A Novel Multi-focus Image Fusion Method Research

Lixia Zhang
School of Computer & Communication Engineering
University of Science and Technology Beijing,
Beijing, China
School of Information Technology Engineering
Tianjin University of Technology and Education
Tianjin, China
lx_zhang@126.com

Guangping Zeng
School of Computer & Communication Engineering
University of Science and Technology Beijing,
Beijing, China
zgp@ustb.edu.cn

Abstract—**Multi-focus image fusion has emerged as a major topic in computer vision and image processing community, and aimed to combine with a set of images that captured from the same scene with different focuses into a single sharper image where all objects in the scene will be truly in focus. In this paper, we propose an efficient image fusion algorithm which combined with the advantage of space domain and transform domain. We employ the different fusion rules in the different frequency level according to the different characteristics of low frequency domain and high frequency domain obtained by decomposition of source image through wavelet transform. That is to say, we employ the Principal Component Analysis (PCA) in the low frequency domain, and combine the biggest value selection method with weighted mean method in the high frequency domain. Finally, the output image is obtained by inverse wavelet transform. The experimental results show that this algorithm can produce high-contrast fusion images that are clearly more appealing and have more useful information than the PCA and the wavelet transform.**

Keywords—image fusion; multi-focus; wavelet transform; PCA

I. INTRODUCTION

The abilities of the imaging devices to capture the information are different from one to another, because the optical lenses are widely employed in imaging devices, the optical lens have a limited depth of field, so within a certain range of distances, only few objects will be captured from the imaging devices and recorded sharply, whereas others will be defocused and be blurred. This is undesirable for accurately interpreting and analyzing images, so the multi-focus image fusion technique is highly desirable to provide a promising way to create a single image in which all the objects within the image are in focus by combining two or multiple images of the same scene that are taken with diverse focuses.[1-4]

According to Information extraction level, image fusion can generally be classified into three types: pixel-level, feature-level and decision-level. Pixel-level fusion selects and merges the information of the source images to construct the fused image, according to some fusion criteria, for example pixel by pixel, region by region. Feature-level fusion first extracts the features of the source images, and then fuses some extracted features into a single image. Decision-level fusion forms the fused by considering the image descriptions such as relational graphs. Currently, most of the fusion algorithms are pixel-level. Pixel-level fusion can be performed in either spatial domain or transformed domain.

In the spatial domain, the sharp and local changes in source images are directly computed from pixels or regions. So pixels or regions are directly selected and combined in either a liner or non-linear way to form the fused image [2]. The main advantages of these methods are easy to be implemented with a low computational complexity, but output images will be at the loss of the details of their input images.

In the transformed domain, the sharp and local changes in intensity are indicated by the high frequency coefficients. So the certain frequency or time-frequency transform is used to fuse images, and the output images can contain large proportion of the details of input images. One of the classical methods is multi-scale methods [1]. However, these methods usually have the high computational complexity and the demanding requirements for memory.

In this paper, we proposed an efficient image fusion algorithm combining the advantage of space domain and transform domain. Wavelet transform is applied on each input image. The different pixel-level fusion rules that will be defined as below is used to combine the wavelet coefficients.

II. IMAGE FUSION RULE

The advantage of wavelet transform for image fusion is that the source image can be decomposed into low frequency domain and high frequency domain, which retain different characteristic. So in the fusion process, different frequency domain can employ the different fusion algorithm, so as to acquire better fusion image with more notable characteristics from source image.

A. Low-Frequency Fusion Method

Low frequency domain usually uses weighted mean method to retain the image contour. But this method is

978-1-4673-8221-2/15 $31.00 © 2015 IEEE
DOI 10.1109/ICINIS.2015.43

simple without considering the correlation of data. Therefore, in this paper, principal component analysis (PCA) method is employed [5-8].

Principal component analysis is an effective method in the statistical analysis of data, its purpose is to reduce dimension, R dimensional space is transformed to M dimensional space (R >= M) in the preservation of the main information of source image [7], so that the data is easier to compute. The algorithm consists of the following 5 steps:

- According to the N sample characteristics, the data matrix of image: $X=(x_1, x_2, \cdots x_N)$ is constructed. Then we can calculate the covariance matrix C of X .

$$C = \begin{bmatrix} \delta_{11} & \cdots & \delta_{11} \cdots \delta_{11} \\ \vdots & & \vdots \quad \vdots \\ \delta_{i1} & \cdots & \delta_{i1} \cdots \delta_{i1} \\ \vdots & & \vdots \quad \vdots \\ \delta_{N1} & \cdots & \delta_{N1} \cdots \delta_{N1} \end{bmatrix} \tag{1}$$

Where δ_{ij}^2 through (2) is the variance of X. $\overline{x_i}$ is the mean value of a vector.

