BLOCK-BASED PIXEL LEVEL MULTI-FOCUS IMAGE FUSION
USING PARTICLE SWARM OPTIMIZATION

ABDUL BASIT SIDDQUI¹, M. ARFAN JAFFAR², AYYAZ HUSSAIN³
AND ANWAR M. MIRZA⁴

¹Department of Computer Science
National University of Computer and Emerging Sciences
A.K Brohi Road, Islamabad 44000, Pakistan
basit.siddiqui@nu.edu.pk

²Department of Mechatronics
Gwangju Institute of Science and Technology
Gwangju, South Korea
arfanjaffar@gist.ac.kr

³Department of Computer Science
International Islamic University
Islamabad, Islamabad, Pakistan
ayyaz.hussain@iiu.edu.pk

⁴Department of Computer Engineering
College of Computer and Information Sciences
King Saud University
ammirza@ksu.edu.sa

Received November 2009; revised March 2010

ABSTRACT. For accurate image segmentation, edge detection and stereo matching, it is significant that all the objects in the image under processing must be in focus. However, due to limited depth of field of optical lenses particularly which have greater focal length, it is not always possible. In such cases, image fusion is performed to obtain an everywhere-in-focus image. In this paper, we have proposed a highly precise method for multi-focus image fusion. We have proposed a method based on Particle Swarm Optimization (PSO) to find out the optimal size of blocks to be fused. Detailed experimentation is performed using different quantitative measures for different set of multi-focus images. We have compared the results of proposed technique with different existing image fusion techniques such as DWT, aDWT, PCA and Laplacian Pyramid based image fusion. Experimental results show that the proposed method outperforms the traditional approach both visually and quantitatively.

Keywords: Fusion, PSO, Optimal block

1. Introduction. Image fusion is a sub-field of image processing in which more than one images of the same scene are combined and a resultant image is created which offers more details and resolves the ambiguities in the input images. In multi-sensor image fusion, the images of the same scene come from different sensors of different resolution. In multi-focus image fusion, the images of the same scene from the same sensor are combined to create an image in which all the objects are in focus. The process of image fusion takes place either in spatial domain or in transformed domain. In spatial domain, the pixel values are directly incorporated in fusion process whereas in transformed domain, the input images are first transformed using wavelet decomposition or pyramid decomposition to exploit the information at different scales or multi-resolutions. An image often contains physically
relevant features at many different scales or resolutions. Multi-scale or multi-resolution approaches provide a means to exploit this fact [1]. The transformed images are then fused using some fusion operation and the fused image is obtained by taking the inverse transform. The process of multi-resolution based image fusion is shown in the figure.

Image fusion is generally performed at three different levels of information representation including pixel level, feature level and decision level [2]. The simplest and the easiest level of fusion is the pixel-level image fusion. In pixel-level image fusion, fusion takes place directly at the pixel intensities. The mean or max (maximum) of the corresponding pixel values of the two registered images is calculated and is taken as the corresponding pixel value of the fused image. However, pixel level image fusion techniques introduce some undesired effects in the fused image such as smoothing the sharp edges or producing blurring effect in the fused image. In feature level image fusion, the input images are first segmented into different regions and then the features of these regions are calculated. On the basis of these feature values, the regions are selected for the fused image using some fusion rule. Decision level image fusion incorporates the detection and classification of different objects in the input images and the output is then supplied to the fusion algorithm.

We find different techniques in the literature to perform image fusion. These techniques spread over the simple pixel level image fusion techniques and the complex techniques such as laplacian pyramid based image fusion [3], PCA based image fusion [4], wavelet transform based image fusion [5] and advance DWT based image fusion [6]. Wavelet transform based techniques are famous because they provide directional information in the input images in addition of approximation coefficients. Pyramid decomposition does not provide the information about sudden intensity changes in the spatial resolution of the input images. Wavelet transform is linear in its original form [7]. The problem with linear wavelets like Haar wavelet is that during signal decomposition or analysis, the original data is not preserved [8]. Since wavelets perform low-pass filtering, so they smooth out the edges and as a result of it, the contrast in the fused images is reduced. The process of DWT-based (multi-scale decomposition) image fusion is shown in Figure 1. R. Hong et al. used the salience map of gradient to preserve the salient features in the source images [18]. They performed the range compression on the target gradient to solve the dynamic range problem.

