Optica Applicata, Vol. XL, No. 4, 2010

An application of swarm intelligence binary particle swarm optimization (BPSO) algorithm to multi-focus image fusion

XINMAN ZHANG, LUBING SUN*, JIUQIANG HAN, GANG CHEN

MOE Key Lab for Intelligent Networks and Network Security,
School of Electronics and Information Engineering, Xi'an Jiaotong University, Xi'an, 710049, China

*Corresponding author: slkenon.bing@stu.xjtu.edu.cn

In this paper, an optimal and intelligent multi-focus image fusion algorithm is presented, expected to achieve perfect reconstruction or optimal fusion of multi-focus images with high speed. A synergistic combination of segmentation techniques and binary particle swarm optimization (BPSO) intelligent search strategies is employed in salience analysis of contrast feature-vision system. Also, several evaluations concerning image definition are exploited and used to evaluate the performance of the method proposed. Experiments are performed on a large number of images and the results show that the BPSO algorithm is much faster than the traditional genetic algorithm. The method proposed is also compared with some classical or new fusion methods, such as discrete wavelet-based transform (DWT), nonsubsampled contourlet transform (NSCT), NSCT-PCNN (pulse coupled neural networks (PCNN) method in NSCT domain) and curvelet transform. The simulation results with high accuracy and high speed prove the superiority and effectiveness of the present method.

Keywords: multi-focus image fusion, binary particle swarm optimization (BPSO), perfect reconstruction, swarm intelligence, image definition evaluation.

1. Introduction

Due to the limited depth-of-focus of optical lenses in CCD devices (*e.g.*, camera with finite depth of field, light optical microscope, *etc.*), it is often impossible to get an image that contains all relevant objects in focus. In an image captured by those devices, only the objects within the depth of field are focused, while other objects are blurred. A possible way to solve this problem is image fusion, in which one can acquire a series of pictures with different focus settings and fuse them to produce an image with extended depth of field. The fused image will then hopefully contain all the relevant objects in focus. Images of this kind are useful in many fields, such as digital imaging, microscopic imaging, remote sensing, computer vision and robotics [1, 2].

Multiscale transforms are very useful for analyzing the information content of images for fusion purposes. Various methods based on the multiscale transforms have been proposed, such as Laplacian pyramid-based, gradient pyramid-based, ratio-of--low-pass pyramid-based, discrete wavelet-based (DWT). The basic idea is to perform a multi-resolution decomposition on each source image, then integrate all these decompositions to form a composite representation, and finally reconstruct the fused image by performing an inverse multi-resolution transform [3].

More recently, many novel image fusion algorithms have emerged rapidly and performed satisfactorily, which include so called beyond-wavelets [4], for example, curvelet transform (CT), and nonsubsampled contourlet transform (NSCT). The CT is suitable for analyzing image edges such as curve and line characteristics. The main difference between NSCT and other beyond-wavelets algorithms is that the contourlet transform can efficiently capture the intrinsic geometrical structures in natural images such as smooth contour edges and is a fully shift-invariant, multiscale and multidirection expansion [4, 5]. Pulse coupled neural networks (PCNN) is a novel biological neural network based on the experimental observations of synchronous pulse bursts in cat and monkey visual cortex. It is characterized by the global coupling and pulse synchronization of neurons. These characteristics benefit image fusion which makes use of local image information [6]. PCNN has been successfully used in image fusion. However, all these methods have some errors when comparing the fused multi-focus image with the reference image.

These techniques belong to any of the following categories: pixel-based, window--based or region-based. Pixel-based methods concentrate on a single pixel and window-based methods concentrate on a $k \times k$ window, where k is very small. It is known that even a very small error in registration results in mismatch of all the pixels under consideration. Pixel-based methods would not be able to tackle the situation and produce erroneous results. So, they are sensitive to misregistration or noise. Window-based and region-based techniques are better in this respect but they require a sequence of complex and time-consuming processes and hence take a large computation time [7].

ZHANG *et al*. [8] proposed a genetic search strategies based image fusion algorithm (GA algorithm). This method can accomplish absolute restoration or optimized fusion of multi-focus images to the reference image. Here absolute restoration is called zero-error reconstruction or perfect reconstruction. Compared to other algorithms, GA algorithm demonstrates superior fusion results. However, the operation speed of the algorithm is not very satisfactory. In this paper, we propose an improved and intelligent algorithm, in which we choose the binary particle swarm optimization (BPSO) method to speed up the algorithm. A large number of image experiments verify the rapidity and superior performance of the algorithm proposed.

The paper is organized as follows: Section 2 presents a detailed BPSO fusion algorithm and a schematic diagram, followed by the measures we suggested, which specially describe the definition of multi-focus images in the next section. Experimental results and analysis are given in Sections 4 and 5. In the last section, the paper is concluded.

2. Multi-focus image fusion scheme-based on BPSO search

The goal in multi-focus image fusion is to capture and preserve in a single output image all the "clear" part that is present within two input images. The basic fusion algorithm will be described in Section 2.1. In this section, the algorithm first decomposes the source images into blocks. Fusion then proceeds by selecting a clearer block according to uniform parameter. Section 2.2 shows the detailed process and procedure of the proposed BPSO fusion algorithm. This section solves the problem of choosing block size that optimizes the fused image furthest and accelerating the block searching process.

