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Fusion of Visible and Infrared Images Based on IHS Transformation and Regional Variance Matching Degree

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Abstract. It is usually necessary to identify and extract specific characteristics by deriving an informative fused image from multiple images. An effective fusion algorithm was proposed by combining the intensity-hue-saturation (IHS) transformation and the regional variance matching degree (RVMD) in our study. Visible and thermal infrared images of wheat were used as the original data sources. After finishing the IHS transformation, a fusion rule was designed to produce the new component *I*. More specifically, the high frequency fusion rule was generated by the RVMD with a threshold of 0.5 and a 3×3 moving window, and the weighted average was used as the low frequency fusion rule. Experimental results show that the proposed algorithm can avoid producing color distortion in comparison with the IHS transformation, and additionally, it can also enhance the edge contrast and produce more obvious texture resolution. In addition, three quantitative indicators including entropy, standard deviation and average gradient were used to validate the proposed algorithm. The analysis results show that the values of three indicators are respectively 7.82, 63.93, 10.06, which are better than the results derived from the IHS transformation and regional variance fusion.

1.   Introduction

As a very important branch of data fusion, remote sensing image fusion involves many fields such as information fusion, sensor, image processing, etc. [1-3]. To meet the specific needs of generating a more informative remote sensing image, it uses a certain algorithm to merge different sensors with various imaging mechanism for describing the same landscape. Consequently, fusion of remote sensing images will have higher reliability, less fuzzy, better comprehensible, more suitable for human visual and computer detection, classification, recognition and understanding of processing [4-7]. The advantages of remote sensing image fusion have been widely applied in various application fields, so it has highly practical significance to propose more effective and useful fusion algorithms from multiple remote sensing sensors. Since the emergence of Earth Observing System (EOS), various fusion remote sensing fusion methods have been proposed at different levels from multisource remotely sensed imagery [8].

   The existing remote sensing image fusion algorithms are usually based on a single pixel, which is the only specific decomposition level based on the fusion results of pixel values. Additionally, the

fusion rules of remote sensing image are the corresponding pixel values take a large (small) and the corresponding pixel value of the weighted average method [9]. Conversely, the pixel value of a single pixel does not fully express the regional characteristics of the whole remote sensing image. The pixels of remote sensing image in a region generally have significant correlation. Therefore, the remote sensing image fusion based on the single pixel value has a certain one-sidedness, and the fusion quality is often not very high. The key step is to improve the fusion rules by considering the regional characteristics of remote sensing image instead of pixel-based fusion [10].

In summary, we proposed a remote sensing fusion algorithm based on the IHS color space and regional variance matching degree. The method can remove the color distortion in comparison with the IHS algorithm. In addition, it can also solve the traditional block fusion based on remote sensing image processing. To validate the fusion method, we compare the results with the IHS algorithm and regional variance fusion. Two visible and thermal infrared images of wheat at the jointing stage were acquired to check our fusion method in the practical application.

2.   Materials and Methods

2.1.   Collection of Experimental Data

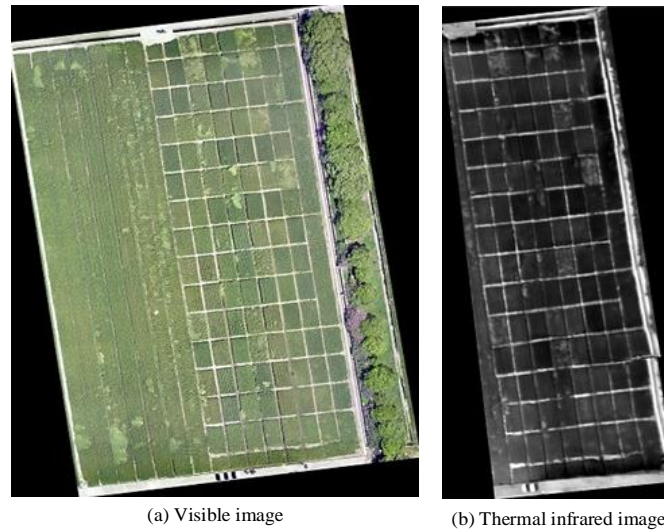(a) Visible image   (b) Thermal infrared image

Figure 1. Acquired original visible and thermal infrared images.

