

A Multi-focus Image Fusion Method Based on Laplacian Pyramid

Wencheng Wang

School of Control Science and Engineering, Shandong University, Jinan, China
Department of Information and Control Engineering, Weifang University, Weifang, China
wwchpaper@126.com

Faliang Chang

School of Control Science and Engineering, Shandong University, Jinan, China
flchang@sdu.edu.cn

Abstract—This paper presented a simple and efficient algorithm for multi-focus image fusion, which used a multi-resolution signal decomposition scheme called Laplacian pyramid method. The principle of Laplacian pyramid transform is introduced, and based on it the fusion strategy is described in detail. The method mainly composed of three steps. Firstly, the Laplacian pyramids of each source image are deconstructed separately, and then each level of new Laplacian pyramid is fused by adopting different fusion rules. To the top level, it adopts the maximum region information rule; and to the rest levels, it adopts the maximum region energy rule. Finally, the fused image is obtained by inverse Laplacian pyramid transform. Two sets of images are applied to verify the fusion approach proposed and compared it with other fusion approaches. By analyzing the experimental results, it showed that this method has good performance, and the quality of the fused image is better than the results of other methods.

Index Terms—multi-focus image, Gaussian pyramid, image fusion, Laplacian pyramid

I. INTRODUCTION

In recent years, digital image processing technology has been widely used in many fields. However, due to the limited depth-of-focus of optical lenses in CCD devices, it is often not possible to get an image that contains all relevant objects in focus. Consequently, the obtained image will not be in focus everywhere, i.e., if one object in the scene is in focus, another one will be out of focus. Fig.1 shows a geometric optical model of image formation. To achieve all objects in focus, a fusion process is required so that all focused objects are selected. So, in general, the problem that image fusion tries to solve is to combine complementary information from several images taken from the same scene in order to achieve a new fused image, which contains the best information coming from the original images. Therefore,

the fused image has better quality than any of the original images[1-4]. And it is more suitable for human visual perception and computer-processing tasks such as segmentation, feature extraction and object recognition.

Generally speaking, image fusion processing is divided into three levels: pixel fusion, feature fusion, and decision fusion. Pixel fusion is the lowest-level fusion, which analyzes and integrates the information before the original information is estimated and recognized. Feature fusion is done in the middle level, which analyzes and deals with the feature information such as edge, contour, direction obtained by pretreatment and feature extraction. Decision fusion is the highest-level fusion, which points to the actual target. Before fusion, the data should be pre-processed to gain the independent decision result, so the cost is high and at the same time the information loss cannot be avoided[5].

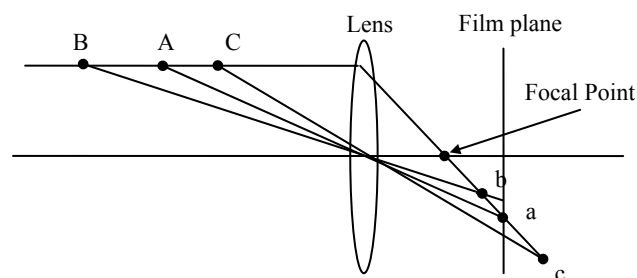


Figure 1. Geometric optics model

Currently, it seems that most image fusion applications employ pixel-based methods. The advantage of pixel fusion is that the images used contain the original information. Furthermore, the algorithms are rather easy to implement and time efficient. The simplest image fusion method just takes the pixel-by-pixel average of the source images. This, however, often leads to undesirable side effects such as reduced contrast. In recent years, many researchers recognized that multi-scale transforms are very useful for analyzing the information content of images for the purpose of fusion. So, various alternatives based on multi-scale transforms have been proposed, such as Laplacian pyramid-based, gradient pyramid-based, discrete wavelet-based (WT)[6-8], et al.. The basic

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Wencheng Wang, Shandong University, Jinan, 250061, China (phone: 86-531-88392664; E-mail:wwchpaper@126.com)

idea of multi-scale transform is to perform a multi-resolution decomposition on each source image, then integrate all these decompositions to produce a composite representation. The fused image is finally reconstructed by performing an inverse multi-resolution transform. The conventional WT idea considers the maximal absolute value of wavelet coefficients or local feature of two images [9-11]. Wavelets are very effective in representing objects with isolated point singularities, while wavelet bases are not the most significant in representing objects with singularities along lines. As a consequence, the method based on the WT can not excavate the edge quality and detail information [12,13]. Considering this, In this paper, we proposed a multi-focus image fusion method based on Laplacian pyramid. This method can take advantage of global and local information, spatial and gray information.

