Wavelet Decomposition in Laplacian Pyramid for Image Fusion

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***Abstract*—The aim of image fusion is to combine information from the set of images to get a single image which contains a more accurate description than any individual source image. While the scene contains objects in different focus due to the limited depth-of-focus of optical lenses in camera then by using image fusion technique we can get an image which has better focus across all area. In this paper, a multifocus image fusion method using combination Laplacian pyramid and wavelet decomposition is proposed. The fusion process contains the following steps: first, the multifocus images are decomposed using Laplacian pyramid into several levels of pyramid. Then at each level of pyramid, wavelet decomposition is applied. The images at every level of wavelet are fused using maximum absolute value rule. The inverse wavelet transform is then applied to the combined coefficients to produce the fused image in laplacian pyramid. The final step is to reconstruct the combined image at every level of pyramid to get the fused image which shows an image retaining the focus from the several input images. Experimental results that are quantitatively evaluated by calculation of root mean square error, peak signal to noise ratio, entropy, and average gradient measures for fused image show the proposed method can give good result.**

***Index Terms*—image fusion, laplacian pyramid, wavelet decomposition**

I. Introduction

Image fusion is the process of combining relevant information from two or more images into a single image where the resulting image will be more informative than any of the input images. The goal of image fusion is to reduce uncertainty and minimize redundancy in the output as well maximize relevant information particular to an application or task. With rapid advancements in technology, it is now possible to obtain information from multi sources images to produce a high quality information from a set of images. In this paper, we deal with multi-focus image. Due to the limited depth-of-focus of optical lenses in camera devices, it is often not possible to get an image with contains all relevant object 'in focus' so that one scene of image can be taken into set of images with different focus of every image. We can use image fusion method to obtain all focused objects.

Many methods exist to perform image fusion. In this work, we used Laplacian pyramid (LP) and the discrete wavelet transform (DWT) image fusion. The LP image fusion and DWT image fusion are multiscale transformation image fusion.

The LP image fusion integrates multi-source information at the basic level and can provide more abundant, accurate and reliable detail information. The important thing in the LP image fusion is to define a selection rule for determining the value of each pixel in the result fused pyramid. The averaging method, maximum method, saliency and match measure [1], and combination of averaging and maximum energy method [2] have been used as selection rules in LP image fusion. Recently, [3] used PCA as selection rule in LP image fusion.

As we know that LP is good in preserving the edge. The LP image fusion with average fusion rule often leads to undesirable side effects such as reduced contrast. While the LP with maximum selection rule tends to have the higher contrast. The wavelet fusion method allows the image decomposition in different kind of coefficients subbands. Image fusion using wavelet method can be seen in [4]-[7]. The wavelet transformation modulus maxima gives better preservation of both edge features and component information of the object in new fused image preserving the detail image information [6].

In this paper, we proposed multifocus image fusion method using combination Laplacian Pyramid (LP) and wavelet transform fusion method. We use discrete wavelet decomposition in each level of LP before undergoing fusion. The fusion rule used is the maximal absolute value of wavelet coefficients. This fusion method gives improvement significantly in the resulting fused image. A maximum absolute value rule effectively retains the coefficients of in focus regions within the image.

This paper is organized as follows: Section 2 briefly gives explanation about Laplacian pyramid and wavelet decomposition. Steps of the proposed method fusion

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process are described in Section 3. Section 4 explains the performance evaluation measures of the result fusion image. The experimental results are shown in Section 5.

II. LITERATURE REVIEW

The Laplacian pyramid was first introduced by [8] as a model for binocular fusion in human stereo vision, where the implementation used a Laplacian pyramid and a maximum selection rule at each point of the pyramid transform [9]. Essentially, the procedure involves a set of band-pass copies of an image is referred to as the Laplacian pyramid due to its similarity to a Laplacian operator. Each level of the Laplacian pyramid is recursively constructed from its lower level by applying the following four basic steps: blurring (low-pass filtering), sub-sampling (reduce size), interpolation (expand), and differencing (to subtract two images pixel by pixel). In the LP, the lowest level of the pyramid is constructed from the original image.

A. Gaussian Pyramid Decomposition

Suppose g_0 is the original image with size *R*x*C*. This image becomes the bottom or zero level of pyramid. Pyramid level 1 contains image g_1, which is reduce and low-pass filtered version of g_0. Pyramid level 2, g_2, is obtained by applying reduce and low-pass filtered version of g_1. The level-to-level process is as followed

$$g_l = reduce\left(g_{l-1}\right)$$

which means, for level $0 < l < N$ and nodes (i, j) such that $0 < i < C_l,\ 0 < j < R_l$.

$$g_l(i,j) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} w(m,n) g_{l-1}(2i+m, 2j+n) \quad (1)$$

N refers to the number of levels in the pyramid and C_lxR_l is the size of the *l*th level image. $w(m,n)$ is generating kernel which is separable: $w(m,n)=w(m)\,w(n)$.