Block based image fusion techniques at pixel level are also introduced in the literature. In these techniques, the input images are first divided into blocks and then on the basis of some criteria such as spatial frequency or visibility level of the block, one of the blocks from the input images is copied for the fused image. The size of a block is an important parameter in order to achieve good fusion results. In multi-focus image fusion, it is necessary to identify clearly the boundaries of the focused and un-focused regions in the input images. It is very clear that block size can not be fixed for every image because the focused and un-focused regions are different in different input images. Therefore, the block size must be found adaptively. Major Contributions of our proposed method are following:

- We have proposed a mechanism to find automatic, adaptive and optimal block size for image fusion using particle swarm optimization (PSO).
- A very simple representation of the particles is chosen. It is composed on two dimensions only which show the width and height of the block.
- We propose a new strategy to initialize the particles within the search space which makes the optimization process faster.
For image fusion, we are interested in small size of blocks because they can well separate the blurred and un-blurred regions from each other. Due to this reason, we initialize 50% of population size from 1/16 of the search space (size of any input image), 30% of population size from 1/8 of the search space and 20% of population size from 1/4 of the search space.

This study is divided into six sections. PSO is briefly discussed in Section 2. In Section 3, proposed method is defined. Section 4 covers the study of quantitative measures used in this paper. Experiments and results are given in Section 5 and Section 6 concludes the study.

2. Particle Swarm Optimization (PSO). Particle swarm optimization (PSO) is a population based stochastic algorithm developed for continuous optimization problem by J. Kennedy et al. [9] in 1995. It is encouraged by societal behavior of bird flocking and fish schooling in nature. Particle Swarm Optimization (PSO) and its variants have been used in different areas such as image processing, classification, sensor networks etc. C. Wang et al. introduced an invariant of PSO based on double mutation [19]. J. Nagashima et al. proposed an efficient technique using PSO to maintain flooding in sensor networks for the effective utilization of bandwidth [20]. G.-D. Li et al. used PSO to optimize GNN-PID control system [21].

In PSO, each bird is called a particle. In the search space, every particle is a solution of the problem. At the start, the velocity and position of every particle is initialized randomly in the search space. Every particle is given a fitness value and this fitness value is evaluated using fitness function to be optimized. Each particle moves to different positions in the search space on the basis of the path followed by it and by other particles in its neighborhood. The velocity and the position of every particle are updated using Equations (1) and (2).

\[
v_i^d(t + 1) = \omega \cdot v_i^d(t) + c_1 \cdot r_1 \cdot (p_i^d - x_i^d(t)) + c_2 \cdot r_2 \cdot (g_i^d - x_i^d(t)) \tag{1}
\]

\[
x_i^d(t + 1) = x_i^d(t) + v_i^d(t + 1) \tag{2}
\]

where \( d = 1, 2 \ldots D \), \( i = 1, 2 \ldots N \). \( D \) is the number of dimensions of a particle and \( N \) is the population size. \( \omega \) is the inertia weight proposed by Y. Shi et al. [10] and it is used to

**Figure 1.** DWT-based image fusion process
control the effect of previous velocity on the new velocity of the particle. \( gb \) is the global best of the whole population. \( pb \) is the local best position of the particle. \( v_i, x_i \) are the velocity and position of the particle respectively. \( r_1 \) and \( r_2 \) are the random values taken in the range \([0, 1]\). \( c_1 \) and \( c_2 \) are the constants which deal with the social and cognitive behaviors of the particle. Due to frequent positions updates of the particle, it may go out of the boundaries of the search space. To deal with this problem, we have performed the velocity clamping.

2.1. Velocity clamping. In optimization algorithms, it is necessary to keep balance between exploitation and exploration in the search space in order to obtain good results. Exploration is the property that addresses the ability of the algorithm to search different regions of the search space to find the global optima whereas in exploitation, some candidate solution in the search space is given preference. The study about different aspects of exploration versus exploitation can be studied in [11]. In PSO, due to frequent velocity updates of the particle to explore different regions, it can go out of the search space. To overcome this problem, maximum velocity update parameter \( v_{\text{max}} \) is defined. If the updated velocity of the particle is greater than \( v_{\text{max}} \) then its velocity is set to \( v_{\text{max}} \). Before updating the position of the particle, its velocity is adjusted according to Equation (3).

\[
v_{ij}(t + 1) = \begin{cases} v_{ij}(t + 1), & \text{if } v_{ij}(t + 1) < v_{\text{max}} \\ v_{\text{max},j}, & \text{otherwise} \end{cases}
\]

(3)

Here \( j \) is the \( j^{th} \) dimension of the particle \( i \). If the value of \( v_{\text{max}} \) is kept large, then it encourages to exploration while smaller value of \( v_{\text{max}} \) supports to exploitation.