Electric eight-rotor unmanned aerial vehicle (UAV) was used to carry the two sensors, with a load weight of 6 kg and an endurance time of 20 min. Two sensors included HD digital camera (Sony DSC-QX100) with a resolution of 5472 $\times$ 3648 pixels and Optris PI thermal imaging system with a temperature resolution of 0.05 K. The flight altitude was set to 50 m. The original digital visible and thermal infrared images of the same plots were acquired at the jointing stage of wheat in March 2016 (Fig. 1).

2.2.   Description of Remote Sensing Image

There are many types of regional features for a remote sensing image, which represent the different physical meanings. In our study, regional energy, regional median and regional mean are just given. The regional energy (E) in the coordinate (n, m) of an image G is defined as Eq. (1).

$$E = \sum_{n^* \in J, m^* \in K} \left[G(n + n^*, m + m^*) \right]^2 \tag{1}$$

where J and K are the sizes of the local area in the remote sensing image (e.g. 3 $\times$3, 5 $\times$5, 7 $\times$7), and the changes of n^* and m^* are within the ranges of J and K.

The definition of regional median and mean of the remote sensing image are respectively shown in Eqs. (2) and (3).

$$M_{ed}(n, m) = M_{\text{median}}\left[G(n + n^*, m + m^*)\right] \tag{2}$$

$$A(n, m) = E(n, m) / N \tag{3}$$

where N is the total number of pixels in the specified region.

2.3. Regional Variance Matching Degree

Definition of the regional variance matching degree (RVMD) of a remote sensing image is shown as Eqs. (4)~(6) [11]. Suppose $C(A)$ is the wavelet coefficient matrix of the remote sensing image A, $p(m, n)$ is the spatial coordinates of wavelet coefficients, and $C(A, p)$ is the coefficient value of coordinates (m, n) in the wavelet coefficient. Firstly, the significance of regional variance of the image is defined. It is the weighted variance of the wavelet coefficients in the Q region centered on the p point, as shown in Eq. (4). The regional variance significance of the coefficient in the Q range of the p center of the wavelet coefficient matrix is shown as Eq. (6), which is expressed as the $G(A, p)$.

$$G(A, p) = \sum_{q \subset Q} w(q)\left|C(A, q) - \bar{u}(A, p)\right|^2 \tag{4}$$

$$w(p) = \frac{1}{2}\left\{\exp\left[-\frac{(m - p1)^2}{2\sigma^2}\right] + \exp\left[-\frac{(n - p2)^2}{2\sigma^2}\right]\right\} \tag{5}$$

$$M_{A,B}(p) = \frac{2\sum_{q \in Q} w(q)|C(A, q) - \bar{u}(A, p)||C(B, q) - \bar{u}(B, p)|}{G(A, p) + G(B, p)} \tag{6}$$

where q represents the coefficients within the region in the Eq. (4), $w(p)$ represents the weight of weighted variance, $M_{A, B}(p)$ is the regional variance matching degree of the coefficients in the wavelet coefficient matrix of remote sensing image A and B respectively with the region Q as the coordinate p, and $G(A, p)$ and $G(A, p)$ are respectively the regional variance significance of each coefficient in the wavelet coefficient matrix of image A and B.

2.4. Proposed Remote Sensing Fusion Method

In our study, a new fusion method was proposed based on the IHS color space and RVMD. Two well-matched original visible (A) and infrared (B) remote sensing images are taken as the examples and specific operation steps are described as follows (Fig. 2).