The one-dimensional $w(m)$, length 5, is

1) Normalized: $\sum_{m=-2}^{2} w(m) = 1$
2) Symmetric: $w(-i)=w(i)$ for i = 0, 1, 2
3) Equal contribution: all nodes at a given level *l* must contribute the same total weight to nodes at the next higher level *l*+1.

Let $w(0)=a$, $w(-1)=w(1)=b$, and $w(-2)=w(2)=c$. It is easy to show that the three constraints are satisfied (see Burt, 1983) when

$$w(0)=a,$$

$$w(-1)=w(1)=\frac{1}{4},$$

$$w(-2)=w(2)=\frac{1}{4}-\frac{a}{2}.$$

So, we can write that w = [1/4–a/2; 1/4; a; 1/4; 1/4–a/2].

Usually the value of *a* is [0.3, 0.6] as in [10]. The sequence images $g_0, g_1, g_2, \ldots, g_N$ form a pyramid of *N* levels where the bottom level is g_0 and the top level is g_N. The image at a higher level *l* is reduced a half both in resolution and size of the image at the predecessor level *l*-1.

Iterative pyramid generation is equivalent to convolving the image g_0 with a set of equivalent functions h_l defined as follows:

$$g_l = h_l \otimes g_0 \quad (2)$$

where we know

$$g_1 = w \otimes g_0 = h_1 \otimes g_0$$

$$g_2 = w \otimes g_1 = w \otimes (w \otimes g_0) = (w \otimes w) \otimes g_0 = h_2 \otimes g_0$$

$$g_3 = w \otimes g_2 = w \otimes ((w \otimes w) \otimes g_0) = (w \otimes w \otimes w) \otimes g_0 = h_3 \otimes g_0$$

$$\vdots$$

$$g_l = w \otimes g_{l-1} = w \otimes ((\underbrace{w \otimes w \otimes \cdots \otimes w}_{l-1\ w's}) \otimes g_0)(\underbrace{w \otimes w \otimes \cdots \otimes w}_{l\ w's}) \otimes g_0 = h_l \otimes g_0$$

So that, we we can write $h_l = \underbrace{w \otimes w \otimes \cdots \otimes w}_{l\ w's}$ or

$$g_l = \sum_{m=-M_l}^{M_l}\sum_{n=-M_l}^{M_l} h_l(m,n) g_0(i2^l + m, j2^l + n) \quad (3)$$

The size of M_l doubles from one level to next level, as does the distance between samples. In the case *a*=0.4, the shape of equivalent functions closely resemble to Gaussian probability density function. So the sequence image $g_0, g_1, g_2, \ldots, g_N$ is called *Gaussian pyramid*.

A function *expand* is the reverse of function *reduce*. Its effect is to expand an (M+1)-by-(N+1) array into a (2M+1)-by-(2N+1) array by interpolating new node values between the given values. Thus, expand applied to array g_l of the *Gaussian pyramid* would yield an array $g_{l,1}$ which is the same size as g_{l-1}.

Let $g_{l,n}$ be the result of expanding g_l *n* times. Then

$$g_{l,0} = g_l$$

and

$$g_{l,n} = expand(g_l, n-1)$$

by expand it means, for level $0 < l \le N$ and $0 \le n$ and nodes $i, j, 0 < i < C_{l-n}, 0 < j < R_{l-n}$

$$g_{l,n}(i,j) = 4\sum_{m=-2}^{2}\sum_{n=-2}^{2} w(m,n) g_{l,n-1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) \quad (4)$$

where

$$g_{l,n-1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right) = \begin{cases} g_{l,n-1}\left(\frac{i-m}{2}, \frac{j-n}{2}\right), & for\ \frac{i-m}{2}, \frac{j-n}{2}\ \text{integer} \\ 0, & otherwise \end{cases}$$

B. Laplacian Pyramid Generation

The Laplacian pyramid is a sequence of error images $L_0, L_1, L_2, \ldots, L_N$. Each is the difference between two levels of the Gaussian pyramid

$$L_l = g_l - expand(g_{l+1}, 1)$$
$$= g_l - g_{l+1,1}$$

and for L_N, $L_N = g_N$.

