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ORIGINAL ARTICLE

Colour image segmentation with histogram and homogeneity histogram difference using evolutionary algorithms

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Abstract Due to the complexity of underlying data in a color image, retrieval of specific object features and relevant information becomes a complex task. Colour images have different color components and a variety of colour intensity which makes segmentation very challenging. In this paper we suggest a fitness function based on pixel-by-pixel values and optimize these values through evolutionary algorithms like differential evolution (DE), particle swarm optimization (PSO) and genetic algorithms (GA). The corresponding variants are termed GA-SA, PSO-SA and DE-SA; where SA stands for Segmentation Algorithm. Experimental results show that DE performed better in comparison of PSO and GA on the basis of computational time and quality of segmented image.

Keywords Segmentation · Evolutionary algorithms · Colour image · Homogeneity

1 Introduction

Colour image segmentation is a complex but crucial task having application in several areas. Two most popular techniques for colour image segmentation include histogram-based methods [5] and neighbourhood based segmentation [6, 7].

Wen-Bing Tao et al. [26] proposed a GA based three level thresholding method for image segmentation. They partitioned the image in three basic parts dark, grey and white then implemented fuzzy region as Z-function, P-function and S-function respectively. GA's are used to find an optimal solution for the fuzzy parameters avoiding the extra chromosomes resulting in a better feasibility. Hammouche et al. [27] proposed a wavelet transform method combined with genetic algorithm. This method reduced the original length of histogram using wavelet transform; GA selects the number of thresholds and values of thresholds in this reduced histogram. Multilevel thresholds are used for image segmentation with better performance.

Minimum cross entropy thresholding (MCET) is a widely used simple and accurate method for image segmentation. In bi-level thresholding MCET works efficiently but for multi-level thresholding it encounters a very expensive computation. So Tang et al. [28] proposed a GA based fastening threshold selection in multilevel MCET. To reduce computational complexity a recursive programming is used for objective function. These values are used as a chromosome representation for GA which search several optimal multilevel threshold values. These values are very close to exhaustive search methods and show a better performance in terms of computational complexity and segmentation aspects.

Du Feng et al. [29] applied PSO for 2-D maximum entropy method to optimize the fitness function developed with the help of a 2-D histogram. PSO provides the threshold values as local average intensity of pixels. Thresholding values successfully works for infrared images and shows its better performance on the basis of

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computation time and segmentation quality. Similarly Peng-Yeng Yin [30] applied PSO for minimum cross entropy thresholding (MCET) successfully and efficiently. PSO embedded fuzzy entropy image segmentation was proposed by Linyi and Deren [31].

Madhubanti and Chatterjee [32], proposed an improved variant of PSO called HCOCLPSO (hybrid cooperative–comprehensive learning based PSO) computing optimal multilevel thresholding for histogram-based image segmentation. This approach consists of cooperative and comprehensive learning. Cooperative learning is basically used for removing the high-dimensional swarm into several one-dimensional swarms and comprehensive learning controls premature convergence.

Valentın et al. [33] successfully apply PSO ABC and DE for making the calculation of parameters used in 1-D histogram. Gaussian function approximates the 1-D histogram, for calculation of threshold point in grey level image segmentation.

Shu-Kai and Yen [34] proposed (PSO + EM) algorithm for estimation of Gaussian' parameters. PSO employed for global search and the best particle was updated through expectation maximization (EM). For multilevel thresholding (PSO + EM) performs swiftly in comparison of other traditional algorithms. Chander et al. [35] also proposed a variant of PSO for multilevel thresholding for reducing the complexity and computational time.

Akay [36] applied global PSO artificial bee colony (ABC), for calculating the optimal multilevel thresholding. Kapur's entropy and between class variance were used as fitness functions for these algorithms. Experiments show a comparative difference for CPU time in comparison of these methods.

FCM (Fuzzy Mean Clustering) algorithm is a traditional algorithm for (MR) magnetic resonance. For improving the efficiency of FCM algorithm a neighbourhood attraction is introduced by researchers. Forouzanfar et al. [37] proposed a PSO/GA based optimization method for finding an optimal neighborhood attraction. All the simulation of results showed an improvement in image segmentation.

Zhang et al. [38] applied PSO in fuzzy clustering for optimizing initial clustering centres for FCM. Similarly Wang et al. [39] proposed a multidimensional PSO for unsupervised planar segmentation. A most advance methodology using PSO initialization in FCM is proposed by Benaichouche et al. [40]. This methodology is successfully applied in image segmentation and shows a better performance in comparison of traditional methods. Gao et al. [41] proposed an advance variant of PSO named (IDPSO) intermediate disturbance searching strategy for enhancing the search ability of particles and increases their convergence rates and applied it for solving image segmentation problems.

Mesejo et al. [43] proposed a method based on evolutionary algorithms on biomedical images for localizing the hippocampus in histological images. They applied DE, Levenberg–Marquardt, GA, PSO, Simulated Annealing, and Scatter Search algorithms and observed that DE outperforms other algorithms. Das and Sil [44], proposed a modified DE algorithm for pixel clustering in images. Similarly Cuevas et al. [45] also proposed a thresholding technique based on DE. In this technique, DE is used for calculating Gaussian parameters. Shahryar and Hamid [46] also proposed a thresholding algorithm based on micro Opposition-based DE (ODE) for minimizing dissimilarity between input image and threshold image. Nakib et al. [47, 48] considered image thresholding as an optimization problem. They considered Gaussian distribution's parameter selection as a nonlinear optimization problem and solve it with new variant of DE called low-discrepancy sequences and a local search (LDE). Ali et al. [49], proposed an advance variant of DE named synergetic differential evolution (SDE) and utilize entropy and approximation of normalized histogram for finding the optimal thresholds. Results showed its better performance in comparison of other methods. Mukesh et al. [50] proposed an automatic segmentation technique of leukocytes tissue images applying DE which is very beneficial for identifying many type of disease. Multilevel thresholding is solved with 2D histogram by Sarkar and Das [51]. 2D histogram has its own advantages in comparison of 1D histogram for multilevel thresholding. So, a 2D histogram based approach is proposed which utilizes maximum Tsallis entropy obtained by DE. Comparison with other nature inspired algorithms like GA, PSO, ABC and Simulated Annealing show the robustness and efficiency of DE.

Colour image segmentation is a process of dividing the colour image into parts which are homogeneous. Lee et al. [42], proposed a modified PSO for extracting high-level image semantics depending upon the colour, intensity and orientation. De et al. [1] proposed a method of colour image segmentation based on neural network with the help of a newly ParaOptiMusig fitness function. Yue et al. [2] proposed a Multiscale roughness measure for colour image segmentation based on multiscale roughness measure using histogram and histon as lower and upper approximation. They have described a peak selection method in their algorithm, which self adaptively selects a peak in histogram. The significant peaks of roughness index always represent colour homogeneity at corresponding intensities. Mohabey and Ray [4] based on neighbourhood similarity to construct the histon concept. Histon basically use pixel scale belonging to the corresponding intensity with uncertainty. Histon method provides a little attention towards small homogeneous regions of an image.

In the past few decades, metaheuristics have emerged as a significant tool for segmentation of colour images out of the various metaheuristics, GA [19] are probably the most frequently used technique for image segmentation [1, 8–16]. Some other metaheuristics used for image processing are: PSO [17, 3], DE [18], ABC [3] [43], Cuckoo Search [24] etc. All these algorithms are well-known in the field of optimization and these algorithms show their applications in various fields of engineering where problems are much complex and multidimensional. Some more techniques based on neural network and genetic algorithms [52–54] also proposed in recent years. In same way colour images have a histogram in 3-D and storing this information in a 3-D array and selecting multilevel threshold value for a 3-D array is a complex task.