(1) Visible and infrared remote sensing image are strictly registered;

(2) Both of them are transformed from red-green-blue (RGB) color space to IHS color space respectively using the Eq. (1);

(3) The I components of visible and infrared images are decomposed into 4 layers where the sym4 is selected as the wavelet base;

(4) The average values of the low-frequency parts of the two sets of wavelet coefficients are taken as the low-frequency part of the I component of the fused image;

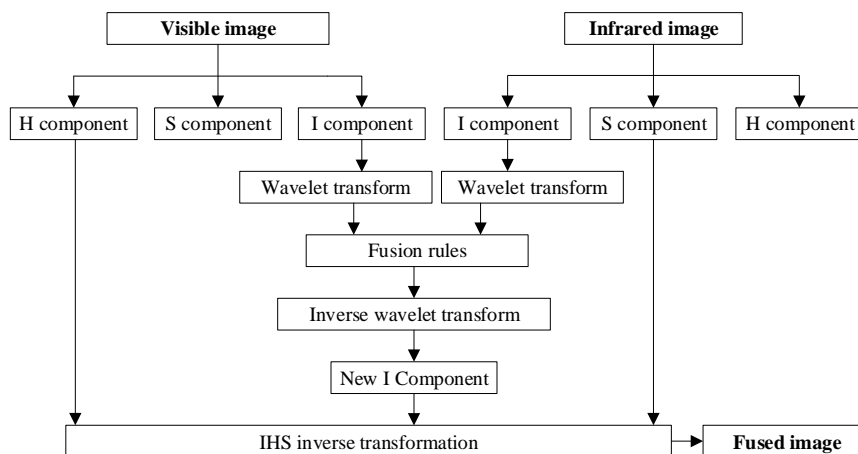(5) To calculate the regional variance degree of the high frequency coefficients of the visible and infrared images.

Figure 2. Schematic diagram of the proposed fusion algorithm.

2.5. Selection of Fusion Rules

The weighted average of the low-frequency sub-bands of component I_A and I_B of the original remote sensing images *A* and *B* is used to obtain the component I_F of the fused remote sensing image (Eq. 7).

$$I_F = (I_A + I_B)/2 \qquad (7)$$

The high-frequency sub-band of the component *I* of the original remote sensing images A and B is taken as the fusion rule based on the RVMD. In general, an odd number of window forms is selected in the region, e. g. 3×3, 5×5, 7×7. In our study, a 3×3 window is used with a weighted template of *P* (Eq. 8). The variance matching degree of the region with the threshold value of 0.5 gets the new component I_F. The method is to use the weighting template *P* and move up and down and left and right, and the variance matching degree in the corresponding window region is calculated in each region.

$$P = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad (8)$$

3.   Results and Discussions

3.1.   Comparison of Fusion Results

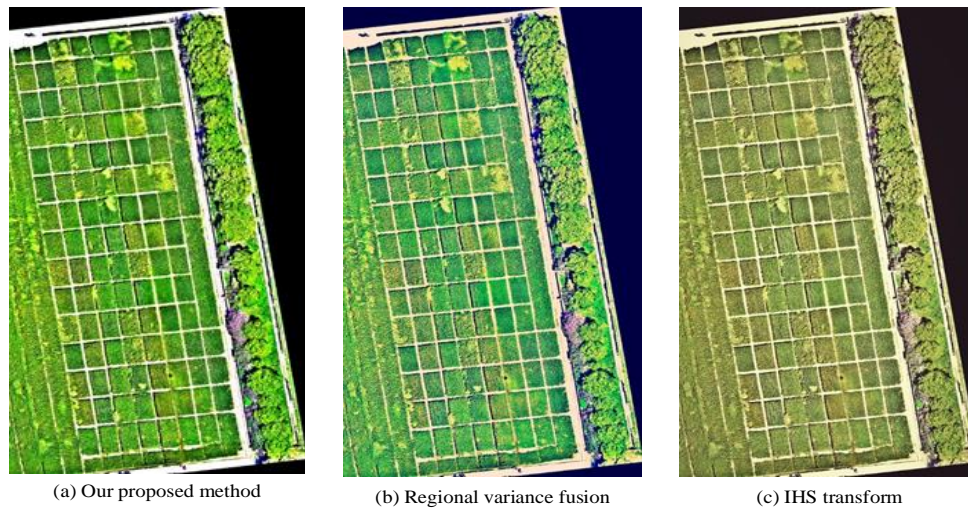(a) Our proposed method   (b) Regional variance fusion   (c) IHS transform

Figure 3. Comparison of the fusion results of three methods.

