Multi-focus image fusion based on multi-resolution analysis

Zhaonan Yang[1,2], Shu Zhang[3*], Zeyuan Gu[3]

[1]*College of Computer Science and Technology, Harbin Engineering University, Harbin, 150001, Heilongjiang, China*

[2]*International Education College, Heilongjiang University of Science and Technology, Harbin, 150022, Heilongjiang, China*

[3]*College of Information Science and Technology, Heilongjiang University of Science and Technology, Harbin, 150022, Heilongjiang, China*

Received 1 June 2014, www.cmnt.lv

Abstract

In order to further improve the effect of image fusion and the performance of fusion algorithm and on the basis of the in-depth analysis of various different image fusion strategies, this paper has proposed a multi-resolution neighborhood energy contract fusion algorithm based on wavelet analysis. This method can better abstract the important features and detail information of the source image and improve the information entropy reflecting the information richness, the average gradient of the image details and marginal information as well as the overall activity level of the image compared with other fusion methods. Moreover, it has better evaluation parameters than other fusion methods, suggesting that this method is effective in multi-focus image fusion and that it can achieve good effects.

Keywords: image fusion; wavelet analysis; multi-resolution

1 Introduction

As an important part of image processing, image fusion can output a fused image which is more suitable for human visual perception or further processing and analysis by the computer by using multi-sensor image information of the same scenario. It can obviously improve the shortcomings of single sensor and enhance the image definition and information packet content. Besides, it is conductive to acquire the information of the objectives or scenarios in a more accurate, reliable and comprehensive way. With the research and development of such important theories as image processing technology, data fusion technology and wavelet multi-resolution analysis, it has become one of the research focuses for numerous domestic and international scholars to obtain a better image which can meet different requirements by fully using the information provided by many images [1].

The image fusion based on wavelet transform is a process to perform wavelet transform on source images to be fused respectively, form their own multi-scale descriptions, fuse the sub-images obtained from wavelet transform according to certain fusion rules, form a new image multi-scale description and get the fused image through invert wavelet transform. The wavelet transform of the image is also a multi-scale and multi-resolution decomposition of the image. After the image goes through wavelet transform, its total amount of data won't increase. In the meanwhile, with directionality, wavelet transform can fuse the image in different directions respectively; therefore, it can obtain the fused image with better effects [2].

This paper introduces the basic concepts and theories of image fusion; determines wavelet transforms the method to be used in image fusion through the comparisons among different fusion algorithms. Discusses the subjective evaluation standards and objective evaluation parameters for the evaluation of image quality in detail. Proposes wavelet multi-resolution neighborhood energy contract fusion algorithm based on the weaknesses of traditional fusion algorithms in multi-focus image fusion. Determines the scale coefficients of the fused image by measuring the relevant coefficients and spatial frequency between its image blocks in the low-frequency component after the wavelet decomposition and the wavelet coefficients of the fused image with direction contract as the criterion in high-frequency component and gets the fused image through invert wavelet transform. The simulation result has shown that compared with traditional fusion algorithms, this algorithm can obtain the fused image with better evaluation indexes such as definition, average gradient and information entropy.

2 The image fusion based on wavelet transform

The image fusion based on wavelet transform is to perform wavelet transform on the source image to be fused to get wavelet pyramid image sequences. To fuse the image sequences in different feature domains with different fusion rules to get the wavelet pyramid image sequences and to get the fused image by performing invert wavelet transform in the fused wavelet pyramid image sequences, namely the image reconstruction.

If performing N-level wavelet decomposition in two-dimensional image, there will be (3N+1) different

* ***Corresponding author's***-e-mail: zs8803@126.com

frequency bands, including 3N high-frequency sub-band and 1 low-frequency sub-band. Where there are higher wavelet decomposition levels, there will be smaller image size in the corresponding level; therefore, every image decomposed by the wavelet also has pyramid structure and it can become wavelet decomposition pyramid. The wavelet transform of the image is also a multi-resolution and multi-scale decomposition and it can also be used in multi-sensor image fusion processing [3].

