Color Image Quantization Algorithm Based on Differential Evolution

Qinghua Su
School of Sciences, Wuhan University of Technology, Wuhan 430070, Hubei, China
Email: suqhdd@126.com

Sidian Guo
School of Public Administration, China University of Geosciences, Wuhan 430074, Hubei, China
Email: huzbdd@126.com

Zhangcan Huang
School of Sciences, Wuhan University of Technology, Wuhan 430070, Hubei, China

Zhongbo Hu
School of Sciences, Wuhan University of Technology, Wuhan 430070, Hubei, China

***Abstract*—Some stochastic optimization methods, such as Particle Swarm Optimization Algorithms (PSO) and Genetic Algorithms (GA), have been used to solve the color image quantization. Differential Evolution Algorithm (DE) is one of the powerful stochastic optimization methods. Few researches have been done for using DE to solve the color image quantization. This paper proposes a DE-based color image quantization algorithm. In the proposed algorithm, a better colormap is designed by using DE to update some randomly initialized candidate colormaps. Numerical experiments are conducted on a set of commonly used test images. The experimental results show that the proposed algorithm is practicable, and it has better performance than the color image quantization algorithm using PSO.**

***Index Terms*—Color Image Quantization, Differential Evolution, Particle Swarm Optimization**

I. INTRODUCTION

Color image quantization, one of the common image processing techniques, is the process of reducing the number of colors presented in a color image with less distortion [1]. The main purpose of color quantization is reducing the use of storage media and accelerating image sending time [2]. Color image quantization consists of two essential phases. The first one is to design a colormap with a set of colors (typically 8-256 colors [3, 4]), which is smaller than the set of a color image. The second one is to map each pixel of the color image to one color in the colormap. Most of color quantization methods focus on creating a colormap. To address this problem, researchers have applied several stochastic optimization methods, such as GA and PSO. Especially, literaure [5]-[8] have compared the color image quantization algorithm using PSO (PSO-CIQ) and several other well-known color image quantization methods. The experimental results show that PSO-CIQ has higher performance.

Differential evolution (DE) [9-11] is a population-based heuristic search approach. DE has been applied to the classification for gray images [12]-[14]. In literature [12]-[14], DE and PSO show similar performance. However, due to simple operation, litter parameters and fast convergence, DE is the better choice to use than PSO [12]. However, few researches have been done for using DE to solve the color image quantization. This paper proposes a DE-based color image quantization algorithm. The proposed algorithm starts with an initialized population, in which each individual represents a candidate colormap. Then each individual (candidate colormap) is repeatedly updated by mutation, crossover and selection operations of DE until a given stopping condition is satisfied. The solution obtained by the above operations is the last colormap, by which the quantized image is generated. By some commonly used color images, the performance of the proposed algorithm is compared with that of the color image quantization approach using PSO.

This paper is organized as follows. Section 2 introduces the classical DE algorithm. In section 3, the DE-based color image quantization algorithm is proposed. In section 4, numerical experiments are given to compare the quantization quality of the proposed algorithm and the color image quantization algorithm using PSO. Section 5 concludes this paper.

II. CLASSICAL DIFFERENTIAL EVOLUTION

The classical DE is a powerful stochastic global optimization algorithm. It regenerates a population through executing some simple arithmetic operations such as mutation, crossover and selection. Here the classical DE will be introduced. For the convenience of introduction, some symbols used throughout this paper are defined.

doi:10.4304/jsw.8.12.3035-3041

- $g(x)$: Objective function or fitness function
- D : Dimension of an optimization problem
- NP : Population size
- $X=\{x^1,x^2,\cdots,x^{NP}\}$: Population
- $x^j=(x_1^j,x_2^j,\cdots,x_D^j)$: j^{th} individual in the population X, $j=1,2,\cdots,NP$
- F : Scaling factor
- CR : Crossover rate

Consider the following optimization problem:

$$\min g(x),\ x=(x_1,x_2,\cdots,x_D)\in\prod_{i=1}^{D}[L_i,U_i],\ i=1,2,\cdots D,$$

where each variable x_i has a lower bound L_i and a upper bound of and U_i, and $\prod_{i=1}^{D}[L_i,U_i]$ is the feasible domain of this problem.

