

Image Texture features analysis for multi-focus image fusion based on discrete wavelet transform

C. Madhavi¹, G.Mamatha², B. N. Shobha³

1-Student, JNTU, 2- Faculty, JNTU, Anantapur, 3-Faculty, MSRSAS, Bangalore

Abstract: An image fusion is the process by which 2 or more images are combined into a single image, retaining the important features from each of the original images. An image fusion methodology consists of two basic stages: image registration, which brings the input images to spatial alignment and fusion itself, i.e., combining image functions (intensities, colors, etc) in the area of frame overlap. An image fusion algorithm based on feature of image texture energy in wavelet domain is proposed. Firstly, the source images are decomposed to the high-frequency and low-frequency components; Secondly, a process for detecting the texture energy of the frequency sub-band images is carried on, following which the wavelet fusion coefficients are obtained in terms of some rules; finally, fused image is produced by the implementation of inverse wavelet transform. Combination with visual evaluation, the standard deviation and information entropy were used for quantitative measure to evaluate the fusion results with different algorithms, the proposed algorithm is an effective image fusion algorithm.

Keywords: Multi-focus image; image fusion; wavelet transform; texture analysis; texture feature

I. INTRODUCTION

Due to the restrictions on depth of field of the optical lenses, it is often unable for visible light imaging system to get a image, in which all targets (objects) are focused. In an image captured by those devices, only those objects within the depth of field are focused, while other objects are blurred. But the problem can be

solved by multi-focus image fusion [11]. This technology can improve the utilization efficiency of the image information and facilitate understanding of human vision and computer, and widely used in machine vision and object recognition and other fields [2]. Image fusion can be separated into three levels: pixel-level image fusion, feature-level image fusion and decision-level image fusion. In this paper, the proposed multi-focus image fusion method based on wavelet transform [5] belongs to the pixel-level image fusion.

Pixel level or signal level image fusion represents image fusion at the lowest level, where a number of raw input image signals are combined to produce a signal fused image signal. At pixel level, images are combined by considering individual pixel values or small arbitrary regions of pixels in order to make fusion decisions. Pixel-level algorithms work either in the spatial domain and or in the transform domain. Feature level image fusion is also known as object level image fusion. This method fuses feature, object labels and property descriptor information that have already been extracted from individual input images. This method produces a fused image reducing the amount of redundant information. Finally, the highest level, symbol or decision level image fusion represents fusion of probabilistic decision information obtained by local decision makers operating on the results of feature level processing on image data.

Aimed at the characteristics of multi-focus image, An algorithm based on wavelet transform commonly used is the

weighted average method in the fusion process of low-frequency domain, and the maximum value method, the regional maximum value method and regional energy method are the fusion methods used commonly in the fusion process of high-frequency domain. Among them, the weighted average method and the maximum value method are the fusion methods based on single pixel, which ignored the correlation between the pixel and the pixels adjacent to it, resulting in fusion with one-sided effect; though the regional maximum value method and regional energy method consider the correlation between neighboring pixels, but it is deficient in measuring the saliency of the texture and edge features. To some extent, those methods limited the further enhancement for fused image clarity. In light of the background information mentioned above, this article presents a texture energy-based image fusion algorithm in wavelet domain, it not only considered the correlation between the pixel and its adjacent pixels, but also the image texture and edge features. Experimental results show that the proposed method, compared with the existing methods aforementioned, is effective for multi-focus image fusion. This method can retain more visual meaningful information of the source image and can improve effectively image clarity.

The rest of the paper is organized as follows. Some concepts related with the proposed method and the proposed algorithm will be presented in section II. In section III, the experiments with different methods and comparison with other existing methods can be found. In the final section IV, the conclusion of whole paper is given.

II. IMAGE FUSION BASED ON WAVELET TRANSFORMATION

Wavelet transform is a kind of multi-resolution analysis[4] technique that represents image variations at different

scales. The computation of wavelet transform of a 2-D image involves recursive filtering and sub-sampling [8]. At each level we will obtain 3 high-frequency sub-images corresponding to horizontal, vertical and diagonal, as well as one low-frequency sub-image, i.e. LH (containing detail information from horizontal direction), HL (containing detail information from vertical direction), HH (containing detail information from diagonal direction) and LL (contains the main contour trait of the original image). As the above, the LL band will be decomposed, recursively. At the end we can obtain the sub-images in each level.

In light of resemblance between multi-resolution filter and human vision system, wavelet transform are often used for image application such as image segmentation, image retrieval, image fusion, etc.

The progress of image fusion wavelet-based can be depicted as follows: firstly, wavelet transformation is carried out on each registered source image, and the wavelet transformation coefficients of the source images are obtained. Then, a fusion decision map which has the same size as the sub-image on the same level is generated based on some defined fusion rules. The value of the fusion decision map is the indexes of coefficients which contain more interested information than other original images on the corresponding locations of the source images. Finally, the coefficients of the fused image are obtained by the fusion decision map, and the fused image will be gained by transforming back to the spatial domain.

