CrossMark

ORIGINAL ARTICLE

# DE-IE: differential evolution for color image enhancement

**Sushil Kumar · Millie Pant · Amiya Kumar Ray**

**Abstract** Color images are not ready to provide a desired
value of information because of illumination or some other
conditions like settings of the captured instrument. So for
improving the quality of color images and making them a
good source of information an improvement of quality is
desired sometimes. To improve the quality of an existing
image or extract some features from a degraded image;
image enhancement techniques are used. Many conven-
tional algorithms are available for color image enhance-
ment; some of them are based on linear gain adjustments.
These algorithms will provide a limited improvement in an
image. For making an overall improvement in an image
many algorithms are advised based on genetic algorithm
and particle swarm optimization. It is very well known that
differential evolution is a very robust and simple algorithm
for optimization. 1D histogram technique of image
enhancement takes information about the pixel value and
manipulates it to a required output value according the
problem nature. Some relevant information of the pixel is
not considered in 1D histogram technique; 2D histogram
will be design considering all the relevant information
around the pixel and manipulate it to an output pixel value
according this information. Each pixel will behave like a
member of population for differential evolution and
manipulated on the basis of best value. Results show a
significant and considerable change in output image. In this
paper a new algorithm with differential evolution is
proposed.

## 1 Introduction

Encouraged by the performance of DE for image seg-
mentation (Kumar et al. 2011; Aslantas and Tunckanat
2007), in the present paper, it is studied for Image
Enhancement; another important aspect of image process-
ing. Since DE gave good results for color image segmen-
tation (Aslantas and Tunckanat 2007), in the present paper
it is used for enhancement of colored images only.

One of the problems with color images is that, these are
not ready to provide a desired value of information because
of illumination or some other conditions like settings of the
captured instrument. Therefore, for improving the quality
of color images and making them a good source of infor-
mation an improvement of quality is desired sometimes. To
improve the quality of an existing image or in order to
extract some features from a degraded image; image
enhancement techniques are used. There are several
methods available in literature for image enhancement for
example: Some vector median filters were proposed by
Astola et al. (1990) for color contrast enhancement. A color
contrast enhancement algorithm proposed by Starck et al.
(2000). Zaharescu et al. (2003) proposed a color contrast
enhancement algorithm. Cohen-Or et al. (2006) proposed a
method based on color harmonization for color image
enhancement. A structured color light can form a 3-D

S. Kumar (✉) · M. Pant · A. K. Ray
Indian Institute of Technology Roorkee, Roorkee, India
e-mail: kumarsushiliitr@gmail.com

M. Pant
e-mail: millifpt@iitr.ac.in

A. K. Ray
e-mail: akrayfpt@iitr.ac.in

shape for a 3-D object; for cameras this technique was proposed by Chen et al. (2008). Chiu et al. (2011); Huang and Yeh (2013) and proposed image correction affects from various factors.

In this paper a new variant inspired from DE called Differential Evolution for Image Enhancement (DE-IE) is proposed. Though, the proposed DE-IE is inspired from DE, there are certain features making it different from the basic DE. In DE-IE, the initial population is the probability density function of the input pixels. Secondly, DE-IE uses only the mutation operator in an adaptive manner. Due to robustness and performance of the algorithm it is very easy to select the best pixel value for the image.

A literature review for color image enhancement is as follows:

| Author (publication year) | Brief description |
| --- | --- |
| Shyu and Leou (1998) | Color image enhancement is formulated as an optimization problem and evaluation is done by genetic algorithm approach |
| Tao et al. (2003) | Proposed a GA based three level thresholding methods for image segmentation. They portioned the image in three basic parts as: dark, gray and white and then implemented fuzzy region as Z-function, P-function and S-function respectively. GA are used to find an optimal solution for all the fuzzy parameters |
| Zahara et al. (2005) | Proposed a hybrid optimization technique called NM–PSO–Otsu method (Otsu's method with Nelder–Mead simplex search and PSO) and NM–PSO-curve method (Gaussian curve fitting by Nelder–Mead simplex search and PSO) |
| Feng et al. (2005) | Applied PSO for 2-D maximum entropy method to optimize the fitness function developed with the help of 2-D histogram. PSO provides the threshold values as local average intensity of pixels |
| Huang et al. (2006) | Natural color image enhancement and evaluation algorithm based on human visual system |
| Jiang et al. (2007) | Proposed a method for micro calcification of clusters in digital mammograms based on GA. In this method a window of size $9 \times 9$ compute mean and standard deviation for each pixel. These computed values of pixels behave like chromosomes for initial population GA detect micro calcification clusters with an optimized way. This method outperforms in comparison of traditional methods |

| Author (publication year) | Brief description |
| --- | --- |
| Nakib et al. (2007) | Considered Gaussian distribution's parameter selection as a nonlinear optimization problem and solved it with new variant of DE called low-discrepancy sequences and a local search (LDE).The proposed method outperforms in comparison to traditional methods for multilevel thresholding |
| Fan and Lin (2007) | Proposed (PSO + EM) algorithm for estimation of Gaussian's parameters. PSO employed for global search and the best particle was updated through expectation maximization (EM). PSO + EM were applied for multilevel image thresholding |
| Tao et al. (2007) | Object segmentation using ant colony optimization algorithm and fuzzy entropy |
| Chung et al. (2008) | Efficient edge-preserving algorithm for color contrast enhancement with application to color image segmentation |
| Li and Li (2008) | Fuzzy entropy image segmentation based on particle swarm optimization |
| Hammouche et al. (2008) | Proposed a wavelet transform method combined with GA. This method reduced the original length of histogram using wavelet transform; GA is used to select the number of thresholds and values of thresholds in this reduced histogram |
| Coelho et al. (2009) | Proposed a chaotic differential evolution schemes for image enhancement. The fitness function is maximized for enhancing the contrast and details of the image by adapting the parameters using a contrast enhancement technique |
| Hashemi et al. (2010) | Proposed a contrast enhancement technique based on GA where chromosome representation is simple and novel together with corresponding operators. Using this method natural look of the images is preserved in comparison of other contrast enhancement methods especially for high dynamic images |
| Zhang et al. (2010) | Proposed an undecimated wavelet transform (UWT) with GA for typhoon cloud enhancement. Modifying the undecimated wavelet coefficients make it efficient to reduce the noise in typhoon cloud image. GA is used for modifying the UWT coefficient efficiently |
| Horng (2010) | Multilevel minimum cross entropy threshold selection based on the honey bee mating optimization |