In this paper we have proposed a new optimization based model for image segmentation and have implemented metheuristics like DE, PSO and GA for its solution. A new objective function is proposed for image segmentation using homogeneity histogram and original histogram of the image. Objective function is optimized with metaheuristics algorithms. These optimized values replace the original values on the basis of constraints used in metaheuristics. Results for CPU time, average values and segmented images show utmost performance of DE-IE over all other algorithms. For CPU time we have compare the results with Homogeneity algorithm [20] also, DE-IE shows its utmost performance with this algorithm also.

The paper is structured as follows: Section-II describes a histogram and homogeneity calculation for colour image, section-III describes the fitness function for DE, PSO and GA, section-IV describes the DE algorithm, section-V describes test problems on which we have tested our algorithm, DE required some parameters, settings for these parameters described in section-VI, section-VII and section-VIII describe results and discussion and quality evaluation for the test images respectively.

2 Histogram for colour image

Colour images have a 3-D histogram and all the information will be stored in a 3-D array. A 3-D array has data space in three dimensions ways, so it is suitable for evolutionary algorithms like DE, PSO and GA where each point of the initial population may be considered as a three dimensional vector. For colour image segmentation a large set of homogeneous regions will be formed with the help of a 3-D histogram.

Homogeneity can be calculated according to [20] as:

Step 1: Calculate standard deviation of a pixel P_{ij} of an image having a size.

$$sd_{ij} = \sqrt{\frac{1}{a^2}\sum_{p=i-(a-1)/2}^{i+(a-1)/2}\sum_{q=j-(a-1)/2}^{j+(a-1)/2}(I_{pq}-\mu_{ij})^2} \tag{1}$$

$a \times a$ represents a window a^1, I_{pq} is the intensity of a pixel P_{ij}. μ_{ij}- Mean value of the grey level image in window $a \times a$.

$$\mu_{ij} = \frac{1}{a^2}\sum_{p=i-(a-1)/2}^{i+(d-1)/2}\sum_{q=j-(a-1)/2}^{j+(a-1)/2} I_{pq} \tag{2}$$

Edge detection is done on the basis of Sobel operator.

$$e_{ij} = \sqrt{G_x^2 + G_y^2} \tag{3}$$

Where, G_x and G_y are the components of the gradient in x and y direction and a different window a^2 with dimension $b \times b$ is used for edge detection.

For normalization

$$S(I_{ij}, a^1) = \frac{sd_{ij}}{sd_{\max}} \tag{4}$$

$$E(I_{ij}, a^2) = \frac{e_{ij}}{e_{\max}} \tag{5}$$

S, E both will be normalized in range (0, 1).

So, homogeneity can be represented as

$$H^h(I_{ij},\ a^1,\ a^2) = 1 - E(I_{ij},\ a^2) \times S(I_{ij},\ a^1) \tag{6}$$

Homogeneity value at each location of an image has a range from [0, 1] which depends on the window size. In the present study, a 5 × 5 window is considered for computing the standard deviation of the pixel, and a 3 × 3 window is considered for computing the edge.

Homogeneity histogram form peaks in the original view. Some image segmentation methods remove peaks from the histogram which may result in the loss of some important information. In the present study we have proposed the use of heuristics for smoothening the peaks rather than removing these peaks, thereby preserving all the useful information.

3 Proposed fitness function

the components of the gradient to make use of all the available pixels. Out of the available histograms, one is homogeneity histogram $H^h(i,\ j)$ and second is original histogram of original image $H^o(i,\ j)$. Let $dH^d(i,\ j)$ be the histogram difference such that:

$$dH^d(i,j) = \text{Difference between } H^h(i,j) \text{ and } H^o(i,j)$$

Histogram difference provides a separation among all the homogeneous regions.

In the present study, the evaluation function is designed on the basis of histogram difference dH^d and standard deviation. Mathematically, it may be written as:

$$\text{Min}\, f = \sum_{i=1}^{M}\sum_{j=1}^{N}\beta(i,\, j).dH^d(i,\, j) \tag{7}$$

$$\beta(i,j) = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(sd_{ij} - \mu_{ij})}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(sd_{ij} - \mu_{ij})}} \tag{8}$$

$\beta(i, j)$ provides a result based on quality of the pixel and provides a normalized value between (0, 1). $M \times N$ is the size of the original image.

Colour images have a broad search space. Since metaheuristics work with a population of solution, these are likely to search this space efficiently. As mentioned in the beginning of the chapter, the metaheuristics used here are PSO, GA and DE and the corresponding algorithms are named PSO-SA, GA-SA and DE-SA respectively. Minimization of the fitness function based on these algorithms will provide an optimized value for pixels. This value, given by these metaheuristics will replace the existing value (if one value is lesser than the other). This fitness function will provide a mixture of similarity adjacency and will permit a certain amount of repetition in the overall summary to capture the rhythm of the colour image.

4 Proposed methodology

The methodology proposed is simple to understand and easy to apply. The colored image is entered and the fitness function is obtained as described in the previous section. Metaheuristics DE, PSO or GA are applied to optimize the fitness function. The proposed methodology can be described in more detail as:

- Input a colour image. Define an integer for desired number of homogeneous regions.
- Calculate standard deviation sd_{ij} and mean μ_{ij} for each pixel.
- For each pixel value of standard deviation and mean provides information about the pixel and its RGB intensity.
- Calculate the difference between histograms and standard deviation of the image which will provide the initial population.
- Design the fitness function as given in Eq. (7) and optimize this function. The minimum value obtained will replace the actual pixel value based on homogeneity.
- Fitness function is optimized using DE-SA, PSO-SA and GA-SA.
- Homogeneity histogram will be comparable with original histogram. The difference of these optimized values will replace the original values existing in the image in a competitive manner. If the value of the pixel obtained after the application of metaheuristics is less than the value of the original pixel, then it will replace the original value otherwise the original pixel will be retained. In this way all the pixels are compared and replacement is done when necessary.

5 Test problems

In the present study, all the test images are taken from Berkley database.

6 Parameter settings and other assumptions

- For DE, the parameters scaling factor and crossover rates are taken as 0.5 and 0.8 respectively.
- Population size is 3-D array having pixel intensity 256 × 256 × 256 for different colour range for RGB.
- Maximum number of function evaluation (NFE) is kept as: NFE = 105 and total runs are kept as 256.
- For PSO, Inertia weight (w) is fixed at 0.5 and acceleration constants (c1 and c2) are taken as 2.0 each.
- For GA, Crossover rate is kept as 0.5 and Mutation rate is kept as 0.05.
- All images will be considered as a 3D complex problem.
- Statistical values as standard deviation, mean value are calculated for forming a homogeneity histogram.

Figure 1 illustrates the flow diagram of the proposed approach: Optimize the fitness function using GA, PSO or DE algorithms to a min value (as the objective function is of minimization) to optimize the values of the pixels providing some new and optimized values. MAX prob or MIN prob.

7 Results and discussion

The following performance metrics are considered for analyzing the proposed approach:

- Percentage of uniform pixels (Table 1)
- Histogram difference before minimization (Table 1)
- Histogram difference after minimization (Table 1)
- CPU Time (Table 2)
- Analysis of quality evaluation (Table 3)
- Statistical analysis (Tables 4 and 5)

- The methods other than the ones proposed in this study are homogeneity method [20] and OptiMUSIG [1].

The corresponding results are given in Table 1.

Table 1 shows a percentage of uniform pixels existed in an image. Information about the uniformity of the pixels calculated with the help of three met heuristics algorithms; GA-SA, PSO-SA and DE-SA. As discussed above; homogeneity of histograms is computed and minimized with the help of metaheuristics algorithms.

7.1 Analysis on the basis of CPU time

Table 2 shows the CPU time taken by GA-SA, PSO-SA and DE-SA and Homogeneity Method [20]. We see that the computational time taken by DE-SA is less in comparison to PSO-SA and GA-SA.