III. TEXTURE FEATURE-BASED IMAGE FUSION

The high-frequency sub-band and low-frequency sub-band of the source image decomposed by wavelet have significant texture saliency. For multi-focus image, the higher texture saliency[6] denotes the important visual meaningful information such as image texture and

edge. The multi-focus images describing the same scene have the different texture saliency in corresponding goals. The goals possessing the higher clarity in a source image have the larger texture saliency than other source images in the same region. This kind of texture saliency can be characterized by the texture feature. Texture feature-based image fusion method is to select the coefficients from the source images with higher texture saliency as the coefficients of the fused image.

A. Texture energy measurement

Image texture is a function of the spatial variation in pixel intensities (gray values). Texture calculated in two ways such as co-occurrence matrix method and run-length matrix method. In this paper, we use co-occurrence matrix method [10].

An algorithm for texture feature extraction as follows:

- Read the input image and store it in a buffer.
 - Requantize the input image to the required gray level, in order to reduce computation time.
 - Set window size for feature calculation.
 - For each window around a pixel, perform the following
 - 1) Calculate the co-occurrence matrix (GLCM)
 - 2) Calculate the feature value
 - 3) Store it in the corresponding position
 - Find the minimum and maximum value.
 - Normalize the feature value by intensity mapping from 0 to 255.
 - Display the resultant feature image.
- The procedure for GLCM:
- Create framework matrix
 - Decide on the spatial relation between the reference and neighboring pixel
 - Count the occurrences and fill in the framework matrix

- Add the matrix to its transpose to make symmetrical
- Normalize the matrix to turn it into probabilities

The calculation for symmetrical normalized GLCM is follows:

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$$

Where $P_{i,j}$ is defined as the texture measurement at location (i,j), $V_{i,j}$ is defined as the each pixel in the GLCM. From that texture measurement we can calculate the texture features like:

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{i,j} (i-j)^2$$

$$\text{Dissimilarity} = \sum_{i,j=0}^{N-1} P_{i,j} |i-j|$$

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$$

Angular second moment (ASM) and energy:

$$\text{ASM} = \sum_{i,j=0}^{N-1} P_{i,j}^2$$

$$\text{Energy} = \sqrt{\text{ASM}}$$

$$\text{Entropy} = \sum_{i,j=0}^{N-1} P_{i,j} (-\ln P_{i,j})$$

Correlation =

$$\sum_{i,j=0}^{N-1} P_{i,j} \left[\frac{(\mu_i - \mu_j)^2}{\sigma_i^2 \sigma_j^2} \right]$$

B. Fusion of wavelet coefficients

Let $\alpha_A(i,j)$ and $\alpha_B(i,j)$ be the wavelet transform coefficient of the source

image A and B at location (i,j) respectively, then $E_A(i,j)$ and $E_B(i,j)$ will be obtained from the above energy equation.

To the wavelet coefficients, we adopt texture energy to determine the wavelet coefficients of the fused image. Let $\alpha_F(i,j)$ be the wavelet transform coefficients of the fused image F at location (i,j).

$$\alpha_F(i,j) = \begin{cases} \alpha_A(i,j), & \text{if } E_A(i,j) \geq E_B(i,j) \\ \alpha_B(i,j), & \text{if } E_A(i,j) < E_B(i,j) \end{cases}$$

The step of image fusion is repeated at each pyramid sample position. Finally, the image is obtained by using the inverse wavelet transform.

IV. SIMULATION RESULTS AND ANALYSIS

The multi-focus source images carried on fusion process in this article are two degraded images those are blurred with a Gaussian smoothing kernel. Fig.1 and Fig.2 show the source images with blurring in the external region and central region respectively. The wavelet be used for wavelet decomposition and reconstruction is the db1 wavelet, and the number of wavelet decomposition layer is 3. In order to evaluate the effectiveness of the proposed algorithm, we take standard deviation and information entropy as the quantitative measures based on the subjective evaluation.

The source images and the results by different algorithms are shown from Fig.1 to Fig.11. Fig.1, Fig.2, Fig.3 and Fig.4 are source images. Fig.5, Fig.6, Fig.7, Fig.8, Fig.9, Fig.10 and Fig.11 are the fused image using weighted average method, maximum value method, texture contrast feature method, texture dissimilarity feature method, texture homogeneity feature method, texture ASM feature method, texture energy feature method,