In three-level image fusion methods, pixel-level image fusion is the most fundamental and important method and it is also the fusion method with the most acquired information, excellent detection performance and most extensive scope of application. At the same time, it is also the foundation of feature-level and decision-level image fusion. This paper mainly introduces the common algorithms of pixel-level image fusion [4].

The methods adopted in pixel-level image fusion can be divided into simple fusion method, pyramid fusion method and wavelet fusion method.

2.1 SIMPLE FUSION METHOD

2.1.1 Weighted average method

Weighted average method is the simplest multi-image fusion method and it performs weighted processing on the corresponding pixel points in multiple source images. For example, if *A* and *B* are the source image to be fused and *F* is the processed fused image, the weighted coefficient fusion can be expressed as:

$$F(j,k)=\alpha[A(j,k)+KB(j,k)]- \\ \beta\left|A(j,k)-KB(j,k)\right| . \quad (1)$$

In this Equation, K, α and β are the weighting factors. The former part $\alpha\left[A(j,k)+KB(j,k)\right]$ is the weighted average of these two images, which affects the energy of the fused image and which plays a decisive role in the height of the fused image while the latter part $\beta\left|A(j,k)-KB(j,k)\right|$ is the weighted difference of these two images and it includes the fuzzy information of the two images. The factor K adjusts the domination ratio of two images to balance these two images with different brightness. The image highlights with the increase of the factor $\alpha$and the image edge enhances with the increase of the factor β. Properly adjust K, α and β to eliminate fuzzy edge and ensure that no excessive edge information will lose in the elimination in different images. As for other high-frequency components, take the maximum value of the two groups of coefficients and get the strongest edge information so as to get the output image with excellent quality [5].

2.1.2 HIS (Hue, intensity, saturation) method

Transform the RGB model of the image into HIS model. In HIS space, calculate the components H, I and S with clear physical significance, namely to fuse multiple source images and demonstrate the fused result in RGB space. Since this technology directly reflects the feeling of human eyes, it has better predictability [6].

2.1.3 PCA (Principal component analysis) method

PCA is an effective tool to reduce multivariate data dimensions. As a conventional data statistic technology, PCA can transform enormous relevant multivariate variables into irrelevant variables and the new variables obtained can be generated from the linear combination of the original variables. PCA reduces the channels or sub-bands of the data by reducing the dependency between the channels. The basic principle of weighted image fusion based on PCA transform is as follows. Firstly calculate the covariance matrix of the source images to be fused. Then seek the eigenvalue and the corresponding eigenvector. Finally, determine the weighted coefficient of the source image by using the corresponding eigenvector to the eigenvalue and get the fused image [7].

2.2 PYRAMID METHOD

Pyramid image fusion algorithm is a commonly-used image fusion method recently. In this algorithm, the source image is continuously filtered to form a tower structure. Fuse the data of every level with a fusion algorithm to get a synthesized tower structure and reconstruct the synthesized tower structure to get the reconstructed image. The detailed information with different resolutions in the pyramid relates to each other. When the multi-sensor images to be fused have a big difference, such relevance can cause instability in the algorithm easily and it can be overcome by the multi-resolution fusion algorithm based on orthogonal wavelet transform.

3 The improved image fusion algorithm

Image fusion is aimed to improve the reliability of the image through the processing of redundant data among multiple images and enhance the definition of the image by the processing of the complementary information among multiple images. The application of wavelet transform theory into image fusion can effectively distinguish the components of different frequencies of the source images and select specific fusion rules according to the features of these components so as to obtain the fused image with better visual effects based on the visual characteristic that the high-frequency component in different directions of human eyes has different resolutions.