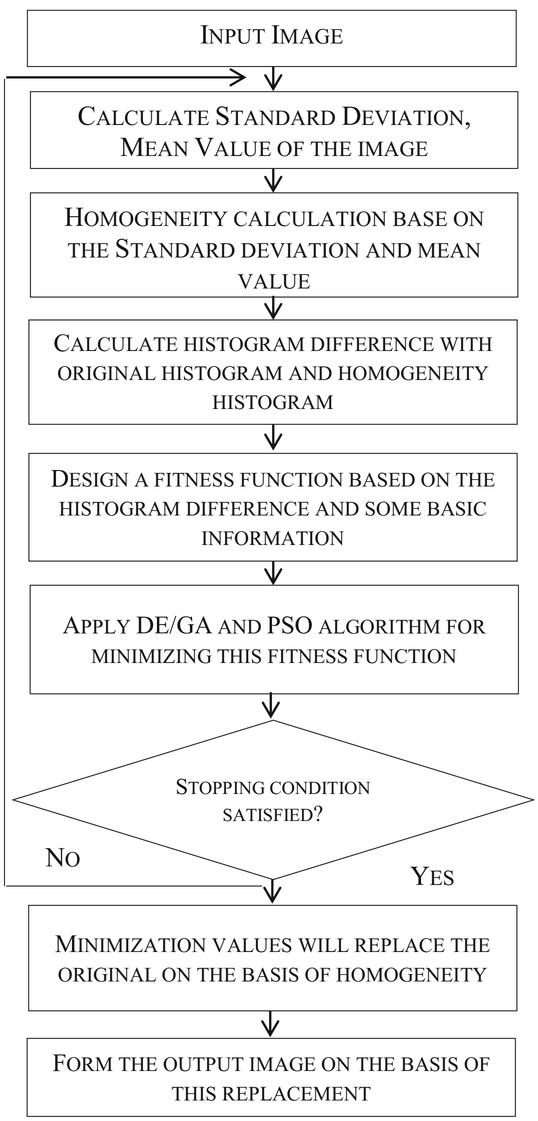


Fig. 1 Flow diagram of proposed approach

Table 1 Segmented result of images

Image	Percentage of uniform pixels (%)	Histogram difference before minimization	Histogram difference after minimization
GA-SA			
Image-01	70	0.8945	0.7894
Image-02	64	0.7654	0.5982
Image-03	56	0.8791	0.7854
Image-04	60	0.6873	0.5693
Image-05	85	0.7864	0.6282
Image-06	75	0.6785	0.6314
Image-07	63	0.7861	0.6790
Image-08	62	0.7362	0.6782
Image-09	71	0.8291	0.6328
Image-10	78	0.7663	0.6943
Image-11	73	0.7542	0.6371
Image-12	68	0.6489	0.7364
Image-13	76	0.8215	0.8825
Image-14	74	0.7213	0.8421
Image-15	67	0.8712	0.8632
PSO-SA			
Image-01	74	0.5453	0.4371
Image-02	66	0.6921	0.6131
Image-03	81	0.7239	0.5627
Image-04	78	0.7856	0.6641
Image-05	84	0.8643	0.7670
Image-06	76	0.9643	0.8793
Image-07	67	0.8654	0.6759
Image-08	65	0.6367	0.5234
Image-09	67	0.6542	0.7311
Image-10	74	0.8536	0.6546
Image-11	64	0.6478	0.7421
Image-12	75	0.7852	0.6686
Image-13	64	0.7342	0.7584
Image-14	67	0.7494	0.9855
Image-15	78	0.6793	0.7632
DE-SA			
Image-01	89	0.7638	0.4214
Image-02	74	0.5372	0.3728
Image-03	56	0.6372	0.5361
Image-04	76	0.7682	0.6783
Image-05	87	0.6785	0.5891
Image-06	67	0.8742	0.7845
Image-07	73	0.6893	0.6734
Image-08	76	0.6573	0.5342
Image-09	65	0.6645	0.4261
Image-10	74	0.4562	0.6272
Image-11	87	0.6467	0.5345
Image-12	69	0.7539	0.6353
Image-13	78	0.7656	0.6736

Table 1 continued

Image	Percentage of uniform pixels (%)	Histogram difference before minimization	Histogram difference after minimization
Image-14	65	0.7432	0.6942
Image-15	76	0.6543	0.7654

Table 2 CPU time for all images using different metaheuristics

Image	GA-SA	PSO-SA	DE-SA	Homogeneity method [20]
Image-01	0.2900	0.4345	0.2197	0.3271
Image-02	0.2431	0.2327	0.2321	0.2182
Image-03	0.3654	0.4683	0.1321	0.2198
Image-04	0.3789	0.6432	0.2761	0.3019
Image-05	0.2341	0.4321	0.1843	0.1726
Image-06	0.4521	0.5431	0.3469	0.4271
Image-07	0.3416	0.4598	0.3457	0.3981
Image-08	0.3745	0.3367	0.3098	0.3021
Image-09	0.4242	0.4321	0.3834	0.3910
Image-10	0.5343	0.5321	0.5378	0.5291
Image-11	0.4636	0.4264	0.3524	0.3761
Image-12	0.5325	0.4532	0.4352	0.4398
Image-13	0.3245	0.3521	0.3142	0.3519
Image-14	0.5325	0.4823	0.5523	0.5871
Image-15	0.5874	0.5432	0.5281	0.5421

Table 3 Average values for segmented images

Image	Average value			
	Genetic algorithm	Particle swarm optimization	OptiMUSIG activation function with DE	Differential evolution
Image-01	139.5	136.8	133.4	**132.4**
Image-02	136.3	137.0	**134.3**	135.3
Image-03	132.5	129.5	130.1	**129.6**
Image-04	131.2	130.2	129.2	**128.4**
Image-05	125.7	124.3	**121.3**	122.8
Image-06	132.4	133.1	130.9	**130.5**
Image-07	130.2	129.7	129.4	**129.0**
Image-08	134.7	133.8	132.8	**132.1**
Image-09	128.7	127.3	124.2	**123.6**
Image-10	142.2	141.3	**139.4**	140.2
Image-11	139.3	137.4	135.9	**135.2**
Image-12	126.3	**124.3**	125.4	125.3
Image-13	143.2	144.2	143.1	**142.7**
Image-14	123.4	122.1	120.2	**119.8**
Image-15	134.8	132.4	132.1	**131.4**

Table 4 Test statistics (Friedman test)

N	15
Chi-square	32.040
Df	3
Asymp. Sig.	0.000

Table 5 Ranks

		Mean rank
1	GA	3.80
2	PSO	2.93
3	DE	1.33
4	OptiMUSIG DE	1.93

7.2 Analysis of quality evaluation

To evaluate the quality of segmented image, a method has described by Kim et al. [16], is considered. Here, the evaluation function F_q is defined as.

$$F_q = \sqrt{R} \times \sum_{i=1}^{R} \frac{e_i^2}{\sqrt{A_i}} \tag{9}$$

Where I is original image, R is regions in the resulted image, A_i is pixels in ith region, e_i is colour error in region i, e_i is defined as the Euclidean distance of the colour vectors between the output image and the input image of each pixel in image. F_q is normalized with a factor of 1/260. The smaller the value of F_q, the better will be the segmentation. The average value of F_q is given in Table 3.

Comparison of output images is done with a well-known method OptiMUSIG activation function [1]. OptiMUSIG activation function has a very good performance based on the GA; in this paper we have used DE instead of GA. Performance measured is shown in Table 3.

Table 3 shows the performance evaluation or quality evaluation described in Sect. 7.2. Function described is considering all the values related to original image, regions related to resulted image, information of a particular pixel and error related to particular colour region. Resultant shows that a minimum value shows a better performance. Table 3, clearly shows that DE performs much better in comparison of other metaheuristics algorithms.