3. Proposed Method. In the proposed method, we have used PSO for image fusion. The proposed system is based on PSO that calculate automatic, adaptive, and optimal block of the input images for fusion. Contrast visibility and spatial frequency are used for determining the optimal block size. First of all, we have modeled our problem according to the PSO. In proposed method, initially a random population of particles is created. Each particle represents the block size in the search space. Search space is the size of any of the registered images. Every particle has two dimensions which relate to width and height of the block as shown in the Figure 2. The particle shown in Figure 2 represents a block of size 43 \( \times \) 118.

| 43 | 118 |

Figure 2. Particle’s structure which shows the block size

The input multi-focus images are divided into blocks according to a particle’s dimensions which express the size of the block. Contrast visibility of the corresponding blocks from both the input images is calculated. The block which has higher contrast visibility is selected as the fused image’s block. This process of selecting blocks for the fused image based on their contrast visibility is repeated for all the blocks of the input images and hence a fused image is generated. The process of creating fused image is given in algorithm 2. Once the fused image is generated against a particle in the population, the fitness of the fused image is calculated using spatial frequency measure. Contrast visibility and spatial frequency are discussed in the following sections. The working of proposed method is shown in Figure 3.
Fused images are created against all the particles in a generation and their fitness values are calculated. For every particle which gives the block size, local best position of the particle in the search space is kept. The global best position of the whole population is also kept. In the next generation, the velocity and position of every particle is updated and all the particles move to their new positions. Again the fused images are calculated according to new specifications of the particles. If the fitness of the particle is greater than its previous fitness, then the new fitness becomes its local best otherwise the previous fitness remains the particle’s local best. Similarly if the fitness of the particle is greater than the fitness of global best then the local best becomes the global best of the whole population. This process of creating fused images according to the dimensions specified by the particles is repeated for a fixed number of generations. The resultant fused image is created using the global best of the last generation.

PSO is used to find optimized block size in order to get optimized fused image.

3.1. **Contrast visibility.** The corresponding blocks from the input images are selected based on their visibility values. Fused image can also be calculated on the basis of blocks variances and means but visibility measure is more suitable because it calculates the deviation of block pixels from the block’s mean value. Hence it addresses the clarity of the corresponding blocks. The visibility of the image block is obtained using Equation
Algorithm 1 Finding Optimal Block Size

Take two multi-focus registered images $I_1(x, y)$ and $I_2(x, y)$ as input
Create an initial population $S$ of particles of size n. Each particle $P_i$ consists of two
dimensions (width and height).
Initialize the dimensions of each particle $P_i$ randomly from the search space range
(size of any input image).
Initialize the $p_i^{(best)}$ of every particle $P_i$
Initialize the $g_{best}$ of the whole population $S$
Repeat
  for each particle $P_i$ do
    Calculate the new velocity $v_{new}$ according to Equation (1)
    Perform velocity clamping using Equation (3)
    Update the position of particle using Equation (2)
    if $P_i$ moves out of search space
      Initialize $P_i$ within the search space
    end if
    Get the values of dimensions of $P_i$ in $d_1$ and $d_2$
    Divide $I_1(x, y)$ and $I_2(x, y)$ according to $d_1$ and $d_2$
    Create the fused image $F_I$ using Algorithm 1
    Calculate the fitness of $P_i$ using equation
    if fitness of $P_i > p_i^{(best)}$
      $p_i^{(best)}$ = new fitness
    end if
    if fitness of $P_i > g_{best}$
      $g_{best}$ = new fitness
    end if
  end for
until last generation
Get fused image using $g_{best}$
end procedure