| Author (publication year) | Brief description |
|---|---|
| Sathya and Kayalvizhi (2011) | Modified bacterial foraging algorithm based multilevel thresholding for image segmentation |
| Fernández-Caballero et al. (2011) | Real-time human segmentation in infrared videos |
| Chander et al. (2011) | Proposed a variant of PSO for multilevel thresholding for reducing the complexity and computational time |
| Li et al. (2011) | Modified local entropy-based transition region extraction and thresholding |
| Celik et al. (2012) | A 2DHE (two dimensional histogram) approach is proposed for enhancing the image quality using contextual information around each pixel |
| Chen and Leou (2012) | Proposed a method of saliency-directed color image interpolation using particle swarm optimization (PSO) and artificial neural network (ANN). PSO is used for determining the weights in interpolation filtering masks and ANN is used to determine the orientation of each image pattern (block). It was shown that this method performs better for color image interpolation |
| Vahedi et al.(2012) | Proposed GA based watermarking approach for color images for copyright purposes |
| Verma et al. (2012) | High dynamic range optimal fuzzy color image enhancement using Artificial Ant Colony System |
| Masra et al. (2012) | Proposed a Histogram Equalization (HE) method based on Particle Swarm Optimization (PSO). Images are split in red green and blue (RGB) channels and PSO finds the best fitness value for each channel. |
| Tsai et al. (2012) | Image enhancement filter named DPSM (Decision tree, Particle swarm optimization, and Support vector regression Median-type filter) |
| Lee et al. (2012) | Proposed a modified PSO for extracting high-level image semantics depending upon the color, intensity and orientation |
| Ghamisi et al. (2012) | An efficient method for segmentation of images based on fractional calculus and natural selection |
| Shanmugavadivu and Balasubramanian (2013) | Otsu method is used for converting the image into two sub-images and formulates a fitness function based on these sub-images. For optimal solution PSO is used which provide better solution |
| Kwok et al. (2013) | Proposed a multi-objective PSO for correcting the color effect and for balancing all effects regarding the scene and environment |
| Hoseini and Shayesteh (2013) | Proposed an evolution based contrast enhancement technique embedded of three techniques named GA, Ant Colony Optimization (ACO) and Simulated Annealing (SA). Input intensities to the output intensities were mapped through ACO, and then SA worked as local search methods for modifying the transfer functions. The processed ants worked as chromosome for GA |
| Zhong et al. (2013) | Image enhancement based on wavelet transformation and pseudo-color coding with phase-modulated image density processing |
| Lan and Zeng (2013) | Multi-threshold image segmentation using maximum fuzzy entropy based on a new 2D histogram |
| Osuna-Enciso et al. (2013) | Successfully applied 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 gray level image segmentation |
| Kumar et al. (2013) | MRLDE, PSO and ABC are successfully applied for bi-level thresholding embedded with Otsu method |

## 2 Proposed algorithm

A 1D histogram does not consider all the local information near a pixel; so a 2D histogram will be constructed for image enhancement. Suppose there is an input image $\chi = \{x(i,j)|1 \leq i \leq M, 1 \leq j \leq N\}$ of size $M \times N$ and there is an enhanced or output image $\gamma = \{y(i,j)|1 \leq i \leq M, 1 \leq j \leq N\}$. For image enhancement a target will be achieved from an input image to output image; making some significant changes like compression and enhancement. For an input image $\chi$ pixel values having a dynamic range $x(i,j) \in [x_l, x_u]$ will produce a target value $[y_l, y_u]$ for an output image $\gamma$.

For designing a 2D histogram a window $w$ is considered; sort the values of pixels for input image $X_s = \{x_1, x_2, \ldots x_n\}$, for an input image $\chi$, where pixels $x_1, x_2, \ldots x_n$ are in a sorted form as $x_1 < x_2 < \ldots x_n, \quad x_1 = x_l, x_n = x_n$. 2D histogram will be expressed as follows:

$$H_x = \{h_x(s,t)|1 \leq s \leq n, 1 \leq t \leq n \tag{1}$$

$$h_x(s,t) = \sum_{\forall i} \sum_{\forall j} \sum_{n=-\lfloor w/2 \rfloor}^{\lfloor w/2 \rfloor} \sum_{m=-\lfloor w/2 \rfloor}^{\lfloor w/2 \rfloor} \varphi_{m,n}(x(i,j),$$
$$x(i+n,j+m))(|x_k - x_l| + 1), \tag{2}$$

For computing 2D histogram a squared window of odd size $w$ is required for neighborhood pixels; the window will move throughout the image and will compute the values around each pixel. Occurrence of gray-level will be measured with functions $x(i, j)$ and $x(i + n, j + m)$ both are the values of $x_k$ and $x_l$ respectively. Both functions work on a similarity index such that if actual pixel value is similar to the computed value of that pixel, then it will be considered as '1' otherwise it will be considered '0'.

2D histogram $h_x(s, t)$ is normalized as:

$$h_x(s,t) = h_x(s,t) \bigg/ \sum_{i=1}^{K}\sum_{j=1}^{K} h_x(i,j) \tag{3}$$

Normalized values form a 2D histogram for an image. If the image has homogeneous regions then diagonal values for a 2D histogram are large. Homogeneous regions have similar values for most pixels in neighborhood, so the diagonal values show this similarity in the form of larger values. In 2D histogram if peaks are large around the diagonal, it represents white color or a large difference between $x_k$ and $x_l$, so a high intensity enhancement is required at these points.

Probability of original histogram is given as:

$$P_x(s) = \sum_{i=1}^{s}\sum_{j=1}^{t} h_x(i,j) \tag{4}$$

The main objective of 2D histogram is to represent the actual information of the image in a managerial way. Main diagonal represents the actual skeleton of the image and values around each pixel represent the homogeneity and dissimilarity. 2D histogram should be uniform for an enhanced image, so the main objective is to uniform the 2D histogram. Probability represented in Eq. (4) is pixel strength of a gray-level image.

Smoothing of 2D histogram provides better results for enhancement. A method is proposed by Celik et al. (2012), in which they have mentioned that minimum value of cumulative difference between distribution functions $P_x(s)$ and $P_x(s')$; where $P_x(s)$ and $P_x(s')$ are distribution functions of input image and target output image will replace the exact value of grey-level in the input image. In this method it is clearly mentioned that desired output image is considered according to grey-level; they have supposed that the output image has a range of grey-level from 0 to L; where 0 is considered as a lower grey-level value and L is considered as a higher grey-level value. So, an optimized value of grey-level will replace the exact value of input image.