The rest of this paper is organized as follows. The principle of Laplacian pyramid decomposition is described in section 2. The scheme of image fusion by using Laplacian pyramid is given in section 3. After that, evaluation rules of fused image are proposed, it is followed by a discussion of the image fusing experiments in section 5, it illustrates the fusion scheme with some practical samples, and experimental results are analyzed. Finally, the last section gives some concluding remarks.

II. PRINCIPLE OF LAPLACIAN PYRAMID TRANSFORM

One effective and pellucid structure used to describe image with multi-resolution is the image pyramid proposed by Burt and Adelson in 1983. The basic principle of this method is to decompose the original image into pieces of sub-images with different spatial resolutions through some mathematical operations [3]. The Laplacian pyramid is derived from the Gaussian pyramid, which is a multi-scale representation obtained through a recursive low-pass filtering and decimation. So, the Laplacian pyramid decomposition is divided into two steps: the first is Gaussian pyramid decomposition, the second is from Gaussian pyramid to Laplacian pyramid[14,15].

A. Gaussian Pyramid Decomposition.

Suppose the zero level of the pyramid G_0 is equal to the source image, G_0 is on the bottom of the pyramid, and the l -th level of Gaussian pyramid which denoted as G_l is obtained by those steps:

Firstly, the convolution is conducted between the l -1-th level images G_{l-1} and the window function

$$G_l^*\left(\frac{i+m}{2}, \frac{j+n}{2}\right) = \begin{cases} G_l\left(\frac{i+m}{2}, \frac{j+n}{2}\right), & \frac{i+m}{2}, \frac{j+n}{2} \text{ are integers} \\ 0, & \text{others} \end{cases} \quad (6)$$

Set

$$\begin{cases} LP_l = G_l - G_{l+1}^*, & 0 \leq l < N \\ LP_N = G_N, & l = N \end{cases} \quad (7)$$

$\omega(m,n)$ which has low-pass characteristics. Then, convolution results were separated out in the down-sampling, which can be expressed as:

$$G_l(i, j) = \sum_{m=-2}^2 \sum_{n=-2}^2 \omega(m,n)G_{l-1}(2i+m, 2j+n) \quad (1)$$

$1 \leq l \leq N, 0 \leq i < R_b, 0 \leq j < C_l$

Where N is the maximal level of pyramid, C_l and R_b represent the column and row number of the l -th level pyramid respectively, $\omega(m,n)$ is called weighting function or generating kernel, which is a two-dimensional separable 5×5 window function defined by:

$$\omega = \frac{1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix} \quad (2)$$

It is convenient to consider this process as a standard *Reduce* operation, and simply write:

$$G_l = Reduce(G_{l-1}) \quad (3)$$

Then the Gaussian pyramid is constituted by G_0, G_1, \dots, G_N , where G_0 is the bottom and G_N is the top of the pyramid, respectively, and the total number of Gaussian pyramid layers is $N+1$.

B. Laplacian Pyramid Decomposition.

In order to reduce the large number of redundant information from Gaussian pyramid, it needs to find the difference between the adjacent two images and get the band-pass filtered images, this set is the Laplacian Pyramid. The specific algorithm is as follows.

Let G_l^* be the image obtained by expanding G_l , then G_l^* has the same size with G_{l-1} . So, the amplification operator *Expand* can be used, namely:

$$G_l^* = Expand(G_l) \quad (4)$$

According to (3), the *Expand* operator is defined as:

$$G_l^*(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 \omega(m,n)G_l\left(\frac{i+m}{2}, \frac{j+n}{2}\right) \quad (5)$$

$1 \leq l \leq N, 0 \leq i < R_b, 0 \leq j < C_l$

Where

where N is the number of Laplacian pyramid levels, LP_l is the l -th level image decomposed from Laplacian pyramid, and *Expand* operator is the inverse of *Reduce* operator. Now we can get the Laplacian pyramid

composed of LP_0, LP_1, \dots, LP_N . Each of them is the difference of its Gaussian pyramid image itself and the last level's which has been interpolated and enlarged, the course just like band-pass filtering.