2.1. The basic algorithm [8]

Considering the contrast vision feature in human vision system, we address uniform parameter to test the definition of focus images. Uniform parameter is more optimal than block variance, which represents the deviations between block pixel and block mean. We shall treat an image as a two-dimensional array of pixels, and the pixel in the i-th row and the j-th column shall be denoted by $I(i,j)$. Using this notation, we define d_k, namely the uniform parameter of partition block of an image I as follows:

$$d_k = \frac{1}{m \times n} \sum_{(i,j) \in B_k} \frac{|I(i,j) - \mu_k|}{\mu_k} \tag{1}$$

where μ_k is the mean of block B_k, and $m \times n$ is the block size.

In the following, we shall assume that there are two out-of-focus inputs A and B. The fusion algorithm breaks up both of them into smaller square regions, *i.e.*, $m \times n$ blocks. Denote the i-th image block pair by BA_i and BB_i. Then image fusion is performed based on uniform parameter of each block. The i-th block BF_i of the fused image is then constructed as

$$BF_i = \begin{cases} BA_i, & \mathrm{d}A_i > \mathrm{d}B_i \\ BB_i, & \text{otherwise} \end{cases} \tag{2}$$

where $\mathrm{d}A_i$ and $\mathrm{d}B_i$ are uniform parameters of the relative blocks BA_i and BB_i of two input images A and B, respectively. Given two of these blocks (one from each source image), the contrast vision model is to determine which one is clearer.

Next, each partition block is incorporated according to Eqs. (1) and (2), so the clear regions are selected and this process yields a merged image F. If the same object appears more legible (in other words, with better contrast), in image A than B, after fusion the object in image A will be preserved while the object in image B will be ignored.

2.2. BPSO search fusion algorithm

Image fusion is carried out as the key step, that is, the most important, to search the desired fused image in terms of different block sizes. Fusion then proceeds by selecting the clearer block in constructing the final image. Even though it seems theoretically reasonable that a very small block size will lead to the best global optimal solution, it is practically infeasible due to a large amount of computation and low speeds.

Here, we propose BPSO search strategies in the image block searching process and have a good effect.

Particle swarm optimization (PSO) is a population based algorithm, which is inspired by the social behavior of animals such as fish schooling and bird flocking. This evolutionary computation technique, based on the information about the previous best performance of each particle and the best previous performance of its neighbors, has been largely applied as a problem-solving technique in engineering and computer science. In PSO, each particle can communicate with every other individual, forming a fully connected social network. In this case, each particle is attracted toward the best particle (best problem solution) found by any member of the entire swarm. BPSO algorithm is a binary version of particle swarm optimization algorithm, which is suitable to solve discrete optimization problems. In this algorithm, the position of each particle is encoded in the binary format. The velocity of a particle is defined as "the rate of change of position", that is, each bit of velocity represents the probability of changing the corresponding bit of position from its previous state to its complementary value. Thus, every particle moves in a binary space to search the best problem solution [9, 10].

If we consider two sources A and B as the input images to be fused, the fusion optimization problem that we examine here can be considered as a search problem. The optimized image is obtained by combining different image blocks chosen according to adaptive BPSO search algorithm.

In detail, the BPSO strategies consist of the following steps:

1. Determine the proper population number P and initialize the position of each particle by stochastic method. Experiments indicated that, within a certain range, when P increases, the fusion effects are better, while the operation speed becomes slower. The most optimized block size is likely to be the position number. Suppose that for an $M \times N$ image, the search range is $(1, M-1)$ and $(1, N-1)$ for simplicity, so the position of particle C_i is composed of two parts representing blocks' length and width code

$$C_i = \left[n_{i,\,u+v} \;\; n_{i,\,u+v-1} \;\; \cdots \;\; n_{i,\,u+2} \;\; n_{i,\,u+1} \;\; m_{i,\,u} \;\; m_{i,\,u-1} \;\; \cdots \;\; m_{i,\,2} \;\; m_{i,\,1} \right]$$

where u refers to the position row code length (of size $\log_2 M$), v refers to the position column code length (of size $\log_2 N$) and i belongs to a range of $[1, P]$ [11].

2. Compute the fitness function of each particle. Here we mean the spatial frequency, *i.e.*, spatial frequency (SF). With a larger SF value, the corresponding particle position is more advantageous and it is more possible to search its surrounding areas.

3. Record the best previous position of each particle and the best previous position of the global population according to the fitness function. Intuitively, we can think of the function as some measure of profit, utility, or goodness that we want to maximize.

4. Use BPSO strategies to update each particle position. In BPSO, each particle is indicated by a binary bit string. Its position updating progress is shown in Fig. 1. The difference between the present position of a particle and its previous best position, and the difference between the present position of a particle and the best position of all particles are expressed by two bit strings, respectively, called difference vectors [12]. Both difference vectors have P bits. Each bit indicates whether the corresponding elements of the two position vectors are the same or not. If they are the same, the bit value is 0, otherwise 1. This comparison process is similar to the logical operation XOR. Then randomly generate two vectors c_1 and c_2, and perform AND operation with the two random vectors, respectively. The two random binary bit vectors are equivalent to the random numbers in real-valued PSO algorithm, the effect of which is to increase the capacity of exploration and exploitation of the algorithm. Then, performing OR operation between the two temporary bit strings generated from the previous step, we get the velocity vector of the algorithm. Finally, the new position