In this article, a new technique based on DE is proposed for optimizing this target. The proposed strategy is particularly designed for image enhancement and its purpose is to enhance all the points so that no important information in the image is missed out. Because the range of target output

---

**Pseudo-code for image enhancement**

Consider $P_x(s)$ as initial population and $P_x(s')$ as a trial vector

Calculate mean value $\mu = \overline{P_x(s) + P_x(s')}\big/2$

$\quad if(|P_x(s) - P_x(s')|) \geq .8$

$\quad\quad F = .8$

$\quad else\ if .7 \leq (|P_x(s) - P_x(s')|) \leq .8$

$\quad\quad F = .7$

$\quad else\ if .6 \leq (|P_x(s) - P_x(s')|) \leq .7$

$\quad\quad F = .6$

$\quad else\ if .5 \leq (|P_x(s) - P_x(s')|) \leq .6$

$\quad\quad F = .5$

$\quad\quad Otherwise$

$\quad\quad F = .4$

$\quad\quad P_x(s^{de}) = F * \{P_x(s) - P_x(s')\}$

$\quad\quad end\ if$

$If(\mu \geq .5)$

$\quad\quad P_x(s^{de})$

$Else$

$\quad\quad P_x(s')$

$\quad end\ if$

**Fig. 1** Pseudocode of proposed differential evolution for image enhancement

image is available for each pixel, so this strategy will work for optimization based on the condition of output image pixels. Range of desired output will work as a conditional statement for enhancement. The proposed strategy tries to minimize the function till the desired output is reached. So, the resultant enhanced image is of good quality.

## 3 Image based population

DE uses an initial population as a search space. For this particular problem, the search space is made up of distribution probability $P_x(s)$ which will act as the initial population; here it is worth mentioning that the distribution probability of each pixel is known with the help of a window of size $w \times w$. Pseudocode for the proposed strategy is given in Fig. 1.

## 4 Analysis of proposed DE-IE

$F$ is a mutant factor which controls the diversity in classical DE algorithm. But in the proposed algorithm $F$ is playing a slightly different role. Here, $F$ works like a catalyst; if the difference of input image probability distribution function and output probability distribution function is high, it will be self-adaptive as seen the above algorithm. Suppose PDF1 (Probability
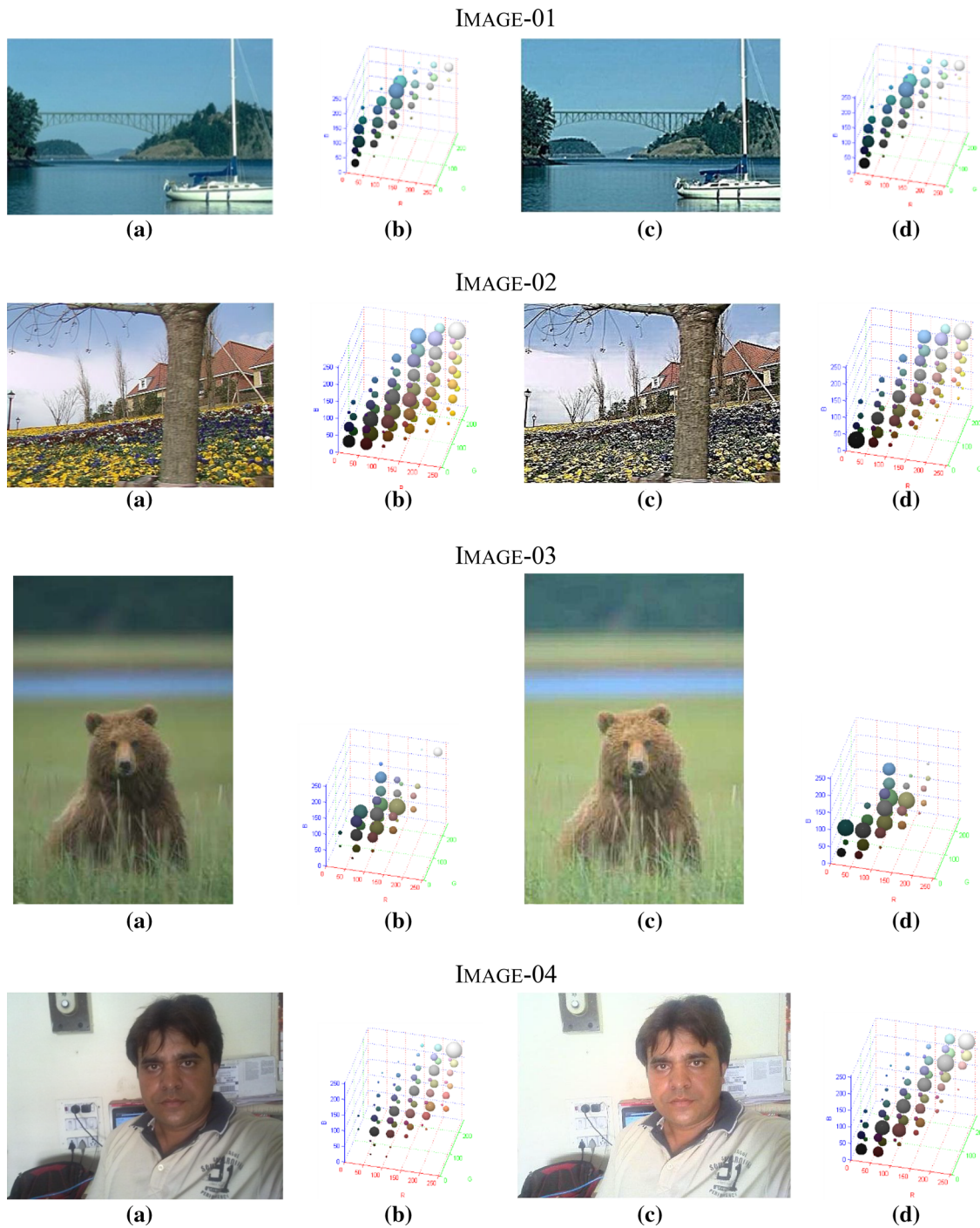
IMAGE-01



(a)  (b)  (c)  (d)

IMAGE-02



(a)  (b)  (c)  (d)

IMAGE-03



(a)  (b)  (c)  (d)

IMAGE-04



(a)  (b)  (c)  (d)

**Fig. 2** **a** Original image, **b** 3D histogram of input image, **c** Output enhanced image, **d** 3D histogram of output image

Density Function 1 for input image) and PDF2 (Probability Density Function 2 for output image) both have different values like 0.9 and 0.1, respectively, then difference between both values will be 0.8. In this case 1st condition of the algorithm will be applied where $F = .8$ and the product output will be 0.64. Mean value of PDF1 and PDF2 is $(0.9 + 0.1)/2 = 0.5$, so the output pixel value will be 0.64.