The original image, g_0, can be obtained by expanding then summing all the levels of *LP*:

$g_l = L_l + expand(g_{l+1}, 1)$ for $l = N-1, N-2, \ldots, 0$. And as we know $g_N = L_N$.

C. Discrete Wavelet Decomposition

Discrete Wavelet Decomposition (DWT) we use in this paper is based on Haar wavelet transform. DWT separately filters and downsamples images in the horizontal direction and vertical directions. This produces four coefficient subbands at each scale. As presented in [4], suppose an image $I(x, y)$ and denote the horizontal frequency first by using 1-D lowpass filter L and highpass filter H produces the coefficient matrices $I_L(x, y)$ and $I_H(x, y)$ and then followed the vertical frequency second by using lowpass filter L and highpass filter H to each column in $I_L(x, y)$ and $I_H(x, y)$, it produces produces four subimages $I_{LL}(x, y)$, $I_{LH}(x, y)$, $I_{HL}(x, y)$, and $I_{HH}(x, y)$ for one level decomposition. By recursively applying the same scheme to the low-low subband a multiresolution decomposition can be achieved.

The detail decomposition as described in [Pajares, 2004], the algorithm can be expressed as follows:

Let $I(x, y)$ original image of size M x N, $l(i)$ the analysis lowpass coefficients of a specific wavelet basis, $i = 0,1,2, \ldots N_l - 1$, where N_l is the support legth of the filter L. $h(j)$ the analysis lowpass coefficients of a specific wavelet basis, $j = 0,1,2, \ldots N_h - 1$, where N_h is the support legth of the filter H. Then,

$$I_L(x, y) = \frac{1}{N_l} \sum_{i=0}^{N_l - 1} l(i).I((2x + i) \bmod M, y) \tag{5}$$

$$I_H(x, y) = \frac{1}{N_h} \sum_{i=0}^{N_h - 1} h(j).I((2x + j) \bmod M, y) \tag{6}$$

for $x = 0,1,2, \ldots, M/2 - 1$ and $y = 0,1,2, \ldots, N/2 - 1$.

$$I_{LL}(x, y) = \frac{1}{N_l} \sum_{i=0}^{N_l - 1} l(i).I_L(x, (2y + i) \bmod N) \tag{7}$$

$$I_{LH}(x, y) = \frac{1}{N_h} \sum_{i=0}^{N_h - 1} h(j).I_L(x, (2y + j) \bmod N) \tag{8}$$

$$I_{HL}(x, y) = \frac{1}{N_l} \sum_{i=0}^{N_l - 1} l(i).I_H(x, (2y + i) \bmod N) \tag{9}$$

$$I_{HH}(x, y) = \frac{1}{N_h} \sum_{i=0}^{N_h - 1} h(i).I_H(x, (2y + j) \bmod N) \tag{10}$$

for $x = 0,1,2, \ldots, M/2 - 1$ and $y = 0,1,2, \ldots, N/2 - 1$. where the modulo operation is an operation to find the remainder of division of one number by another. The algorithm can iterate on the smooth subimage $I_{LL}(x, y)$ to obtain four coefficient matrices in the next decomposition level and so on. Generally, an image $I(x, y)$ has its multi scale decomposition (MSD) representation as D_I and the activiti level as A_I. Let $p = (m, n, k, l)$ indicates the index corresponding to a particular MSD coefficient, where *m* and *n* indicate the spatial position in given frequency band, *k* the decomposition level, and *l* the frequency band of the MSD representation. Thus, $D_I(p)$ and $A_I(p)$ are MSD value an activity level of the corresponding coefficients. The activity level of an MSD reflects the local energy in the space spanned by the term expansion corresponding to this coefficients. In this work, $A_I(p) = |D_I(p)|$.