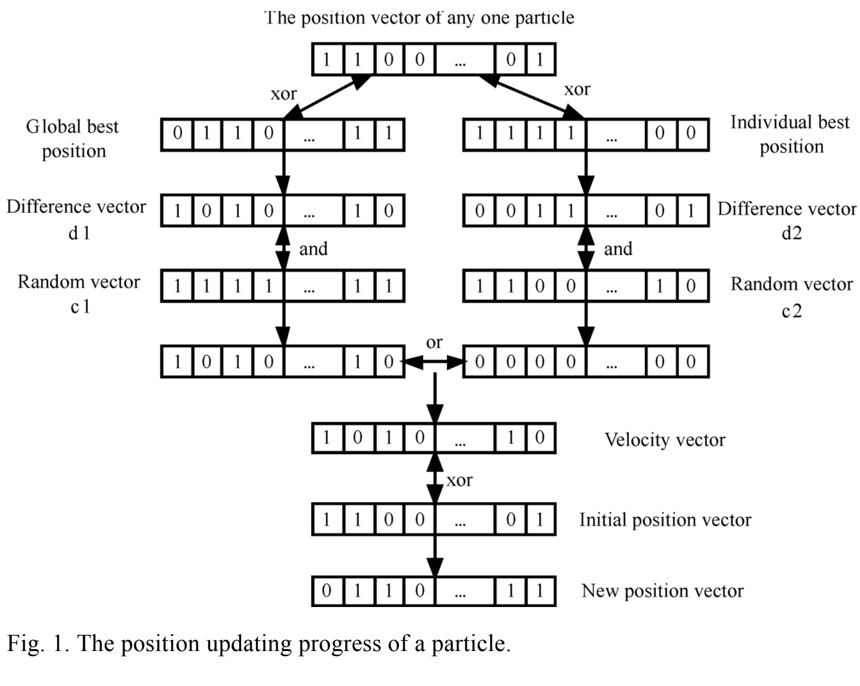

Fig. 1. The position updating progress of a particle.

vector is obtained after XOR operation between the velocity vector and the initial position vector.

5. Perform genetic folding operation. If the terminate condition is satisfied, end the operation, if not, go to the next step. Here, the terminate condition is met when the ratio of the average fitness value of the present population to the average fitness value of the parent population locates in the interval $[1, \alpha]$. The choice of α should ensure good convergence speed of the algorithm and avoid premature. In image vision applications, the optimal value of α is 1.005. The folding operation times are not more than $\log_2 (MN/4)$.

6. Choose the optimized blocks to reach the best effect.

Figure 2 illustrates the block diagram of the proposed multi-focus image fusion scheme.

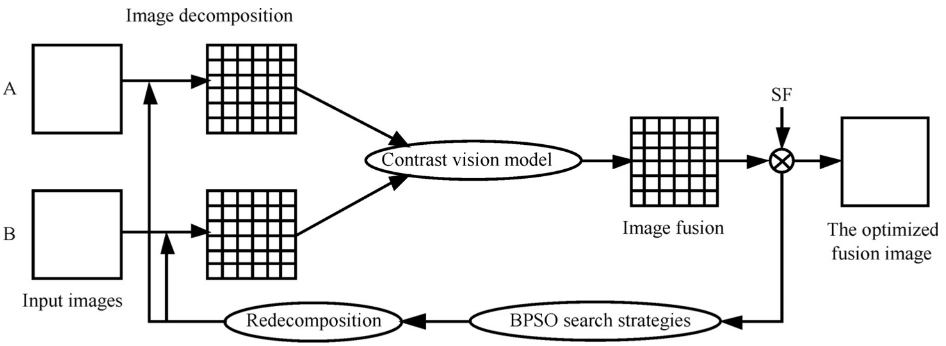

Fig. 2. Block diagram of the proposed multi-focus image fusion scheme.

The detailed procedure of BPSO search fusion algorithm is described as follows:

1. Begin
2. Input the source images
3. Initialize the population and the parameters, *e.g.*, *P*, α and the greatest folding operation times
4. Check whether each position is properly coded
5. While (the folding operation times are within bounds)
6. Begin
7. Compute the fitness function of each particle, respectively
8. Record the global best position and the individual best position
9. Judge whether the terminate condition is satisfied, if satisfied, exit the loop
10. Use BPSO strategies to update the position of each particle
11. Check whether each position is properly coded
12. End
13. Choose the optimized block and perform fusion
14. Output the fused image
15. End

3. Performance measures

The performance measures used in this paper provide some quantitative comparison among different fusion schemes, mainly aiming at measuring the definition of an image. Consider R as the reference image and F the fused image, both of size $M \times N$. $F(i, j)$ is the gray value of pixel at the position (i, j).

3.1. Root mean square error (RMSE)

RMSE is the most valuable performance evaluation criterion when reference image is available. It is defined as

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \left[R(i,j) - F(i,j) \right]^2}{M \times N}} \tag{3}$$

If RMSE equals 0, it corresponds to the perfect image reconstruction. Namely, the fused image is a perfect image, which has been achieved through accurate reconstruction of multi-focus images to the reference image.