As we have seen in last example the desired output value is 0.1 and output from the algorithm is higher value 0.64 and vice versa. This suggested algorithm will work for one-by-one values of pixels. It will replace and pixels whenever it is required other the pixel value will be as it is in the input image. Consequently, it is expected to give better results.

IMAGE-05



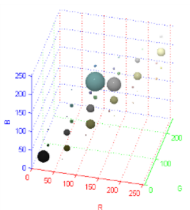(a)     (b)     (c)     (d)

IMAGE-06



(a)     (b)     (c)     (d)

IMAGE-07



(a)     (b)     (c)     (d)

IMAGE-08



(a)     (b)     (c)     (d)
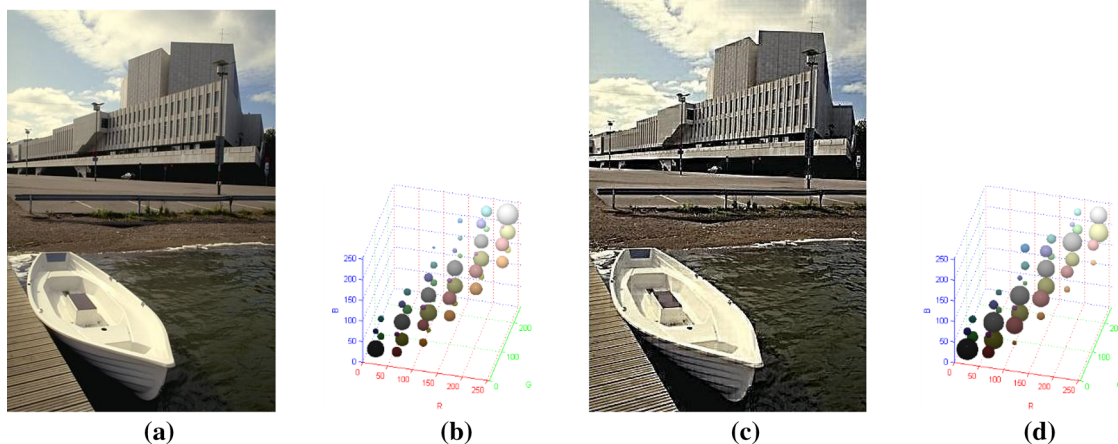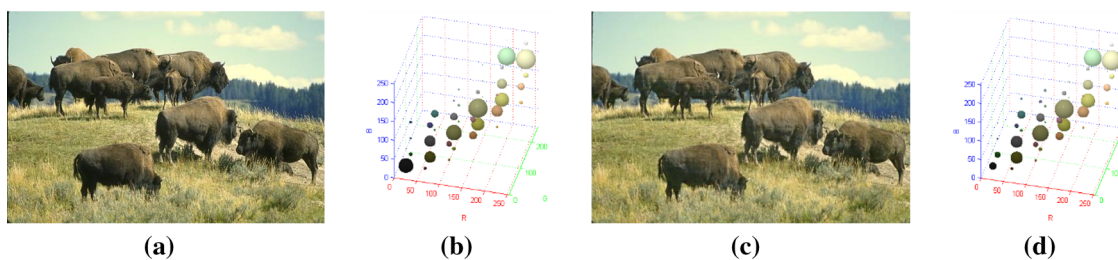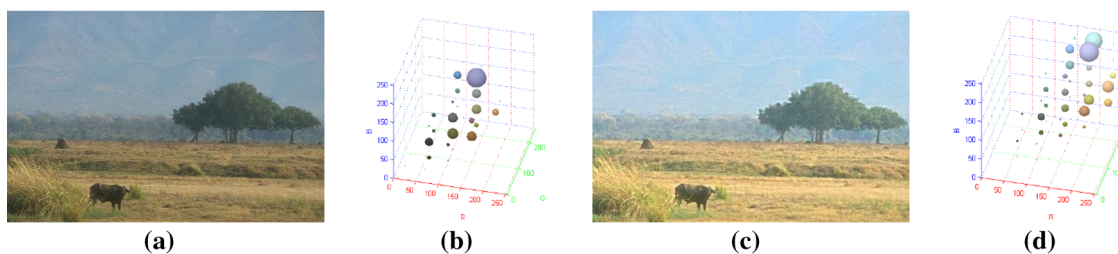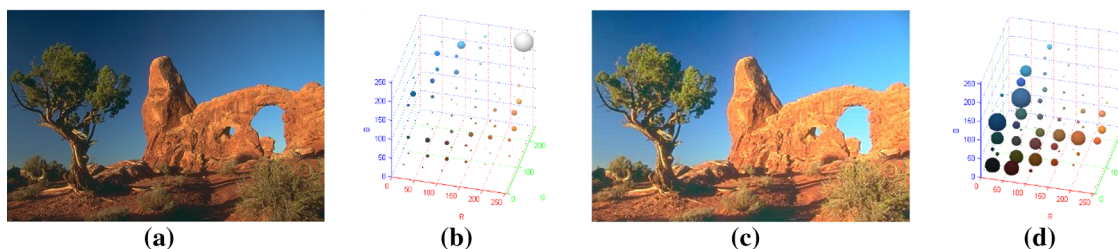
**Fig. 2** continued

If difference between probability distributions of input image and desired output image is large it depicts pixel value difference or dissimilarity; lower value of this difference depicts similarity of pixels. Enhancement is required when dissimilarity exists. With the above algorithm one can measure that if difference is higher, output pixel value will also be higher which produces a higher pixel value. This in turn indicates that the quality of the given image will visibly improve through enhancement. On the other hand, if difference is a small value then algorithm will produce a small value of output pixel resulting in small enhancement or in other words it can be said that the original image do not require more enhancement to improve its quality.

