Investigation of Shift Dependency Effects on Multiresolution-Based Image Fusion Performance

LI Yufeng[1,2], FENG Xiaoyun[1]
[1]Southwest Jiaotong University, Chengdu, China
Email: liyufeng@swust.edu.cn

FAN Yong[2]
[2]Southwest University Science and Technology, Mianyang, China
Email: fanyong@swust.edu.cn

***Abstract*—Image fusion techniques using multiresolution decomposition have become a hot research area due to the fact that it is suitable for multi-scale properties of the human vision system. According to subsampling methods, multiresolution decompositions can be divided into redundant and non-redundant which corresponds to different shift dependency such as shift-variant or shift-invariant. However, there have been comparatively few studies that have focused on its effects on the fusion performance. This paper investigates shift dependency of various multiresolution-based fusion schemes and analyzes its effects on image fusion performance by quantitative and qualitative methods. We conduct experiments by combining 8 popular multiresolution decomposition methods such as pyramid, wavelet and beyond wavelet with two popular fusion rules. By analyzing and comparing the experimental results, we propose some guidance for using multiresolution-based fusion schemes.**

***Index Terms*—image fusion; multiresolution decomposition; shift dependency**

I. INTRODUCTION

The goal of image fusion is to integrate complementary information from multiple images such that the new images are more suitable for the purpose of human visual perception and computer processing tasks such as segmentation, feature extraction, and object recognition [1]. Pohl prompted that according to the stage in which image fusion is performed, there are pixel, feature and decision level [2].

The simplest pixel level image fusion method is to take the average of two images pixel by pixel. The pixel averaging method is easily implemented, fast to execute and has the advantage of suppressing any noise present in the source imagery. Unfortunately, it also suppresses salient image features, inevitably produces a low contrast fused image with a 'washed-out' appearance [3].

The limitations of pixel averaging methods led to the development of multiresolution(MR)-based image fusion schemes. MR decomposition of a signal was fist studied by Burt [4][5] who established that MR transform can be useful in image fusion process. With the development of MR decomposition techniques, the first wavelet fusion scheme emerged in the mid-1990s and reported both qualitative and quantitative improvements over the standard pyramidal techniques.

More recently, many researchers realized that MR decomposition of wavelet and beyond wavelet (such as curvelet and contourlet etc.) are very useful for analyzing the content information of images for the purpose of fusion. MR-based Image fusion is to decompose the source (input) images into a series of frequency channels, then combine the different features and details at multiple decomposition levels and at many directions in multi-frequency bands, which is suitable for multi-scale properties of the human vision system[6].

All of the MR-based fusion methods have advantages and disadvantages because of the utilized decomposition and the fusion rule. Nevertheless, one parameter may affect the final result of fusion is shift dependency of MR which few studies have been devoted to. MR decomposition techniques such as discrete wavelet transform， pyramid transform, generally yields a shift-variant signal representation. This means that a simple shift of the input signal may lead to complete different transform coefficients. The lack of translation invariance can be avoided if the outputs of the filter banks are not subsampled. The resulting non-subsampled transform yields a redundant MR representation where the approximation and detail signals have all the same size as the original signal. Thus, In term of subsampling method, MR decomposition can be divided into redundant or non-redundant which corresponds to different shift dependency such as shift-variant or shift-invariant.

In this paper, we analysis shift dependency of MR-based image fusion schemes and investigate its effect on fusion result. We select three of most popular MR decompositions such as pyramid, wavelet and beyond wavelet transforms. Our investigation uses multi-focus and multi-sensors images as source images to compare several popular MR-based fusion schemes and analyze their shift dependency effects on fusion result in qualitative and quantitative.

The rest of this paper is organized as follows. Section 2 reviews the MR-based fusion framework and fusion rules. In section 3, we introduce our experiment of shift dependency for different fusion schemes. Section 4 is

doi:10.4304/jsw.6.3.475-482

devoted to the effects of shift dependency on fusion results. Section 5 concludes this paper.