3.2. Spatial frequency (SF)

Spatial frequency indicates the overall active level of an image. At the same time it represents minus details of contrast and texture commutation characteristic. The spatial frequency for a fused image is defined as follows:

$$\mathrm{SF} = \sqrt{\mathrm{RF}^2 + \mathrm{CF}^2} \tag{4}$$

where RF and CF are the row frequency and column frequency, respectively:

$$\mathrm{RF} = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=2}^{N} \left[F(i,j) - F(i,j-1) \right]^2} \tag{5}$$

$$\mathrm{CF} = \sqrt{\frac{1}{M \times N} \sum_{j=1}^{N} \sum_{i=2}^{M} \left[F(i,j) - F(i-1,j) \right]^2} \tag{6}$$

3.3. Visual sensitivity (VS)

The visual sensitivity of an image, which originated from the human visual system, is defined as

$$\mathrm{VS} = \frac{1}{M \times N} \sum_{i} \sum_{j} \frac{|F(i,j) - \mu|}{\mu} \tag{7}$$

where μ is the intensity mean value of the image.

3.4. Energy of Laplacian (EOL) of the image [13]

Another focus measure for analyzing high spatial frequencies associated with image border sharpness is the Laplacian operator

$$\text{EOL} = \sum_i \sum_j (f_{ii} + f_{jj})^2 \tag{8}$$

where

$$f_{ii} + f_{jj} = -F(i-1, j-1) - 4F(i-1, j) - F(i-1, j+1) - 4F(i, j-1) + \\ + 20F(i, j) - 4F(i, j+1) - F(i+1, j-1) - 4F(i+1, j) - F(i+1, j+1)$$

The fusion results with smaller value of RMSE or larger values of EOL, SF, and VS are generally considered better.

4. Experimental results

Experiments are performed on several sets of images to evaluate the proposed fusion algorithm. The results on two sets of fully registered 256-level gray images will be shown here (size of 128×128). For comparison purposes, the fusion is also performed using the DWT method [14], the CT method [4], the NSCT method [4], the NSCT-PCNN method (PCNN method in NSCT domain) [6] and the previously proposed algorithm – GA method [8]. Experiments are implemented on an Intel Core2 2.61 GHZ computer with 2.00 GB RAM. The simulation software is Matlab 7.01.

The parameters of our BPSO algorithm are: the population number $P = 8$, $\alpha = 1.005$, the greatest folding times are 12. The parameters of GA algorithm are: the population number $P = 10$, $\alpha = 1.005$, the crossover ratio $P_c = 0.8$, the mutation ratio $P_m = 0.1$, the greatest folding times are 12. For the DWT method, the wavelet basis "db8" and a decomposition level of 3 are used. The curvelet transform is implemented into two levels, and the second level contains eight orientations. The fusion rule is the maximum-selection scheme and the verification rule is major voting in 5×5 window. Three decomposition levels, with 2, 4, 16 directions from coarser scale to finer scale, are used in NSCT algorithm, in which the lowpass subband coefficients and the bandpass subband coefficients are simply merged by the averaging method and the maximum regional gradient method, respectively. In NSCT-PCNN method, parameters of PCNN are set as follows: $\alpha_L = 0.06931$, $\alpha_\theta = 0.2$, $\beta = 0.2$, $V_L = 1.0$, $V_\theta = 20$, and the maximal iterative number is 200. For NSCT parts, four scales of decomposition with 1, 2, 4, 16 directions are used, and the PCNN and SF-PCNN rules are used in the low-frequency and high-frequency domain, respectively.

For the two sets of fully registered images, we consider two blurring cases in detail. In one case, two objects areas are not overlapped blurred, just like Fig. 3. Figure 4 shows another case that two objects areas are overlapped blurred. Fusion results of the two blurring cases by using five algorithms are shown in Figs. 3 and 4, respectively. It is hard to subjectively find the difference between the fusion results among the five

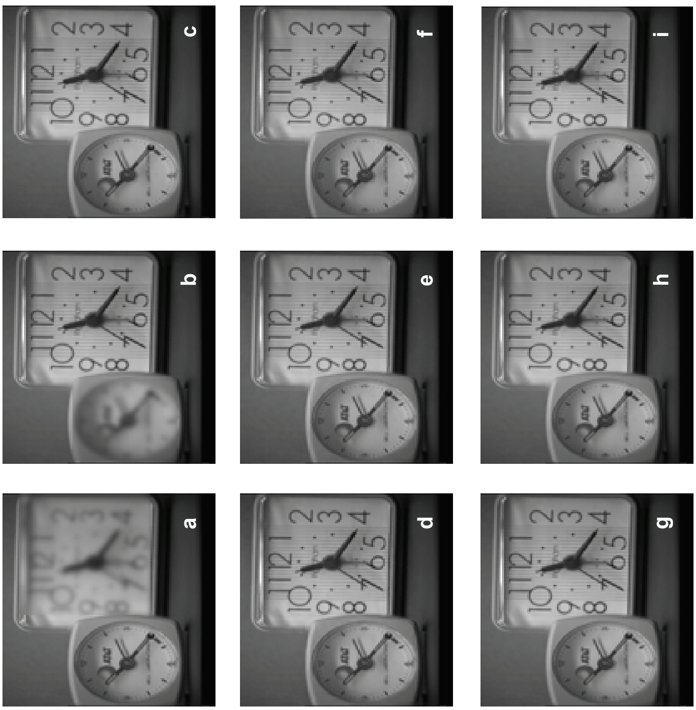

Fig. 3. Example of image fusion (without overlapped blurred regions). Source image (focus on the left, size of 128×128) – **a**; source image (focus on the right) – **b**; reference image (all in focus) – **c**; fused image obtained by DWT algorithm – **d**; fused image obtained by CT algorithm – **e**; fused image obtained by NSCT algorithm – **f**; fused image obtained by NSCT-PCNN algorithm – **g**; fused image (corresponding to minimum of RMSE) obtained by GA algorithm – **h**; fused image (corresponding to minimum of RMSE) obtained by BPSO algorithm – **i**.

