposed scale is $j = 3$ while the Daubechies wavelet base is accepted. The fused subbands images on feature level are shown in Fig. 4 (here, in order to show the decomposed image clearly, j just is decomposed on one level). It is clearly to find the typical high frequency detail image information.

In conclusion, the OIHS method combines the advantages of IHS fusion method and WT fusion method. In IHS space, the high frequency of intensity component I is fused on feature level with multi-resolution wavelet, and the low frequency of it is fused on pixel level with optimal weight coefficients. As a result, the fused image has the maximum spatial resolution while the color distortion keeps least. This method has an ideal tradeoff between spatial and spectral resolution, especially the spectral information of fused image is improved.

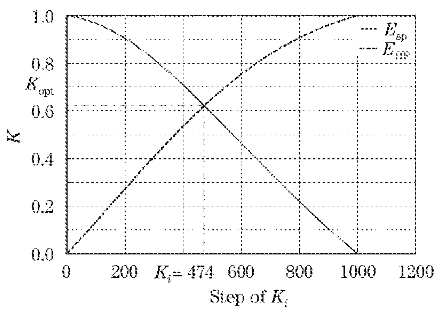

Fig. 3. The evaluation indexes curves.

Table 1. The Compare Evaluation Indexes for Fused Images

	Band	CORR	AG
IHS	R	0.5624	10.6146
	G	0.4644	11.3663
	B	0.5060	9.5875
OIHS	R	0.8488	8.9448
	G	0.7691	9.4102
	B	0.8247	7.9353

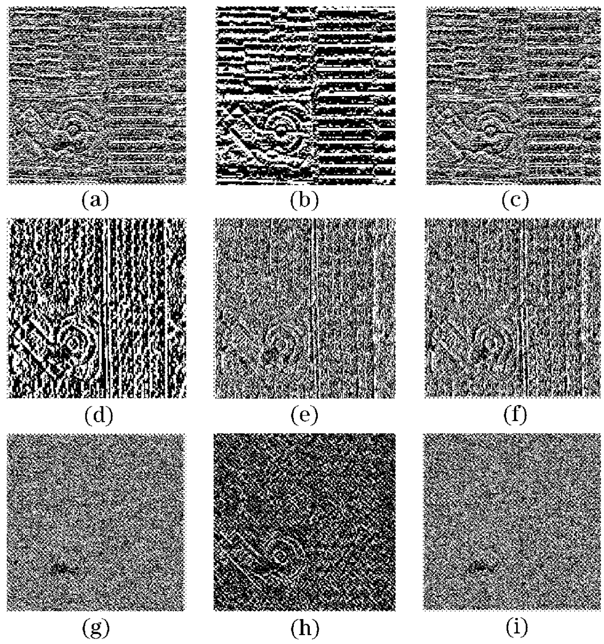

Fig. 4. Fused sub-band on feature level (shown as $j = 1$). The horizontal high frequency of the panchromatic image (a), the multi-spectral image (b), and the fused image on feature level (c); the vertical high frequency of the panchromatic image (d), the multi-spectral image (e), and the fused image on feature level(f); the diagonal high frequency of the panchromatic image (g), the multi-spectral image (h), and the fused image on feature level (i).

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