7.3 Statistical analysis

7.3.1 Friedman test

Data available in Table 1 fulfill all the conditions which have a requirement of Friedman Test. So we have

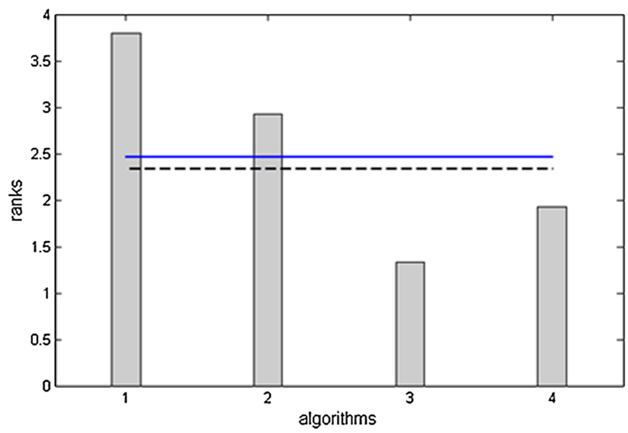


Fig. 2 Bonferroni *Dunn bar* chart for Table 4. The *Bar* present rank of correspondence algorithm and *Horizontal cut lines* shows the significant level

performed Friedman test. The next Table 4 shows the Ranks and Table 5 shows all other values computed by Friedman Test.

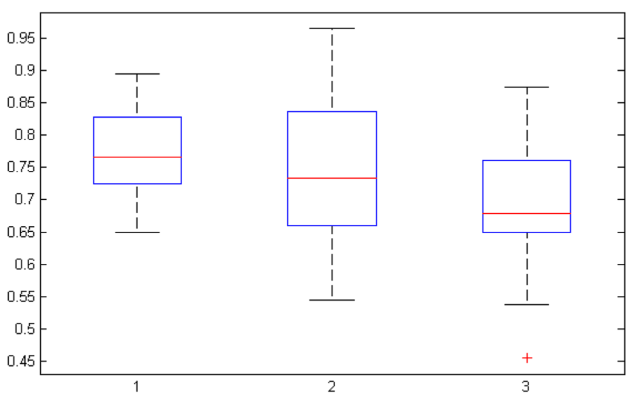


Fig. 3 *Boxplot* for Table 1, *X*-axis having values *1*, *2*, and *3* shows algorithms corresponding to GA, PSO and DE respectively

Figure 2 shows the result of Bonferroni-Dunn's test performed on the basis of ranks available in Table 4 computed with Friedman test. The horizontal line shown in this bar graph represents a threshold value. Algorithm having a bar above this horizontal line is a worst performer and below this line is a good performer. So, it is very clear that DE and OptiMUSIG with DE outperforms the other algorithms.

Figure 3, shows boxplot for the data available in Table 1 based on histogram difference minimization. This shows that DE is more robust and efficient for minimizing

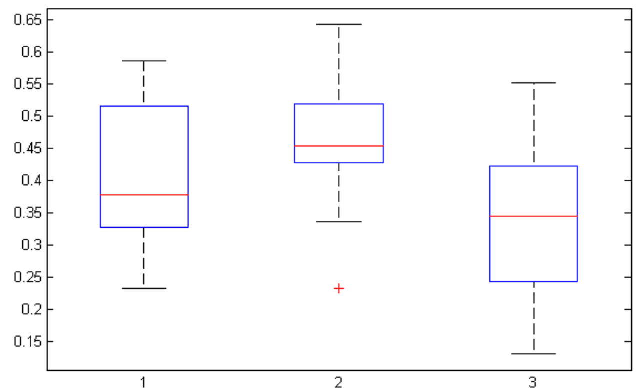


Fig. 4 *Boxplot* for Table 2, *X*-axis having values *1*, *2*, *3* and *4* shows algorithms corresponding to GA, PSO and DE

the histogram difference in comparison to GA and PSO in the present study.

Figures 4 represents a boxplot for CPU Time consumed by GA, PSO and DE which clearly shows that DE is performing better than others. In boxplot *X*-axis having a value '1' represents GA-SA '2' shows PSO-SA and '3' represents DE-SA.

7.4 Graphical results

Experiments are performed on a set of 100 images; out of 100 only 15 images are taken here. Images are taken from Berkley database. Results are shown here for all the algorithms. (A) Represents the original image taken from database. (B) Represents the result of segmented image by Genetic Algorithm, (C) by Particle Swarm Optimization and (D) by Differential Evolution Algorithm (Fig. 5).

All the images have the corresponding histograms on the right hand side. Representation of the images is very clear having a number system. As the results associated with Image-01 completed, next results will start for Image-02 and so on.

8 Summary

In the present study a novel objective function is suggested for colour image segmentation. The problem is formulated as a minimization problem and is solved using DE, PSO and GA and the corresponding variants are called GA-SA, PSO-SA and DE-SA. Various performance metrics like CPU time, quality evaluation are considered for evaluating the algorithms. Statistical

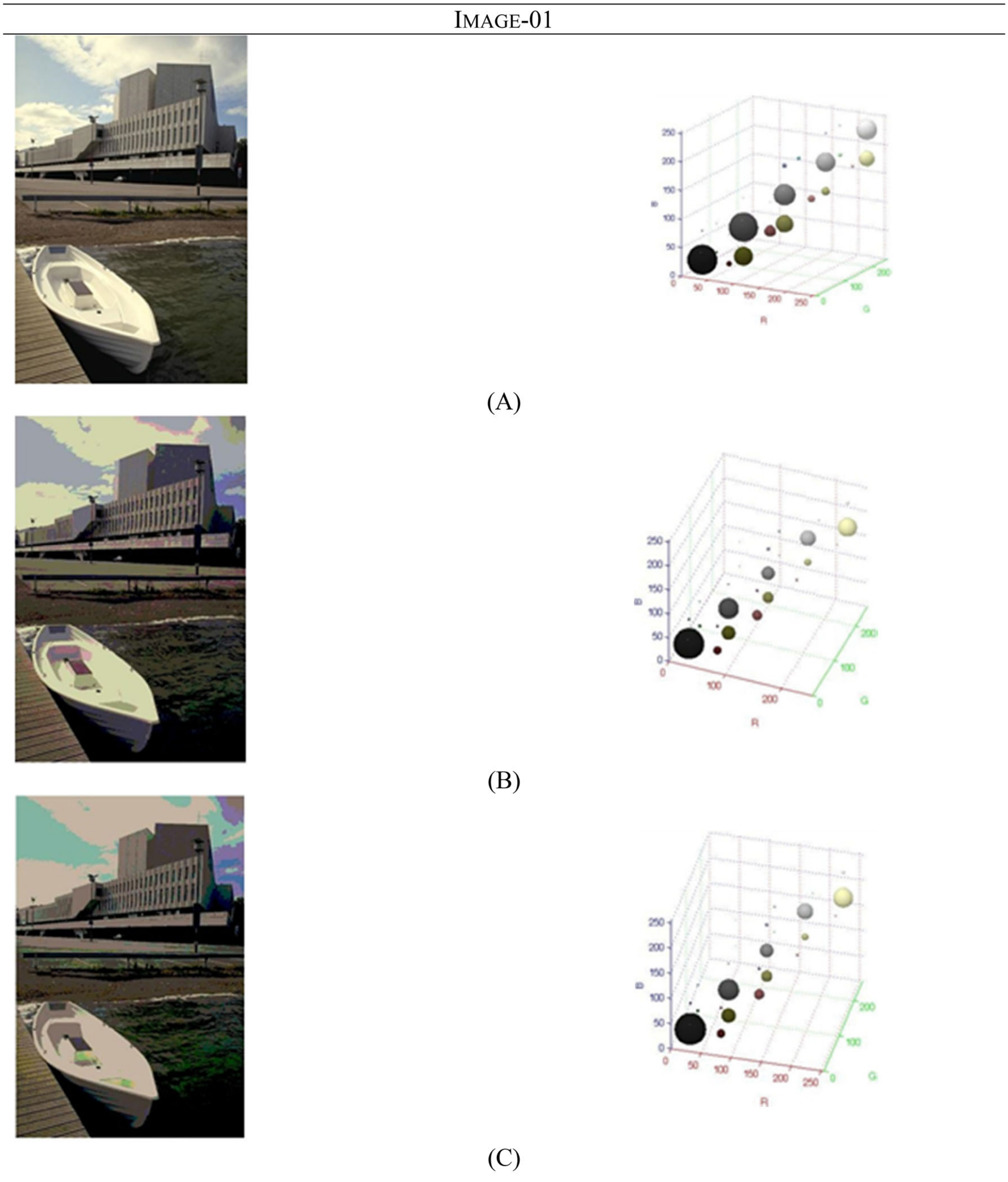
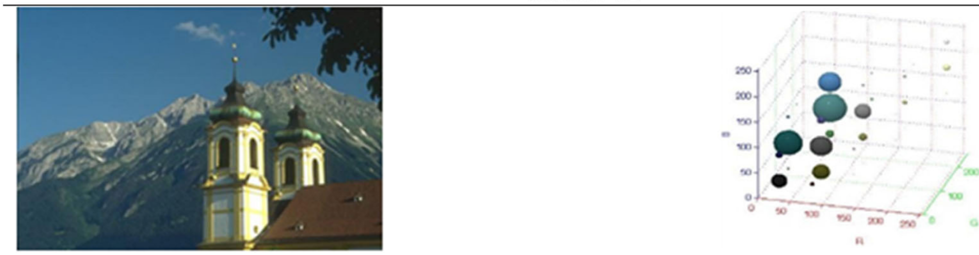