IMAGE-09
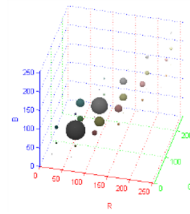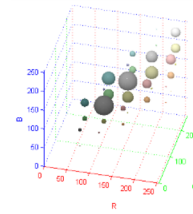


(a)     (b)     (c)     (d)

IMAGE-10
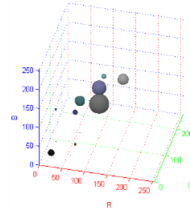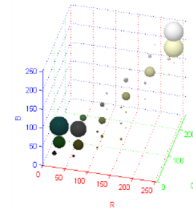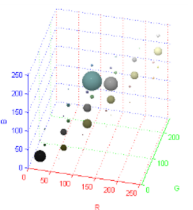


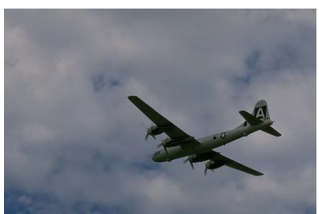(a)     (b)     (c)     (d)
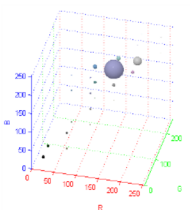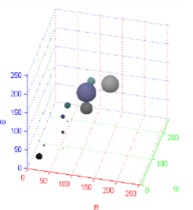
IMAGE-11
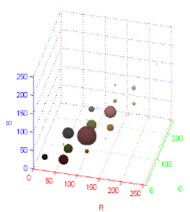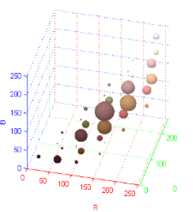


(a)     (b)     (c)     (d)

IMAGE-12



(a)     (b)     (c)     (d)
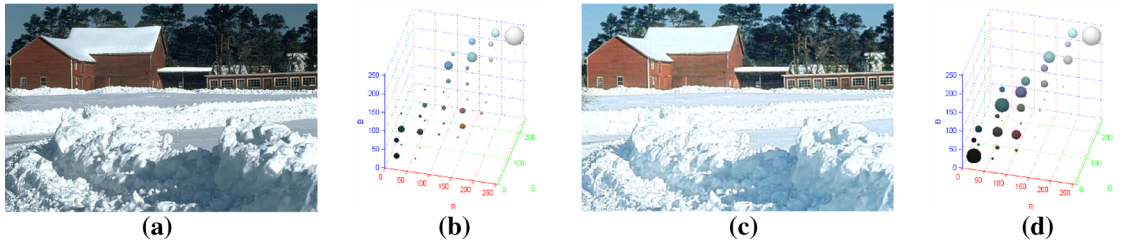
IMAGE-13



(a)     (b)     (c)     (d)

**Fig. 2** continued

IMAGE-14

(a)    (b)    (c)    (d)

IMAGE-15

(a)    (b)    (c)    (d)

IMAGE-16
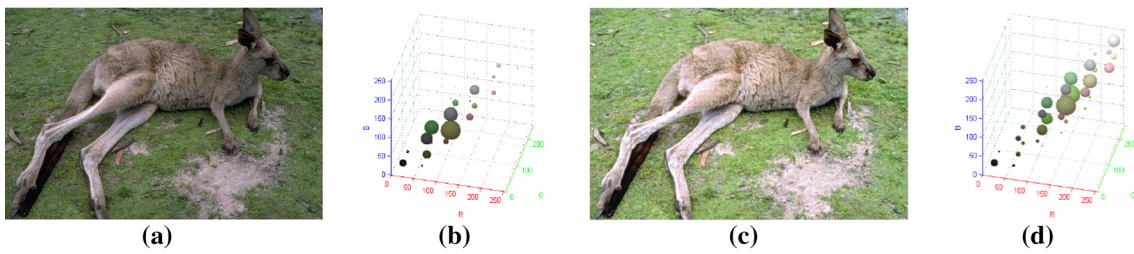
(a)    (b)    (c)    (d)

IMAGE-17

(a)    (b)    (c)    (d)
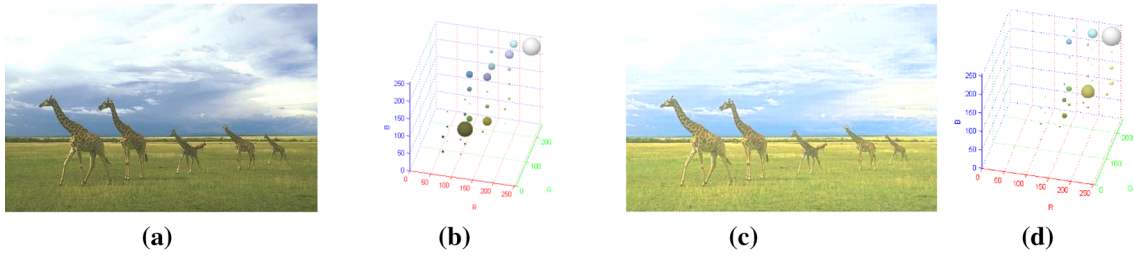
IMAGE-18

(a)    (b)    (c)    (d)
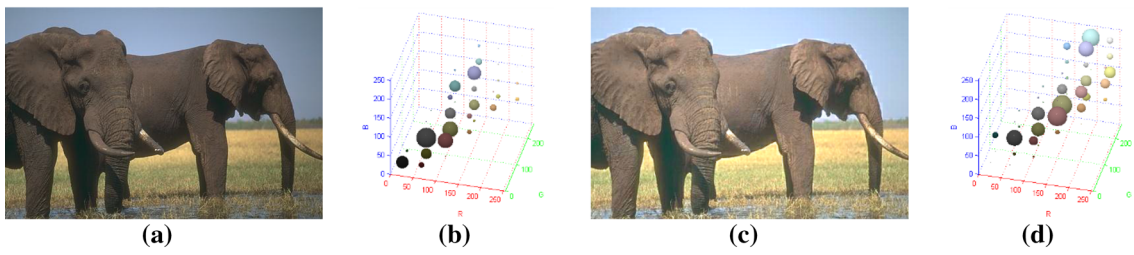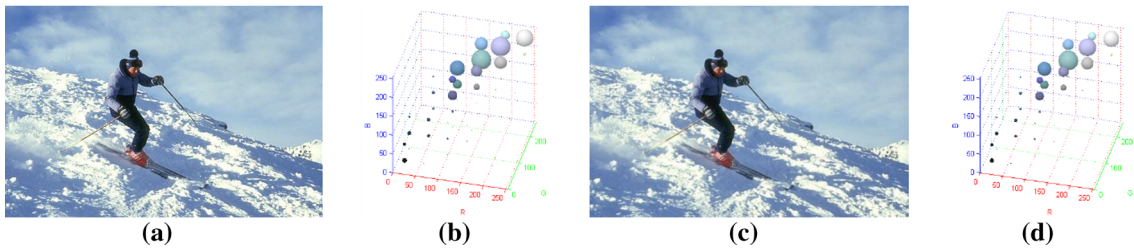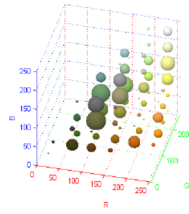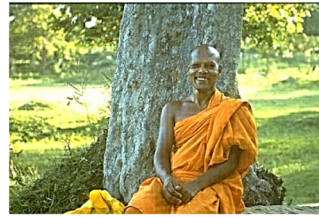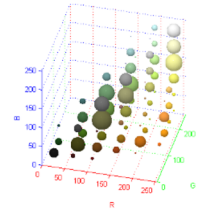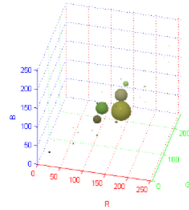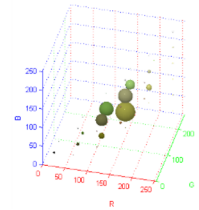
Fig. 2 continued
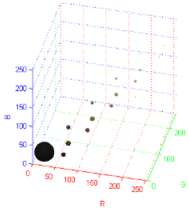
IMAGE-19