For solving the optimization problem, an initial population is sampled in the feasible domain randomly. Set

$$X=\{x^1,x^2,\cdots,x^{NP}\}$$

is a population with NP individuals. Each individual is D-dimensional, and we denote the j-th one as

$$x^j=(x_1^j,x_2^j,\cdots,x_D^j),\ j=1,2,\cdots,NP.$$

To obtain the optimum solution of the problem, the classical DE works through a simple cycle of operators including the following mutation, crossover and selection operations.

a) Mutation

For each individual x^j, DE creates a donor vector y^j by using the following mutation operator.

$$\begin{cases} u^j &= (u_1^j,u_2^j,\cdots,u_D^j) \quad = x^{r_1}+F\cdot(x^{r_2}-x^{r_3}), \quad j=1,2,\cdots,NP,\\ y_i^j &= \begin{cases} L_i, & if\,(u_i^j<L_i)\\ U_i, & if\,(u_i^j>U_i)\\ u_i^j, & otherwise \end{cases} ,i=1,2,\cdots,D, \quad j=1,2,\cdots,NP,\\ y^j &= (y_1^j,y_2^j,\cdots,y_D^j) \quad , \quad j=1,2,\cdots,NP. \end{cases} \tag{1}$$

Here r_1,r_2,r_3 are three different integers randomly obtained on $[1,NP]$. The scaling factor, F, is a empirical parameter belong on $[0,1]$.

b) Crossover

For each individual x^j, do

$$\begin{cases} z^j = & (z_1^j,z_2^j,\cdots,z_D^j),\ j=1,2,\cdots,NP,\\ z_i^j = & \begin{cases} y_i^j, & if\,(rand_i\le CR \quad or \quad i=rnbr_j)\\ x_i^j, & if\,(rand_i>CR \quad and \quad i\ne rnbr_j) \end{cases} ,i=1,2,\cdots,D. \end{cases} \tag{2}$$

Here a trial vector z^j is generated for the individual x^j by a random value $rand_i$ on $[0,1]$. CR, a crossover rate, is a empirical parameter on $[0,1]$. $rnbr_j$, a random integer on $[1,D]$, is used to assure that at least one component of z^j is taken from the donor vector.

c) Selection

Finally, for each individual x^j, the following section operator is employed to maintain the most promising individual in the next generation.

$$x^{j\prime}=\begin{cases} x^j, & if\,(g(x^j)\le g(z^j))\\ z^j, & if\,(g(x^j)>g(z^j)) \end{cases},\ j=1,2,\cdots NP. \tag{3}$$

Here $x^{j\prime}$ represents the updated individual according to the fitness values of $g(x)$ for the next generation population $X'=\{x^{1\prime},x^{2\prime},\cdots,x^{NP\prime}\}$.

As stated above, for obtaining the best solution of the fitness function $g(x)$, DE starts with a randomly generated initial population and then repeatedly updates the population by using the mutation, crossover and selection operations until the stopping condition is satisfied.

III. The DE-based Color Image Quantization Algorithm (DE-CIQ)

In the RGB color space $[0,255]^3$, a color image is a set of some color pixels consisting of red, green and blue values, which determine the color of these pixels. Set I is a color image with N different colors, and S is the collection of the N different colors. For the problem of color quantization, the first phase is to determine K different colors in $[0,255]^3$, where $K<N$. The collection S' of this K colors is called a colormap. The second phase is to create a map $f:S\to S'$, by which each color pixel in S is replaced by one of the colors in S'. Thus a new color image I', called the quantized image of I, is constructed. In the image S', there are K colors. Commonly, the corresponding rule in the map f is the minimum Euclidean distance between two colors.

The objective to quantize the color image I is to minimize the color error between the color image I and its quantized image I'. The mean square error (MSE) is the most general measure of quality of a quantized image [4]. It is defined as follows:

$$MSE=\frac{1}{N_p}\{\sum_{r=1}^{N_p}[\min_{k=1}^{K} d(p_r,c_k)]\}, \tag{4}$$

where the symbols used in Eq.(4) are explained as follows.