3.1 THE FUSION RULE IN LLW-FREQUENCY DOMAIN

Many image fusion algorithms based on wavelet transform only adopts weighted average method or coefficient maximum/minimum method in low-frequency coefficient fusion simply. It is a feasible method in the images to be fused with similar low-frequency components and it has simple and few calculations. However, in the case where there is contrast polarity reversion between the images to be fused, this method will generally reduce the image contract, making the objective fuzzy. Because the low-frequency coefficient determines the image outline, accurate selection of low-frequency coefficient has a significant role in improving the visual effects of the fused image. This paper determines the scale coefficients of the fused image through the correlation coefficient and spatial frequency between the corresponding sub-image blocks.

Decompose the low-frequency component into several sub-image blocks with a size of $m \times n$ marked as A_{1k} and B_{1k} and calculate the correlation coefficients between their spatial frequencies and the corresponding sub-blocks respectively.

The correlation coefficient of the image is a statistic to describe the image correlation and it reflects the overlap degree of the information included in these two images, namely the correlation of tow images. Define the correlation between the image blocks with the given size of $m \times n$ in Image F and G as follows:

$$r = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}[(f_{i,j}-e_f)\times(g_{i,j}-e_g)]}{\sqrt{[\sum_{i=1}^{m}\sum_{j=1}^{n}[(f_{i,j}-e_f)^2]\times[\sum_{i=1}^{m}\sum_{j=1}^{n}[(g_{i,j}-e_g)^2]}}. \quad (2)$$

In this Equation, $f_{i,j}$ is the pixel value of Point (i,j) in Image F; $g_{i,j}$ is the pixel value of Point (i,j) in Image G; e_f is the average of pixels in the image block $m \times n$ in Image F and e_g is the average pixels in the image block $m \times n$ in Image G.

Assuming that ω_A and ω_B are the weighting factors and $\omega_A + \omega_B = 1$, record that the spatial frequencies of sub-block images A_{lk} and B_{lk} are SF_A and SF_B and the correlation between them is r_k. Determine the weighting coefficient through the correlation and spatial frequency between the images. If the correlation r_k is bigger than the determined threshold T, the low-frequency coefficient of the fused image is the average of pixels in the corresponding position of the source image; if the correlation r_k is smaller than the determined threshold T, determine the low-frequency coefficient according to the spatial frequency of the corresponding sub-block image.

In this way, the fusion function of the low-frequency domain is:

$$C_{Fk} = \omega_{Ak}C_{Ak} + \omega_{Bk}C_{Bk}. \quad (3)$$

In this Equation, $\omega_{Ak} = \begin{cases} 0.5 & r_k \ge T \\ r_k & r_k \le T \text{ and } SF_{Ak} \le SF_{Bk} \\ 1-r & r_k \le T \text{ and } SF_{Ak} \ge SF_{Bk} \end{cases}$

The low-frequency coefficient of the image can be determined by Equation (3).

3.2 THE FUSION RULE OF HIGH-FREQUENCY DOMAIN

Since human visual system is very sensitive to the local contrast of the image, to introduce direction contract in the wavelet decomposition can have better fusion effects. The definition of the image contract R is:

$$R = \left(L - L_B\right)/L_B = L_H / L_B. \quad (4)$$

In this equation, L is the local grayscale; L_B is the local background brightness of the image (namely the local low-frequency component) and $L_H = L - L_B$ is equal to high-frequency component. According to the formula of the definition of image contract, define the direction contract of the wavelet domain as follows:

$$R_j^i = D_j^i / C_j, i = 1,2,3. \quad (5)$$

i=1, 2, 3 are the vertical direction, horizontal direction and diagonal direction.

As for the high-frequency image, calculate the direction contract in the frequency and directions according to Equation (5) respectively. Determine the wavelet coefficient of the fused image with direction contract as the evidence.

$$D_{j,F}^i = \begin{cases} D_{j,A}^i & R_{j,A}^i \ge R_{j,B}^i \\ D_{j,B}^i & D_{j,A}^i \le R_{j,B}^i \end{cases} \qquad i = 1,2,3 \quad (6)$$

In this equation, $R_{j,A}^i$ and $R_{j,B}^i$ are the direction contrasts of the high-frequency images after wavelet decomposition in i-th direction and j-th level of Image A and Image B.

