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Image contrast enhancement using an artificial bee colony algorithm

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ABSTRACT

The objective of image contrast enhancement is to improve the contrast level of images, which are degraded during image acquisition. Image contrast enhancement is considered as an optimization problem in this paper and the *artificial bee colony* (ABC) algorithm is utilized to find the optimal solution for this optimization problem. The contribution of the proposed approach is two-fold. First, in view of that the fitness function is indispensable to evaluate the quality of the enhanced image, a new objective fitness function is proposed in this paper. Second, the image transformation function is critical to generate new pixel intensities for the enhanced image from the original input image; more importantly, it guides the searching movements of the artificial bees. For that, a parametric image transformation function is utilized in this paper so that only the optimal parameters used in the transformation function need to be searched by the ABC algorithm. This is in contrast to that the whole space of image intensity levels is used in the conventional ABC-based image enhancement approaches. Extensive experiments are conducted to demonstrate that the proposed approach outperforms conventional image contrast enhancement approaches to achieve both better visual image quality and higher objective performance measures.

1. Introduction

Image contrast enhancement aims to improve the contrast level of images, since the image quality can suffer due to several factors, such as contrast, illumination and noise during image acquisition procedure. Image contrast is defined as the separation factor between the brightest spot and the darkest spot in images [1]. A larger separation factor indicates higher contrast; on the other hand, the smaller separation factor indicates lower contrast. Image contrast enhancement is useful in many real-world application areas. For example, the high-quality photographic images can be produced by embedding this technology into the digital camera to handle low light image acquisition environment [2].

In view of the importance of the image contrast enhancement technology, many algorithms have been developed in the literature. A widely used image enhancement method in the spatial domain is called histogram equalization, which can be further improved by the adaptively modified histogram equalization [3]. It scales the magnitudes of the probability density function of the original input image before applying histogram equalization. The scaling factor is adaptively adjusted according to the averaged image intensity values of the image. The non-parametric modified histogram equalization effectively handles the histogram spikes and reduces the distortion in smooth regions without the empirical adjustment of parameters [4,5]. The image intensity values can also be adjusted based on various contrast and sharpness measure [6]. In addition, gray transformation function can be also combined with evolutionary algorithms [7–11] to process low-quality images. These evolutionary algorithms are utilized to search for the optimal mapping of the gray levels of the input image into new gray levels, so that the image contrast is enhanced [12].

In recent years, many bionic algorithms have been developed for image enhancement, such as bat algorithm [13], cuckoo algorithm [14], and immune algorithm as follows [15]. In [13], the neuron network and bat algorithm is combined, where the bat algorithm has been applied to tune the parameters of the modified neuron model for the maximization of two competitive image performance indices contrast enhancement factor and mean opinion score. In [14], the enhanced cuckoo algorithm and optimum wavelet is utilized to perform medical image enhancement by selecting the optimum scale value of the wavelet. The improved algorithm can adaptive rebuilding the worst nests. Fitness of each nest is estimated for all iterations and the threshold value is fixed based on the fitness value. An improved

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immune algorithm is proposed in [15] to enhance MRI images. The main improvement of this approach is divided into three points. Firstly, instead of the simple binary coding, the real coding approach of the MRI brain image is designed. Secondly, the mutation distance is added into the mutation operator to better control the mutation progress and avoid any narrow local optimization. Finally, both the clone selection and the mutation are adjusted together in the Gauss distribution, the uniform distribution, and the chaotic distribution, rather than in only the Gauss distribution. The above three papers are all designed for enhancing the medical image, but the evaluation criteria for image quality has not been described in detail.

Recently, the *artificial bee colony* (ABC) technique has been introduced into tackling the image contrast enhancement problem, motivated by the fact that the ABC technique is an effective optimization tool for solving the objective optimization problem [16,17]. The ABC algorithm is motivated by the intelligent behavior of the honey bees. It can provide a population-based search procedure, where the food positions (i.e., image intensity values in the context of image contrast enhancement) are evaluated and modified by the artificial bees in the iterations, and the artificial bees aim to discover the optimal food sources places (i.e., the best enhanced image in the context of image contrast enhancement) [18,19]. Yimit et al. [20] exploits a grayscale transformation function using local gray-level distribution in the neighborhood of each pixel of the image. Draa and Bouaziz [21] proposes to use the ABC technique to find the optimal image solution based on a new gray-level mapping technique and a new image quality measure. Joshi and Prakash [22] proposes to incorporate the direction constraints into the conventional ABC algorithm so that artificial bees can move adaptively to obtain better solution. They also add a new contrast-based quality estimation into the objective function of the ABC algorithm. Bhandari et al. proposes a wavelet-domain image enhancement approach, where the ABC technique is employed to learn the parameters of the adaptive thresholding function required for optimal image contrast enhancement [23].

This paper proposes a new ABC-based image contrast enhancement approach. The proposed approach has the following two contributions, which are significantly different with conventional ABC-based image contrast enhancement approaches.