Figure 1. original image blurred on left corner side



Figure 2. original image blurred on middle left side



Figure 3. original image blurred on middle right side

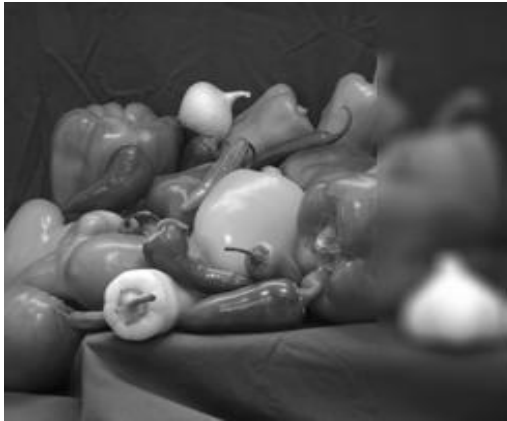


Figure 4. original image blurred on right corner side

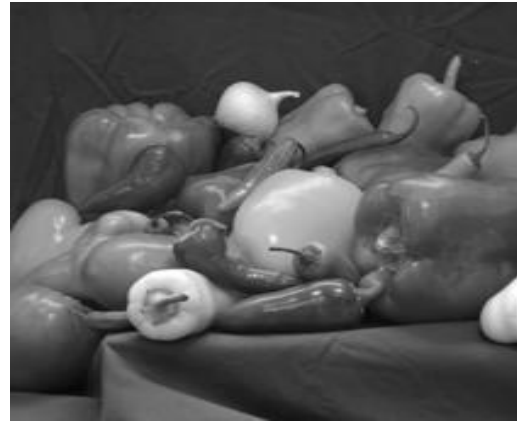


Figure 7. Texture Contrast feature method



Figure 5. Weighted average method

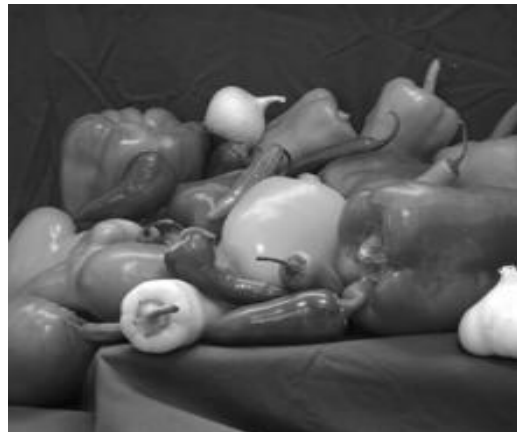


Figure 8. Texture Dissimilarity feature method



Figure 6. Maximum value method



Figure 9. Texture homogeneity feature method



Figure 10. Texture ASM feature method

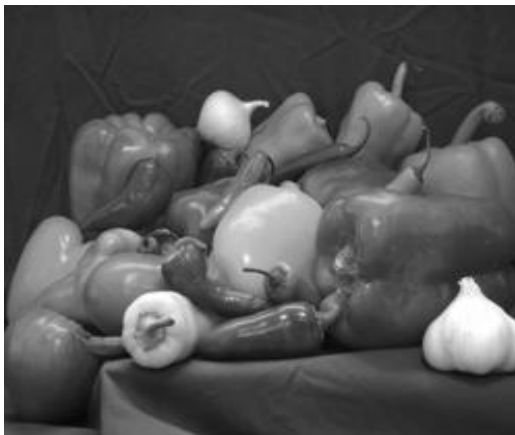


Figure 11. Texture Energy feature method

The maximum value method, the regional maximum value method and the regional energy method carry on fusion in low frequency domain by abstracting from the weighted average of the transform coefficients of the two source images as the coefficients of the fused image, but in the high-frequency domain obtained the transformation coefficients of fused image by the rules based on the maximum value method, the regional maximum value method and regional energy method, respectively. The proposed method carries out the texture energy based image fusion in whole frequency domain.

Investigating Fig.7, Fig.8, Fig.9, Fig. 10 and Fig.11, we can see that the proposed algorithm outperform the weighted average method, maximum value method. Tab.1 shows the quantitative measure results of the all fusion methods. From the Tab.1, the proposed algorithm is better than other methods. The experimental results show that the fused image of the proposed algorithm can preserve more visual meaningful information than those of the other methods.

TABLE I. The quality Assessment of Different Fusion methods[1].

Performance metrics	Weighted average method	Maximum Value method	Texture contrast method	Texture ASM method	Texture energy method	Texture homogeneity method	Texture dissimilarity method
Standard Deviation	14.4143	13.9791	19.9634	19.8041	19.9708	19.7899	19.7028
Information Entropy	6.9586	6.9699	6.9762	6.9817	6.9833	6.9918	7.0003

V. CONCLUSION

Due to the ignoring the correlation between the pixel and the pixels adjacent to it, image fusion based on the weighted average method and the maximum value method have one-sided effect. Though the regional maximum value method and regional energy method consider the correlation between neighboring pixels,

but it is deficient to evaluate the texture salient of the images, limiting the further improvement of the clarity of fused image. The proposed algorithm in this article consider the correlation between the pixel and its neighboring pixels as well as texture salience in the all frequency sub-band of the source images, the fused image has richer details and further improvement

in the overall clarity. The table 1 shows that the metric information entropy has been improved in the proposed method. As a future enhancement, the proposed method can be tried for fusion of medical images.

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