Focused Region Detection Based on Improved Spatial Frequency and Morphology for Multifocus Image Fusion in Spatial Domain

Weiwei Jiao
Computer Center, Liaoning University of Technology, Jinzhou 121001, Liaoning, China

Defa Hu*
School of Computer and Information Engineering, Hunan University of Commerce, Changsha 410205, Hunan, China
*Corresponding author (E-mail: hdf666@163.com)

Hailiang Shi
College of Mathematics & Information Science, Zhengzhou University of Light Industry, Zhengzhou 450002, Henan, China

Abstract—A novel multifocus image fusion method is proposed in spatial domain. It uses the technique of focused region detection which is based on improved spatial frequency and mathematical morphology. Firstly, improved spatial frequency is put forward to generate an initial logical decision map with morphological dilation operator, then morphological opening and closing are performed iteratively to eliminate the potential defects, such as protrusions and holes, to obtain the perfect focused regions as far as possible. Finally, the fusion is not simply copy the pixels in the focused region into the resultant image, but also take into consideration of coherence of the conventional consistency verification and the proposed improved spatial frequency maximum selection results to reduce block effect. The proposed fusion method is tested on four datasets of multifocus images and compared with some conventional fusion methods including spatial domain based methods and transform domain based methods, and experimental results demonstrate that the proposed method is effective and can provide better performance in terms of several quantitative evaluation measures.

Keywords- image fusion; focused region detection; improved spatial frequency; multifocus

I. INTRODUCTION

As per optical theory only one point (and all the points at exactly the same distance from the lens, often called a plane of focus) can be in perfect focus. In reality, objects on either side of the plane of focus will also be in focus, that is, they will be acceptably sharp. Out this zone they are definitely not sharp. This zone is called depth of field, or in short DOF. Simply put DOF is a band of acceptable sharpness in a photograph. It is the distance between the nearest and farthest objects which are in focus.

DOF depends on a variety of factors, simply speaking, such as the aperture and the focal length [1]. Generally, the smaller the aperture and the smaller the focal length, the larger the DOF, and the more objects in focus. As an extreme ideal case of infinite DOF, the optical power in the image plane is reduced considerably [1]. So due to the limited DOF of optical lenses, it is often impossible to get all the objects of a scene in focus [2-4]. One solution is to reduce the aperture size and the focal length as much as possible. Another solution is to use multifocus image fusion processing.

Image fusion can be defined as a process by which a set of images are combined to generating a single image that integrates complementary, multi-temporal or multi-view information from the sources. Multifocus image fusion attempts to increase the apparent DOF through the fusion to create one image with the maximum number of objects in focus [5]. The fused image acquired from image fusion is more informative and appropriate for the purposes of human vision perception and computer processing tasks such as segmentation, feature extraction and recognition [2].

Basically, there are two types of methods for multifocus image fusion [2]. One is the spatial domain methods which select pixels or regions of sharp parts to composite the fused image. Another is the transform domain methods, which fuse images using frequency or time-frequency transform. The simplest fusion method is to take the average of the source images pixel by pixel. However, along with simplicity come several undesired side effects including reduced contrast. In spatial domain, some more reasonable fusion methods were proposed with divided blocks or segmented regions instead of single pixels [2].

In transform domain, the commonly used multiscale transform include the Laplacian pyramid, discrete wavelet transform, stationary wavelet transform (DWT), contourlet transform (CT), nonsubsampled contourlet transform (NSCT) [6] etc. The general framework of transform based fusion method always have three basic steps: first, the source image are decomposed into multiscale representations; second, the coefficients of the representations are composited based on some fusion rules; third, the fused image is reconstructed using the corresponding inverse transform with the fused coefficients [7]. These methods can successfully overcome the disadvantages of the spatial based methods since the actual fusion process happens in decomposed
subbands, instead the image directly. However, no matter which one of the multiscale transforms is used, image fusion still could not be achieved perfectly. The reason is that the multiscale decomposition and reconstruction is required in the multiscale transform for fusion, thus the reliable information of the source images may be changed to a certain degree (due to the different image content, the reliability of fusion results differs), and block textures and ringing effect are probably obvious in the fused image which affect the image quality [8]. In addition, the transform based methods often involve huge computation using floating-point arithmetic and thus require a lot of time and memory.