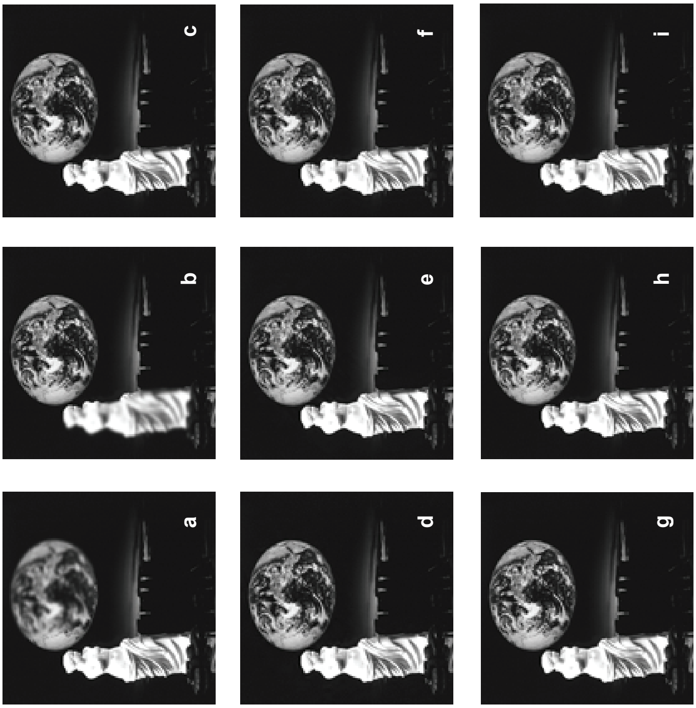

Fig. 4. Example of image fusion (with overlapped blurred regions). Source image (focus on the sculpture, size of 128×128) – **a**; source image (focus on the moon) – **b**; reference image (all in focus) – **c**; fused image obtained by DWT algorithm – **d**; fused image obtained by CT algorithm – **e**; fused image obtained by NSCT algorithm – **f**; fused image obtained by NSCT-PCNN algorithm – **g**; fused image (corresponding to minimum of RMSE) obtained by GA algorithm – **h**; fused image (corresponding to minimum of RMSE) obtained by BPSO algorithm – **i**.

algorithms. So, we use RMSE to evaluate the overall performance of the different algorithms, and use EOL, SF, and VS to evaluate the definition of the fused images.

Tables 1 and 3 show the fusion results of DWT, CT, NSCT and NSCT-PCNN methods. Considering the randomness of GA and BPSO method, 100 repeated runs are performed, and the average results are summarized in Tabs. 2 and 4.

From Tab. 1 through Tab. 4, we can see that both BPSO method and GA method can accomplish absolute restoration or optimized fusion according to RMSE. The fused images of DWT, CT, NSCT and NSCT-PCNN methods all have some small errors. According to EOL, SF, and VS, the fusion effects (definition) of BPSO and GA method are almost the same, but the execution speed of BPSO method is much faster. In

Table 1. Objective fusion performance of DWT, CT, NSCT and NSCT-PCNN algorithm on processing Fig. 3.

	Evaluation parameters				
Algorithm	RMSE	EOL	SF	VS	Time [s]
DWT	1.9005	8.9050	22.2230	0.4188	0.0610
CT	1.4748	8.8581	22.0738	0.4176	0.5470
NSCT	1.4038	8.9796	22.1066	0.4170	55.953
NSCT-PCNN	1.0313	8.6956	21.9918	0.4188	46.281

Table 2. Objective fusion performance of GA and BPSO algorithm on processing Fig. 3.

	Evaluation parameters (Avg: average results of 100 repeated runs)					
Algorithm	Min(RMSE)	Avg(RMSE)	Avg(EOL)	Avg(SF)	Avg(VS)	Avg(time) [s]
GA	0	0.1582	8.7469	22.0741	0.4195	0.1891
BPSO	0	0.1523	8.7464	22.0740	0.4195	0.1175

Table 3. Objective fusion performance of DWT, CT, NSCT and NSCT-PCNN algorithm on processing Fig. 4.

	Evaluation parameters				
Algorithm	RMSE	EOL	SF	VS	Time [s]
DWT	1.3934	2.0413	33.8861	0.8153	0.0780
CT	0.8123	2.0547	33.9101	0.8140	0.6400
NSCT	0.8913	2.0603	33.8947	0.8149	56.047
NSCT-PCNN	0.7800	2.0454	33.8618	0.8157	45.641

Table 4. Objective fusion performance of GA and BPSO algorithm on processing Fig. 4.

	Evaluation parameters (Avg: average results of 100 repeated runs)					
Algorithm	Min(RMSE)	Avg(RMSE)	Avg(EOL)	Avg(SF)	Avg(VS)	Avg(time) [s]
GA	0.5462	0.6233	2.0515	33.9095	0.8163	0.2133
BPSO	0.5462	0.5879	2.0521	33.9143	0.8164	0.1327

Table 2, the average run time of GA is 0.1891 s, while BPSO is 0.1175 s, decreasing by 37.9%. And in Tab. 4, the average run time of GA is 0.2133 s, while BPSO is 0.1327 s, decreasing by 37.8%. Compared with the other three methods, BPSO is only slower than the DWT method. So, the conclusion can be drawn that the proposed algorithm has higher accuracy and high speed.