3.3 THE PROCEDURE OF THE IMPROVED IMAGE FUSION ALGORITHM

The main procedures of the improved image fusion algorithm based on wavelet transform are classified as follows.

Firstly, perform wavelet decomposition on the registered source image, namely to filter with a group of high-low frequency passing filter and separate high-frequency and low-frequency information.

Secondly, adopt different fusion strategies in high-frequency and low-frequency information from the decomposition of every level according to the information characteristics, abstract the information according to the characteristics in different transform domains and fuse respectively, perform low-frequency fusion by using normalized neighborhood energy and conduct high-frequency fusion taking the bigger neighborhood energy contract.

Finally, perform invert transform on the processed wavelet coefficient from the wavelet transform in Step 1 to reconstruct the image and get the fused image.

The flow chart of the improved contract fusion method is classified as follows [8, 9]:

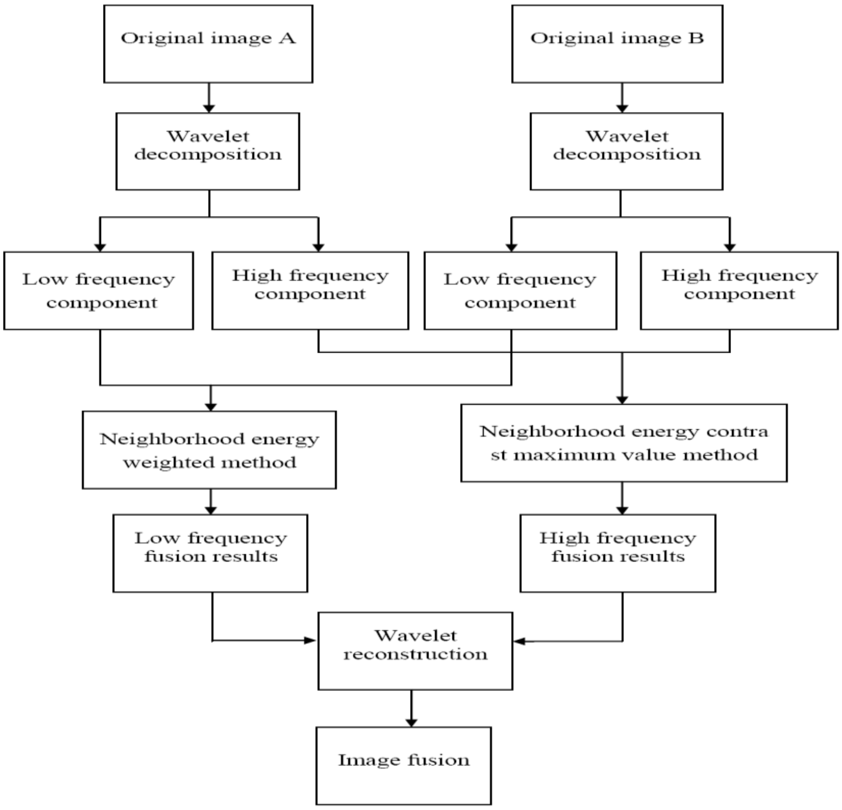

FIGURE 1 Flow chart of Improved contract fusion based on wavelet analysis

4 Simulation result

4.1 THE EVALUATION INDEXES OF STATISTICAL CHARACTERISTICS OF FUSED IMAGE

F is the image and $M \times N$ is the size of the image.

4.1.1 Information entropy

The definition of image information entropy is the average information included in the image, namely the measurement of the average information and the entropy value of the fused image reflects the volume of its information. The bigger the entropy value indicates better fusion effect. And its definition is as follows:

$$H = -\sum_{i=1}^{L-1} p(i) \log_2 p(i) \tag{7}$$

In this equation, $p(i)$ is the ratio between the pixels with a grayscale value of i and the total pixels N of the image, namely $P(i)=N_i/N$, It reflects the probability distribution of the pixels with a grayscale of i in the image and it can be seen as the normalized histogram of the image.