- N_p : the number of image pixels
- K : the color number in the colormap
- $p_r=(p_{r1},p_{r2},p_{r3})$: the r^{th} pixel of the color image I, $r=1,2,\cdots,N_p$
- c_k : the k^{th} color triple in the colormap, $k=1,2,\cdots,K$

Shown in the above two phases of color quantization problem, a better colormap could improve the quality of a quantized image. Some heuristic techniques, including some pre-clustering approaches and some post-clustering approaches, have been applied to design colormaps. Among these techniques, the post-clustering approaches are superior to the pre-clustering approaches in the quantization quality. Post-clustering approaches perform clustering of the color space [15]. Post-clustering algorithms start with a randomly given colormap including K colors. Then each color pixel of the image I is mapped to a color in the colormap according to their color similarity. Thus all the color pixels in image I are clustered into K clusters which centers are separately the K colors in the colormap. Iteratively, the colormap and the K clusters are adjusted. Post-clustering algorithms are different in their iterative process. This section presents a new post-clustering color image quantization approach using DE, called the DE-based color image quantization algorithm (DE-CIQ), in which the classical DE introduced in section 2 is used.

```
Input color image  I = {z}

Set parameters  NP ,  F ,  CR ,  t_max
     x_i^{j,0} = rand(0,1)·255 ,  i = 1,2,···,D
     x^{j,0} = (x_1^{j,0}, x_2^{j,0}, ···, x_D^{j,0}) , j = 1,2,···,NP
                                          //population initialization
for  t = 0 to t_max
    for  j = 1,2,···,NP
         rnbr_j = rand(1,D)
         u^{j,t} = x^{r1,t} + F·(x^{r2,t} − x^{r3,t})
    for  i = 1,2,···,D
         if  u_i^{j,t} < 0  then  y_i^{j,t} = 0
         else if  u_i^{j,t} > 255  then  y_i^{j,t} = 255
              else  y_i^{j,t} = u_i^{j,t}
              end if
         end if                                    //mutation
         rand_i = rand(0,1)
         if  rand_i ≤ CR  or  i = rnbr_j  then  z_i^{j,t} = y_i^{j,t}
         else  z_i^{j,t} = x_i^{j,t}                //crossover
       z^{j,t} = (z_1^{j,t}, z_2^{j,t}, ···, z_D^{j,t})
    Calculate  g(x^{j,t}) and g(z^{j,t})
    if  g(x^{j,t}) > g(z^{j,t})  then  x^{j,t+1} = z^{j,t}
    else  x^{j,t+1} = x^{j,t}                       //selection

Find the optimal solution x^best = (x_1^best, x_2^best, ···, x_D^best)
Output the optimal colormap {c_1, c_2, ···, c_K} ,
     c_k = (x_{1+3(k-1)}^best, x_{2+3(k-1)}^best, x_{3+3(k-1)}^best) ,  k = 1,2,···,K

Construct the quantized image  I′
```

Figure 1. The pseudocode of the DE-CIQ algorithm

In the DE-CIQ algorithm, the fitness function is as follows:

$$\begin{aligned} g(x) &= MSE(x) \\ &= \frac{1}{N_p}\{\sum_{r=1}^{N_p}[\min_{k=1}^{K} d(p_r, c_k)]\} \\ &= \frac{1}{N_p}\{\sum_{r=1}^{N_p}[\min_{k=1}^{K}\sqrt{\sum_{q=1}^{3}(p_{rq}-x_{q+3(k-1)})^2}]\} \quad . \end{aligned} \tag{5}$$

Where $x = (x_1, x_2, \cdots, x_D) \in [0,255]^{3\times K}$.

A population $X = \{x^1, x^2, \cdots, x^{NP}\}$ represents a set of candidate colormaps. Each individual represents a candidate colormap with K color triples in the RGB color space $[0,255]^3$, that is, the dimension of each individual is $D = 3\times K$. The j^{th} individual is denoted by

$$x^j = (c_1^j, c_2^j, \cdots, c_K^j) = (x_1^j, x_2^j, x_3^j, x_4^j, x_5^j, x_6^j, \cdots, x_{3K-2}^j, x_{3K-1}^j, x_{3K}^j) ,$$

$$\mathrm{j} = 1,2,\cdots, NP \ ,$$

where $c_k^j = (x_{1+3(k-1)}^j, x_{2+3(k-1)}^j, x_{3+3(k-1)}^j)$, $k = 1,2,\cdots,K$.