In order to overcome or avoid the disadvantages of the above-mentioned fusion methods, an effective multifocus image fusion method is proposed in spatial domain based on focused region detection technique. First, an improved spatial frequency (ISF) measure is proposed and conjoined with mathematical morphology operation and some experimental adjustment is applied in focused region detection. Then, the focused regions are fused into a single image by copying them into the resultant image firstly. For improving the fusion quality and reducing block effect to strengthen consistency, the boundary pixels of the focused regions are reselected according to ISF values and the conventional consistency verification. If the difference of the two pixels at the same location in source images is not significant, the weighted average operation is performed. The visual and quantitative analysis of the different fusion results prove that the proposed fusion method improves the fusion quality and outperforms some conventional fusion methods.

The remaining sections of this paper are organized as follows. Section II reviews the theory of spatial frequency, and put forward an improved spatial frequency. Section III presents the focused region detection technique. Section IV describes the proposed multifocus image fusion method. Experimental results and discussion are given in Section V. Followed by conclusion in Section VI.

Figure 1. Focused region detection for 'clock' images: (a) focus on right; (b) focus on left; (c) ISF values of (a); (d) morphological dilation result; (e) the initial decision map; (f) morphological result using 3×3 SE with p =98.43; (g) morphological result using 5×5 SE with p =99.11; (h) morphological result using 19×19 SE with p =99.97.

II. IMPROVED SPATIAL FREQUENCY

The conventional spatial frequency (SF) metric [9-11] which is used to measure the overall activity level of an image is defined as follows.

\[
SF = \sqrt{RF^2 + CF^2}
\]

(1)

\[
RF = \frac{1}{m(n-1)} \sum_{i=1}^{m-1} \sum_{j=1}^{n} (I(i,j+1) - I(i,j))^2
\]

(2)

\[
CF = \frac{1}{m(n-1)} \sum_{i=1}^{m-1} \sum_{j=1}^{n} (I(i+1,j) - I(i,j))^2
\]

(3)

where \(RF\) and \(CF\) are row frequency and column frequency respectively, \(m\) and \(n\) denote the size of the image and \(I(i,j)\) denotes the grayscale value of the input image.

Inspired by the multidirection property of the DWT, we found that the conventional SF only considers the limited directions, such as horizontal (row frequency) and vertical (column frequency) directions, without taking into account the other directions which may be very important in expressing the edge information of an image. Similar to Eq. (2) and Eq. (3), two diagonal frequencies along the main diagonal and the secondary diagonal directions can be defined as below.

\[
DF = \frac{1}{(m-1)(n-1)} \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} (I(i,j+1) + I(i+1,j) - I(i,j))^2
\]

(4)
According to human visual system characteristic, for detail information in the different directions but the same decomposition scale, human sensibility to the information loss and error in the diagonal directions is lower than that in the horizontal and vertical directions [7]. For this reason, it can be concluded that the contribution of each direction to the spatial frequency is different, so the weight coefficients are added in the calculation of the conventional SF as follows.

\[
DF_{i,j} = \sum_{n=1}^{m} \sum_{j=1}^{n-1} \frac{1}{(m-1)(n-1)} \left( I(i-1,j+1) - I(i,j) \right)^2
\]

For multifocus image, the pixels with great sharpness and clarity can be seen as coming from focused regions. Inspired by it, focused region can be identified by the sharpness measure of the pixels. Therefore, the sharpness measure is a key point. The above-mentioned improved spatial frequency is used as the measure in this paper. For simplicity, let A and B denote the source images respectively, and F the fused image. The focused region detection can be described as following steps.

Step-1. Compute the ISF values of each pixels of the source images A and B within a sliding window which is of size 3×3 or 5×5 typically, denoted by \( ISF_A(i,j) \) and \( ISF_B(i,j) \), respectively. In this paper, the weights of Eq. (6) are set to 1, 1, 1, and 1, respectively.

\[
ISF = w_1 \cdot RF^2 + w_2 \cdot CF^2 + w_3 \cdot PDF^2 + w_4 \cdot SDF^2
\]

where \( w_1, w_2, w_3, w_4 \) are the weights of the four directions.