4.1.2 Average

Average is the arithmetic average of all the pixel grayscales in the image and the average brightness of human eyes. Its definition is as follows:

$$\overline{F} = \frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} F(m,n) \tag{8}$$

4.1.3 Standard Deviation

Standard deviation reflects the discrete state of the grayscale to the average grayscale and its definition is:

$$Std = \sqrt{\frac{1}{M \times N} \sum_{m=1}^{M} \sum_{n=1}^{N} \left(F(m,n) - \overline{F} \right)^2} . \tag{9}$$

To some point, standard deviation can be used to evaluate the image contract. The bigger standard deviation indicates that the grayscale of the image is distributed dispersedly that the image has big contract and that more information can be seen; otherwise, the smaller standard deviation suggests that image contract is small and that the color is single and even.

4.1.4 Average gradient

Human eyes can quickly see where there is a big difference in the edge information of the image instead of where there is a little difference in information. The average gradient of the image describes the ability of tiny detail change and texture transformation of the image. Generally speaking, the bigger average gradient indicates obvious edge information and detail. Its calculation formula is Equation (10):

$$\nabla G = \frac{1}{(M-1)\times(N-1)} \cdot \sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{\nabla xF(i,j)^2 + \left(\nabla yF(i,j)\right)^2} . \tag{10}$$

In this equation, $\nabla xF(i,j)$ is the difference of $F(i,j)$ in Direction x and $\nabla yF(i,j)$ is the difference of $F(i,j)$ in Direction y.

4.1.5 Definition

Definition is also called average gradient and it is defined as follows:

$$\Delta\overline{G} = \frac{1}{M\times N}\sum_{m=1}^{M}\sum_{n=1}^{N}\sqrt{\frac{\Delta F_x(m,n)^2 + \Delta F_y(m,n)^2}{2}} . \tag{11}$$

In this Equation, ΔF_x and ΔF_y are the differences of the fused image F in Direction x and Direction y and the average gradient reflects the image detail difference and the texture change characteristic. In general, the bigger average gradient suggests that the image is clearer and that the fusion effect is better.

4.1.6 Spatial frequency

Spatial frequency reflects the total activity level of an image in the spatial domain. The bigger spatial frequency indicates better fusion effects and its definition is as follows:

$$RF = \sqrt{\frac{\sum_{m=1}^{M}\sum_{n=2}^{N}\left[F(m,n) - F(m,n-1)\right]^2}{M\times N}} , \tag{12}$$

$$CF = \sqrt{\frac{\sum_{n=1}^{N}\sum_{m=2}^{M}\left[(m,n) - F(m-1,n)\right]^2}{M\times N}} , \tag{13}$$

$$SF = \sqrt{RF^2 + CF^2} . \tag{14}$$

In these Equations, RF is Row Frequency and CF stands for Column Frequency.

These methods are relatively simple and all they need is to compare the statistic characteristics of the source image and the fused image. We can also see the changes before and after the fusion. The fusion effect and the algorithm performance can also be evaluated by comparing the statistic characteristics of different fused images by different fusion algorithms.

4.2 THE ANALYSIS OF VISUAL EFFECT

Fuse the multi-focus image according to the fusion method of this paper. Figure 2 is the source image and the fused image. Figure 2a is the right-focus image; Figure 2b is the left-focus image; Figure 2c is the image obtained by HIS method; Figure 2d is the image obtained by PCA method and Figure 2e is the image obtained by the algorithm of this paper.