In the performance of the DE-CIQ algorithm, a population including NP candidate colormaps are randomly initialized in the color space $[0,255]^3$. Then the population is updated by the mutation, crossover and selection operations in DE. During the selection operation, some better colormaps are determined by the values of the fitness function in Eq.(5). The mutation, crossover and selection operations are repeated until a specified maximal number of iteration $t_{\max}$. The optimal solution obtained by DE is the optimal colormap. Finally, according to the minimal color distance rule, the color of each pixel in the image I is replaced with its corresponding color in the optimal colormap. And the quantized image of I is reconstructed.

The pseudocode of the DE-CIQ algorithm is shown in Figure 1.

IV. NUMERICAL EXPERIMENTS

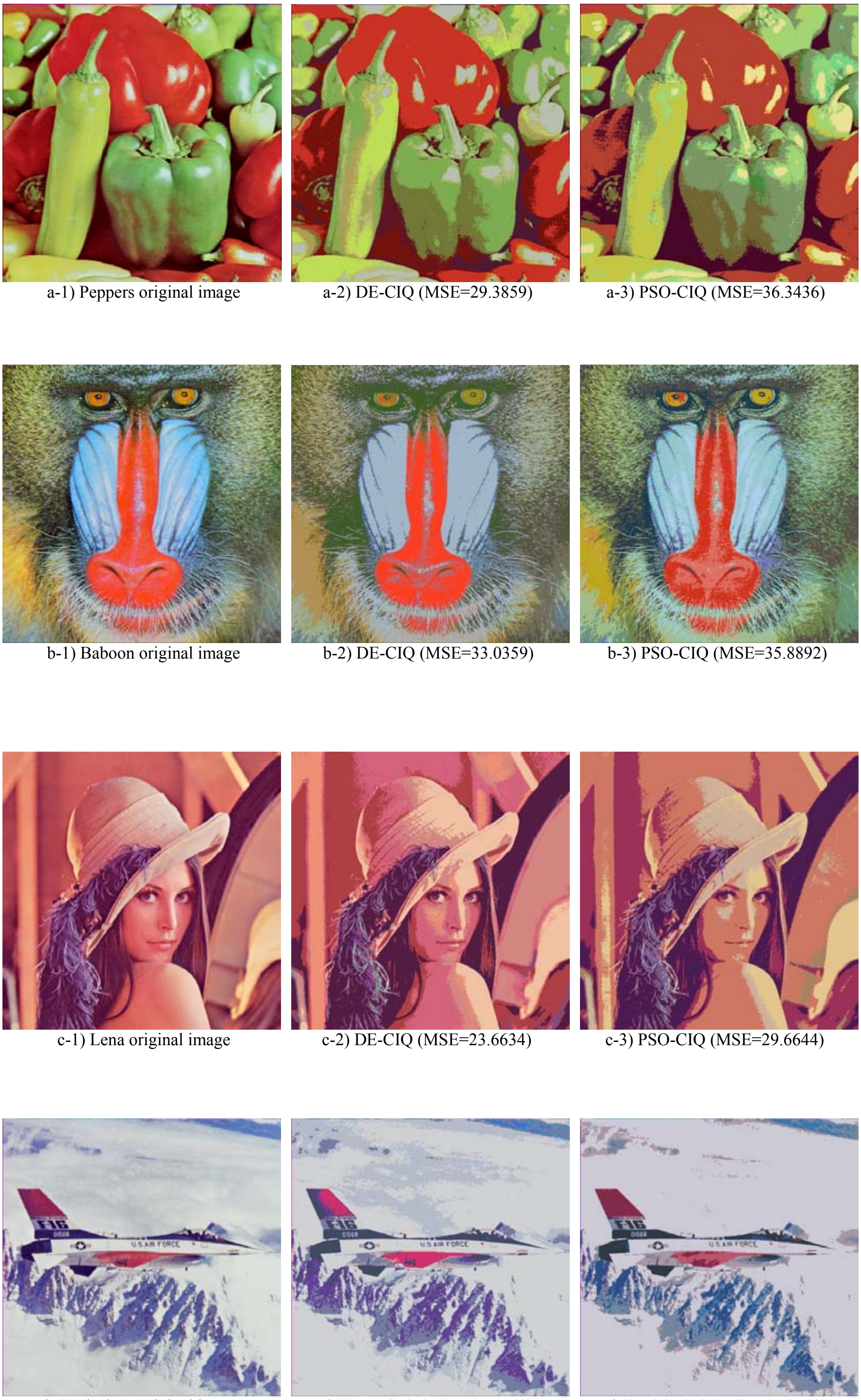
In this section, the DE-CIQ algorithm is tested on a set of four commonly used test images in the quantization literature. In addition, the performance of the DE-CIQ algorithm is compared with that of the color image quantization algorithm using PSO (PSO-CIQ) presented in literature [5].