5. Digital camera multi-focus image application

In practice, images are usually captured by a hand-held or mobile camera. Due to the limited depth-of-field of digital cameras, it is often not possible to get an image that contains all relevant objects sharply focused. And the multi-focus digital camera images are usually not registered. So, it is an important issue to study image fusion of digital camera images.

Experiments are performed on the “Lab” images (size of 480×640), which are not registered, as shown in Fig. 5. Figures 5**a** and 5**b** are the source images focused on the clock and the student, respectively. Figure 5**c** is the image obtained using

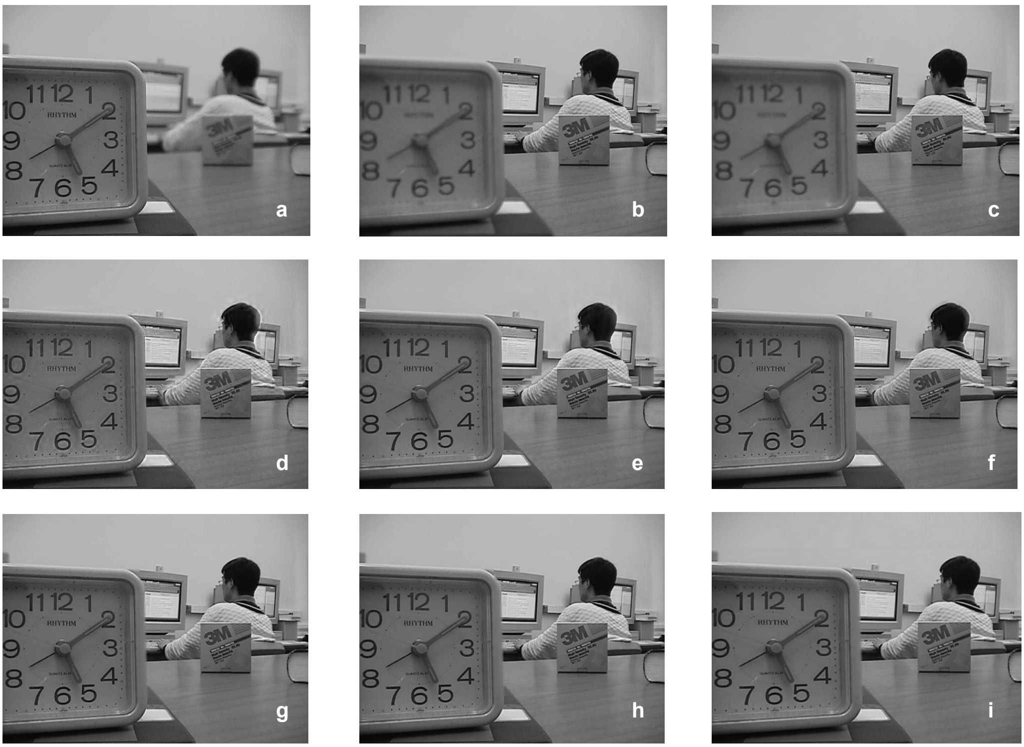

Fig. 5. Digital camera image fusion. Source image (focus on the clock, size of 480×640) – **a**; source image (focus on the student) – **b**; auto-focus image – **c**; fused image obtained by DWT algorithm – **d**; fused image obtained by CT algorithm – **e**; fused image obtained by NSCT algorithm – **f**; fused image obtained by NSCT-PCNN algorithm – **g**; fused image obtained by GA algorithm – **h**; fused image obtained by BPSO algorithm – **i**.

T a b l e 5. Objective fusion performance of the five algorithms on processing Fig. 5.

Algorithm	Evaluation parameters EOL	SF	VS	Time [s]
DWT	3.6313	12.9274	0.3119	1.2340
CT	3.5523	12.9463	0.3158	10.359
NSCT	3.6884	12.8550	0.3161	1071.4
NSCT-PCNN	3.5135	12.9235	0.3121	844.12
GA	3.4385	12.9107	0.3241	5.8900
BPSO	3.4774	12.9475	0.3222	1.5940

the auto-focus function of the camera. Fusion results on using DWT, CT, NSCT, NSCT-PCNN, GA and the proposed BPSO method are shown in Figs. 5**d**–5**h**. Objective comparisons of their performance are given in Tab. 5. For a clear comparison, parts of the source images and fusion results are extracted and put into Fig. 6 [15], and the difference images between the fused image and the source images are given in Fig. 7.