C. Reconstruction from the Laplacian Pyramid.

An important property of the Laplacian pyramid is that it is a complete image representation: the steps used to construct the pyramid may be reversed to recover the original image exactly. From (7), then

$$\begin{cases} G_N = LP_N, & l = N \\ G_l = LP_l + G_{l+1}^*, & 0 \leq l < N \end{cases} \quad (8)$$

So, the reconstruction of source image from the Laplacian pyramid can be expressed as:

$$G_0 = LP_0 + \text{Expand}(LP_1 + \text{Expand}(LP_2 + \dots + \text{Expand}(LP_N))) \quad (9)$$

Take three levels decomposition as an example, the flow chart is shown in Fig.2.

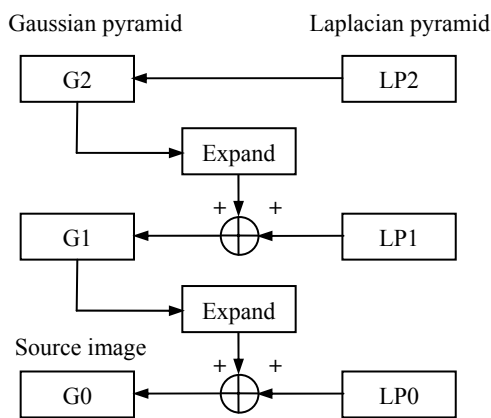


Figure2. Reconstruction of Laplacian pyramids

III. IMAGE FUSION METHOD

A. Fusion Strategy

Laplacian pyramid represents the edge of the image detail at every levels, so by comparing the corresponding Laplace-level pyramid of two images, it is possible to obtain the fused image which merge their respective outstanding detail, and makes the integration of the image retaining the amount of information as rich as possible. The source image is decomposed into a series of resolution spaces, and how to choose integration factor and fusion rule will directly affect the final quality of fused image[17,18]. Generally speaking, there are two fusion methods: the pixel-based and region-based. Though pixel-based method is simple and has less computation, the performance is poor. Because the local characters of a image are not dependent each other, there are more relationships among one pixel with its neighbors. So we designed the fusion operators based on the region method. The principle is as shown in Fig.3.

In order to reflect the tiny details and texture characteristics of the image, to different level of pyramid, different fusion operators are proposed. Suppose LP_l^A and LP_l^B are the l -th level images obtaining through Laplacian pyramid decomposition of source images A and B, and the fused result is LP_l^F ($0 \leq l \leq L$). When $l = N$, then LP_l^A and LP_l^B will be the top images after Laplacian pyramid decomposition. The specific fusion rule is as follows:

(1)To the top level N , we adopt the regional information based fusion method, to the same scene of different images; it selects the regions of richer information as the result. The indicators which reflect the amount of information for the region mainly are deviation and entropy, which can be denote as D and E , respectively.

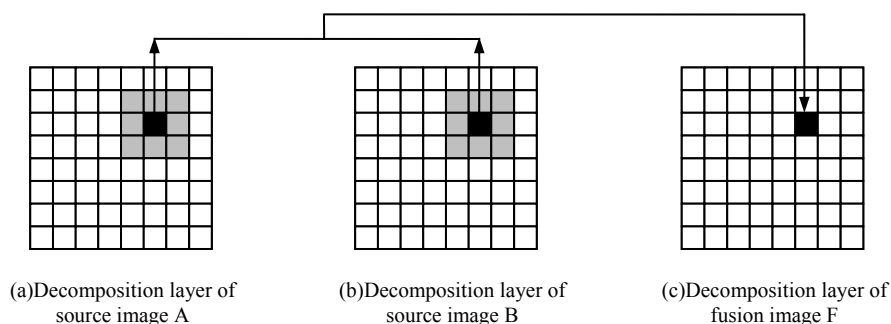


Figure.3 Fusion strategy based region

$$D = \sum_{m=1}^J \sum_{n=1}^K (X(m,n) - \bar{X})^2 / (J \times K) \quad (10)$$

$$E = -\sum_{i=0}^{L-1} P_i \log P_i \quad (11)$$

Where X is the region of size $J \times K$ pixels, $X(m,n)$ is the gray value of (m,n) in X , \bar{X} is the average gray value of X , L is the overall gray-scales of image, P_i is the probability of gray level i . Then, the strategy will be expressed as:

$$LP_N^F(m,n) = \begin{cases} LP_N^A(m,n) & (D^A(m,n) \geq D^B(m,n)) \& (E^A(m,n) \geq E^B(m,n)) \\ LP_N^B(m,n) & (D^A(m,n) < D^B(m,n)) \& (E^A(m,n) < E^B(m,n)) \\ (LP_N^A(m,n) + LP_N^B(m,n)) / 2 & otherwise \end{cases} \quad (12)$$

where $D^A(m,n)$, $D^B(m,n)$ are deviations corresponding to $LP_N^A(m,n)$ and $LP_N^B(m,n)$, respectively; $E^A(m,n)$, $E^B(m,n)$ are entropies corresponding to $LP_N^A(m,n)$ and $LP_N^B(m,n)$, respectively.

(2) To the rest levels ($0 \leq l < N$), we adopt the “maximum region energy” rule. Supposing $RE_l(m,n)$ is the local region energy of the l -th Laplacian pyramid which takes (m,n) as the center. Then, its definition is:

$$RE_l = \sum_{m' \in J, n' \in K} \omega^l(m', n') [LP_l(m+m', n+n')]^2 \quad (13)$$

where LP_l is the l -th Laplacian pyramid; $\omega^l(m', n')$ is the weight matrix operator; J, K are defined as the size of local region.

So, the strategy of levels from 0 to $N-1$ will be:

$$LP_l^F(i,j) = \begin{cases} LP_l^A(i,j) & |RE_l^A(i,j)| \geq |RE_l^B(i,j)| \\ LP_l^B(i,j) & |RE_l^A(i,j)| < |RE_l^B(i,j)| \end{cases} \quad (14)$$

After obtaining the all levels of the fused images such as $LP_1^F, LP_2^F, \dots, LP_N^F$, the ultimate fusion images can be obtained through the reconstruction according to Eq.8.

B. Fusion Steps.

The basic steps of image fusion based on Laplacian Pyramid transform are as follows. Here, we only take the fusion of two source images as an example, though it can be extended to handle mere tan two images straightforwardly. Suppose A and B are original images of registration, F is the fused image.

(1) To perform Laplacian pyramid decomposition for the images to be fused separately and establish Laplacian pyramid for each image.

(2) To fuse the image pyramid layers decomposed separately, different layers can be used to mix with different fusion operators, the Laplacian pyramid of fused image can be obtained ultimately.

(3) To perform pyramid inverse transform on the new fused Laplacian pyramid, the reconstructed image will be fused image.

In this approach, we can obtain an optimum fused image which has richer information in the spatial domain. Fig.4 gives an overview of the organization of the algorithm.

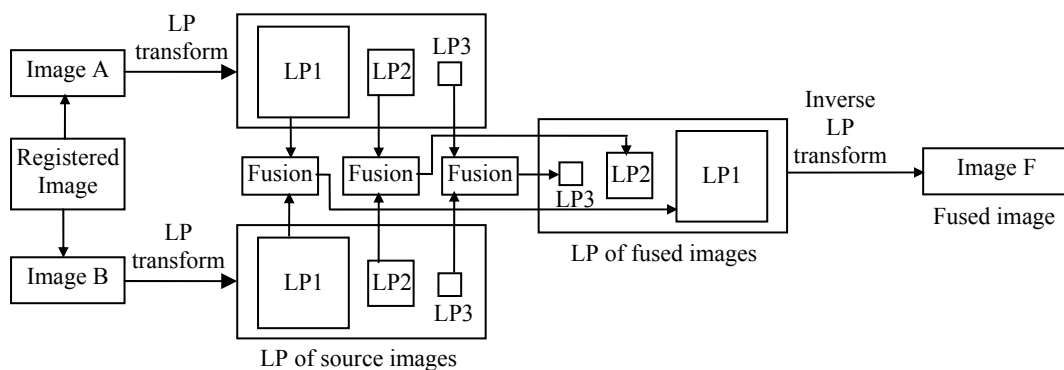


Figure4. The framework of fusion method based on Laplacian transform

From Fig.4 it can be seen that the purpose of Laplacian decomposition is to decompose the original image into different spatial frequency bands, and to the different decomposition layers with different spatial resolutions, it can effectively merge the characteristics or details of the different images together by using different operators. It

can get the visual effect close to peoples’ vision characteristics finally.