Algorithm 2 Creating Fused Image

$N$: Size of block list. Each block of size $d_1 \times d_2$
for $i = 1$ to $N$ do
  $B_1$: $I_1(i)$ ith block of first image of size $d_1 \times d_2$
  $B_2$: $I_2(i)$ ith block of second image of size $d_1 \times d_2$
  $V_1$: Calculate the contrast visibility of $B_1$ using Equation (4)
  $V_2$: Calculate the contrast visibility of $B_2$ using Equation (4)
  if $V_1 > V_2$
    Select $B_1$ for the fused image
  else
    Select $B_2$ for the fused image
  end if
end for
end procedure
(4).
\[ VI = \frac{1}{m \times n} \sum_{(i,j) \in B_k} |I(i,j) - \mu_k| \]  
Here \( \mu_k \) and \( m \times n \) are the mean and size of the block \( B_k \) respectively.

3.2. Spatial frequency. Spatial frequency is used to measure the activity level in an image. We have used spatial frequency as fitness measure of the fused images generated against different particles in all the generations to obtain optimized fused image. A detail study about spatial frequency and its performance can be found in [12]. Spatial frequency of an image can be calculated using Equation (5).

\[ SF = \sqrt{(RF)^2 + (CF)^2} \]  
where
\[ RF = \sqrt{\frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=2}^{n} [F(i,j) - F(i,j-1)]^2} \]
and
\[ CF = \sqrt{\frac{1}{m \times n} \sum_{j=1}^{n} \sum_{i=2}^{m} [F(i,j) - F(i-1,j)]^2} \]
Here \( F \) is the fused image and \( m \times n \) is the fused image size. A large value of spatial frequency describes the large activity level in the image which represents the clarity of the image.

4. Performance Metrics. We have used different metrics to perform the quantitative comparison of the proposed method with existing image fusion techniques. We used two sets of performance metrics because the quantitative measure of the fused image is performed when the reference image is available and when it is not available (blind image fusion).

4.1. Root mean square error (RMSE). Root mean square error finds out the difference between the reference image \( R \) and the fused image \( F \). It 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

\[ RMSE = \sqrt{\frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} [R(i,j) - F(i,j)]^2} \]  
where \( m \times n \) 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.

4.2. 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

\[ PSNR = 20 \log_{10} \left[ \frac{L^2}{\frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} [R(i,j) - F(i,j)]^2} \right] \]
where \( m \times n \) 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 images are.

4.3. Correlation (CORR). CORR gives the correlation between the reference and fused images. It is used to find the association between two images in order to check the similarity of the two images. Correlation between two images is calculated using the following equation

\[
CORR = \frac{2C_{rf}}{C_r + C_f}
\]  

where

\[
C_r = \sum_{i=1}^{m} \sum_{j=1}^{n} R(i,j)^2, \quad C_f = \sum_{i=1}^{m} \sum_{j=1}^{n} F(i,j)^2
\]

and

\[
C_{rf} = \sum_{i=1}^{m} \sum_{j=1}^{n} R(i,j)F(i,j)
\]

Here \( i, j \) represents the pixel locations and \( R, F \) are the reference and fused images respectively. \( m \) is the number of rows and \( n \) is the number of columns of the input image. Maximum value of correlation is 1 if the fused and reference images are exactly same. Correlation value decreases from 1 to 0 as the dissimilarity between the reference and fused images increases.

4.4. Mutual information (MI). Mutual Information measures the extent of information retrieved in the fused image from the input images. When the reference image is available then it is computed as

\[
MI = \sum_{i=1}^{m} \sum_{j=1}^{n} h_{RF}(i,j) \log_2 \left[ \frac{h_{RF}(i,j)}{h_R(i,j)h_F(i,j)} \right]
\]

where \( h_{RF} \) is the normalized joint grayscale histogram of the reference and fused images. \( h_R, h_F \) are the normalized grayscale histogram of reference and fused images respectively. When the reference image is not available then we take the sum of mutual information between input image \( I_1 \) and fused image \( F \) and mutual information between \( I_2 \) and fused image \( F \). Larger value of mutual information gives the better fusion results.

4.5. Entropy. Entropy is used to measure the amount of information present in an image. It is susceptible to noise and sharp fluctuations. Entropy is calculated as

\[
H = - \sum_{i=0}^{L-1} h_F(i) \log_2 h_F(i)
\]

\( h_F \) is the normalized grayscale histogram of the fused image and \( L \) is the number of grayscale levels.