(a)     (b)     (c)     (d)
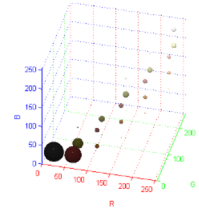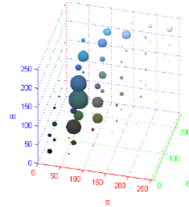
IMAGE-20



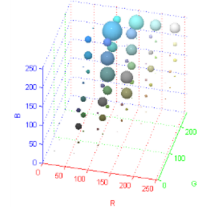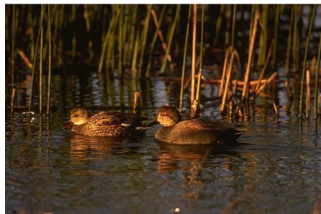(a)     (b)     (c)     (d)
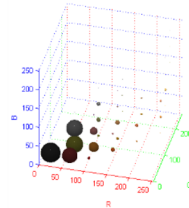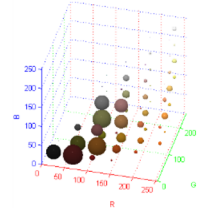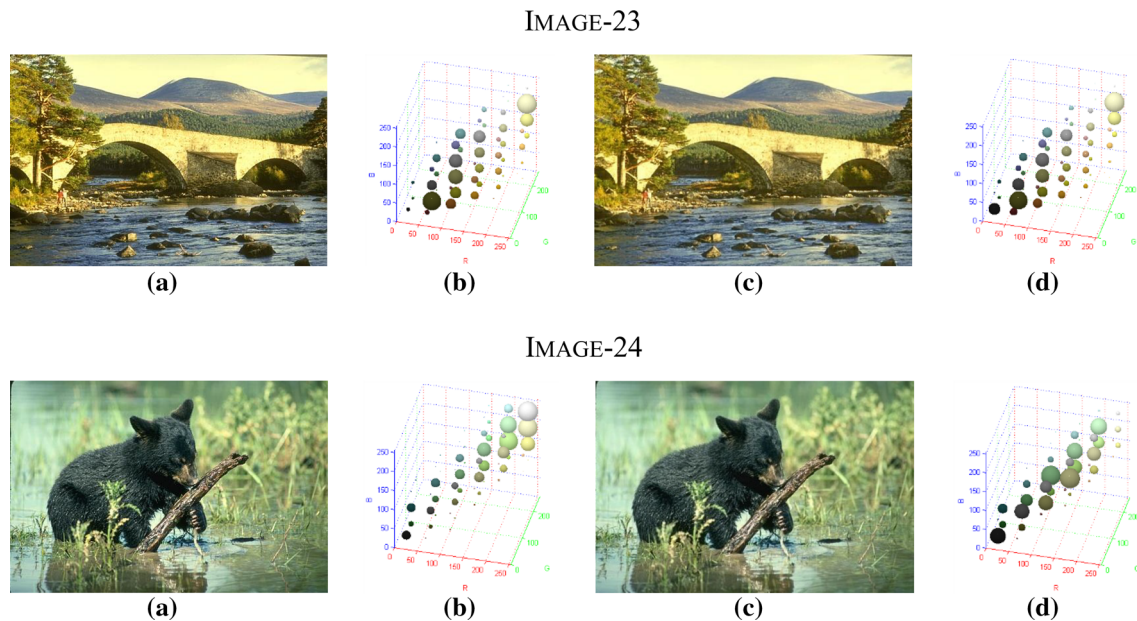
IMAGE-20



(a)     (b)     (c)     (d)

IMAGE-21



(a)     (b)     (c)     (d)

IMAGE-22



(a)     (b)     (c)     (d)

**Fig. 2** continued

IMAGE-23



(a) (b) (c) (d)

IMAGE-24



(a) (b) (c) (d)

**Fig. 2** continued

**Table 1** Result for entropy based quantitative measurement

| IMAGE | HE | CEBGA | HMF | FHSABP | DE-IE |
|---|---|---|---|---|---|
| IMAGE-01 | 0.4428 | 0.4371 | 0.4562 | 0.4231 | **0.4641** |
| IMAGE-02 | 0.4298 | 0.4232 | 0.4231 | 0.4318 | **0.4361** |
| IMAGE-03 | 0.3716 | 0.3412 | 0.3271 | 0.3321 | **0.3861** |
| IMAGE-04 | 0.4182 | 0.4017 | 0.4123 | 0.4172 | **0.4218** |
| IMAGE-06 | 0.4598 | 0.4472 | 0.4421 | 0.4517 | **0.4681** |
| IMAGE-07 | 0.4382 | 0.4271 | 0.4298 | 0.4187 | **0.4384** |
| IMAGE-08 | 0.4559 | 0.4592 | 0.4572 | 0.4521 | **0.4598** |
| IMAGE-09 | 0.4762 | 0.4747 | 0.4698 | 0.4673 | **0.4723** |
| IMAGE-10 | 0.4398 | 0.4193 | 0.4332 | 0.4401 | **0.4398** |
| IMAGE-11 | 0.4763 | 0.4761 | 0.4543 | 0.4653 | **0.4794** |
| IMAGE-12 | 0.4276 | 0.4209 | 0.4254 | 0.4194 | **0.4287** |
| IMAGE-13 | 0.3872 | 0.3694 | 0.3827 | 0.3854 | **0.3971** |
| IMAGE-14 | 0.4582 | 0.4537 | 0.4553 | 0.4498 | **0.4651** |
| IMAGE-15 | 0.4487 | 0.4376 | 0.4365 | 0.4386 | **0.4489** |
| IMAGE-16 | 0.4023 | 0.4162 | 0.4122 | 0.4182 | **0.4185** |
| IMAGE-17 | 0.4252 | 0.4161 | 0.4121 | 0.4132 | **0.4278** |
| IMAGE-18 | 0.4523 | 0.4520 | 0.4525 | 0.4505 | **0.4567** |
| IMAGE-19 | 0.4621 | 0.4572 | 0.4602 | 0.4514 | **0.4656** |
| IMAGE-20 | 0.4352 | 0.4312 | 0.4281 | 0.4352 | **0.4451** |
| IMAGE-21 | 0.4172 | 0.4160 | 0.4123 | 0.4142 | **0.4209** |
| IMAGE-22 | 0.4324 | 0.4312 | 0.4326 | 0.4320 | **0.4383** |
| IMAGE-23 | 0.4276 | 0.4254 | 0.4245 | 0.4263 | **0.4289** |
| IMAGE-24 | 0.4172 | 0.4142 | 0.4127 | 0.4136 | **0.4179** |