To demonstrate the fusion result of our proposed method, additional two methods are used including reginal variance fusion and IHS transformation (Fig. 3). It can be visually found that they have similar fusion result for regional variance fusion (Fig. 3b) and our proposed fusion method (Fig. 3a), but it has more fine features and obvious texture in Fig. 3a. In addition, three quantitative indicators including entropy, standard deviation and average gradient are used to further compare the fusion results (Table 1). We can also find that all the values of three evaluation indicators are the most in the fused image derived from our method.

Table 1.   Comparison of fusion results using quantitative indicators.

Image	Entropy	Standard deviation	Average gradient
Fig. 1a	7.74	60.14	9.64
Fig. 1b	7.76	57.92	4.59
Fig. 3a	**7.82**	**63.93**	**10.06**
Fig. 3b	7.54	58.08	9.32
Fig. 3c	7.77	57.92	9.34

3.2.   Analysis of Image Fusion Algorithms

Image fusion is a branch of data fusion technology. It is to combine multiple images of the same scene that are usually obtained by two or more imaging sensors at the same or different time. Since different sensors have different imaging mechanism, the redundancy and complementarity between the images of the same scene can be inevitablely produced [12-14]. Consequently, it is of great significance to synthesize or fuse multiple images to generate a more informative image.

At present, there are several widely used image fusion methods including wavelet transform, Contourlet transform, median filtering algorithm, principal component transform, Brovey fusion, IHS transform, etc. Among them, the basic idea of image fusion based on wavelet transform is that the wavelet transform can effectively separate the frequency characteristics of the image [15-17]. The low

frequency part reflects the whole visual information of the image, and the high frequency component reflects the details of the image. Because the wavelet fusion retains the high frequency characteristics of high-resolution image, the fusion effect is good. The difficulty of the fusion algorithm is the selection of fusion rules [18]. The appropriate fusion rules can't be chosen often makes the loss of the image details and the decrease of the information contains.

In summary, this paper presents a remote sensing image fusion method based on HIS color space and regional variance matching degree. Firstly, the remote sensing image is transformed from RGB space to IHS color space, the wavelet transformation of the components *I* of the infrared and visible remote sensing images are performed respectively. The coefficients of wavelet coefficients are chosen according to the fusion rule of region variance matching degree.

3.3. Performance of the Proposed Fusion Method
From the above quantitative analysis, we can see that the fusion result obtained by the proposed method is superior to traditional fusion methods based on IHS transform method and regional variance matching degree. First, from the spatial detail information, the information entropy is larger than that of traditional methods based on IHS transform and region variance matching, so the fused remote sensing image contains more information. The average gradient is a sign of clarity, the method used in this paper to obtain a higher degree of clarity, the maximum standard deviation indicates that the fusion remote sensing image obtained in this paper has the best visual effect. This shows that the objective evaluation results and subjective evaluation results are consistent.

4. Conclusion
Traditional fusion methods are usually based on the regional feature, which makes the fused remote sensing image prone to block phenomenon. Conversely, the IHS color space based methods can solve this problem well. However, IHS-based methods are prone to color distortion. It can be concluded that the proposed fusion algorithm based on IHS transform and regional variance matching degree can produce better fused image than traditional IHS transform and regional variance fusion. The fused image has more information entropy and more clear texture edge. In this study, however, we only make a preliminary study on the image fusion based on IHS spatial and regional features. Visible and thermal infrared images of wheat are just considered to validate the fusion method. The availability and significance of this method is still required to be validated by more remote sensing images.

5. Acknowledgements

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