In general, \( w_1 = w_2, w_3 = w_4, w_1 > w_3 \).

Step-2. Perform mathematical grayscale morphological dilation on the \( ISF_A(i,j) \) and \( ISF_B(i,j) \) using a 'disk' SE which is chosen according to experimental results, respectively. Then \( ISF_A^*(i,j) \) and \( ISF_B^*(i,j) \) are obtained.

Step-3. Compare the modified ISF value \( ISF_A^*(i,j) \) and \( ISF_B^*(i,j) \) to determine which pixel is in focus, and thus an initial logical decision map \( M(i,j) \) is obtained by the following expression

\[
M(i,j) = \begin{cases} 
1, & \text{if } \frac{ISF_A^*(i,j)}{ISF_B^*(i,j)} \geq \frac{ISF_A^*(i,j)}{ISF_B^*(i,j)} \\
0, & \text{if } \frac{ISF_A^*(i,j)}{ISF_B^*(i,j)} < \frac{ISF_A^*(i,j)}{ISF_B^*(i,j)} 
\end{cases}
\]

where 1-values indicates that the pixel of A at location \( i,j \) is in focus, otherwise the pixel of B in focus.

Step-4. Perform mathematical morphological opening and closing operation iteratively on the initial decision map to improve the performance of the initial detected focused region.

There are thin protrusions, thin gulfs, narrow breaks, small holes etc. in \( M \), which indicates that the focused region is still not a continuity. To correct these defects, binary morphological opening and closing with small SE are performed. The conjoint of opening and closing can remove thin connections and thin protrusions, join narrow breaks and fill long thin gulfs. Unfortunately, holes larger than SE cannot be removed. Therefore, opening and closing are performed iteratively with a SE of size...
(2n + 1)’ (2n + 1), n = 1, 2, L, N, until the p% pixels have no further change or until exhaustion until the predetermined number of iterations. p is set to 99.95 here.

Fig. 1 illustrates the process of focused region detection of 'clock' multifocus images. Fig. 1(a, b) are the source images, and Fig. 1(c) is the result of the ISF calculation of Fig. 1(a). Fig. 1(d) shows morphological dilation result of Fig. 1(c). Fig. 1(e-h) show the initial decision map and the corresponding morphological results with 3’ 3’, 5’ 5’, 19’ 19’ SE (19’ 19’ is the resultant size of the last iteration). It can be observed the intermediate result of the decision map of the focused region detection contain many erroneous results, especially on the boundary of the focused region, and the last decision map performs better. Another experiment on the dataset of ‘disk’ multifocus images can get the similar conclusion, shown in Fig. 2.

IV. PROPOSED FUSION METHOD BASED ON FOCUSED REGION DETECTION

Based on focused region detection, the fused image can be constructed by simply copying the pixels which are in focused region into the resultant image, described as

\[ F(i, j) = \begin{cases} A(i, j), & \text{if } M(i, j) = 1 \\ B(i, j), & \text{if } M(i, j) = 0 \end{cases} \]

However, the fused image using the above method may contain many erroneous results at the boundary of the focused regions since the boundary cannot be identified accurately [3]. It will compromise the fusion performance significantly, which is vital for human and machine perception. Although consistency verification may be applied to improve the performance, these effects could only be suppressed to a certain degree. That is why we cannot use the above method directly. To further improve the fusion performance, the combination of conventional consistency verification method and ISF maximum selection method is adopted in this paper. For the pixels on the focused region boundary, if the result of the consistency verification is consistent with ISF maximum selection, then it is confirmed that these pixels come from focused region, otherwise, the weighted averaging method based on ISF measure is used to process these pixels. It can be described as

\[ F(i, j) = \begin{cases} A(i, j), & \text{if } N(i, j) = mn \\ A(i, j), & \text{if } \frac{3mn}{4} < N(i, j) < mn \text{ and } ISF_A(i, j) > ISF_A(i, j) \\ B(i, j), & \text{if } N(i, j) = 0 \\ B(i, j), & \text{if } 0 < N(i, j) < \frac{3mn}{4} \text{ and } ISF_B(i, j) < ISF_A(i, j) \\ \{w_A \times A(i, j) + w_B \times B(i, j)}, & \text{otherwise} \end{cases} \]

\[ N(i, j) = \hat{A}_u \hat{A}_v M(i + u, j + v) \]

where

\[ w_A = \frac{ISF_A(i, j)}{ISF_A(i, j) + ISF_B(i, j)}, w_B = 1 - w_A \]

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed image fusion method, experiments were conducted on four datasets.