II. FRAMEWORK OF MR-BASED IMAGE FUSION

A. Framework of multiresolution-based image fusion

The images to be combined will be referred to as input or source images, and the resultant combined image (or images) as fused image. The basic idea underlying the MR-based image fusion approach is to perform a MR transform on each source images and, following some specific fusion rules, construct a composite MR representation from these inputs. The fused image is obtained by applying the inverse transform on this composite MR representation. A general framework of this process is shown in Figure1. for the case of two source images [7].

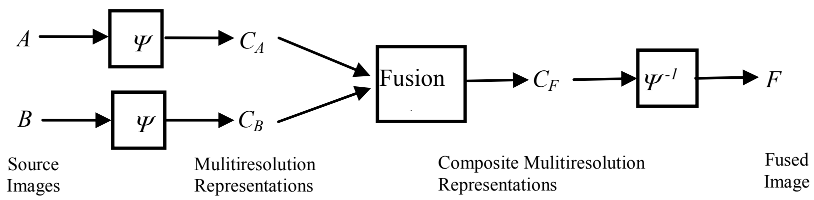

Figure 1. The framework of multiresolution-based image fusion

B. Multiresolution decomposition

A MR decomposition scheme decomposes the signal being analyzed into several components, each of which captures information present at a given resolution (scale).

The MR decomposition of a source image I^A (or I^B) is denoted by C and it is assumed to be of the form

$$I^A(x,y) \xrightarrow{\Psi} \left\{C_{j_0}^A(x,y), C_{j,l}^A(x,y)\right\} \quad (1)$$

Where, Ψ is MR transform, x and y indicate the spatial position in a given frequency band, $C_{j_0}(x,y)$ represents the approximation image (approximation coefcient matrice) at the highest level (lowest resolution) of the MR structure, while $C_{j,l}^A(x,y); j=1,2...J; l=1,2...L$ represent the detail images(detail coefcient matrices) at level j. The detail at level j will, in general, comprise various frequency or orientation bands l, depending on the type of MR transform that has been used.

B. Redundancy of Multiresolution decomposition

In this paper, our investigation selects three of most popular MR decompositions such as pyramid, wavelet and beyond wavelet transforms. The pyramid transforms include (1) the laplacian pyramid (LP) and (2) the ratio-of-low-pass pyramid (RoLP). The wavelet transforms include (3) the discrete wavelet transform (DWT), (4) the shift-invariant discrete wavelet transform (SIDWT) and (5) the stationary discrete wavelet transform (SWT). The beyond wavelet transforms we investigate is (6) the curvelet(CV) transform, (7) the contourlet (CT) and (8) the nonsubsampled contourlet transform (NSCT).

The idea of a MR decomposition with perfect reconstruction is to obtain a more convenient representation (analysis) of the signal such that no information is lost, i.e., the signal can be recovered through some reconstruction process (synthesis).

Under satisfying perfect reconstruction condition, comparing the decomposition coefcient matrices size with source image is known as redundancy. Among this MR decomposition methods，only DWT transform is non-redundant decomposition in which the total size of coefcient matrics is same as source image. Other MR transform all are redundant decomposition.

Assuming source image is $m \times n$ pixels, MR decomposition redundancy can be expressed as：

$$R = \frac{\sum_{j=1,l=1}^{J,L} sizeof(C_{j,l}) - m \times n}{m \times n} \quad (1)$$

Where，the fuciton $sizeof(C_{j,l})$ compute total number of element in all coefcient matrices.

TABLE I
THE REDUNDANCY OF MR DECOMPOSITON

Type	MR decomposition	Abbreviation	Redundancy
1	laplacian pyramid transform	LP	0.38
2	ratio-of-low-pass pyramid transform	RoLP	0.38
3	discrete wavelet transform	DWT	0.0
4	shift-invariant discrete wavelet transform	SIDWT	12.0
5	stationary discrete wavelet transform	SWT	12.0
6	curvelet transform	CV	1.82
7	contourlet transform	CT	0.33
8	nonsubsampled contourlet transform	NSCT	30.0

In our investigation, expect the CT (wrapping-based transform) highest decomposition leve is 6, the other MR decompositions is 4, the redundancy of each MR decomposition is list in TableI. It can be seen that DWT is non-redundant decomposition and its redundancy is 0, while SIDW, SWT and NSCT possess very high redundancy.