In addition of the performance measures described above, we have used Mean Absolute Error (MAE), Percentage Fit Error (PFE), Universal Quality Index (QI), Standard Deviation (SD) and Fusion Similarity metric. All these performance metrics can be studied in [13-16].

5. Experiments and Results.
5.1. **Test images and their characteristics.** We have taken multi-focus images from [17]. These images set include balloon, lab, clock, pepsi and rock images. For balloon and lab images, the reference images are available. The characteristics of these test images set are given in Table 1. All the images used in this paper are registered images.

<table>
<thead>
<tr>
<th>Image Name</th>
<th>Image Property</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balloons.bmp</td>
<td>Reference / grayscale</td>
<td>640 × 480</td>
</tr>
<tr>
<td>Balloonsgs1.bmp</td>
<td>Left Focus / grayscale</td>
<td>640 × 480</td>
</tr>
<tr>
<td>Balloonsgs2.bmp</td>
<td>Right Focus / grayscale</td>
<td>640 × 480</td>
</tr>
<tr>
<td>Reflab.gif</td>
<td>Reference / grayscale</td>
<td>640 × 480</td>
</tr>
<tr>
<td>Llab.gif</td>
<td>Left Focus / grayscale</td>
<td>640 × 480</td>
</tr>
<tr>
<td>Rlab.gif</td>
<td>Right Focus / grayscale</td>
<td>640 × 480</td>
</tr>
<tr>
<td>ClockA-t.jpg</td>
<td>Left Focus / grayscale</td>
<td>256 × 256</td>
</tr>
<tr>
<td>ClockB-t.jpg</td>
<td>Right Focus / grayscale</td>
<td>256 × 256</td>
</tr>
<tr>
<td>Pepsi1.bmp</td>
<td>Left Focus / grayscale</td>
<td>512 × 512</td>
</tr>
<tr>
<td>Pepsi2.bmp</td>
<td>Right Focus / grayscale</td>
<td>512 × 512</td>
</tr>
<tr>
<td>RemoteA-t.jpg</td>
<td>Left Focus / grayscale</td>
<td>256 × 256</td>
</tr>
<tr>
<td>RemoteB-t.jpg</td>
<td>Right Focus / grayscale</td>
<td>256 × 256</td>
</tr>
</tbody>
</table>

5.2. **Population initialization.** Through the detailed experimentation, we observed that the blocks of smaller size give the better fusion results as compare to blocks of bigger size. It is due the reason that the blocks of smaller size can well separate the blurred region from the un-blurred regions than the blocks of bigger size. Blocks of smaller size may produce best fusion results. To find an optimal block size, we initialize 50% of population size from 1/16 of the search space (size of any input image), 30% of population size from 1/8 of the search space and 20% of population size from 1/4 of the search space. This scheme of initialization of particles not only finds out the optimal block size but also makes the optimization process faster. The population initialization mechanism is shown in Figure 4.

We form three buckets of the search space to initialize the particles. These are 1-1/16, 1-1/8 and 1-1/4 of the search space.

5.3. **Experimental details.** We have used a population size $S$ of 15 particles for all the input set of images. Number of generations $N$ is fixed as 10. The values of $c_1$ and $c_2$ which are used to define the social and cognitive behaviors of the particle are fixed as 2. We observed that when we take their values greater than 2 then the velocity of particle is updated by a greater factor and as a result of it, the particle takes a big jump in the search space which may skip the important region boundaries. The value of inertia weight $\omega$ is taken as 0.3. Maximum velocity $v_{\max}$ update for a particle is fixed as 15. The experimental details are summarized in the Table 2.

5.4. **Stopping criteria.** There are different criterions to stop the optimization process including maximum fitness achieved, number of generations and if the fitness remains same over a number of iterations. We have used number of generations as the stopping criteria because we cannot guess the maximum fitness value of the fused image to achieve in advance. We used fixed number of generations given in Table 1 for all the sets of input images. Through the detailed experimentation, we observed that almost for all of the sets of input images, the fitness value of fused image tends to increase in 5 to 10
5.5. Results. The performance of different image fusion techniques is estimated when the reference image is available and when it is not available. The results of the proposed method are compared with four existing image fusion techniques including DWT based image fusion, advance DWT based image fusion, PCA based image fusion and Laplacian Pyramid based image fusion. Five set of multi-focus input images are used in order to prove the correctness and effectiveness of the proposed method.