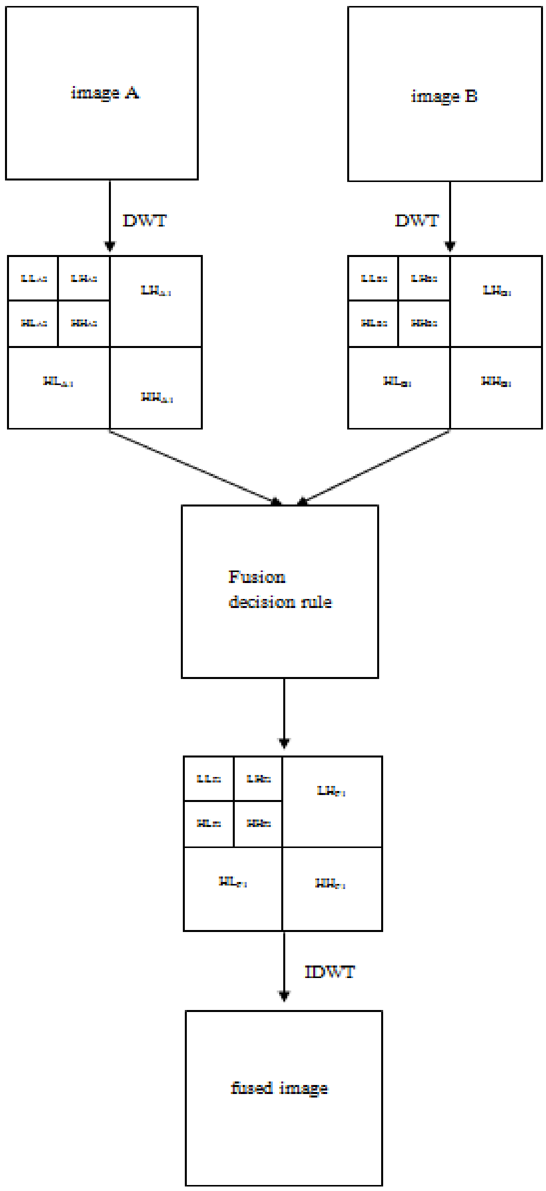


Figure 1. DWT image fusion

Fig. 1 shows 2-level discrete wavelet decomposition and fusion image using wavelet transform. In the DWT, only coefficients of the same level and representation can be fused. The fused coefficient can be achieved by various strategies. The process of fused coefficeints in this paper is described in Section 4. After the new fused multiscale coefficients then by using Inverse Discrete Wavelet Transform (IDWT) as described in [4], the final fused image is obtained.

III. The Proposed Method

The image fusion methods keep progressing to get the better result of fused image. In this work, we fuse images using combination Laplacian pyramid and wavelet transform fusion method where we decompose each source image by Laplacian pyramid at first and then apply wavelet decomposition at each level of Laplacian pyramid.

We fuse image in wavelet decomposition by merging the DWT coefficient of every corresponding frequency band. The Choose-Max Absolute scheme is used as a selection rule. Low-frequency subbands related to the coarse part of the images, while high-frequency corresponds to the region boundaries or edges. Except for the LL band, which has all positive transform values, all other bands contain transforms that fluctuating around zero. Therefore, the general principle of making fusion rules is to keep the salient features in the new images such as regions and edges as much as possible. Thus the fusion parameter selection rule can be obtained:

If X and Y are the source images and Z is the fused image, Z image can be described as

$$D_Z(p) = D_i(p) \tag{11}$$

where $i =$ X or Y that satisfies

$$A_i(p) = \max\left(\left|A_X(p)\right|, \left|A_Y(p)\right|\right) \tag{12}$$

The larger transform values in these bands correspond to sharper brightness changes and thus to the salient features in the image such as edges, lines and region boudaries. Anda maximum absolute value rule effectively retains the coefficients of in focus regions within the image.

The steps of image fusion in this work as follows. Suppose there are two original source images, A and B, with different focus to be fused:

1) To perform Laplacian pyramid decomposition to create Laplacian pyramid for each source image,
2) To perform discrete wavelet decomposition to every level of Laplacian pyramid for each image in different kinds of coefficient,
3) To merge an appropriate coefficient of the corresponding subband to obtain new coefficients by using maximum absolute selection rule. The fused wavelet image is achieved through the inverse discrete wavelete transform,
4) The final fused image is obtained by performing pyramid inverse transform on the fused wavelet image.

The process of pyramid image fusion can be seen in Fig. 2 which the fusion LPi's (i=1, 2, 3) is obtained by applying wavelet transform fusion.Actually it can be extended more than two source images.