C. Fusion rules

Two general fusion rules to each MR decomposition are used in our test. One is choose-max rule (CM), which just picks corresponding detail coefficients with larger absolute value and discard the others. Another is area-based rule (AB) proposed in[6], which calculates a measure of local saliency and a measure of similarity using a 3x3 window and then combine corresponding detail coefficients by weighted averaging. Both rules combine approximation coefficients by averaging.

In follow of this paper, combining 8 MR methods and 2 fusion rules for example LP_CM and LP_AB etc., a total of 16 fusion schemes would be investigated.

III. Analysis of Shift-dependency

A. Investigation way

The MR-based fusion generally produces good results. Unfortunately, though majority MR decompositions are not shift invariant because of the subsampling process used in their calculation. This affects the combination of the coefficients in the fusion rule because the magnitude of a coefficient does not necessarily reflect the true transform content at that point. Rockinger [8] mentioned this issue and compared the dependency of the wavelet and pyramid fusion schemes.

We use Rockinger's way to investigate the shift dependency of various MR-based fusion schemes. Our test use Multi-foucs images (Figure2.(a) and (b)) and Multi-sensor images (Figure3.(a) and (b)) as inputs. The experiment consisted of three steps:

- A fused image, which serves as reference image, is computed of the two input images using all 16 schemes under investigation.
- Both input images are shifted in the horizontal direction form 1 pixel to 32 pixels, fused and the fused image was shifted back to the original location.
- Compute the root mean square error (RMSE) between the reference fused image and the shifted-backshifted fused image in the area not affected by the shift operation.

$$RSME = \left(\frac{1}{MN} \sum_{n=1}^{N} \sum_{m=1}^{M} \left(I^R(x,y) - I^S(x,y) \right)^2 \right)^{1/2} \tag{2}$$

where I^R is the reference fused image, I^S t the shifted-backshifted fused image, and M, N are the dimensions of the images.

B. Analysis

Figure 4. and 5. depicts the result of RMSE for each fusion schemes using CM rule and AB rule respectively. Lines indicate the shift error when a variable MR-based fusion scheme was used.

- Only the SIDWT and NSCT possess shift-invariant due to non-subsampling in their decomposition process. The CT and DWT are high shift-dependency whereas others exhibit lower shift-dependency.
- The shift dependency for each MR can be reduced by the application of an area based rule. In our experiment, we also chose variable wavelets for wavelet MR and the results show that it can be further reduced by a better choice of the wavelet (Due to the limited paper space we only present the results of 'db2' wavelet in Figure 4. and 5.)
- Except CV and CT, the shift error is periodic in 16 pixels shift. It can be concluded that, in case of a subsampling decomposition process, a shift of the input image cannot produce simple shift of the transform coefficients, unless the shift is a multiple of all subsampling factors in the system. In our experiment, the decomposition level is 4, resulting an shift dependency error with period 2^4 =16 (pixels). Because subsampling of the CV and CT decomposition process is not only in horizontal and vertical directions, their shift error corresponding to the shift of input images is not periodic in 16.
- It is surprisingly that the stationary discrete wavelet transform (SWT) is not shift-invariant. In this paper, we use wavelet toolbox function swt2 in Matlab7.0. Although it's help document state that the function implemented with a non-subsampling decomposition process, the shift error may be caused by its reconstruction process which is not strictly inverse the decomposition process. We would address this issue more depth investigation.