5.5.1. Experimental details when reference image is available. We have used balloon and lab images for which the reference images are available. Figures 5 and 7 provide visual comparisons of the fused images generated by proposed method with the other techniques whereas Table 3 gives the experimentation results based on different quantitative measures. Visual inspection of Figures 5 and 6 shows that proposed method performs better than the other techniques. The optimal blocks size found by the algorithm 1 for balloon and lab images are $83 \times 71$ and $33 \times 35$ respectively. The performance of the proposed method can be observed on the basis of the results obtained for different quantitative measures discussed in Section 4 and clearly the proposed method performs extremely well. Especially in case of balloon images shown in Figure 5, the performance of the proposed method has been excellent. RMSE value for the balloon image is very close to 0 and it
can also be verified from the errors images generated for different image fusion techniques. The error images for different fused techniques and the proposed method are shown in Figure 7 for balloon and lab images. Error image can be obtained using Equation (11).

$$E(x, y) = R(x, y) - F(x, y)$$  \hspace{1cm} (11)

where \(R, F\) are the reference and fused images respectively.

![Figure 5. Balloon fused images generated by different image fusion techniques and the proposed method (using block size of 83 x 71)](image)

![Figure 6. Lab fused images generated by different algorithms and the proposed method (using a block size of 33 x 35)](image)

For lab image, value of RMSE is 2.2047 and it is significantly less than the existing techniques. Mutual information (MI) value of the lab fused image generated by proposed method is almost double than the values obtained for DWT, aDWT and PCA. Since in these methods, the decomposed coefficients are operated at lower resolutions and as a result of it, the original information is not retrieved in the fused image.

5.5.2. Experimental details when the reference image is not available. In order to check the performance of the proposed method, when the reference image is not available, we have used three different multi-focus image sets. These sets of images include pepsi, clock and remote images. The detail of these images is given in Table 2. Optimal blocks sizes found by the algorithm 1 are 40 x 34, 16 x 10 and 51 x 38 for pepsi, clock and remote images respectively. For visual comparison, fused images generated by different image fusion techniques and the proposed method are shown in Figure 8.
Table 3. Results based on different quantitative measures for fused balloon and lab images generated by different image fusion techniques and the proposed method

<table>
<thead>
<tr>
<th>Image</th>
<th>Method</th>
<th>RMSE</th>
<th>PSNR</th>
<th>MAE</th>
<th>PFE</th>
<th>CORR</th>
<th>MI</th>
<th>QI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balloon</td>
<td>DWT</td>
<td>5.1025</td>
<td>33.9751</td>
<td>2.1629</td>
<td>0.9594</td>
<td>0.9991</td>
<td>12.6004</td>
<td>0.9943</td>
</tr>
<tr>
<td></td>
<td>aDWT</td>
<td>5.0781</td>
<td>34.0168</td>
<td>2.1568</td>
<td>0.9495</td>
<td>0.9992</td>
<td>12.6122</td>
<td>0.9943</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>6.0099</td>
<td>32.5535</td>
<td>2.5488</td>
<td>1.0418</td>
<td>0.9988</td>
<td>12.0784</td>
<td>0.9920</td>
</tr>
<tr>
<td></td>
<td>Laplacian</td>
<td>2.8222</td>
<td>39.1191</td>
<td>1.992</td>
<td>0.7412</td>
<td>0.9997</td>
<td>16.2871</td>
<td>0.9983</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>0.001</td>
<td>78.1308</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>24.3969</td>
<td>1</td>
</tr>
<tr>
<td>Lab</td>
<td>DWT</td>
<td>6.8450</td>
<td>31.4234</td>
<td>3.5299</td>
<td>1.8371</td>
<td>0.9986</td>
<td>6.6182</td>
<td>0.9892</td>
</tr>
<tr>
<td></td>
<td>aDWT</td>
<td>6.8088</td>
<td>31.4694</td>
<td>3.5168</td>
<td>1.8215</td>
<td>0.9987</td>
<td>6.6366</td>
<td>0.9893</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>7.0536</td>
<td>31.1625</td>
<td>3.5577</td>
<td>1.8444</td>
<td>0.9986</td>
<td>6.7882</td>
<td>0.9885</td>
</tr>
<tr>
<td></td>
<td>Laplacian</td>
<td>4.2743</td>
<td>35.5135</td>
<td>1.7704</td>
<td>1.0396</td>
<td>0.9995</td>
<td>9.3071</td>
<td>0.9959</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>2.2047</td>
<td>41.2639</td>
<td>1.1727</td>
<td>0.9959</td>
<td>0.9998</td>
<td>14.9926</td>
<td>0.9990</td>
</tr>
</tbody>
</table>