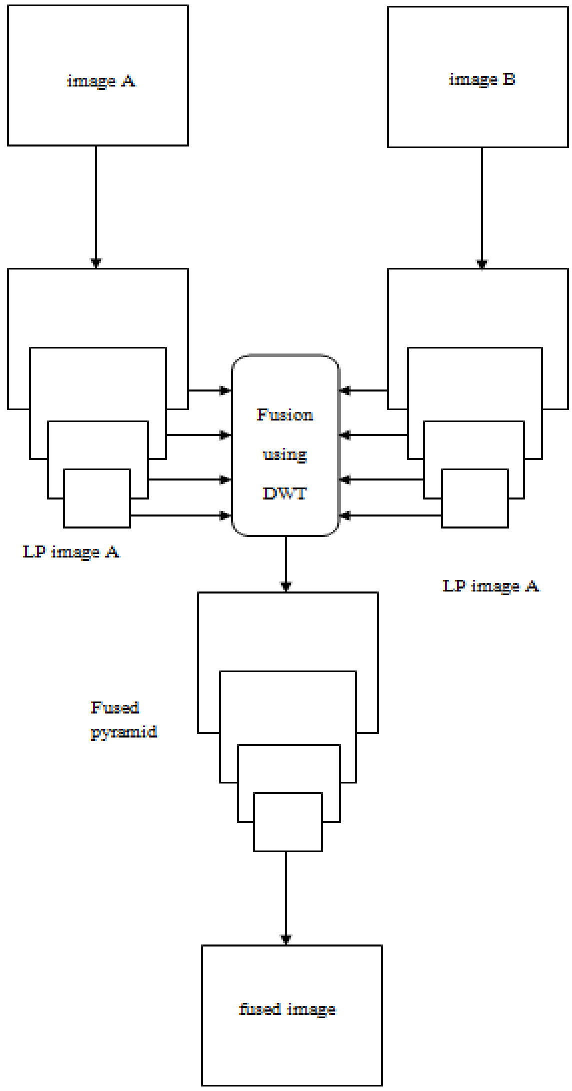


Figure 2. The proposed method

IV. Fused Image Performance Evaluation Measures

In this section, we discuss some quantitative analysis that will be used to evaluate the performance of the result fused image. Let $F(i, j)$ be the gray level intensity of pixel (i, j) of the fused image and $R(i, j)$ be the gray level intensity of pixel (i, j) of the reference image.

A. Root Mean Square Error (RMSE)

RMSE gives the information how the pixel values of fused image deviate from the reference image. RMSE between the reference image and fused image is computed as:

$$RMSE = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left[R(i, j) - F(i, j)\right]^2} \tag{13}$$

where m x n is the size of the input image and i, j represents to the pixel locations. A smaller value of RMSE shows good fusion result. If the value of RMSE is 0 then it means the fused image is exactly the same as reference image.

B. Peak Signal to Noise Ratio (PSNR)

PSNR is the ratio between the signal (image data) and the noise. In image processing, PSNR is calculated between two images. We find the peak signal to ratio between the fused image F and the reference image R. PSNR is computed as

$$PSNR = 20\log\left[\frac{L^2}{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left[R(i,j)-F(i,j)\right]^2}\right] \quad (14)$$

where m x n is the size of the input image. L is the total gray levels in the image. A higher value of PSNR gives better fusion results and this value shows how alike the fused and reference image are.

C. Entropy

Image entropy is to evaluate the richness of image information; it represents the property of combination entropy of an image. The entropy on an image is:

$$H = -\sum_{l=0}^{L-1} p(l)\log p(l) \quad (15)$$

where $p(l)$ is probability of gray level l.

The larger the combination entropy of an image, the richer the information contained in the image.

D. Average Gradient

Average gradient, G, reflects the contrast between the detail variation of pattern on the image. The larger value of G, the clearer of image. In image fusion, the larger average gradient means a higher spatial resolution

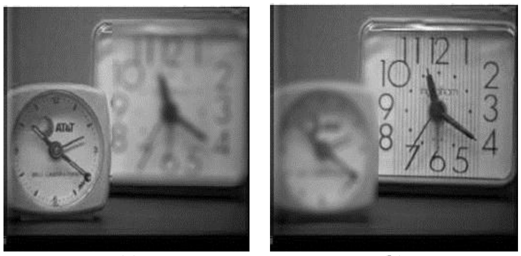
$$G = \frac{1}{(m-1)(n-1)}\sum_{i=1}^{m-1}\sum_{j=1}^{n-1}\sqrt{\left(\left(\frac{\partial F(x_i,y_j)}{\partial x_i}\right)^2 + \left(\frac{\partial F(x_i,y_j)}{\partial y_i}\right)\right)/2}$$

V. EXPERIMENTAL RESULT

The proposed algorithm was tested on two datasets of image using Matlab 2013a. All images have size 256 x 256 pixels. The first dataset, clocks image, consists of two images with different focus because of taken from different distance and the second dataset, image of three objects consists of three images that each image focuses on one object.

A. Clock Image

The images in first data set are taken from different distance. One image has focus in near distance of camera, which focuses on the smaller clock and the larger clock is out of focus. The other image focuses on the larger image that is taken far from the camera and seems blurred on the smaller image as shown in Fig. 3. Where Fig. 3(a) focuses on the smaller clock and Fig. 3(b) focuses on the larger clock.