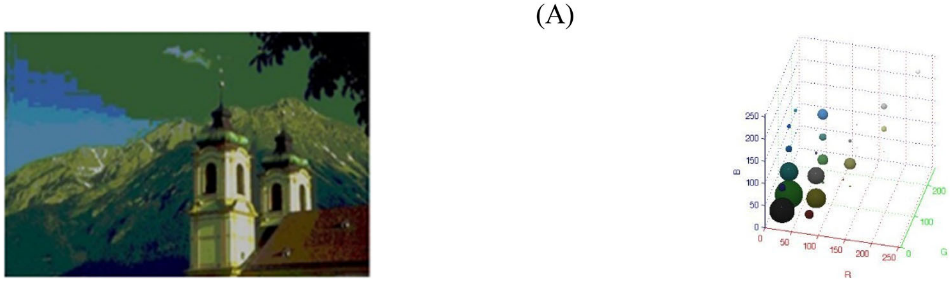
Fig. 5 **a** Original image, **b**, **c** and **d** segmented image with genetic algorithm, particle swarm optimization and differential evolution

(D)

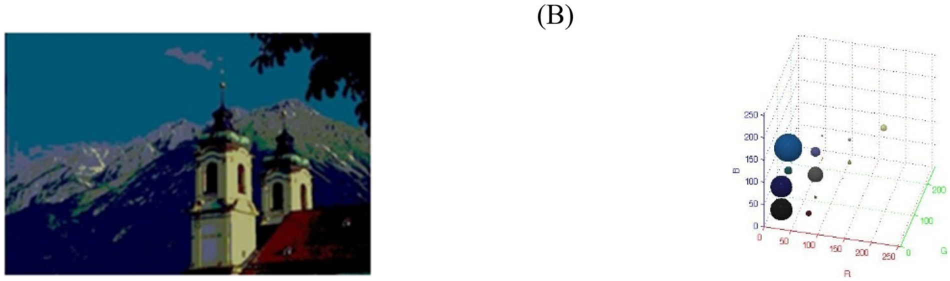
IMAGE-02



(A)



(B)



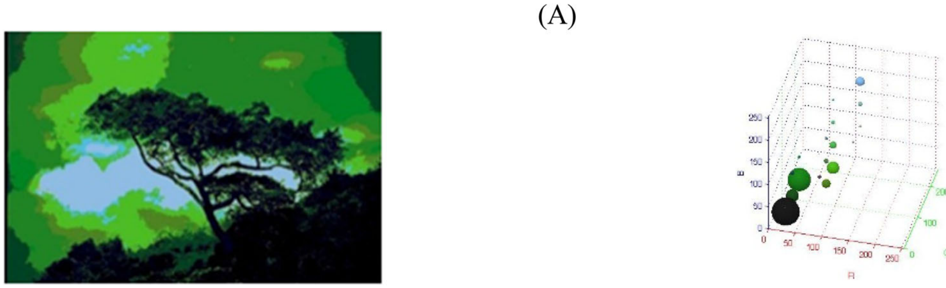
(C)

Fig. 5 continued

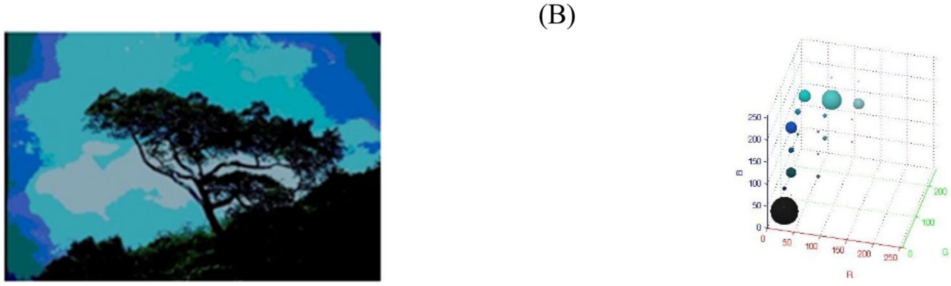
(D)

IMAGE-03

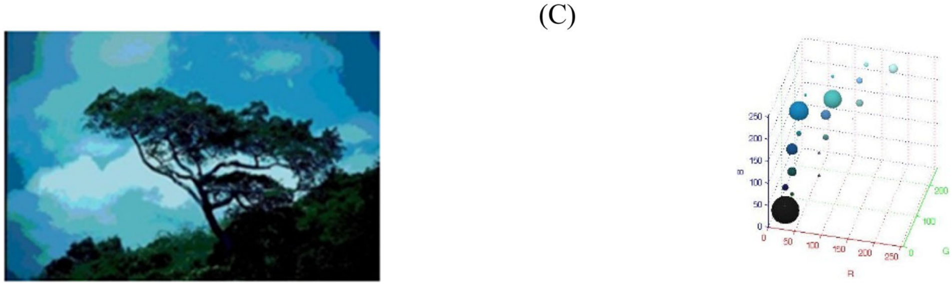
(A)



(B)



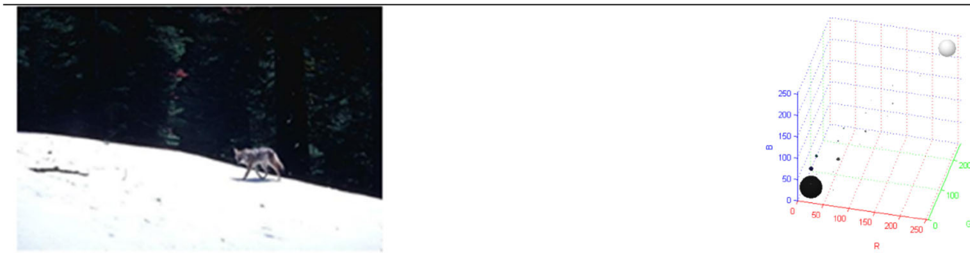
(C)