Figure 3. The fused image of ‘clock’ images: (a)-(f) the fused images using SA, PCA, DWT, CT, NSCT based fusion method and the proposed fusion method.

For comparison purpose, the fusion is also performed using the following methods.

Method 1: spatial average (SA) image fusion method [12].

Method 2: PCA based image fusion method [12].
Method 3: DWT with DBlS(2, 2) based image fusion method [12]. In this method, the average fusion rule is used for the low-frequency coefficients fusion and the maximum selection rule for the high frequency coefficients. The decomposition level is 3.

Method 4: CT based image fusion method. The similar fusion rules as Method 3 are used with decomposition level=[2, 3, 4].

Method 5: NSCT based image fusion method. The same parameters as Method 4 are used.

The first experiment is performed on the 'clock' images, which is a continuation of the experimental process shown in Fig. 1. Fig. 3 shows the fusion results using the above different methods. From human visual system, it can be observed that the fused images using SA and PCA based methods have obviously reduced contrast. The other fused images have equivalent performance.

For further comparison, standard deviation, mutual information etc. are used to evaluate the fusion performance quantitatively in this paper. Those evaluation criteria are respectively defined as follows.

(1) Standard deviation (SD) [9, 11] is used to measure the contrast in the fused image. When the value of SD is high, it indicates the fused image as high contrast.

\[
SD(F) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (F(i,j) - \bar{F})^2
\]  

(12)

where \( \bar{F} = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} F(i,j) \).

(2) Gradient based fusion performance [4, 13] associates important visual information with gradient information and assesses fusion by evaluating the success of gradient information transferred from the inputs to the fused image.

The total fusion information denoted by \( Q(A,B,F) \) is evaluated as a weighted sum of edge information preservation values for both input images, where the weights factors \( w^A \) and \( w^B \) represent perceptual importance of each input image pixel.

\[
Q(A,B,F) = \frac{\hat{A} \cdot Q^F_{mn} w^A_{mn} + \hat{B} \cdot Q^F_{mn} w^B_{mn}}{\hat{A} \cdot w^A_{mn} + \hat{B} \cdot w^B_{mn}}
\]  

(13)

The range is \( 0 \leq Q(A,B,F) \leq 1 \).

The lost information (fusion loss) \( L(A,B,F) \) is a measure of the information lost during the fusion process. This is information available in the input images but not in the fused image. It is defined as

\[
L(A,B,F) = \frac{\hat{A} \cdot w^A_{mn} + \hat{B} \cdot w^B_{mn}}{\hat{A} \cdot w^A_{mn} + \hat{B} \cdot w^B_{mn}}
\]  

(14)

The introduced artificial information (fusion artifacts) \( N(A,B,F) \) represents visual information introduced into the fused image by the fusion process that has no corresponding features in any of the inputs. Fusion artifacts are essentially false information that directly detracts from the usefulness of the fused image, and can have serious consequences in certain fusion applications. It is defined as

\[
N(A,B,F) = \frac{\hat{A} \cdot N_{mn} w^A_{mn} + \hat{B} \cdot N_{mn} w^B_{mn}}{\hat{A} \cdot w^A_{mn} + \hat{B} \cdot w^B_{mn}}
\]  

(15)

(3) Mutual Information (MI) [10] measures the degree of dependency between two variables by measuring the distance between the joint distribution and the distribution associates with the case of complete independence. The joint and marginal distributions are simply obtained by normalization of the joint and marginal histograms of both images.