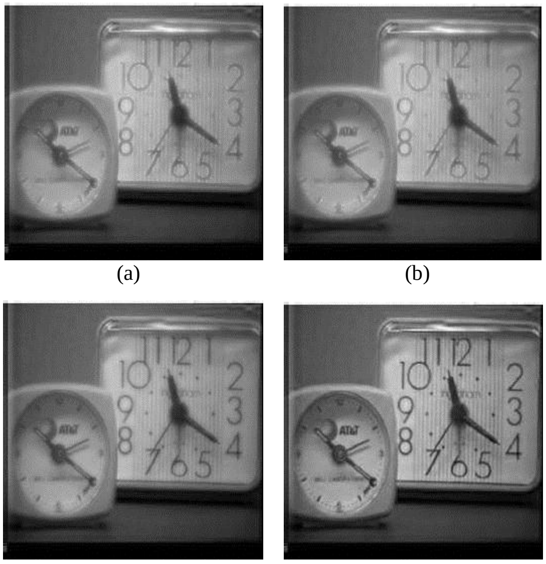


(a) (b)

Figure 3. Source images ‘clock’: (a) image with focus on the left, (b) image with focus on the right

In this experiment, we fuse image using four different methods, the proposed method and the three other methods as the comparison. Three methods performed are laplacian pyramid fusion methods with different integration rules, the integration rules used are average method, maximum selection and wavelet (as proposed method in this work). The other method is non-laplacian pyramid fusion method, it is used wavelet method. And we compare the result of using proposed methods and the other methods. In these methods, the ‘haar’ wavelet is used in methods: wavelet and laplacian pyramid (LP) method using wavelet as fusion rule (proposed method). The Choose-max coefficients method is used in merging the coefficients as explained in Section 4.

The result of proposed image Fig. 4(d) is more obvious in details comparing with the result of wavelet method, Fig. 4(c). It is also can be seen that the proposed method has a smaller RMSE, 1.9383, than the wavelet does, 3.8714. Fig. 4(d) has greater value in average gradient than Fig. 4(c), the larger of average gradient indicates the clearer of image.



(a) (b)

(c) (d)

Figure 4. The ‘clock’ fusion result of LP based average method and proposed method: (a) LP based average method, (b) LP based maximum method, (c) wavelet method and (d) proposed method

We also can see that the fused image of LP fusion based average method, Fig. 4(a), has lower contrast than the result of proposed method Fig. 4(d). As we know that one of the disadvantage of average method, it reduces the contrast. Comparing with the result of the proposed method, the fused image of the proposed result gives the sharper brightness in contrast and also more clarify.

The more contrast is obtained in the fused image by the proposed method, Fig. 4(d), compared with the result of LP fusion based on maximum selection, as shown in Fig. 4(b). Again, the RMSE and average gradient of the proposed method have the larger values the RMSE and average gradient of LP with maximum selection as we see in Fig. 5 and Fig. 6, respectively.

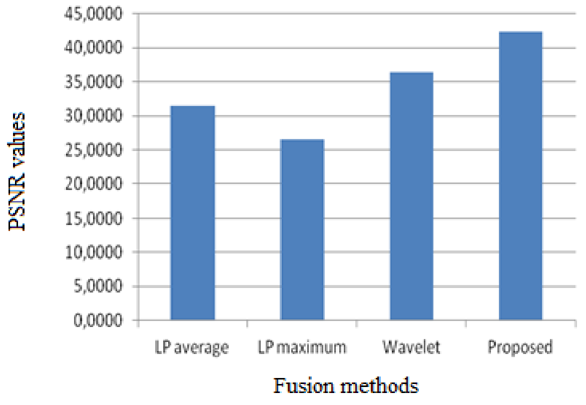


Figure 5. RMSE of the LP average, LP maximum, wavelet, and proposed fusion methods

Fig. 5 shows that the proposed method gives the best fusion result, it has the lowest value of RMSE. The lower value of RMSE, the more similar the fuse image with the reference image.