A. Images and Parameters Set

The set of test images include *Lena*, *Peppers*, *Baboon* and *Airplane*, which have the same size 512×512 pixels. They are shown in Figure 2.

The parameters in the DE-CIQ algorithm are set as the population size $NP = 100$, the scaling factor $F = 0.4$, the crossover rate $CR = 0.7$ and the maximal number of iteration $t_{\max} = 200$. The values of F and CR are suggested by literature [13], in which the classical DE is applied to solve the image binarization.

The PSO-CIQ algorithm has more parameters than the DE-CIQ algorithm. Suppose the swarm size $NP = 100$,



a-1) Peppers original image | a-2) DE-CIQ (MSE=29.3859) | a-3) PSO-CIQ (MSE=36.3436)

b-1) Baboon original image | b-2) DE-CIQ (MSE=33.0359) | b-3) PSO-CIQ (MSE=35.8892)

c-1) Lena original image | c-2) DE-CIQ (MSE=23.6634) | c-3) PSO-CIQ (MSE=29.6644)

d-1) Airplane original image | d-2) DE-CIQ (MSE=17.7342) | d-3) PSO-CIQ (MSE=21.3540)

Figure 2. The quantized images obtained by DE-CIQ and PSO-CIQ (K=16)

TABLE Ⅰ.

MSEs RESULTING FROM DE-CIQ AND PSO-CIQ

Alg.	K=16			K=32			K=64		
	DE-CIQ	PSO-CIQ	*diff*	DE-CIQ	PSO-CIQ	diff	DE-CIQ	PSO-CIQ	*diff*
Peppers									
min	29.3859	36.3436		25.6201	31.2216		22.3553	25.9479	
max	32.4772	40.9532		27.6566	34.1909		23.7204	28.1259	
average	30.5839	38.2374	*7.6535*	26.9611	32.5946	*5.6335*	23.0299	27.1976	*4.1677*
Baboon									
min	33.0359	35.8892		27.1708	29.8687		24.1160	25.9415	
max	34.8839	41.9940		29.681	32.8485		25.5325	27.2513	
average	33.8430	38.6166	*4.7736*	28.7939	31.6166	*2.8227*	25.0039	26.5373	*1.5334*
Lena									
min	23.6634	29.6644		22.2463	26.2454		19.4587	21.7606	
max	27.0157	34.5867		24.0410	28.9036		20.8881	24.5253	
average	25.5068	32.5824	*7.0756*	23.0439	27.6132	*4.5693*	20.1177	23.4568	*3.3391*
Airplane									
min	17.7342	21.3540		14.6976	18.3879		13.7173	15.0305	
max	19.9349	24.3200		17.3456	21.7221		16.0489	16.8403	
average	18.9830	22.7153	*3.7323*	16.6086	19.4472	*2.8386*	14.7488	16.4407	*1.6919*