## 5 Test problems

A total of 24 images given in Fig. 2 are considered. These images are taken from Martin et al. (2001) or Berkley database. Figure 2a, b represents the original image and the histogram obtained respectively. Figure 2c, d represents the enhanced image and the corresponding histogram obtained using the proposed DE-IE.

## 6 Result analysis

The algorithms are compared on the basis of the following analysis:

- Entropy based measurement or quality measurement (Table 1)
- Visual analysis (Fig. 2)
- Histograms (Fig. 2)

## 7 Algorithms used for comparison

- HE [histogram equalization (Gonzalez and Woods 2006)]
- CEBGA [contrast enhancement based on GA (Hashemi et al. 2010)]

- HMF [histogram modification framework (Arici et al. 2009)]
- FHSABP [flattest histogram specification with accurate brightness preservation (Wang et al. 2008)]

## 8 Quality measurement on the basis of entropy

Normalized discrete entropy (NDE) and normalized edge based contrast measure (CM) are used for measuring contrast enhancement. Discrete entropy for an input image $I$ having grey levels $N$ is defined as

$$E_I = -\sum_{n=1}^{N} p(x_n) \log_{10} p(x_n) \tag{5}$$

where; $p(x_n)$ represents the probability of a pixel intensity $x_n$. Normalized histogram is used for making all the calculations.

Similarly entropy for output image $O$ is defined as

$$E_O = -\sum_{m=1}^{M} p(y_m) \log_{10} p(y_m) \tag{6}$$

where, $p(y_m)$ is the probability of pixel intensity $y_m$ for an output image $O$.

Small value of entropy indicates that the image have a lesser details and a high value indicates image have more details. Normalized entropy ($E_N$) for input image $I$ and output image $O$ is defined as follows:

$$E_N = \frac{1}{1 + \frac{(\log_{10}(256) - E_O)}{(\log_{10}(256) - E_I)}} \tag{7}$$

For a grey level image $\log_{10}(256)$ is the maximum value of entropy for an input image. Now, the very basic idea is that a high number of normalized entropy $E_N$ represents a better value for output image. From Eq. (7) it is very clear that if $E_N \geq 0.5$ then output image always has a higher entropy value which in turn implies a more detailed image. All the measurement can be used for color images. Convert a color image into CIE L*a*b (The CIE (L*, a*, b*) color space (CIELAB), showing only colors that fit within the RGB gamut (and can therefore be displayed on a typical computer display) color space. After processing the enhancement process transform the image into its previous form.

The numerical analysis of the results based on entropy is given in Table 1, which represents a quantitative measurement for output enhanced images. From this Table it can be seen that although all the algorithms used for comparative analysis give more or less similar results, the proposed DE-IE outperforms the other algorithms.

## 9 Visual analysis and analysis on the basis of histograms

The superior performance of DE-IE can also be observed from Fig. 2, from where the difference between the original image and the enhanced image is clearly visible. Also, from the histogram of the original image and the enhanced image it can be easily seen that the histogram of the enhanced image contains much more data in comparison of original image histogram.

## 10 Summary

A new DE variant called DE-IE is proposed for image enhancement. DE-IE is particularly designed for image enhancement so as to preserve most of the information of the image as the initial population here is made up of the probability distribution of each pixel. It is a simple and novel DE strategy making use of only the scaling factor F. Note that the proposed DE-IE does not make use of any crossover parameter Cr like the usual DE.

The proposed variant is compared with other algorithms like HE, CEBGA, HMF and FHSAB, where it is observed that the proposed DE-IE gives a better performance. The good performance of DE-IE can also be visualized with the help of Fig. 2, where the difference between the input and the output image after enhancement through DE-IE can be easily observed. Performance of DE-IE can also be seen through histograms. The above analysis shows that DE-IE can be an efficient method for image segmentation.

## References

Arici T, Dikbas S, Altunbasak Y (2009) A histogram modification framework and its application and itsapplication for image contrast enhancement. IEEE Trans on Image Process 18(9):1921–1935

Aslantas V, Tunckanat M (2007) Differential evolution algorithm for segmentation of wound images. In: Proceedings of IEEE international symposium on intelligent signal processing-2007, pp 1–5

Astola J, Haavisto P, Neuvo Y (1990) Vector median filters. In: Proceedings of the IEEE, pp 678–689

Celik T (2012) Two-dimensional histogram equalization and contrast enhancement. Pattern Recogn 3810–3824

Chander A, Chatterjee A, Siarry A (2011) A new social and momentum component adaptive PSO algorithm for image segmentation. Expert Syst Appl 38:4998–5004

Chen H, Leou J (2012) Saliency-directed color image interpolation using artificial neural network and particle swarm optimization. J Vis Commun Image R 23:343–358

Chen SY, Li YF, Zhang J (2008) Vision processing for realtime 3-d data acquisition based on coded structured light. IEEE Trans Image Process 17(2):167–176

Chiu YS, Cheng FC, Huang SC (2011) Efficient contrast enhancement using adaptive gamma correction and cumulative intensity distribution. In: Proceedings of the IEEE international conference on systems, man, and cybernetics (IEEE SMC 2011), pp 2946–2950

Chung K, Yang W, Yan W (2008) Efficient edge-preserving algorithm for color contrast enhancement with application to color image segmentation. J Vis Commun Image R 19:299–310

Coelho LDS, Sauer JG, Rudek M (2009) Differential evolution optimization combined with chaotic sequences for image contrast enhancement. Chaos, Solitons Fractals 42:522–529

Cohen-Or D, Sorkine O, Gal R, Leyvand T, Xu YQ (2006) Color harmonization. In: Proceedings of the 2006 ACM SIGGRAPH, pp 624–630