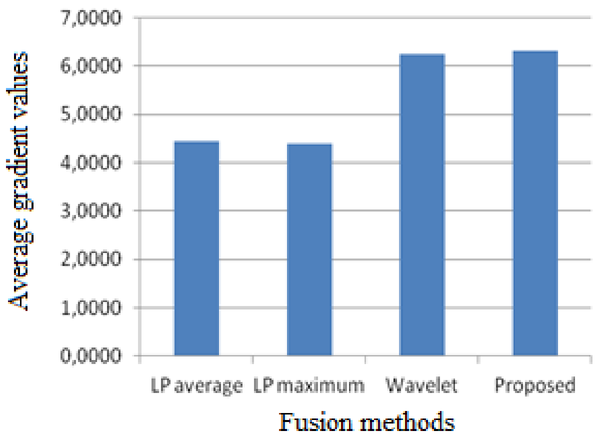


Figure 6. Average gradient of the LP average, LP maximum, wavelet, and proposed fusion methods

PSNR measures how alike the fused image with the reference image. The fused image is the most alike to reference image if it has high value of PSNR. In the Fig. 7, again the proposed method results the best performance with its highest value of PSNR followed by wavelet, LP average, and LP maximum. For the clarity of image, it is showed by average gradient. The larger average gradient means a higher spatial resolution. It can be seen on chart from Fig. 6 that the average gradient value of the proposed method is the largest and the average gradient value of the LP maximum method is the smallest.

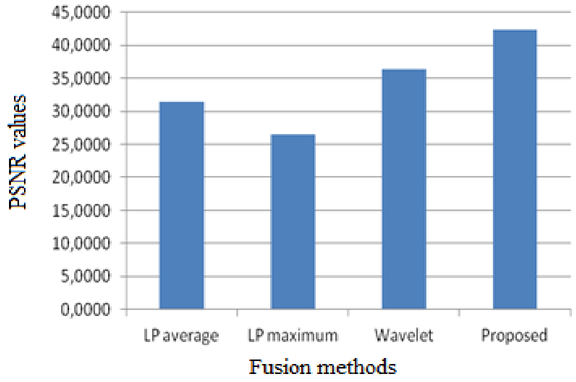
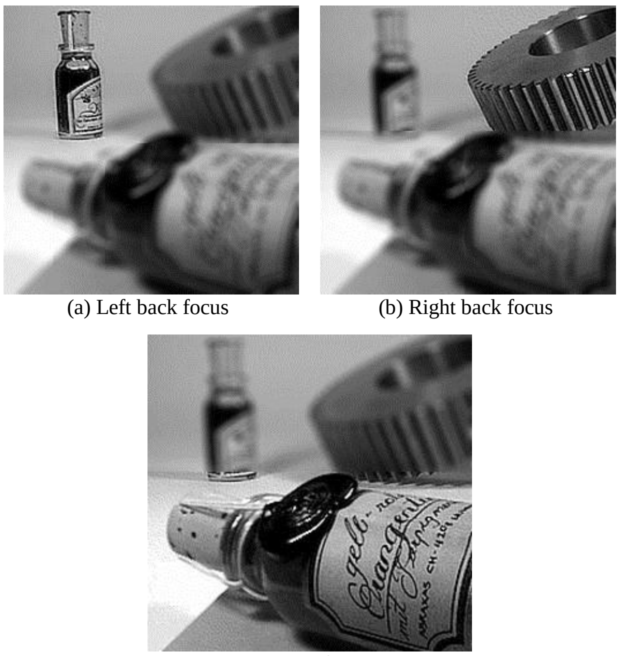


Figure 7. PSNR of the LP average, LP maximum, wavelet, and proposed fusion methods

The result of proposed method has obvious advantages in the details of information. It also gives the better both in visual clarity and quantitative performance evaluation in comparison to other methods. It is clear that the proposed method produce better quality fusion image than the other methods that are performed in this experiment.

B. Bottle Image

In the previous experiment, the proposed method gives the best result among the methods presented. Hence, we will use the proposed method in this experiment for the fusion of three images. Three images in the second dataset show three different object focuses. The first image focuses on the small bottle, the left back of the image. The focus gear is on the second image. And the third image has focus on the big bottle. These images are shown in the Fig. 8, respectively Fig. 8(a), Fig. 8(b) and Fig. 8(c).



(a) Left back focus (b) Right back focus

(c) near focus

Figure 8. Source images of the second dataset

We found something interesting while fused these images using different steps combination of images. We fuse these images with several combinations: all three images are fused once at the same time and to fuse every two images firstly then the result to be fused with another image. In the fusing of not all image together at the same time, we fuse two image at first using LP based on wavelet, we decompose two source images using Laplacian pyramid, then decompose images at each level by DWT, and to fuse them by Choose-max method of wavelet coefficients,

We apply inverse wavelet on the fused coefficients then to reconstruct them by inverse pyramid to get the fused image. We applied again LP based on wavelet on the first fused image with another image to get all three fused image. Four combination rules are used in this fusion:

- The first combination, F1

We do the laplacian pyramid decomposition for all three images then we fuse all images together at the same time. The result fused images is F1.