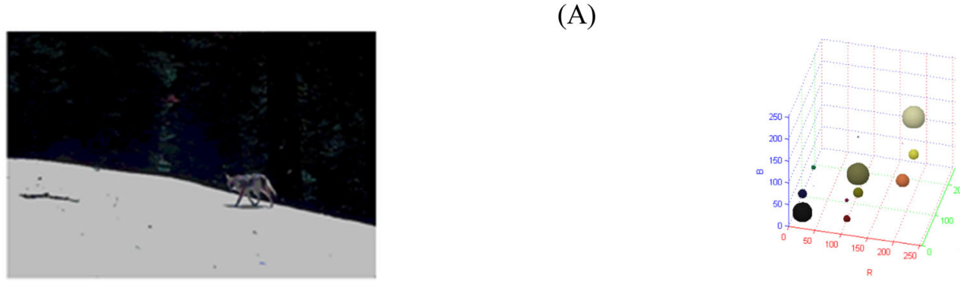
(D)

IMAGE-04

Fig. 5 continued

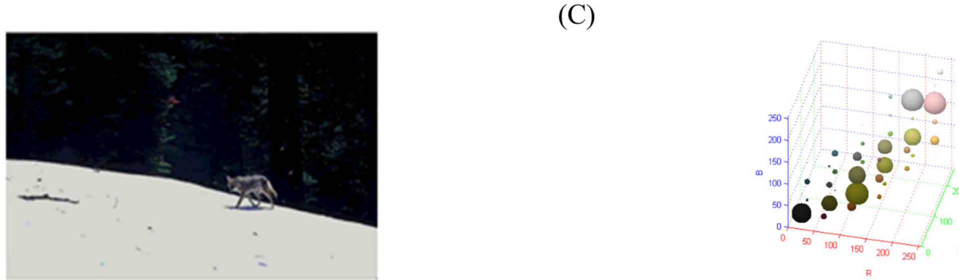


(A)



(B)

(C)



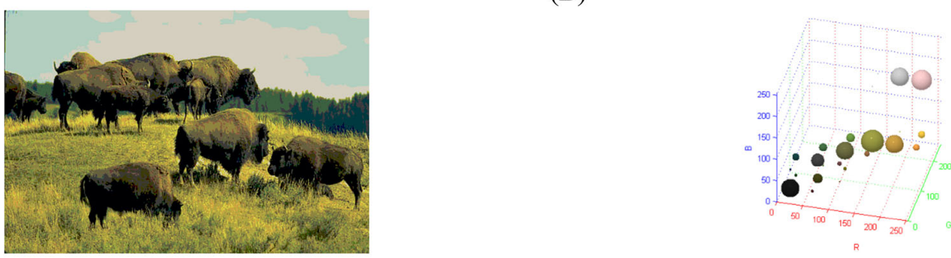
(D)

IMAGE-05

(A)

Fig. 5 continued

(B)

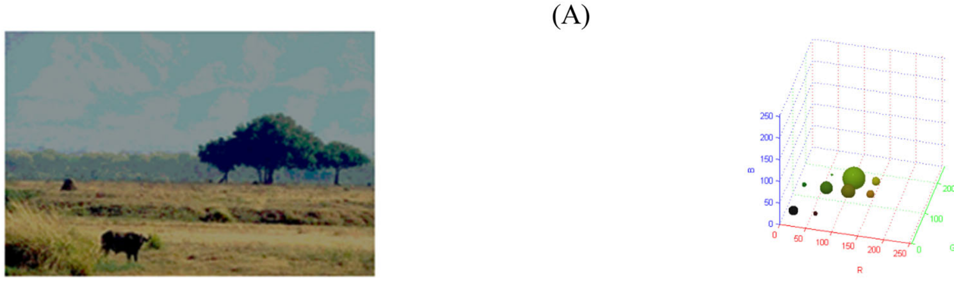


(C)

(D)

IMAGE-06

(A)



(B)

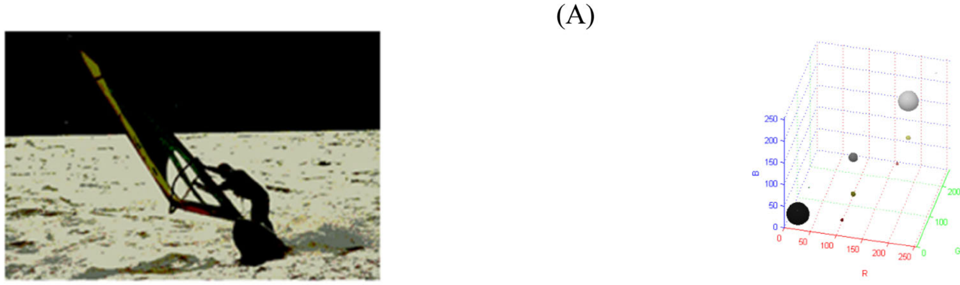
Fig. 5 continued

(C)

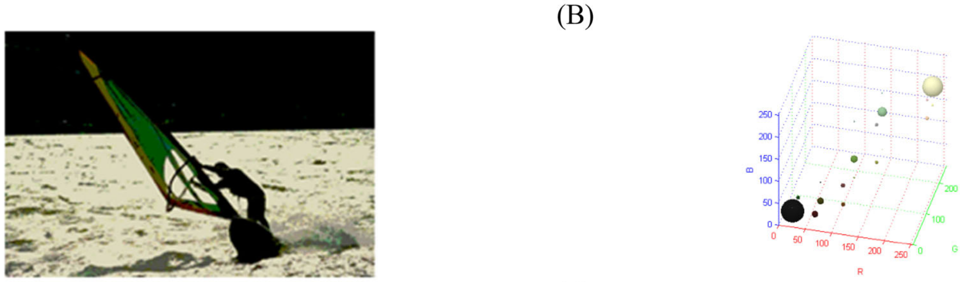
(D)

IMAGE-07

(A)



(B)



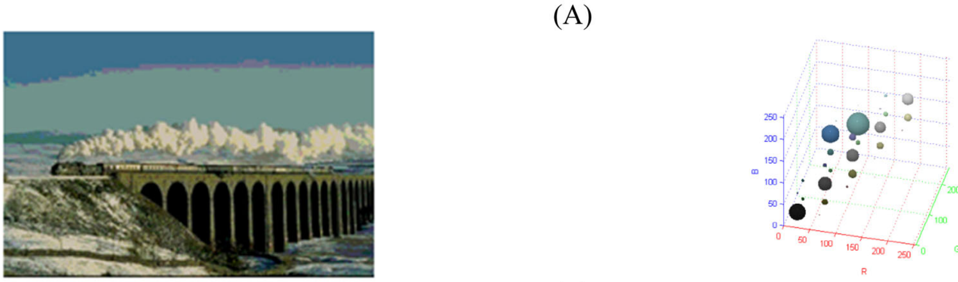
(C)

Fig. 5 continued

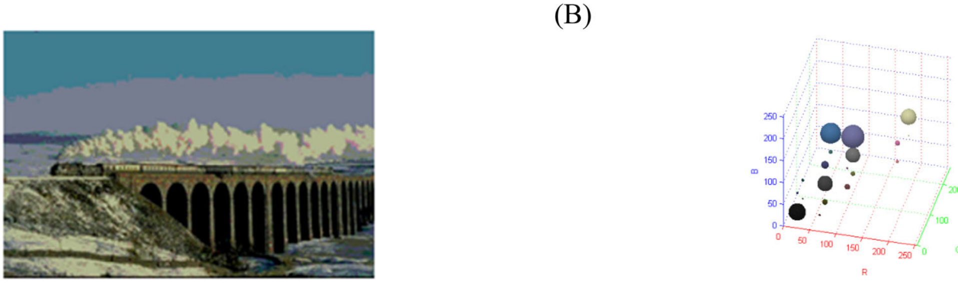
(D)