Figure 7. Error images for balloon (row 1) and lab (row 2) for different fusion techniques (a) DWT, (b) aDWT, (c) PCA, (d) Laplacian pyramid and (e) proposed method.

The proposed method performs better than other techniques, however, it introduces some block effects in the pepsi fused image given in Figure 8. It is because the block taken from a part which is out of focus in one of the input images may be clearer than the corresponding block in the other image where it is in focus. The performance of the proposed method can be observed on the basis of the results obtained for different quantitative measures given in Table 4 for pepsi, clock and remote sensing images respectively.

The experimental results obtained for different quantitative measures show that how the proposed method is superior to the other image fusion techniques. However, in case of clock image, entropy value for DWT-based fusion technique is 7.3710 shown in Table 4 and it is more accurate. Similarly spatial frequency value of the fused remote image generated by Laplacian Pyramid image fusion technique is 48.6907 shown in Table 4 and it is greater than the proposed method.

6. Conclusion. In this paper, we established a method for finding optimal block size using Particle Swarm Optimization (PSO) to perform fusion of multi-focus images. In the search space, every particle represents a block size. The algorithm is run for a fixed number of iterations and the final fused image is obtained according to the global best
Figure 8. Row 1: Source images (a) (b) fused by DWT (c), aDWT (d), PCA (e), Laplacian-Pyramid (f) and proposed PSO (g). (a) and (b) are left-focused and right-focused pepsi, clock images at row 1 and row 2 respectively. At row 3, remote sensing images (a) and (b) are given

Table 4. Results based on different quantitative measures for fused pepsi, clock and remote images generated by different image fusion techniques and the proposed method

<table>
<thead>
<tr>
<th>Image</th>
<th>Method</th>
<th>Quality Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Entropy</td>
</tr>
<tr>
<td>Pepsi</td>
<td>DWT</td>
<td>7.1110</td>
</tr>
<tr>
<td></td>
<td>aDWT</td>
<td>7.1104</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>7.0895</td>
</tr>
<tr>
<td></td>
<td>Laplacian</td>
<td>7.1254</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>7.1296</td>
</tr>
<tr>
<td>Clock</td>
<td>DWT</td>
<td>7.3710</td>
</tr>
<tr>
<td></td>
<td>aDWT</td>
<td>7.3706</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>7.0895</td>
</tr>
<tr>
<td></td>
<td>Laplacian</td>
<td>7.1254</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>7.3285</td>
</tr>
<tr>
<td>Remote</td>
<td>DWT</td>
<td>7.1935</td>
</tr>
<tr>
<td></td>
<td>aDWT</td>
<td>6.7120</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>7.1553</td>
</tr>
<tr>
<td></td>
<td>Laplacian</td>
<td>7.2363</td>
</tr>
<tr>
<td></td>
<td>Proposed</td>
<td>7.2993</td>
</tr>
</tbody>
</table>

particle. A detailed comparison between the proposed method and other image fusion techniques is performed using different quantitative measures. Fused images generated by different image fusion techniques and the proposed method are also shown for visual comparison. In the literature, we find similar kind of effort where Genetic Algorithm (GA) is used to find optimal block size. However, the proposed method is faster than
such existing techniques as the proposed method does not involve crossover and mutation like heavy operations.

The performance of the proposed method proves its accuracy and strength over different image fusion techniques with the help of visual and quantitative measures. However, in some cases, it introduces block effects in the fused image which are undesired. This idea of finding optimal block size provides a significant study for other image processing fields. In the future, we will try to remove undesired block effects in the fused image to obtain a more comprehensive and informative fused image.

REFERENCES