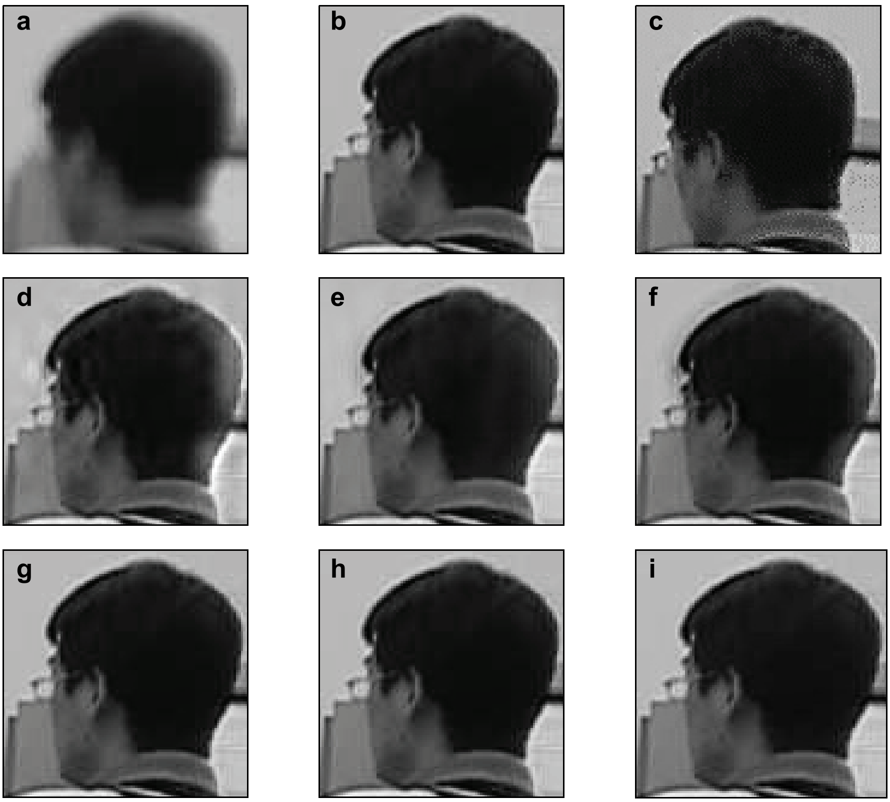

Fig. 6. Parts of the fused results of Figs. 5**a**–5**i**, respectively.

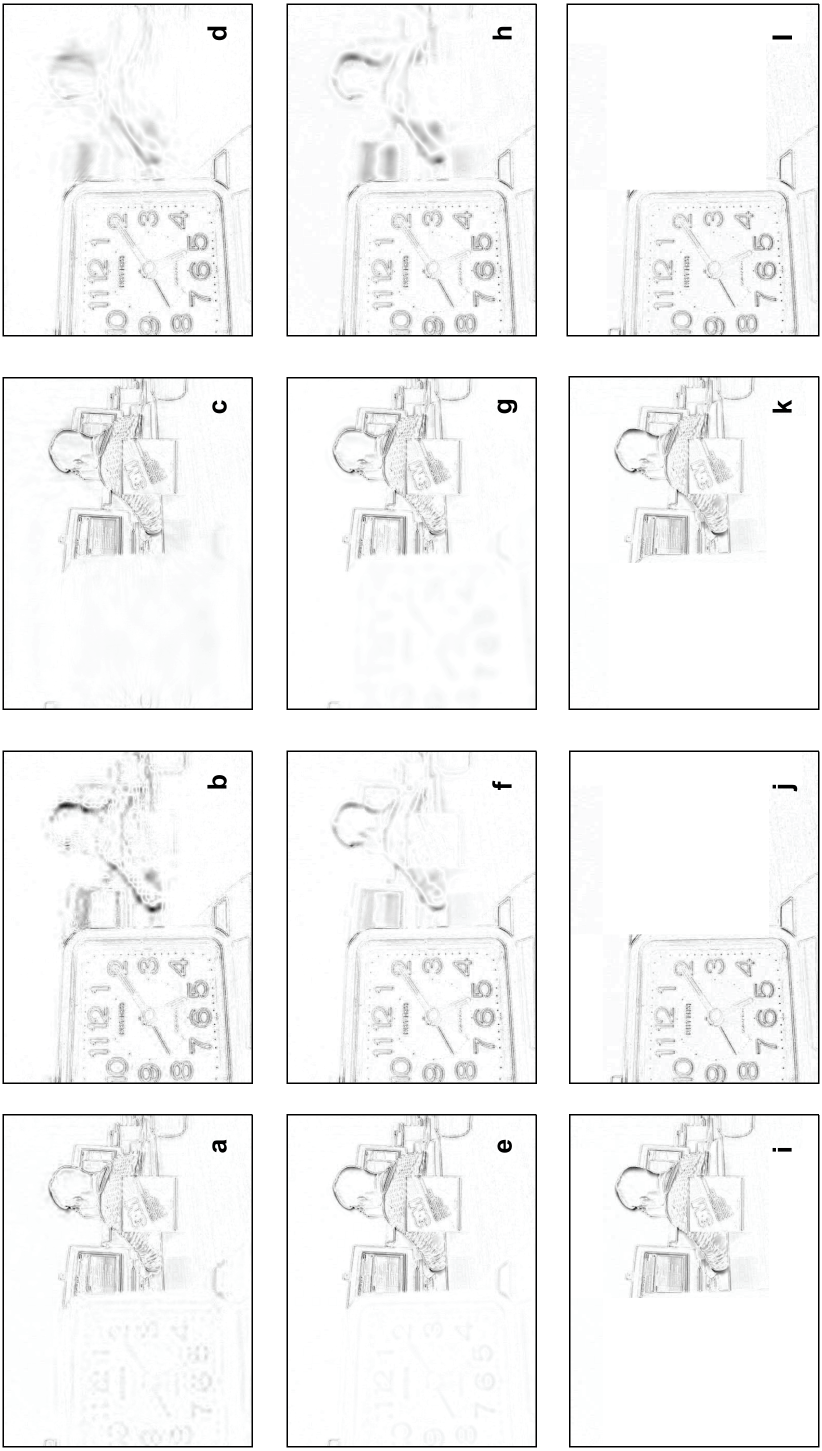

Fig. 7. Difference images between fused image and source images. Difference between Figs. 5**d**–5**i** and Fig. 5**a** – **a**, **c**, **e**, **g**, **i**, **k**. Difference between Figs. 5**d**–5**i** and Fig. 5**b** – **b**, **d**, **f**, **h**, **j**, **l**.