IMAGE-08

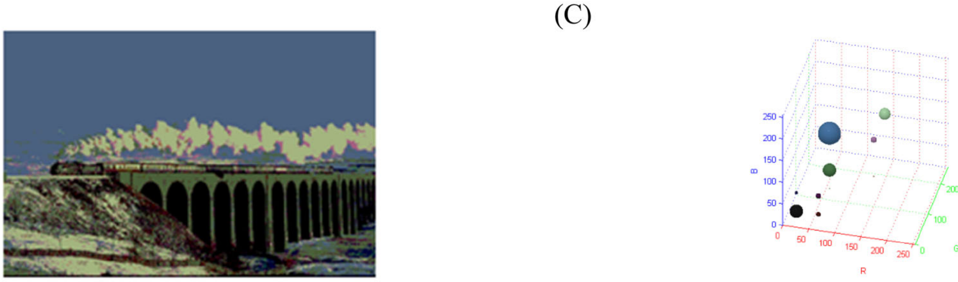
(A)



(B)



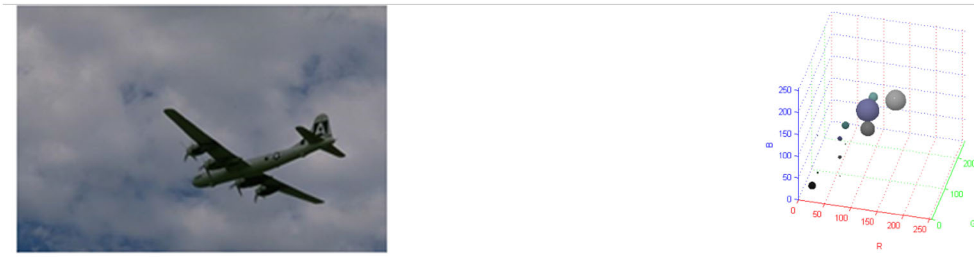
(C)



(D)

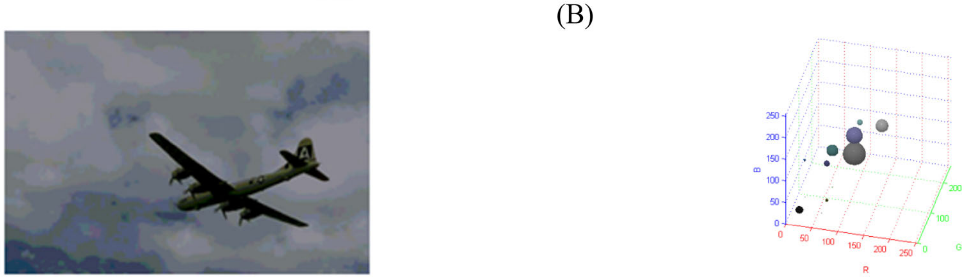
IMAGE-09

Fig. 5 continued

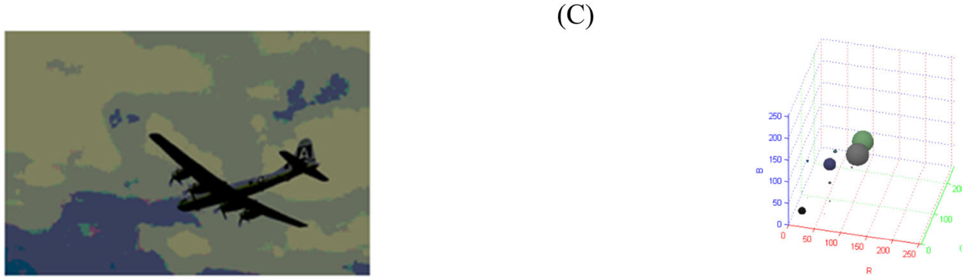


(A)

(B)



(C)

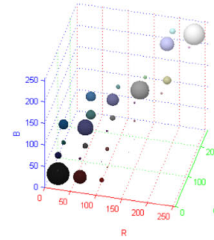


(D)

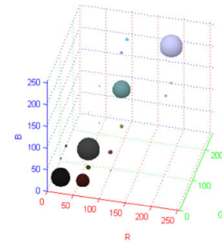
IMAGE-10

(A)

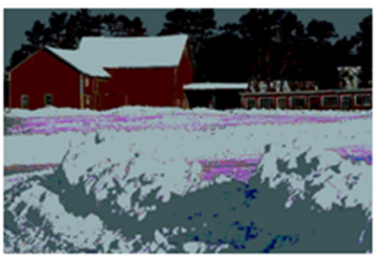
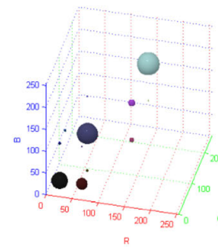
Fig. 5 continued

(B)

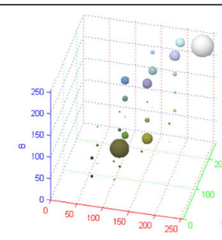



(C)

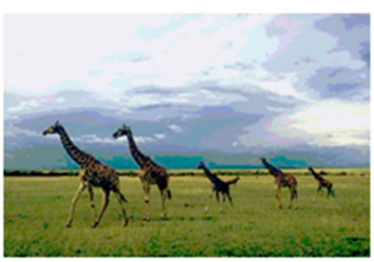
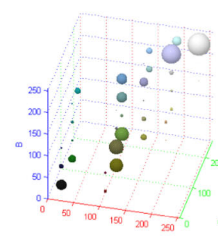



(D)

IMAGE-11

(A)

(B)

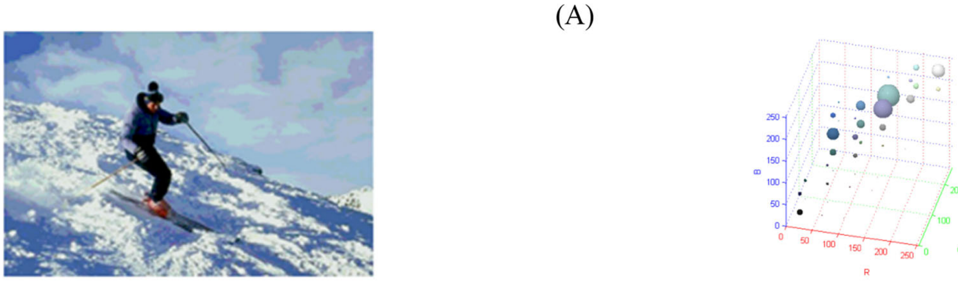
Fig. 5 continued

(C)

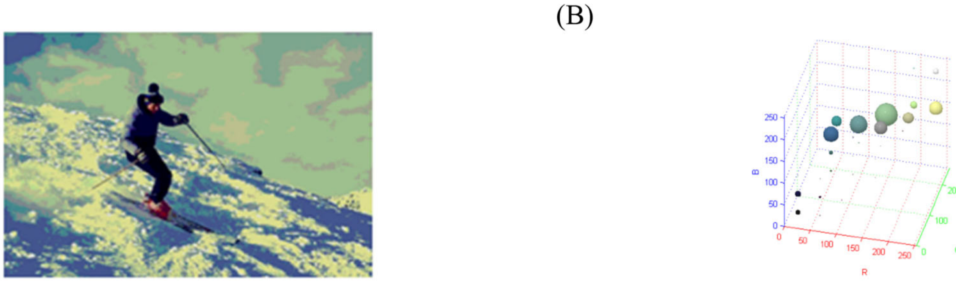
(D)

IMAGE-12

(A)



(B)



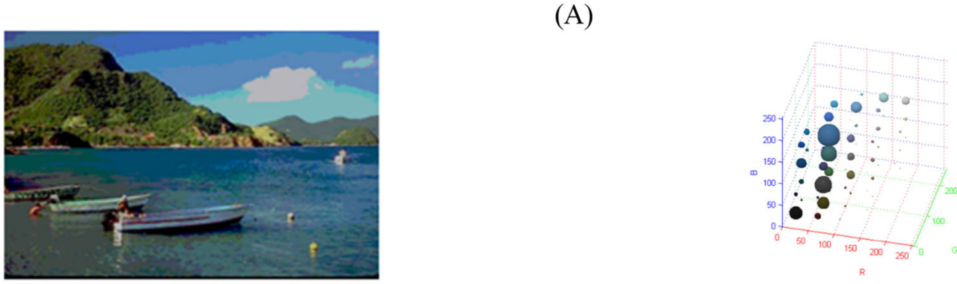
(C)

