# Remote Sensing Image Fusion Algorithm Based on Wavelet Coefficients

*Xiaolei Zhao*

*Weinan Normal University, Weinan, Shaanxi, 714000, China*

Abstract: The regional characteristics of the low frequency subband coefficients after wavelet transform and the directional region characteristics of each high frequency subband coefficient are analyzed and calculated. A new image fusion method based on the wavelet coefficient region features is proposed. For each coefficient of the low-frequency sub-band, according to the regional correlation, the fusion rule of the regional variance is adopted to determine the low-frequency fusion coefficient; for each coefficient of each high-frequency subband, according to the directional characteristic of the sub-band in which it is located, Energy fusion rules, and then determine the high-frequency fusion coefficient. Fusion experiments of multifocus images and medical images are conducted, and the fusion results are objectively evaluated with information entropy and average gradient. The experimental results show that the image fusion algorithm based on the directional characteristics of wavelet coefficients is better than the traditional fusion algorithm and has some practicality.

Keywords: Remote Sensing, Image Fusion, Algorithm, Wavelet Coefficients

## 1. INTRODUCTION

As a new discipline that integrates the technologies of sensors, signal processing, image processing and artificial intelligence, image fusion has been applied in many fields such as airport navigation, earth observation, intelligent transportation, geographic information system, security monitoring, medical diagnosis and so on. It combines different images obtained by different sensors on the same target or scene or different images acquired by the same sensor or at different times by the same sensor into one image to make the newly acquired image more suitable for the visual perception or Computer processing. Image fusion usually can be divided into pixel level, feature level, decision-making level three levels, of which pixel-level fusion as a direct role in the bottom of the image pixel fusion, is the current research focus. In this paper, wavelet-based pixel-level image fusion algorithm is studied. At present, there are two typical methods of image fusion based on wavelet, that is, image fusion method based on weighted average and image fusion method based on coefficient area energy. The former obtains the fusion coefficient by weighting the low frequency subband coefficients and the high frequency subband coefficients after wavelet transform. The method is simple and intuitive, and is suitable for real-time processing. However, the method has the following disadvantages: the method only performs weighted processing separately on the coefficients to be fused, neglects the regional correlation between adjacent wavelet coefficients, and further reduces the fusion precision; The low frequency sub-band wavelet coefficients of the fusion image adopt the weighted average fusion rule, while for the high frequency sub-band coefficients, the energy of eight neighborhoods is used to measure the regional correlation so as to adaptively determine the fusion coefficient. This method has a strong ability to capture the edge coefficients of high frequency subbands and achieves a better fusion effect. However, this method has two disadvantages: (1) a simple weighted average rule is still adopted for low frequency subband coefficients, Thus affecting the definition of image fusion and information entropy, reducing the image contrast. In fact, because the low frequency coefficients of the wavelet focus most of the energy of the original image, it determines the appearance of the image. We have found through a large number of experiments that the low frequency coefficients of the image after wavelet transform still retain the regional correlation of the image in the spatial domain. Therefore, the reasonable selection of the fusion rules and operators of low frequency coefficients will inevitably improve the image fusion effect. (2) The coefficients to be fused for all high frequency subbands use eight neighborhood energies as a measure of regional correlation. In fact, however, the coefficient distribution of each high frequency subband in the image wavelet transform shows obvious directional characteristics. In this way, for the high-frequency subbands, when calculating the energy of the eight neighborhoods of a coefficient to be fused, if a weight coefficient with certain adaptive characteristics is adopted for the neighboring coefficients along different directions, it is bound to make full use of the wavelet transform pair Texture capture ability to improve the image fusion accuracy.

Analysis and discussion on the characteristics of wavelet coefficients

After the image is decomposed by the lifting scheme wavelet, low-frequency sub-bands with different directionality and high-frequency sub-bands with different directivities are obtained respectively, as shown in Fig.1. LLk represents the low frequency component of the image (k represents the wavelet decomposition level of the image, k = 3 in this paper, the same applies below). HL1, HL2, ..., HLk represent the vertical edge and detail components of the image in different resolutions; LH1, LH2, ..., LHk and HH1, HH2, Edge and detail components in horizontal and diagonal directions.