$$\delta_{ij}^2 = \frac{1}{n} \sum_{l=0}^{n-1} (x_{il} - \overline{x_i})(x_{il} - \overline{x_j}) \tag{2}$$

- All of the characteristic value $(\lambda_1, \lambda_2, \cdots , \lambda_N)$ of C and their eigenvectors: $u_1, u_2, \cdots u_N$ can be obtained by the characteristic equation: $|\lambda I - C| = 0$. And λ_i should be in accord with the equation: $\lambda_1 > \lambda_2 > \cdots \lambda_N$.
- To obtain the new eigenvectors according to $= U^T X$.

$$Y = (y_1, y_2, \cdots y_m)^T \tag{3}$$

$$U = (u_1, u_2, \cdots u_m)^T \tag{4}$$

$$C_y = \Lambda = diag[u_1, u_2, \cdots u_m] \tag{5}$$

Where y_i is the number i principal component. After transformed, the variance of y_1 is the biggest, which contains the principal information of source image. So in the fusion process, we regard y_1 as the first principal component.

- To construct the weighting of fusion:

$$\omega_i = \sum_{j=1}^{n} \omega_{1j} ; \qquad i = 1,\ 2, \cdots, n \tag{6}$$

$$\omega_{1j} = |\lambda_j| / \sum_{i=1}^{n} |\lambda_i| \tag{7}$$

Where ω_{1j} is the proportion of sub-image in the whole.

- To obtain the fusion image:

$$X(x, y) = \sum_{i=1}^{n} \omega_i X_i(x, y) \tag{8}$$

B. High-frequency fusion method

The details of image can be showed by the high frequency domain of wavelet transform. Their processing can influence the qualities of fusion image. In order to retain the original image details, we adopt the biggest value selection method and the weighed mean method. How to select is decided by the matching degree of the source image [7]. The algorithm consists of the following 5 steps:

- Regional characteristics $(E_A(i,j), E_B(i,j))$ of the matching area in the source image are calculated by the wavelet coefficients $(C_{Ad}(x,y), C_{Bd}(x,y))$.

$$E_A(i,j) = C_{Ad}^2(i,j) \big/ i * j = \sum_{(x,y)\epsilon\Omega} C_{Ad}^2(x,y) \big/ i * j \tag{9}$$

Where Ω is the sub-block of source images. The difference value of regional characteristics is obtained by:

$$D_F(i,j) = E_A(i,j) - E_B(i,j) \tag{10}$$

- the coefficients of matching degree is calculated by:

$$M(i,j) = 2 * C_{AD}(i,j) * C_{BD}(i,j) \big/ (C_{AD}^2(i,j) + C_{BD}^2(i,j)) \tag{11}$$

- Range of $D_F(i,j)$ is determined:

$$D_F(i,j) \in (-\infty, M(i,j)) \cup [-M(i,j), M(i,j)] \cup (M(i,j), +\infty) \tag{12}$$

- If $|D_F(i,j)| > M(i,j)$, the wavelet coefficient of fused image is obtained through the biggest value selection method.

$$C_{FD}(i,j) = \begin{cases} C_{AD}(x,y) & if\ D_F(i,j) \in (-\infty, -M(i.j)) \\ C_{BD}(x,y) & if\ D_F(i,j) \in (M(i.j), \infty) \end{cases} \tag{13}$$

Where $C_{FD}(i,j)$ is the wavelet coefficient of fused images.

- If $|D_F(i,j)| \le M(i,j)$, the wavelet coefficient of fused image is obtained through the weighted mean method.

$$C_{FD}(i,j) = \begin{cases} M(i,j) * C_{AD}(x,y) + (1 - M(i,j) * C_{Bd}(x,y)) \\ \qquad \text{if}(E_A(i,j) \ge E_B(i,j)) \\ M(i,j) * C_{BD}(x,y) + (1 - M(i,j) * C_{Ad}(x,y)) \\ \qquad \text{if}(E_A(i,j) < E_B(i,j) \end{cases} \tag{14}$$

III. THE IMAGE FUSION SCHEME

The proposed approach utilizes multiple source images that are captured at different focus levels to reconstruct a single image. A summary of the proposed approach is provided as follows.

- Perform the wavelet transform on the source images to obtain their multi-scale representation: low frequency coefficients and high frequency coefficients.
- In low frequency domain, construct the weighting of fusion using (3), and combine the fusion image using (8).
- In high frequency domain, estimate the difference value of regional characteristics using (9) and (10), then confirm the wavelet coefficient of fused image using (13) and (14).
- Apply an inverse wavelet transform to obtain a fused image.