- The first combination, F2

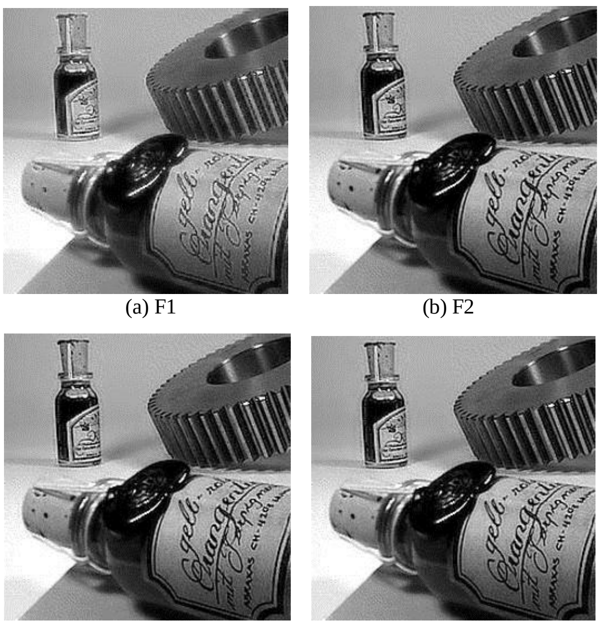
The laplacian pyramid decomposition is applied to all image. We fuse first two image, image (i) and image (ii), then we reconstruct the fused laplacian pyramid (F12). The result fused F12 we fuse with image ii to get th fused image F2.

- The first combination, F3

F3 is obtained by using similar way with F2 but the first fusion is image B and image C. The result of first fusion (F23), image (ii) and image (iii), is fused with image (i) to get the fused image F3.

- The first combination, F4

By fusing image (i) and image (iii) to get the fused image F13 and then to combine F13 and image (ii) to get the fused image F4.



(a) F1 (b) F2

(c) F3 (d) F4

Figure 9. The result of combination fusion: (a) F1, (b) F2, (c) F3, (d) F4

In this experiment, there is evident that the focus area of image has corelation with the step of combination. The focus areas of image (i), the focus areas of image (ii), and the focus of areas image (iii) are 8077 units, 15639 units, and 38307 units, respectively.

Fig. 9 shows the result of the proposed method in vary combination steps. In this case, the fusion of two images at first and followed fusion with another image gives much better result than to fuse all three images together at once. The fusion result of three images together, at once, Fig. 9(a), produces the fused image with the lowest in contrast among the combinations. Visually, F2 gives the better result than F3 and F4. The contrast on the object ‘gear’ in the image F2 is the nearest to the contrast of object ‘gear’ on the source image Fig. 8(b), where the object ‘gear’ is focus object of it. F2 also has the sharper brightness for the object ‘big bottle’ compared with F3 and F4. It is also can be seen that the RMSE of F2, 4.3673, is the smallest, although not very different from F3, 4.5964, and F4, 4.5892.

From Table I, in comparing F2, F3, and F4, F2 has the highest PSNR that F2 is the best result followed F4 and F3, as we know that PSNR show how alike the result image and the reference image are. The clear of image can be measured by average gradient, the clearer of image the higher the value of average gradient. Again, F2 has the highest value of average gradient, the second is F4, and followed by F3. From these performance evaluation values, F2 is better than F4 and F3.

TABLE I. PERFORMANCE MEASURE EVALUATION OF THE FUSED IMAGE

Image	F1	F2	F3	F4
RMSE	17.0812	4.3673	4.5964	4.5892
PSNR	23.4805	35.3265	34.8824	34.8961
Average Gradient	10.4235	12.5301	12.4922	12.5082

Related to the focus areas, from the result, by combining one by one, it is better to combine from the first two smallest focus area, then the result is combined with the third smaller and so on to the bigger. In this experiment, we see that the first two smallest is combination image (i) and image (ii) first, F12, then fused with image (iii) that produced F2, and followed with F13 that yields F4, and F23 that resulted F3. It is because when we fuse from the smallest focus area to the bigger focus area, the loss of originality of the focus areas on the big focus image is not as big as others since it is proceed at last time.

VI. CONCLUSION

In the present work, the image fusion method using combination Laplacian pyramid and discrete wavelet transformation. The principal method of fusion is described in detail. The result of experiment shows that the proposed method gives improved result in both visually and quantitatively image fusion in comparison with the other fusion methods. The fusion of more than two images is better done one by one from the smallest focus image to the bigger focus image. It gives better result than other combinations.

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