(a) outer blurred (b) middle blurred (c) reference image

Figure 2. Multi-foucs images

(a) visual image (b) infrared image

Figure 3. Multi-sensor images

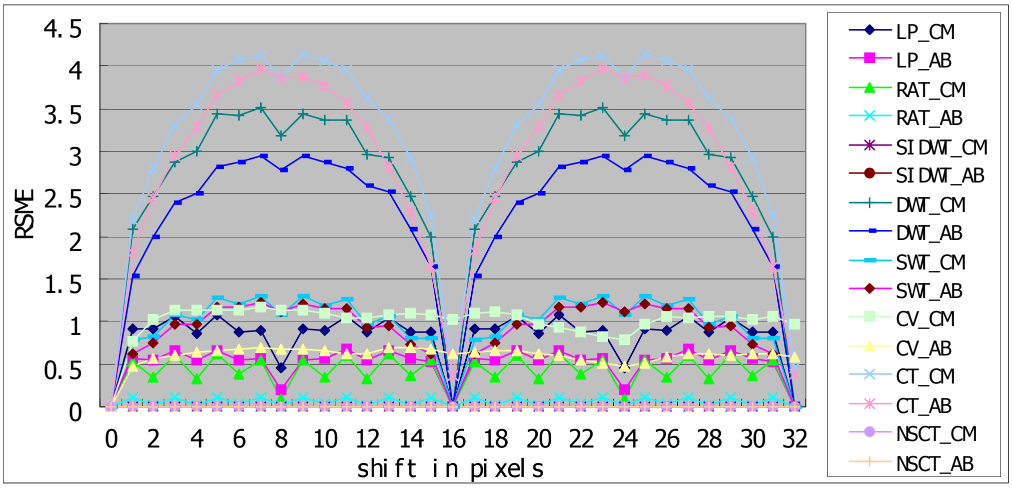

Figure 4. Shift dependency of multiresolution-based fusion schemes for multi-foucs images.

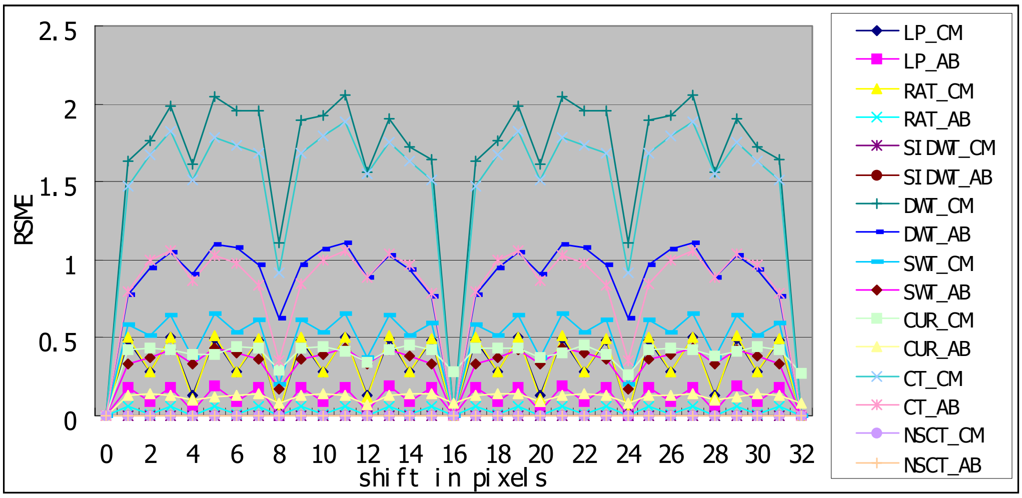

Figure 5. Shift dependency of multiresolution-based fusion schemes for multi-sensor images.

C. summary

As discussed above, lower redundant decomposition would lead to more shift dependency and vice versa. In other words, to obtain shift-invariant we have to use redundant decomposition process which has poor computational performance. One should use MR with low redundant or low shift dependency in their application, except for special occasions such as in image sequence fusion, where a shift dependent fusion scheme leads to unstable and flickering results sequences [7]. In the following section, we will discuss this in detail.

IV. SHIFT-DEPENDENCY EFFCTS ON FUSION PROFORMANCE

In this section, we compare a series of MR fusion schemes which have low or high shift dependency to evaluate their effects on fusion results of accurate registration input images. Then we also investigate their effects on fusion results of misregistration input images.