As illustrated in Fig. 6, we can see that the BPSO method and the GA method perform better. There are more or less some blurred parts in the results of the other three methods. Notice that there is a slight movement of the student's head between Figs. 6**a** and 6**b**, and this influences the clarity. GA and BPSO method solve the problem and get the legible images. Figure 7 shows the difference images between the fused image and the source images. For the focused regions, the difference between the source image and the fused image should be zero [3]. For example, in Fig. 5**a** the clock is clear, and in Fig. 7**a** the difference between Fig. 5**d** and Fig. 5**a** in the clock

Fig. 8. The 12 test images.

region is blank. This demonstrates that the whole focused area is contained in the fused image successfully. In this way, from Fig. 7, we can conclude that the BPSO and GA method can extract more legible information from source images.

From Table 5, we can see that the run time of GA method is 5.8900 s, while for the BPSO method it is 1.6570 s, decreasing by 71.9%. The BPSO method is much faster than the GA method, only slightly slower than the DWT method. According to the other three evaluation measures, the fused image definition of BPSO method is also satisfactory.

In addition to the above images, extensive reference or digital camera images (including color images) are employed in our tests and have verified the high speed and high accuracy of BPSO algorithm. Figure 8 lists some of them.

6. Conclusions

A multi-focus image fusion algorithm combing human visual feature and BPSO intelligent search strategies is presented in this paper. Several image definition measures are used to objectively evaluate the performance of the approach proposed. Compared with the previously proposed approach – GA algorithm, the BPSO method can also realize absolute restoration or optimized fusion of multi-focus image to the reference image, and its running speed is faster. We have also compared our algorithm with the DWT method, the curvelet transform (CT) method, the NSCT method and the NSCT-PCNN method. Experiments on 20–30 sets of manually produced multi-focus images and digital camera images show that the proposed method is an adaptive and reliable image fusion technique with high speed and high accuracy, and it is robust to misregistration and noise. So, the proposed BPSO image fusion method is statistically significant.

Acknowledgements – The work is supported by the grants from the National Natural Science Foundation of China (No. 60972146 and No. 60602025).

References

[1] Li S.T., Yang B., *Multifocus image fusion by combining curvelet and wavelet transform*, Pattern Recognition Letters **29**(9), 2008, pp. 1295–1301.

[2] Huang W., Jing Z.L., *Multi-focus image fusion using pulse coupled neural network*, Pattern Recognition Letters **28**(9), 2007, pp. 1123–1132.

[3] Li S.T., Yang B., *Multifocus image fusion using region segmentation and spatial frequency*, Image and Vision Computing **26**(7), 2008, pp. 971–979.

[4] Yan J.W., Qu X.B., *Beyond Wavelets and its Applications*, 1st Edition, National Defense Industry Press, China, 2008, pp. 21–33, 556–570.

[5] Yang B., Li S.T., Sun F.M., *Image fusion using nonsubsampled contourlet transform*, Fourth International Conference on Image and Graphics, 2007, pp. 719–724.

[6] Qu X.B., Yan J.W., Xiao H.Z., Zhu Z.Q., *Image fusion algorithm based on spatial frequency-motivated pulse coupled neural networks in nonsubsampled contourlet transform domain*, Acta Automatica Sinica **34**(12), 2008, pp. 1508–1514.

[7] ISHITA D., BHABATOSH C., BUDDHAJYOTI C., *Enhancing effective depth-of-field by image fusion using mathematical morphology*, Image and Vision Computing **24**(12), 2006, pp. 1278–1287.
[8] ZHANG X.M., HAN J.Q., LIU P.F., *Restoration and fusion optimization scheme of multifocus image using genetic search strategies*, Optica Applicata **35**(4), 2005, pp. 927–942.
[9] LU H., *A particle swarm optimization based on immune mechanism*, 2009 International Joint Conference Sciences and Optimization, February 1, 2009, pp. 670–673.
[10] KHANESAR M.A., TESHNEHLAB M., SHOOREHDELI M.A., *A novel binary particle swarm optimization*, 2007 Mediterranean Conference on Control and Automation, June 27–29, 2007, Athens, Greece, p. T33-001.
[11] XU Y.L., BI D.Y., MAO B.X., MA L.H., *A genetic search algorithm for motion estimation*, Journal of Image and Graphics **6**(2), 2001, pp. 164–167 (in Chinese).
[12] KENNEDY J., EBERHART R.C., *Discrete binary version of the particle swarm algorithm*, IEEE International Conference on Systems, Man and Cybernetics, Vol. 5, 1997, pp. 4104–4108.
[13] HUANG W., JING Z.L., *Evaluation of focus measures in multi-focus image fusion*, Pattern Recognition Letters **28**(4) , 2007, pp. 493–500.
[14] LI H., MANJUNATH B.S., MITRA S.K., *Multisensor image fusion using the wavelet transform*, Graphical Models and Image Processing **57**(3), 1995, pp. 235–245.
[15] ZHANG Q., GUO B.L., *Multifocus image fusion using the nonsubsampled contourlet transform*, Signal Processing **89**(7), 2009, pp. 1334–1346.

Received January 30, 2010
in revised form April 19, 2010