** diff is the difference between the average MSEs of DE-CIQ and PSO-CIQ.*

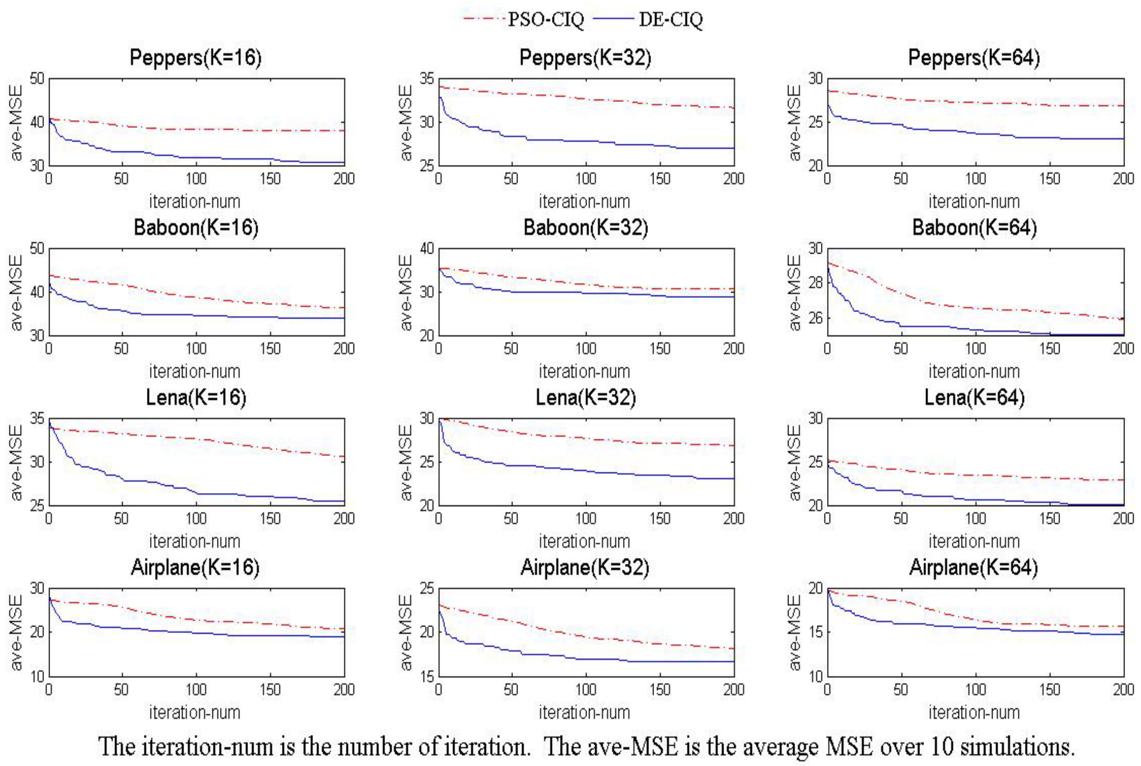


Figure 3. The average MSE variations with the number of iteration of DE-CIQ and PSO-CIQ

the inertia weight $\omega = 0.72$, the acceleration constants $c_1 = c_2 = 1.49$, the maximum velocity $V_{\max} = 0.4$, the maximal number of iteration $t_{\max} = 200$. These parameters except for the last one are as same as those in the literature [5].

B. Experimental Results

For each algorithm, the test images are quantized into 16, 32, 64 colors. The 16 colors quantized images with the smallest MSEs over 10 simulations are shown in Figure 2. The smallest, the largest and the average MSEs over 10 simulations are listed in TABLE I. The Figure 3 shows the evolution landscapes of the average MSE.

C. Analysis of Experimental Results

As shown in Figure 2, the DE-CIQ algorithm outperforms the PSO-CIQ algorithm in the visual quality of the quantized images for all test images. The quantized image a-2, b-2, c-2 and d-2 have richer layers and more details than the quantized image a-3, b-3, c-3 and d-3.

As illustrated in TABLE I, the DE-CIQ algorithm generates a smaller MSEs than the PSO-CIQ algorithm for each test image. Moreover, the smaller K is, the larger the differences between the MSEs of the two algorithms are.

Shown in Figure 3, the DE-CIQ algorithm has a smaller average MSE than the PSO-CIQ algorithm at each same number of iteration. Moreover, the average MSE resulting from the DE-CIQ algorithm decreases more quickly than that resulting from the PSO-CIQ algorithm with the increasing number of iteration.

The above experimental results can be summarized as follows:

- The DE-CIQ algorithm is an effective color image quantization method;
- The DE-CIQ algorithm has the better quantization quality than the PSO-CIQ algorithm on the test images set;
- The smaller the color number in a colormap is, the better the DE-CIQ algorithm performs than the PSO-CIQ algorithm on the test images set;
- The DE-CIQ algorithm converges more quickly than the PSO-CIQ algorithm on the test images set.

V. CONCLUSIONS

This paper presents a novel color image quantization, called the DE-based color image quantization algorithm (DE-CIQ). Numerical experiments are implemented to investigate the performance of the DE-CIQ algorithm, and to compare it against the color image quantization algorithm using PSO (PSO-CIQ) presented in literature [5]. For a set of commonly used test images, the experimental results demonstrate the feasibility of the DE-CIQ algorithm and its superiority to the PSO-CIQ algorithm in the quantization quality. In addition, the DE-CIQ algorithm has simpler operation, litter parameters and faster convergence than the PSO-CIQ algorithm.