In our experiments, we selected multi-focus images and multi-sensors images as inputs. Multi-focus images were obtained by blurring the different parts of the lena image. Figure 2.(c) is original lena image as a reference image, Figure 2.(a) and 2.(b) were obtained by blurring the different parts of the lena image. Figure 3. is visual and infrared image pair.

A. Accuracy Registration Input Images.

The 16 fusion schemes are computed in Matlab7.0. For an objective quantitative comparison of the fusion schemes, we adopt the quality measure RSME to evaluate fusion result of the multi-focus images since the reference image could be regarded as ideal fused image (Table II). For fusion result of the multi-sensor images, we use three objective quality measures (Table III). These three objective measures are Mutual Information (MI) [9], Weighted Fusion Quality Index (WFQI) [10] and Edge Information Preservation Measure ($Q^{AB/F}$) [11] .

Comparing RSME of multi-focus fused images in Table II, the shift-invariant NSCT obtained best score while shift-invariant SIDWT has worst quality. Although the SWT and CUR is high shift dependency, their performance was fairly excellent. Then comparing quality measures of multi-sensor fused images in Table III, we get consistent results with the previous that the performance of NSCT is still best and SIDWT worst.

It can be concluded that, shift-dependency of MR has little to do with the quality of fused image, and the quality mainly depends on the MR's own properties (such as directionality and anisotropy etc.) or fusion rules. Therefore, in case of source images registered accurately, we should select MR with low redundant in order to achieve good computational performance.

B. Imisregistration input images

We simulated misregistration by this way, assuming input image pair is registered accurately, one image was shifted several pixels in the horizontal direction and another was not shifted. In our experimental, we shift input images (Figure 2(b) and Figure3.(b)) from 1 pixels to 5 pixels and fused it with the another input images (Figure 2.(a) and Figure 3.(a)). All of 16 fusion schemes were tested and due to the limited paper space we only list part of fused images with 5 pixels shift in Figure 6. and Figure7.

The experiment results show that, in case of misregistration source images, all the fused images perform aliasing and ringing artifacts and with the increase of shift, these artifacts become more and more distinctive. An area-base fusion rule could reduce the artifacts. Comparing fused images In Figure 6. and 7., it can be seen clearly that the artifacts in DWT and CT fused images is most serious, this related to their low-redundancy decomposition and the high shift dependency. Whereas the SIDWT and NSCT fused images perform less artifacts due to their high redundant and shift-invariant.

Therefore, in case of source images are difficult to be registered accurately, we should use low shift dependency MR or shift-invariant MR, or design a sophisticated fusion rule.

TABLE II TYPE SIZES FOR CAMERA-READY PAPERS

Fusion Scheme		*LP*	*RoLP*	*SIDWT*	*DWT*	*SWT*	*CV*	*CT*	*NSCT*
RSME	***CM***	1.0945	6.1919	13.5028	2.1665	0.7953	0.8128	1.3340	0.5669
	AB	1.0160	3.7906	13.3999	1.3946	1.2478	1.2826	1.3628	1.0793

TABLE III TYPE SIZES FOR CAMERA-READY PAPERS

Fusion Scheme		*LP*	*RoLP*	*SIDWT*	*DWT*	*SWT*	*CV*	*CT*	*NSCT*
MI	***CM***	0.1831	0.1846	0.1685	0.3320	0.1843	0.1653	0.1758	0.1890
	AB	0.1883	0.2130	0.1695	0.3609	0.1852	0.1669	0.1801	0.19055
WQI	***CM***	0.5009	0.5803	0.2727	0.4100	0.4988	0.5000	0.4947	0.4963
	AB	0.4997	0.6228	0.2736	0.4074	0.5004	0.4981	0.4923	0.4977
$Q^{AB/F}$	***CM***	0.5357	0.6239	0.1860	0.4412	0.5325	0.5352	0.5290	0.5295
	AB	0.5353	0.6641	0.1865	0.4461	0.5350	0.5348	0.5281	0.5317

Figure 6. The fused images of multi-foucs images with 5 pixels shift misregistration.