C. Pseudo Code.

From what have been discussed above, the key steps of this algorithm are as follows.

Algorithm

For every source images do

Laplacian pyramid decomposition and establish Laplacian pyramid for each image.

End for

For the N -th level Laplacian pyramid do

If $(D^A(m, n) \geq D^B(m, n)) \& (E^A(m, n) \geq E^B(m, n))$

$LP_N^F(m, n) = LP_N^A(m, n)$

Else if $(D^A(m, n) < D^B(m, n)) \& (E^A(m, n) < E^B(m, n))$

$LP_N^F(m, n) = LP_N^B(m, n)$

Else

$LP_N^F(m, n) = (LP_N^A(m, n) + LP_N^B(m, n)) / 2$

End for

For the other levels Laplacian pyramid do

If $|RE_i^A(i, j)| \geq |RE_i^B(i, j)|$

$LP_i^F(m, n) = LP_i^A(m, n)$

Else

$LP_i^F(m, n) = LP_i^B(m, n)$

End for

Do inverse Laplacian pyramid transform, and obtain the fused image.

IV. EVALUATION OF FUSED IMAGE

In order to verify the efficiency of image fusion, it needs a method of evaluation[19-23]. The evaluation methods commonly can be divided into two broad categories: the subjective assessment method and the objective evaluation method.

A. Subjective Evaluation.

Subjective assessment method is a man-made visual analysis for fused image, it is simple and intuitive. In addition to this, it has many advantages, such as it can be used to determine whether the image has shadow, whether the fusion image texture or color information is consistent, and whether the clarify has been reduced et al.. Therefore, the subjective assessment method is often used to compare the edges of fused images. It can get the differences of images in space decomposed force and clarity intuitively.

B. Objective Evaluation

As the subjective assessment methods are not comprehensive and with certain one-sidedness. When the observation conditions change, the assessment results may be different. So, researchers made a number of methods named objective evaluation, those are quantitative analysis. For the metallographic image fusion evaluation, we should take consideration of the

enhancement of spatial details and the maintenance of spectral information comprehensively. In this section we describe a number of different focus functions studied in this paper. Let $f(i, j)$ be the gray level intensity of pixel (i, j) .

Standard Deviation (STD). It is an important index to weigh the information capability of images and it reflects the discrete level of gray-scale image's mean value, The Standard deviation is defined as

$$STD = \sqrt{\sum_{i=1}^M \sum_{j=1}^N (f(i, j) - \hat{\mu})^2 / MN} \quad (15)$$

The greater the standard error, the more dispersed the distribution of gray-scale image, the better the quality of fused image. That is to say, it contains more information.

Information Entropy(IE). Image entropy is an important indicator for evaluating the richness of image information; it represents the property of combination between images. The larger the combination entropy of an image, the richer the information contained in the image. The entropy of an image is

$$H = -\sum_{i=0}^{L-1} p_i \log p_i \quad (16)$$

where H is the entropy, L is the overall gray-scales of image, p_i is the probability of gray level i .

Average Gradient (AG). It reflects the contrast between the details variation of pattern on the image, so it

$$\bar{G} = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \sqrt{\left(\frac{\partial f(x_i, y_j)}{\partial x_i}\right)^2 + \left(\frac{\partial f(x_i, y_j)}{\partial y_i}\right)^2} / 2 \quad (17)$$

Generally speaking, larger the value of \bar{G} , clearer that image.

Therefore, in order to make the evaluation of image quality more effective and more comprehensive. In this paper, we adopt a comprehensive evaluation which makes the combination of the subjective visual evaluation and objective evaluation.

V. EXPERIMENTAL RESULTS ANALYSIS

In order to test the performance of the proposed fusion algorithm, we have designed the experiments on two sets of images using Matlab 2008a. Each set image has different focuses and is partly blurring, its size is 256×256 pixels. The proposed method compared with other

is often used to evaluate the clarity of the image.

fusion methods such as average method, maximum method and wavelet transform method. Experimental results are shown in following figures.