After the wavelet transform, the low frequency subband maintains the basic outline of the original image. After the wavelet transform of the image, the coefficients between the adjacent coefficients of the low frequency subband Regional characteristics of the spatial domain will also be preserved. In order to verify the correctness of the conclusion, we use variance as a measure of regional correlation. Taking the initial Lena image and the Lenaleft image and Lenaright image with focus on the left and right sides as an example, the following statistical work is carried out. Since the low-frequency sub-band is not clear enough after the N-th enhancement wavelet transform, we can not directly judge whether the low-frequency subband coefficients and their neighboring coefficients preserve the regional correlation of the spatial domain through vision. Therefore, we use the variance as the region Relevance of the standard, the regional correlation of low frequency coefficients were statistically and compared with the regional correlation of space domain, the specific process of judging as follows:

Step1 traverses the pixels in the left half of Figure 2a and Figure 2b to calculate the variance of 3 × 3 regions and compare them.

Step2 traverses the pixels in the corresponding positions on the right half of Fig.2a and Fig.2c and computes and computes the variance of 3 × 3 region.

Step3 traverses the coefficients of the corresponding positions on the left half of the low-frequency subbands in Figure 2d and 2e to calculate the variance of 3 × 3 regions for comparison and statistics;

Step4 traverses the coefficients of the corresponding positions of the right half of the low-frequency subbands in Figs. 2d and 2f, and computes and computes the variance of 3 × 3 regions. By comparing the statistical results obtained in Step 1 to Step 4, the statistical results as shown in Table 1 are obtained.

## 2. IMAGE FUSION RULES AND FUSION OPERATOR

After the wavelet transform of the image, the low-frequency subband coefficients concentrate most of the energy of the original image and basically maintain the overall shape of the original image. At the same time, as can be seen from the statistical analysis of Section 2.2, the low frequency subband coefficients are retained between their adjacent coefficients In order to make better use of the regional correlation characteristics of low frequency subbands after wavelet transform, we propose the following fusion rules based on the variance of regions: traversing each position (x, y) in the low frequency subband, , The mean μk (x, y) of eight neighborhoods centered at (x, y) (k = 1, 2, representing the two subbands to be fused, respectively, the same applies hereinafter) is calculated.

The variance σk2 (x, y) of eight neighborhoods centered on (x, y) is calculated by traversing each position (x, y) in the low frequency subband.

According to the above steps, traversing all the coefficient points of the low-frequency subband to finally obtain the fused low-frequency subband coefficients.

The coefficients of each high frequency subband after wavelet transform contain the details and edge components of the image, and the distribution of each high frequency subband coefficient shows obvious directional features. As can be seen from the statistical results in Section 2.3, the coefficients in the subbands of the subbands in the vertical direction generally have the correlation in the vertical direction for the subbands HL1, HL2, ..., HLk in the vertical direction. Likewise, the direction subbands LH1, LH2, HH1, HH2, ..., HHk generally meet the horizontal and diagonal regions, respectively. Accordingly, we propose the following high frequency subband fusion rules based on the energy of the directional region.

## 3. IMAGE FUSION ALGORITHM

In this paper, the image fusion algorithm based on the characteristics of wavelet coefficients is implemented as follows: Step1: The two images to be fused are respectively subjected to wavelet transform of N-layer lifting scheme to obtain low frequency subband LL (k) N and high frequency subband LH (k) 1, LH (k) 2, ..., LH (k) N in the horizontal direction, HL k1, HL k2, ... HL k in the vertical direction, (k) 1, HH (k) 2, ..., HH (k) N (diagonal direction), where k = 1,2 represent two different fused images respectively; For each position (x, y), all the coefficients in subbands are traversed, then the variance σ12 (x, y) of the eight neighborhoods centered on (x, y) (x, y); Step3 respectively traverse the high-frequency sub-band in each direction, the high-frequency subbands in different directions For each position (x, y), the area energy and matching degree of the coefficient to be fused are calculated according to the process described in Section 3.2, and the fusion coefficient f (x, y) After the low-frequency and high-frequency sub-band coefficients to enhance the program wavelet inverse transform, and then get the fusion of the image.