Figure 4. The fused image of 'disk' images: (a)-(f) the fused images using SA, PCA, DWT, CT, NSCT based fusion method and the proposed fusion method.
The mutual information used in this paper is calculated by averaging the two corresponding values between the source images and the fused image.

\[ MI(A, B, F) = \frac{1}{4}(MI(A, F) + MI(B, F)) \]  

The first quarter of Table 1 gives the quantitative results of the Fig. 3. The best results are indicated in bold. As can be seen, in spite of the poor performance in \( N(A, B, F) \), the proposed fusion method provides the best overall performance in terms of larger values of SD(F), \( Q(A, B, F) \), \( MI(A, B, F) \) and \( FMI(A, B, F) \), together with smaller values of \( L(A, B, F) \). The reason for the poor performance of \( N(A, B, F) \) is that the proposed fusion method still has a certain block effect. On the contrary, few artifacts are introduced into the fused images obtained by SA and PCA methods, but much more useful information is also lost during the fusion process.

\[
MI(I, F) = \frac{1}{2} \sum_{i_1=1}^{L} \sum_{i_2=1}^{L} h_{I,F}(i_1, i_2) \log_2 \left( \frac{h_{I,F}(i_1, i_2)}{h_{I_1}(i_1)h_{I_2}(i_2)} \right)
\]

where \( h_{I_i}(i) \) is the entropy of the corresponding window.
TABLE I. QUANTITATIVE PERFORMANCE RESULTS OF THE FUSED IMAGE IN FIGURE 3

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Method</th>
<th>(SD(F))</th>
<th>(Q(A,B,F))</th>
<th>(L(A,B,F))</th>
<th>(N(A,B,F))</th>
<th>(MI(A,B,F))</th>
<th>(FMI(A,B,F))</th>
</tr>
</thead>
<tbody>
<tr>
<td>clock</td>
<td>SA</td>
<td>0.1978</td>
<td>0.6919</td>
<td>0.3080</td>
<td><strong>0.0001</strong></td>
<td>2.4811</td>
<td>0.8749</td>
</tr>
<tr>
<td>PCA</td>
<td>0.1978</td>
<td>0.6913</td>
<td>0.3086</td>
<td><strong>0.0001</strong></td>
<td>2.4878</td>
<td>0.8745</td>
<td></td>
</tr>
<tr>
<td>DWT</td>
<td>0.2064</td>
<td>0.7219</td>
<td>0.1823</td>
<td>0.0957</td>
<td>2.2561</td>
<td>0.8789</td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>0.2047</td>
<td>0.7088</td>
<td>0.1944</td>
<td>0.0968</td>
<td>2.1837</td>
<td>0.8807</td>
<td></td>
</tr>
<tr>
<td>NSCT</td>
<td>0.2045</td>
<td>0.7450</td>
<td>0.1885</td>
<td>0.0665</td>
<td>2.3974</td>
<td>0.8834</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td><strong>0.2069</strong></td>
<td><strong>0.7559</strong></td>
<td><strong>0.1318</strong></td>
<td><strong>0.1124</strong></td>
<td><strong>3.0430</strong></td>
<td><strong>0.8940</strong></td>
<td></td>
</tr>
<tr>
<td>disk</td>
<td>SA</td>
<td>0.1727</td>
<td>0.5520</td>
<td>0.4478</td>
<td>0.0002</td>
<td>2.0796</td>
<td>0.9014</td>
</tr>
<tr>
<td>PCA</td>
<td>0.1729</td>
<td>0.5624</td>
<td>0.4375</td>
<td><strong>0.0001</strong></td>
<td>2.1055</td>
<td>0.9020</td>
<td></td>
</tr>
<tr>
<td>DWT</td>
<td>0.1821</td>
<td>0.6777</td>
<td>0.2249</td>
<td>0.0974</td>
<td>1.9049</td>
<td>0.9045</td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>0.1814</td>
<td>0.6625</td>
<td>0.2371</td>
<td>0.1004</td>
<td>1.8634</td>
<td>0.9037</td>
<td></td>
</tr>
<tr>
<td>NSCT</td>
<td>0.1813</td>
<td>0.7130</td>
<td>0.2259</td>
<td>0.0611</td>
<td>2.0270</td>
<td>0.9069</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td><strong>0.1837</strong></td>
<td><strong>0.7470</strong></td>
<td><strong>0.1375</strong></td>
<td><strong>0.1154</strong></td>
<td><strong>2.7989</strong></td>
<td><strong>0.9106</strong></td>
<td></td>
</tr>
<tr>
<td>pepsi</td>
<td>SA</td>
<td>0.1725</td>
<td>0.6733</td>
<td>0.3266</td>
<td><strong>0.0001</strong></td>
<td>2.3838</td>
<td>0.9124</td>
</tr>
<tr>
<td>PCA</td>
<td>0.1725</td>
<td>0.6788</td>
<td>0.3211</td>
<td><strong>0.0001</strong></td>
<td>2.4147</td>
<td>0.9124</td>
<td></td>
</tr>
<tr>
<td>DWT</td>
<td>0.1767</td>
<td>0.7680</td>
<td>0.1410</td>
<td>0.0910</td>
<td>2.2389</td>
<td>0.9191</td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>0.1763</td>
<td>0.7615</td>
<td>0.1593</td>
<td>0.0792</td>
<td>2.2150</td>
<td>0.9181</td>
<td></td>
</tr>
<tr>
<td>NSCT</td>
<td>0.1763</td>
<td>0.7986</td>
<td>0.1421</td>
<td>0.0593</td>
<td>2.3475</td>
<td>0.9209</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td><strong>0.1786</strong></td>
<td><strong>0.7997</strong></td>
<td><strong>0.1054</strong></td>
<td><strong>0.0949</strong></td>
<td><strong>2.8713</strong></td>
<td><strong>0.9238</strong></td>
<td></td>
</tr>
<tr>
<td>book</td>
<td>SA</td>
<td>0.2344</td>
<td>0.6487</td>
<td>0.3513</td>
<td><strong>0.0000</strong></td>
<td>2.6001</td>
<td>0.8664</td>
</tr>
<tr>
<td>PCA</td>
<td>0.2345</td>
<td>0.6529</td>
<td>0.3471</td>
<td><strong>0.0000</strong></td>
<td>2.6039</td>
<td>0.8667</td>
<td></td>
</tr>
<tr>
<td>DWT</td>
<td>0.2454</td>
<td>0.7161</td>
<td>0.1707</td>
<td>0.1132</td>
<td>2.2714</td>
<td>0.8780</td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>0.2441</td>
<td>0.7058</td>
<td>0.1911</td>
<td>0.1032</td>
<td>2.2589</td>
<td>0.8785</td>
<td></td>
</tr>
<tr>
<td>NSCT</td>
<td>0.2442</td>
<td>0.7336</td>
<td>0.1838</td>
<td>0.0825</td>
<td>2.5424</td>
<td>0.8813</td>
<td></td>
</tr>
<tr>
<td>Proposed</td>
<td><strong>0.2460</strong></td>
<td><strong>0.7444</strong></td>
<td><strong>0.1185</strong></td>
<td><strong>0.1371</strong></td>
<td><strong>3.1745</strong></td>
<td><strong>0.8850</strong></td>
<td></td>
</tr>
</tbody>
</table>