Fig. 5 continued

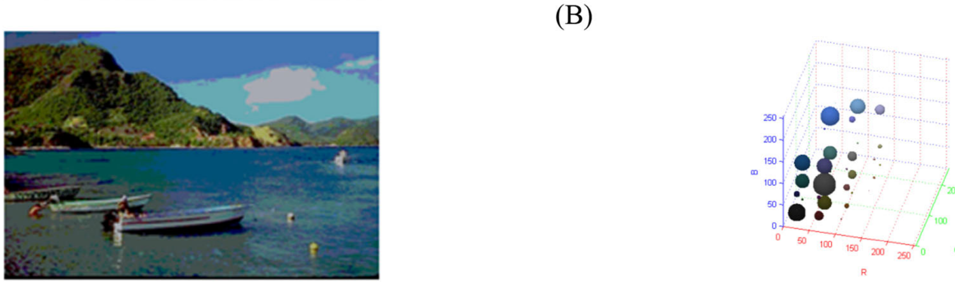
(D)

IMAGE-13

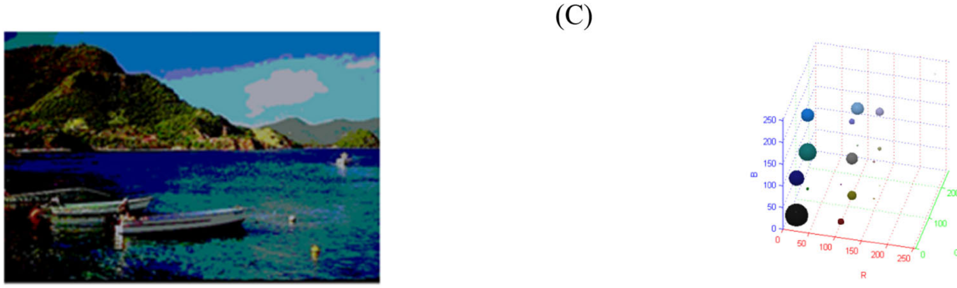
(A)



(B)



(C)

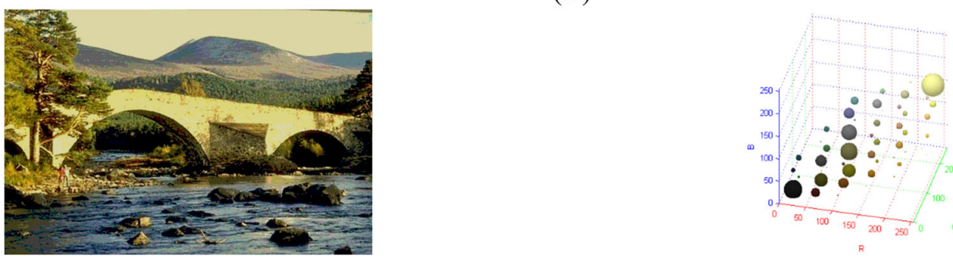


(D)

IMAGE-14

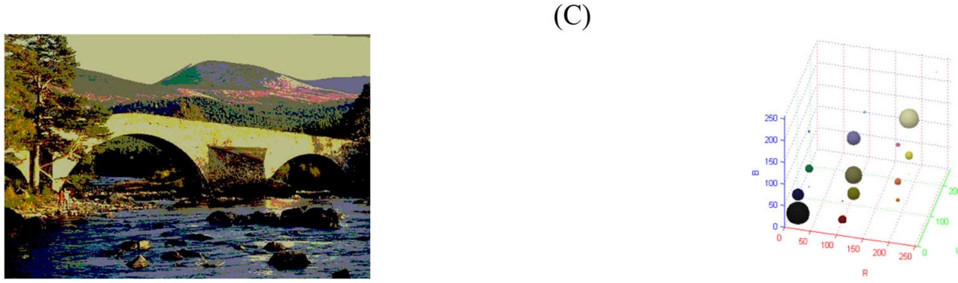
Fig. 5 continued

(A)



(B)

(C)



(D)

IMAGE-15

(A)

Fig. 5 continued

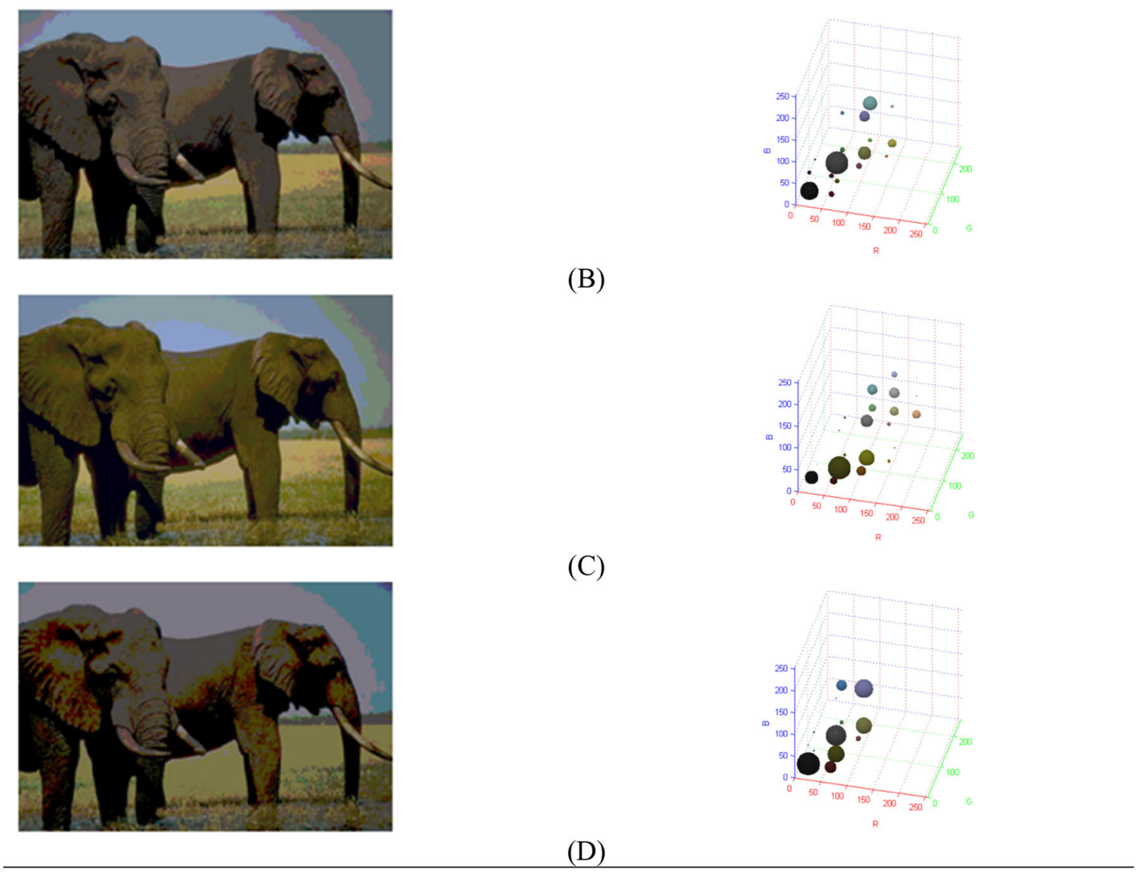


Fig. 5 continued

analysis also done to further analyze the algorithms. All the results and analysis indicates that the proposed objective function is a good option for colour image segmentation and DE is the best metaheuristic for optimizing it.

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