A. Experiment on Clock Images

The experiment on a set of clock images is conducted and the results are shown in Fig.5. Fig 5(a) and Fig.5(b) show the multi-focus test images which focus on right and left focal plane, respectively, and Fig. 5(c), Fig.5(d), Fig.5(e) and Fig.5(f) show the results of average method, maximum method, wavelet transform method and proposed method, respectively. It can be seen from that the fused image produced by those methods are basically a combination of the good-focus parts in the source images to some extent.

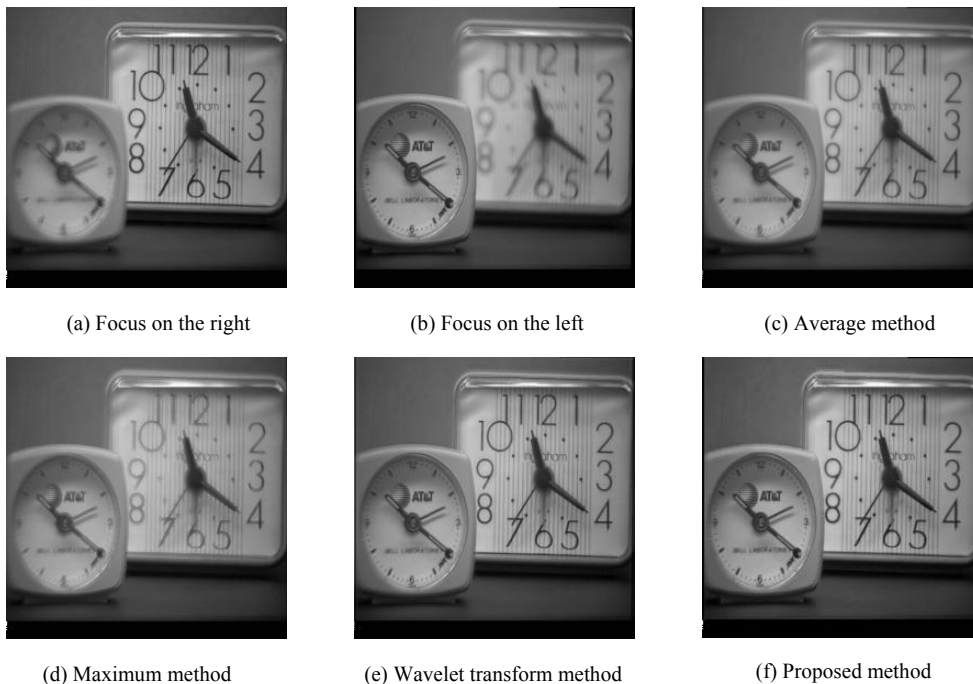


Figure5. Comparison of the experimental results on clock images

From the fused image of proposed method in Fig.5(f), it should be noted that both the spatial resolutions and clarity have been enhanced in comparison to the other images, it has obvious advantages in the details of information. Comparing with Fig.5(c), it is more clarify. Comparing with Fig.5(d), it has more contrast, and comparing with Fig.5(e), it is of the more obvious details. Therefore, from a subjective evaluation of view point, the overall effectiveness of the new method is better.

From the perspective of an objective assessment, Tab.1 presents a comparison of the experimental results of image fusion using the average-based image fusion method, maximum-based method, wavelet-based method and pyramid-based method in terms of standard deviation, entropy, and the mean gradient. In Tab.1, the indicator values of the Laplacian pyramid-based fused image are greater than those of other methods.

TABLE 1. QUANTITATIVE RESULTS FOR VARIOUS FUSION METHODS.

Fused images	STD	IE	AG
Image of Fig.5(c)	50.45	7.29	5.01
Image of Fig.5(d)	51.34	7.31	4.81
Image of Fig.5(e)	51.28	7.37	7.15
Image of Fig.5(f)	53.18	7.41	7.44

B. Experiment on Metallurgical Images.

Other practical application can be found in Fig.6. Fig 6(a) and Fig.6(b) are the metallurgical images which focus on top and bottom focal plane, respectively. The results are achieved by the average method, maximum

method, wavelet transform method and proposed method. From the visual effect, the blurred parts are improved by several methods after fusion. Tab.2 shows the difference from the objective evaluation.