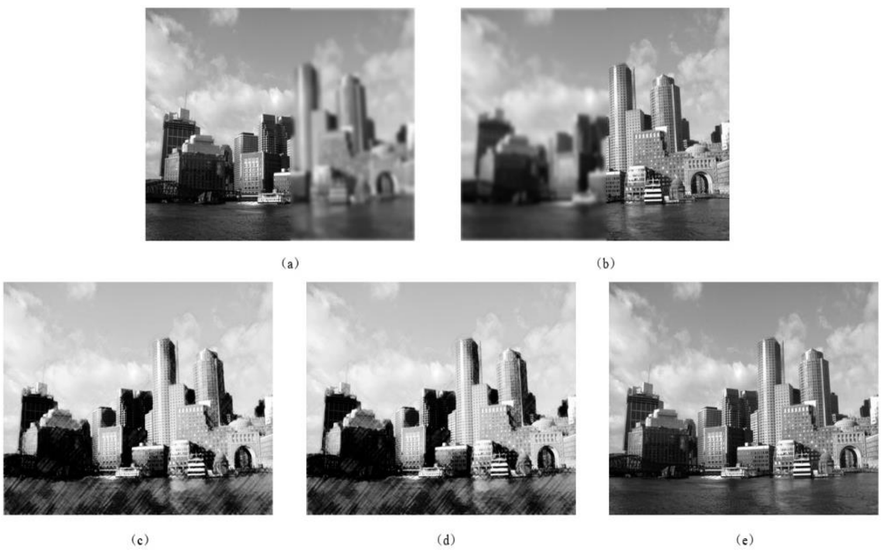

FIGURE 2 The comparison of the experiment of fusion effect

Comparing the source image and the fused image in Figure 2, it can be seen that HIS method can obviously see the mosaic effect; that the overall image contract is not high and that it is not clear in human eyes. Compared with HIS method, PCA method has small mosaic effect and improved contract; however, the left edge is quite fuzzy. The improved algorithm of this paper can greatly improve the comfortableness for human eyes and the image contract and it can also make the edge clear.

TABLE 1The fusion consequence evaluation values of different fusion rules

Fusion algorithm	**Information entropy**	**Average gradient**	**Standard deviation**	**Definition**	**Spatial frequency**
HIS	4.6936	5.1365	49.9873	6.7356	14.9625
PCA	4.7648	5.5738	51.0162	6.8731	15.2637
Method of this paper	4.8015	6.0352	52.2134	7.4653	17.0831

Table 1 is the evaluation comparison of the experiments and the objective data of the fused image by different methods. Because image is not merely composed by pixel points, it also has local properties, which can be demonstrated by multiple elements in the region. Having considered the local characteristics of the image and made some improves based on the fundamental algorithms, PCA is better than HIS. Having correlated the energy and contract of the image, the method of this paper has not only considered the overview of the image, but also related the low frequency and high frequency of the image together to depict the image details; thus improving the quality of the fused quality.

5 Conclusion

This paper firstly briefly discusses the imaging characteristics of image fusion. Then it introduces the applications of wavelet analysis in image fusion in detail, based on which, it proposes the fusion algorithm of neighborhood energy contract. It determines the wavelet basis and wavelet levels through experiments and makes simulation experiments on the improved contract fusion algorithm. Through simulation, it can be seen that the fused image obtained from this method includes more information and high definition and its visual effects are consistent with the objective evaluation result, suggesting the effectiveness of this method.

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Authors

Zhaonan Yang, 1974.11.29, China.

Current position, grades: PhD student in Harbin Engineering University, China.
University studies: MSc in Computer Science from Harbin Engineering University, China in 2007.
Scientific interest: image processing and data mining.

Shu Zhang, 1973.05.22, China.

Current position, grades: a professor in Heilongjiang University of Science and Technology, China.
University studies: MSc in Computer Science from Harbin University of Science and Technology, China in 2009.
Scientific interest: image processing and data mining.

Zeyuan Gu, 1975.11.24, China.

Current position, grades: in Heilongjiang University of Science and Technology.
University studies: MSc in Computer Science from Harbin Engineering University, China in 2005.
Scientific interest: image processing and software engineering.