V. Conclusions

The higher shift dependency caused by subsampling in non-redundant decomposition process and more redundant will lead to lower shift dependency and vice versa. In this paper, we investigated shift dependency (shift-variant or shift- invariant) of various MR-based fusion schemes and analyzed its effect on image fusion by quantitative and qualitative methods.

Our experimental results show that shift-dependency of MR have little to do with the quality of fused image and the quality mainly depends on the fusion rules and the MR's own properties (such as directionality and anisotropy etc.) when input images was registered. One should select non-redundant MR decomposition in order to achieve good computational performance in their application.

For many applications, such as there were difficult to register images, or in image sequence fusion, shift-invariance properties are often required. In general, sampling causes a deterioration in the quality of the fused image by introducing heavier blocking effects or flickering results sequences than would have obtained by using decompositions without sampling.

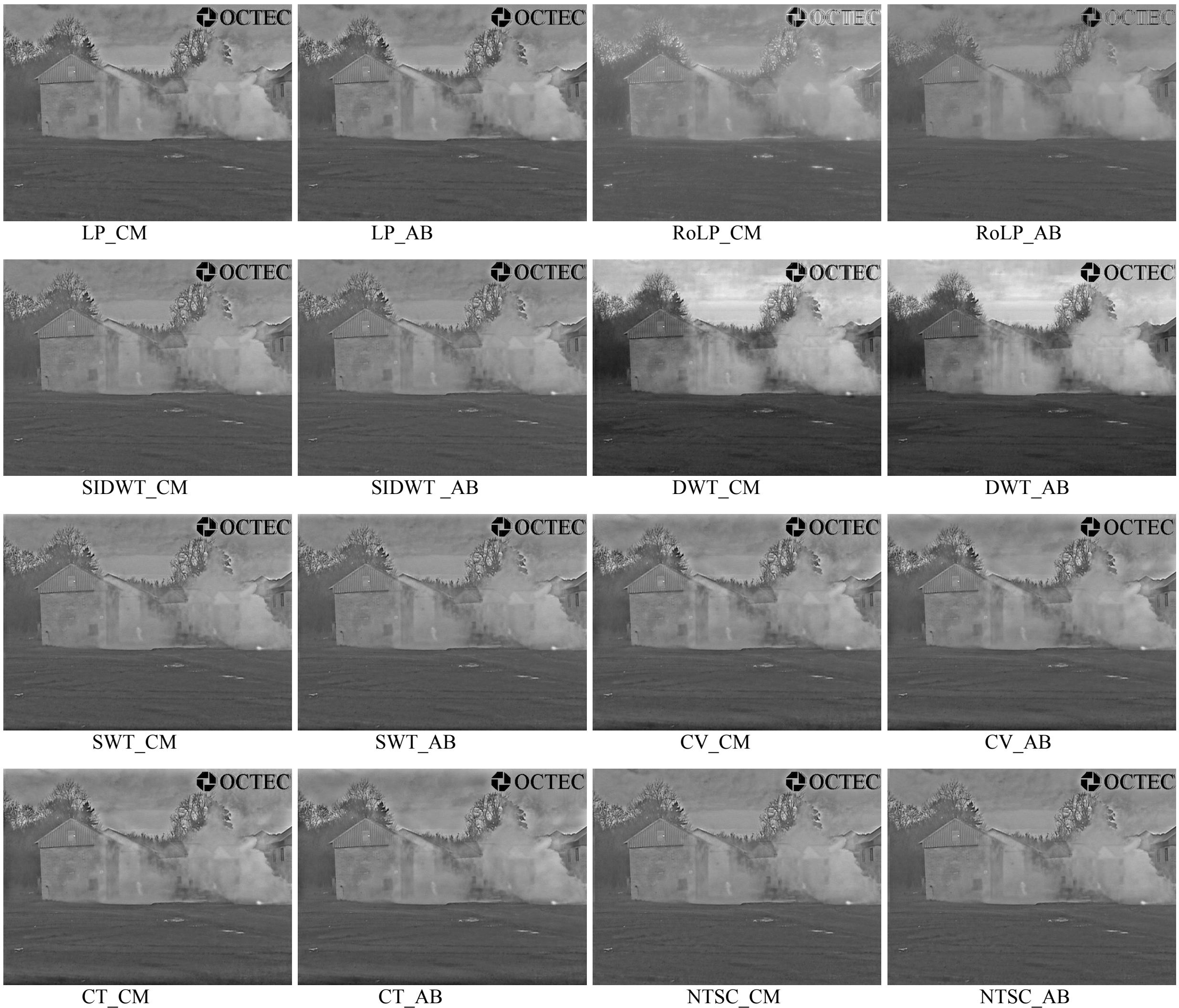

Figure 7. The fused images of multi-sensor images with 5 pixels shift misregistration.

ACKNOWLEDGMENT

This research was supported by NSAF (No. 10676029, No. 10776028).

REFERENCES

[1] Youcef Chibani, Amrane Houacine, “Redundant versus orthogonal wavelet decomposition for multisensor image fusion”, Pattern Recognition, vol. 36 (4), pp. 879-887, April 2003.

[2] C.Pohl and J. L. Van Genderen, “Multisensor image fusion in remote sensing: concepts, methods and applications,” International Journal of Remote Sensing, vol. 19(5), pp. 823~854, March 1998.

[3] Moira I. Smith, Jamie P. Heather, “Review of image fusion technology in 2005,” Proceedings of the SPIE - The International Society for Optical Engineering, vol. 5782(1), pp.29-45, March 2005.

[4] P. J. Burt, “The pyramid as structure for efficient computation,” in Multiresolution Image Processing and Analysis, Berlin, Germany: Springer-Verlag, pp. 6–35, 1984.