ACKNOWLEDGMENT

This work was supported in part by the National Natural Science Foundation of China under Grant No.61070009, the Fundamental Research Funds for the Central Universities under Grant No.2012-YB-19, and the Nature Science Foundation of Hubei, China under Grant No.2011CDC161.

REFERENCES

[1] J. Braquelaire, L. Brun, "Comparison and optimization of methods of color image quantization", IEEE Transactions on Image Processing, vol. 6, no. 7, pp. 1048-1052, 1997.
[2] F. Alamdar, Z. Bahmani, S. Haratizadeh, "Color Quantization with Clustering By F -PSO-GA". 2010 IEEE International Conference on Intelligent Computing and Intelligent Systems, vol. 3, pp: 233-238, 2010.
[3] P. Scheunders, "A genetic C-means clustering algorithm applied to color image quantization", Pattern Recognition, vol. 30, no. 6, pp. 859-86, 1997.
[4] M.G. Omran, A.P. Engelbrecht, A.Salman, "A Color Image Quantization Algorithm Based on Particle Swarm Optimization", Soft Computing in Multimedia Processing, vol. 29, no. 3, pp. 261-269, 2005.
[5] Q. SA, X. LIU, X. HE, D. YAN, "Color Image Quantization Using Particle Swarm Optimization", Journal of Image and Graphics, vol. 12, no. 9, pp. 1544-1548, 2007. (in Chinese)
[6] X. ZHOU, Q. SHEN, J.WANG, "Color Quantization Algorithm Based on Particle Swarm Optimization", MICROELECTRONICS & COMPUTER, vol. 25, no. 3, pp. 51-54, 2009. (in Chinese)
[7] Y. XU, Z. JIANG, "A K-mean color image quantization method based on particle swarm optimization", Journal of Northwest University (Natural Science Edition), vol.42, no.3, 2012. (in Chinese)
[8] F. Alamdar, Z. Bahmani, S. Haratizadeh, "Color Quantization with Clustering By F -PSO-GA", 2010 IEEE International Conference on Intelligent Computing and Intelligent Systems, vol. 3, pp. 233-238, 2010.
[9] R. Storn, K. Price, "Differential Evolution - a Simple and Efficient Adaptive Scheme for Global Optimization over Continuous Spaces", Technical Report TR-95-012, ICSI, 1995.
[10] Y. Shen, M. Li, H. Yin, "A Novel Differential Evolution for Numerical Optimization", IJACT, Vol. 4, No. 4, pp. 24-31, 2012.
[11] H. Li, J. Tang, "Improved Differential Evolution with Local Search", JCIT, Vol. 7, No. 4, pp. 197-204, 2012.
[12] Mahamed G. H. Omran, Andries P Engelbrecht, Ayed Salman. Differential Evolution Methods for Unsupervised Image Classification. 2005 IEEE Congress on Evolutionary Computation, vol. 2, pp. 966 - 973, Sept. 2005.
[13] S. Das, A. Konar, "Automatic image pixel clustering with an improved differential evolution", Applied Soft Computing, vol. 9, pp. 226-236, 2009.
[14] Q. Su, Z. Huang, Z. Hu, "Binarization algorithm based on differential evolution algorithm for gray images", vol. 6, pp. 2624-2628, ICNC-FSKD, 2012.
[15] S. Cheng, C. Yang, "A fast and novel technique for color quantization using reduction of color space

dimensionality", Pattern Recognition Letters, vol. 22, pp. 845-856, 2001.

Qinghua Su received her B.S. degree from School of Mathematics and Physics, China University of Geosciences in 2001. She received her M.S. degree from School of Mathematics and Statistics, Huazhong University of Science and Technology in 2009. She is also an associate professor in Hubei Engineering University.

She is currently pursuing the Ph.D. degree in School of Sciences, Wuhan University of Technology. Her main research interests include evolutionary computation and image processing.

Sidian Guo is currently pursuing her bachelor degree in School of Public Administration, China University of Geosciences. She majors in management of land resources.

Zhangcan Huang is a professor and a PhD director in School of Sciences, Wuhan University of Technology. He main research interests include intelligence computation and image processing.

Zhongbo Hu received his M.E. degree from School of Computer Sciences and Technology, Wuhan University of Technology in 2006. He is currently pursuing the Ph.D. degree in School of Computer Sciences and Technology, Wuhan University of Technology. His main research interests include evolutionary computation.