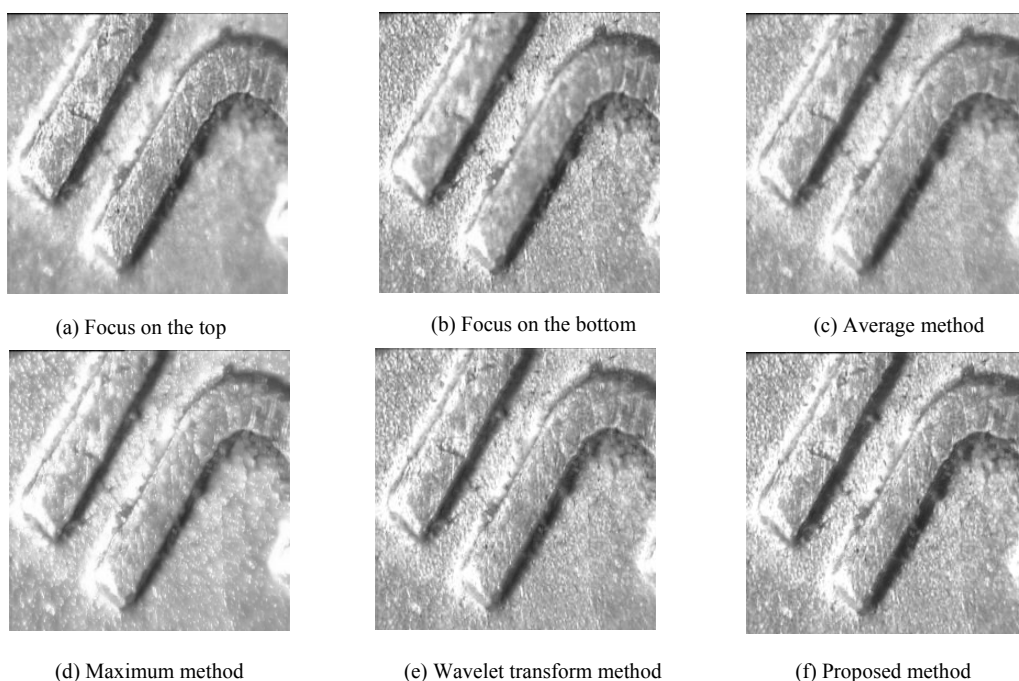


Figure.6 Comparison of the experimental results on metallurgical images

TABLE 2. QUANTITATIVE RESULTS FOR VARIOUS FUSION METHODS.

Fused images	STD	IE	AG
Image of Fig.6 (c)	42.41	7.29	8.96
Image of Fig.6 (d)	42.79	7.27	9.80
Image of Fig.6 (e)	44.21	7.34	13.72
Image of Fig.6 (f)	46.45	7.38	14.56

From what have been discussed above, it can be seen that the amount of image information will have different levels improvement after fusing with different methods, and finer features can be obtained in the fusion results. However, compared to the other traditional methods, the pyramid-based algorithm proposed in this paper can not only make the detail image inosculate together but also render the fusion result more clearly. Its fusion performance is better.

VI. CONCLUSIONS

In this paper, we have presented a newly developed method based on the Laplacian pyramid transform for fusing multi-focus images. The principle of Laplacian pyramid and the fusion strategy of different pyramids are described in detail. Experimental studies were conducted by applying the proposed method, and also other image fusion methods. The comparisons of the fused images

from the difficult methods were made. Based on the experimental results, it can be seen that the proposed method provides a good result, both visually and quantitatively for multi-focus images fusion. However, to the algorithm in terms of complexity and real-time, there are still enough to be further improved.

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Wen-Cheng Wang was born in 1979. He received his M.S. degree in 2005. He is currently pursuing the Ph.D. degree at School of Control Science and Engineering, Shandong University. The main research interests include pattern recognition and image processing.



Fa-Liang Chang was born in 1965. He received the M.S. and Ph.D. degree from Shandong University in 1989 and 2005, respectively. From January 2008 to January 2009, he has been a visiting scholar in the University of Pittsburgh in USA for one year. He has published two books and more than 100 papers. Now he is a professor, doctorate supervisor. His

main research interests include digital signal processing, computer vision, pattern recognition, and visual tracking.