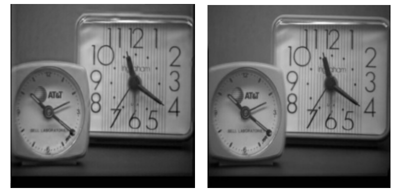
IV. EXPERIMENTS

In order to validate the performance of the proposed fusion method, we choose some simple and widely-used fusion scheme to compare with the proposed fusion method, such as PAC method, DWT method. Fig.1 shows the example to fuse two gray-scale images focusing on left or right side. The original images with size of 512*512 pixels are displayed in Fig.1 (a-b). The fusion results associated with two original images are illustrated in Fig.1(c-e).

By inspecting the fused images, the fused image achieved from proposed method is better than that from other two methods. The fusion result obtained from PCA method shows vague edges appearing on the big clock. Fig.1 (d) obtained from DWT-based method is subject to a severe ringing effect, making the entire image blur.

In addition to the subjective study above, with the use of three image quality evaluation criterions, such as information entropy, mutual information, mean grads, spatial frequency, where larger metric values show better image quality, we can conduct an objective analysis on the experimental results given by different fusion algorithms. The objective performance comparisons are presented in Table 1, where one can see that the proposed method always outperforms other two conventional approaches.

(a) (b) (c)



(d) (e)

Figure1. Input images and fused images obtained by different methods: (a) Original image: Clock 1, (b) Original image: Clock2, (c) PCA method. (d) DWT method. (e) Proposed method.

TABLE I. OBJECTIVE EVALUATION OF RESULTS

	information entropy	**mutual information**	**mean grads**	**spatial frequency**
PAC approach	7.4380	3.2130	5.4537	11.1021
DWT approach	7.4755	3.2435	5.4524	12.4565
Proposed approach	7.4973	3.5634	5.5472	13.8960

V. CONCLUSION

As the optical lenses for most of the widely-used imaging devices have a limited focus range. In the same image, some objects will be truly in focus while out-of-focus objects will become blurry. Multi-focus image fusion is aim to combine with focus point of all of image to reconstruct a sharper image. In this paper, we have presented a novel image fusion scheme to effectively combine multi-focus images into a single all-in-focus image. In this paper, fully considering the related information among the fused images, according to the result of wavelet transform, we employ the Principal Component Analysis (PCA) in the low frequency domain, and the biggest value selection method with weighted mean method in the high frequency domain. Our proposed image fusion algorithm realizes the advantageous combination of the spatial domain and the transform domain. The experiments were conducted to show that this algorithm occupies smaller memory, and has faster computing speed. The output image has greater useful informational content than the PCA and the wavelet transform.

In the future study, we will continue to optimize the current fusion algorithm in order to further reduce the computational complexity, and improve the effect of fusion. Besides, designing the new fusion scheme is flexible to adopt different types of features to suit for a variety of fusion tasks, such as remote sensing images, medical images.

ACKNOWLEDGEMENT

This work has been supported by the Science Foundation of Tianjin University of Technology and Education by under Grant No. KJ14-20.

References

[1] Jing Tian, Li Chen, “Adaptive multi-focus image fusion using a wavelet-based statistical sharpness measure,” Signal Processing, vol.92, 2012, pp. 2137-2146.9, doi:10.1016/j.sigpro.2012.01.07

[2] Z.Zhou, S. Li and B. Wang, “Multi-scale weighted gradient-based fusion for multi-focus image, ” Information Fusion, vol.20, 2014, pp. 60-72, doi:10.1016/j.inffus.2013.11.005

[3] Zhiping xu, “Medical image fusion using multi-level local extrema,” Information Fusion, vol.19, 2014, pp. 38-48, doi:10.1016/j.inffus.2013.01.001

[4] Yong Jiang, Minghui Wang , “Image fusion with morphological component analysis, ” vol.18, 2014, pp.107-118, doi: 10.1016/j.inffus.2013. 06. 001

[5] Tao Wan, Chenchen Zhu, Zengchang Qin, “Multifocus image fusion based on robust principal component analysis,” Pattern Recognition Letters, vol.34, 2013, pp.1001-1008, doi:10.1016/ j.patrec.2013.03.003

[6] Z. Liu, D. S. Forsyth and Y. R. Laganiere, “A feature-based metric for the quantitative evaluation of pixel-level image fusion,” Computer Vision and Image Understanding, Vol.109, No.1, 2008, pp: 56-68, doi:10.1016/j.cviu.2007.04.003

[7] Xiaohui Niu, Ke bing. “Image fusion algorithm based on PCA & self-adaptive region variance,” Application Research of Computes, China, Application Research of computes, China, Vol.27, No.8, 2014, pp: 3180-3181.

[8] Xiaoxi MA. “PCA-based Laplacian pyramid in image fusion.,” Computer Engineering and Applications, China, Vol.48, No.8, 2012, pp: 211-213.