[5] P. J. Burt and Raymond J. Kolczynski, “Enhanced image capture through fusion,” IEEE 4th International Conference on Computer Vision, pp. 173-182, May 1993.

[6] Arash Golibagh Mahyari, Mehran Yazdi, “A novel image fusion method using curvelet transform based on linear dependency test,” 2009 International Conference on Digital Image Processing, pp. 351-354, March 2009.

[7] Gemma Piella, “A general framework for multiresolution image fusion:from pixels to regions.” Information Fusion, vol. 4(4), pp. 259–280, Dec. 2003.

[8] Oliver Rockinger, “Image sequence fusion using a shift-invariant wavelet transform.” Proceedings of International Conference on Image Processing, vol. 3, pp.288-291, Oct. 1997.

[9] Guihong Qu, Dali Zhang and Pingfan Yan, “Information measure for performance of image fusion,” Electronics letters, vol. 38(7), pp. 313-315, March 2002.

[10] Gemma Piella and Henk Heijmans, “A new quality metric for image fusion,” Proceedings 2003 International Conference on Image Processing, vol. 2, pp.173-176, Sept. 2003.

[11] Vladimir Petrovic, Costas Xydeas, “Objective evaluation of signal-level image fusion,” Optical Engineering, vol. 44(8), pp. 1-8, August 2005.

Li Yufeng received his B.S. and M.S. degree from Southwest Jiaotong University, Chengdu, China, in July 1995 an April 2004. Currently, he is a Ph.D. candidate in School of Electrical Engineering of Southwest Jiaotong University, Chengdu, China. he also is a teacher in school of Compter Sicence and Technology of Southwest University of Science and Technology, Mianyang, China. His current research interests include image processing and image fusion technology.

Feng Xiaoyun, a professor and doctoral advisor in School of Electrical Engineering of Southwest Jiaotong University, Chengdu, China. His current research interests include rail electrification and automation.

Fan Yong, a professor in school of Compter Sicence and Technology of Southwest University of Science and Technology, Mianyang, China. His current research interests include image processing and machine vision technology.