## 4. EXPERIMENTAL RESULTS AND ANALYSIS

In order to validate the effectiveness of the proposed algorithm, we simulate two Lena (256 × 256) standard images and Clock (512 × 512) standard images and medical CT images and MR images with different focuses, and compare them with the traditional space Domain weighted average fusion algorithm, image fusion algorithm based on wavelet weighted average, and image fusion algorithm based on wavelet domain energy are compared.

CT can only distinguish the tissue with poor density, the resolution of soft tissue is not high; and MRI on the soft tissue better resolution, and medical image fusion helps doctors more comprehensive observation of the patient's condition, the medical research is important effect. Fig. 4c-Fig. 4f, Fig. 5c-Fig. 5f and Fig. 6c-Fig. 6f respectively show the fusion results of the spatial domain weighted averaging algorithm, the wavelet domain weighted average averaging algorithm, the wavelet domain energy fusion algorithm and the algorithm in this paper. It can be seen that the experimental results of this algorithm are more contrasting and the texture is clearer than the traditional image fusion algorithm. In order to give an objective evaluation of the performance of the above image fusion algorithm, this paper introduces Entropy and sharpness as objective evaluation criteria for the fusion results. It can be seen that both the entropy and the sharpness of the proposed algorithm, Image fusion method has improved compared with the traditional methods, especially for medical image images have a better fusion effect.

## 5. CONCLUSION

In this paper, we propose a new image fusion algorithm based on the regional characteristics of wavelet coefficients. First of all, since the low-frequency subband coefficients of the image after wavelet transform reflect the approximate outline of the image and concentrate most of the energy of the initial image, and retain the regional characteristics of the original image, we determine the variance of its eight neighborhoods Low frequency fusion coefficient. Compared with the traditional weighted average fusion rules, this rule can reflect the outline of the initial image more accurately and accurately. Secondly, after wavelet transform, each high frequency subband coefficient reflects the detail and edge components of the image, and the distribution of high frequency coefficients has obvious directional features. Therefore, we adopt a series of templates with obvious directional features, The energy of the directional area defined by the directional template is used as a measure of the regional correlation to determine the high frequency fusion coefficient. Compared with the traditional eight-neighborhood energy fusion rule, the rule of participation in determining the high-frequency fusion coefficient is more important and significant, and thus improves the fusion accuracy, and because the participation of adjacent coefficients is reduced, The complexity of fusion. Finally, we apply this algorithm to multi-focus image fusion and medical image fusion respectively. Through the simulation results, it can be concluded that the image fusion algorithm based on the characteristics of wavelet coefficients is more effective and has better practicability.

## ACKNOWLEDGEMENTS

Fund Project: Shaanxi Province supporting discipline math fund project (project number 14SXZD011) Shaanxi Provincial Department of Education research project (16JK1272)

## REFERENCES

[1] De I, Chanda B.A. simple and efficient algorithm for multi focus image fusion using morphological wavelets[ J].Signal Proce-ssing,2006,86: 924-936.

[2] Otazu X, Gonzalez- Audicana M, Fors O, *etal*. Introduction of sensor spectral response into image fusion methods. Application to wavelet-based methods[J].IEEE Transactions on Geoscience and Remote Sensing,2005,43(10):2376-2385.

[3] Kor S, Umashanker. Feature level fusion of multi model medical images in lifting wavelet transform domain[C] // Proceedings of the 26th Annual International Conference of the IEEE EMBS:1479-1482.

[4] Sweldens W. The lifting Scheme: a construction of second gene-ration wavelets[ R].Industrial Mathematics Initiative, Depart-ment of mathematics, University of South Carolina,1995.

[5] Ramesh C, Ranjith T. Fusion. Performance Measures and a Lif-ting Wavelet Transform based algorithm for Image Fusion. ISIF, 2002:317-320.

.