The other experiments on the 'disk', 'pepsi' and 'book' multifocus images are shown in Fig. 4, Fig. 5 and Fig. 6, respectively, and the corresponding quantitative evaluation results are shown in Table 1. From the table, it can be easily observed that the similar conclusion to the first experiment can be obtained, that is, the proposed fusion method performs the best.

VI. CONCLUSION

In this paper, a novel method for multifocus image fusion is proposed using the focused region detection which is based on improved spatial frequency and mathematical morphology. The improved spatial frequency not only considers horizontal and vertical directions, but also take into account the main diagonal and the second diagonal directions, which is inspired by the multidirection property of the DWT. The focused region detection is completely performed in spatial domain, which reduces the computational complexity and improves the speed of detection and fusion relative to transform domain based methods. In fusion process, the boundary pixels of the focused regions are fused according to the conventional consistency verification and ISF maximum selection to eliminate the block effect. The experimental results on four datasets of multifocus images have demonstrated the superior performance of the proposed fusion method.

ACKNOWLEDGMENT

This work has been supported by National Natural Science Foundation of China (No.61202464 and No.11501527) and Natural Science Research Program of Henan Educational Committee (No. 14A120012).

REFERENCES

[1] Ishita De, Bhabatosh Chanda, Buddhayoti Chattopadhyay, “Enhancing effective depth-of-field by image fusion using