Fan SS, Lin Y (2007) A multi-level thresholding approach using a hybrid optimal estimation algorithm. Pattern Recogn Lett 28:662–669

Feng D, Wenkang S, Liangzhou S, Yong D, Zhenfu Z (2005) Infrared image segmentation with 2-D maximum entropy method based on particle swarm optimization (PSO). Pattern Recogn Lett 26:597–603

Fernández-Caballero A, Castillo JC, Serrano-Cuerda J, Maldonado-Bascón S (2011) Real-time human segmentation in infrared videos. Expert Syst Appl 38:2577–2584

Ghamisi P, Couceiro MS, Benediktsson JA, Ferreira NMF (2012) An efficient method for segmentation of images based on fractional calculus and natural selection. Expert Syst Appl 39:12407–12417

Gonzalez RC, Woods RE (2006) Digital Image Processing, 3rd edn. Prentice-Hall, Inc., Upper saddle river, NJ, USA

Hammouche K, Diaf M, Siarry P (2008) A multilevel automatic thresholding method based on a genetic algorithm for a fast image segmentation. Comput Vis Image Underst 109:163–175

Hashemi S, Kiani S, Noroozi N, Ebrahimi MM (2010) An image contrast enhancement method based on genetic algorithm. Pattern Recogn Lett 31:1816–1824

Horng M (2010) Multilevel minimum cross entropy threshold selection based on the honey bee mating optimization. Expert Syst Appl 37:4580–4592

Hoseini P, Shayesteh MG (2013) Efficient contrast enhancement of images using hybrid ant colony optimisation, genetic algorithm, and simulated annealing. Digit Signal Proc 23:879–893

Huang SC, Yeh CH (2013) Image contrast enhancement for preserving mean brightness without losing image features. Eng Appl Artif Intell 26:1487–1492

Huang K, Wang Q, Wu Z (2006) Natural color image enhancement and evaluation algorithm based on human visual system. Comput Vis Image Underst 103:52–63

Jiang J, Yao B, Wason AM (2007) A genetic algorithm design for microcalcification detection and classification in digital mammograms. Comput Med Imaging Graph 31:49–61

Kumar S, Pant M, Ray AK (2011) Differential evolution embedded Otsu's method for optimized image thresholding. In: International conference world congress on information and communication technologies WICT-2011, pp 325–329

Kumar S, Kumar P, Sharma TK, Pant M (2013) Bi-level thresholding using PSO, artificial bee colony and MRLDE embedded with Otsu method. Memetic Comput. doi:10.1007/s12293-013-0123-5

Kwok NM, Shi HY, Ha QP, Fang G, Chen SY, Jia X (2013) Simultaneous image color correction and enhancement using particle swarm optimization. Eng Appl Artif Intell

Lan J, Zeng Y (2013) Multi-threshold image segmentation using maximum fuzzy entropy based on a new 2D histogram. Optik 124:3756–3760

Lee C, Leou J, Hsiao H (2012) Saliency-directed color image segmentation using modified particle swarm optimization. Sig Process 92:1–18

Li L, Li D (2008) Fuzzy entropy image segmentation based on particle swarm optimization. Prog Nat Sci 18:1167–1171

Li Z, Zhang D, Xu Y, Liu C (2011) Modified local entropy-based transition region extraction and thresholding. Appl Soft Comput 11:5630–5638

Masra SMW, Pang PK, Muhammad MS, Kipli K (2012) Application of particle swarm optimization in histogram equalization for image enhancement. In: IEEE colloquium on humanities, science and engineering research (CHUSER 2012), pp 294–299

Martin D, Fowlkes C, Tal D, Malik J (2001) A database of human segmented natural images and its application to evaluating segmention algorithms and measuring ecological statistics. In: Proceedings of 8th International Conference on Computer, vol 2, pp 416–423

Nakib A, Oulhadj H, Siarry P (2007) Image histogram thresholding based on multi-objective optimization. Sig Process 87:2516–2534

Osuna-Enciso V, Cuevas E, Sossa H (2013) A comparison of nature inspired algorithms for multi-threshold image segmentation. Expert Syst Appl 40:1213–1219

Sathya PD, Kayalvizhi R (2011) Modified bacterial foraging algorithm based multilevel thresholding for image segmentation. Eng Appl Artif Intell 24:595–615

Shanmugavadivu P, Balasubramanian K (2013) Particle swarm optimized multi-objective histogram equalization for image enhancement. Opt Laser Technol

Shyu M, Leou J (1998) A genetic algorithm approach to color image enhancement. Pattern Recogn 871–880

Starck JL, Murtagh F, Candes EJ, Donoho DL (2000) Gray and color image contrast enhancement by the curve let transform. IEEE Trans Image Process 12:706–717

Tao W, Tian J, Liu J (2003) Image segmentation by three-level thresholding based on maximum fuzzy entropy and genetic algorithm. Pattern Recogn Lett 24:3069–3078

Tao W, Jin H, Liu L (2007) Object segmentation using ant colony optimization algorithm and fuzzy entropy. Pattern Recogn Lett 28:788–796

Tsai H, Jhuang Y, Lai Y (2012) An SVD-based image watermarking in wavelet domain using SVR and PSO. Appl Soft Comput 12:2442–2453

Vahedi E, Zoroofi RA, Shiva M (2012) Toward a new wavelet-based watermarking approach for color images using bio-inspired optimization principles. Digit Signal Proc 22:153–162

Verma OP, Kumar P, Hanmandlu M, Chhabra S (2012) High dynamic range optimal fuzzy color image enhancement using artificial ant colony system. Appl Soft Comput 12:394–404

Wang C, Peng J, Ye Z (2008) Flattest histogram specification with accurate brightness preservation. IET Image Process 2(5):249–262

Zahara E, Fan SS, Tsai D (2005) Optimal multi-thresholding using a hybrid optimization approach. Pattern Recogn Lett 26:1082–1095

Zaharescu E, Zamfir M, Vertan C (2003) Color morphology-like operators based on color geometric shape characteristic. In: Proceedings of international symposium on signal circuit and systems, Iasi, Romania, July 2003, pp 145–148

Zhang C, Wang X, Duanmu C (2010) Adaptive typhoon cloud image enhancement using genetic algorithm and non-linear gain operation in undecimated wavelet domain. Eng Appl Artif Intell 23:61–73

Zhong S, Jiang X, Wei J, Wei Z (2013) Image enhancement based on wavelet transformation and pseudo-color coding with phase-modulated image density processing. Infrared Phys Technol 58:56–63