- First, a new objective fitness function is proposed in this paper with the incorporation of a new image contrast measure. The spatial neighborhood information of the image is critical to enhance the image contrast [24]. However, such spatial information is neglected in conventional ABC-based image contrast enhancement approaches. In view of this, a new image contrast measure is incorporated into the cost function of the proposed approach. The proposed new fitness function consists of four performance measures: (i). sum of edge intensities; (ii). number of edge pixels; (iii). entropy of the image; and (iv). image contrast. This fitness function automatically measures the quality of the produced image; consequently, it determines the quality of the enhanced image. Therefore, the artificial bees are guided by this new cost function to find the optimal transformation function.
- Second, a parametric image enhancement method is utilized in the proposed approach, rather than searching for optimal pixel values in the whole image intensity space. Conventional ABC-based approaches treat image contrast enhancement in the spatial domain, by using a transformation function that produces a new intensity for each pixel of the original image to generate the enhanced image. Intuitively, if the image resolution increases, the size of the solution space for the artificial bees will increase. Consequently, the time complexity of the algorithm will increase hugely. To overcome this challenge, the proposed approach exploits a parametric image enhancement method, more specifically, the *Incomplete Beta Function* (IBF) [25], which has been proven to be effective in image contrast enhancement [26]. The solution space has a smaller size is compared with that of image intensity levels for all pixels in the image.

The rest of this paper is organized as follows. A brief introduction to the conventional ABC algorithm is presented in Section 2. A new ABC-based image contrast enhancement approach is proposed in Section 3. The proposed approach is evaluated in Section 4 in extensive experiments. Finally, Section 5 concludes this paper.

2. Artificial bee colony algorithm

A brief introduction to the ABC algorithm is provided in this Section. The ABC algorithm is a swarm-based metaheuristic for solving numerical optimization problems [16]. This metaheuristic is inspired by the intelligent foraging behavior of natural honeybees. The population in an artificial bee colony is subdivided into three subgroups: (i). employed bees; (ii). onlooker bees; and (iii). scout bees. These artificial bees move in a search space and choose food sources, which are possible solutions to the target optimization problem.

To be more specific, the employed bees are responsible for studying various food sources and sharing the information with the onlooker bees. The food source that yields higher score and higher quality will have a larger chance to be selected by onlooker bees. On the other hand, those food sources with lower marks will have smaller chances to be selected. The food source could also be rejected due to its low quality. In this case, the scout bees will conduct the random search for new food sources. Therefore, in each cycle of searching iteration, three steps are involved: (i). the employed bees are sent to search the food sources and measure their quality; (ii). the food sources are selected by the onlookers after sharing the information with the employed bees; (iii). the scout bees are sent to search for new possible food sources, if certain food sources are rejected due to low quality.

The aforementioned ABC algorithm is briefly described as below.

- *Initialization stage*: Every solution of the bee colony is initialized, and the fitness of each solution is measured.
- Iteratively perform the following steps until the maximum number of iterations is reached or the stop condition is satisfied.
  - *Employed bee stage*: A new solution is produced by the employed bee, which randomly moves in the neighbor of its current solution. The new generated solution will replace the old solution, if it yields a better fitness value.
  - *Onlooker bee stage*: After all employed bees have completed their works, each onlooker bee probabilistically selects a solution according to its fitness value of the solution.
  - *Scout bee stage*: A solution will be abandoned if its fitness value has not been improved for a given number of generations. Then a new solution is re-generated using the initialization method.
- The solutions are updated using the greedy criteria, and the best solution and its corresponding fitness value are recorded.

3. Proposed ABC-based image contrast enhancement approach

3.1. Motivation and challenges of using ABC algorithm in image contrast enhancement

The ABC algorithm is a stochastic technique used for searching for optimal solutions of a combinatorial optimization problem. Basically, its idea is to assign artificial bees to examine the search space to search for feasible solutions. Moreover, these artificial bees collaborate and exchange information so that bees concentrate on more promising solutions in terms of the fitness functions.

The ABC algorithm is exploited in this paper to address image contrast enhancement problem due to the following motivations. The image contrast enhancement optimization problem is regarded as a foraging process of bee colony. The position of a food source denotes a possible solution of this image contrast enhancement problem. The fitness value of a food source represents the quality of the associated solution. The key advantage of the ABC algorithm is that both the global and local searches are carried out in each iteration step, which greatly avoids the local optimal solution; consequently, the probability of finding the optimal solution is increased.

There are two challenges need to be addressed when the ABC algorithm is used to address the image contrast enhancement problem in this paper. The first challenge is how to design the transformation function, which will generate new pixel intensities for the enhanced image from the original input image. The second challenge is how to design an objective evaluation criterion, which automatically measures the quality of the produced image. These two important factors influence the quality of the enhanced image; they will be presented in following sections in details.

3.2. Proposed image contrast enhancement approach

As described in previous section, in order to apply the ABC algorithm in image contrast enhancement, we need to consider: (i). the design of the transformation function, which will generate new pixel intensities for the enhanced image from the original image; and (ii). the design of the fitness function, which examines the quality of the produced image. Both these two challenges are addressed in following sections in details.

3.2.1. Transformation function

Image contrast enhancement is conducted in the spatial domain by using a transformation function, which produces a new intensity for each pixel of the original image to generate the enhanced image. Conventional methods use piecewise-linear transformation function have been proposed to deal with low-quality images [27,28]. However, pixels at the point of subsection may become negative or greater than 255 after the transformation function is applied. To overcome this issue, the piecewise curve needs to be replaced by the continuous curve. The Incomplete Bate Function, which is developed by Tubbs [25], can meet this requirement, since it is a continuous and adjustable function. Given the original image intensity level (denoted as x), this function applies the transformation defined in (1) to generate a new image intensity level (denoted as $T(x)$). This can be mathematically defined as

$$T(x) = \frac{1}{\int_0^1 t^{\alpha-1}(1-t)^{\beta-1}dt} \times \int_0^x t^{\alpha-1}(1-t)^{\beta-1}dt, \tag{1}$$

where t is the variable of integration, α and β are two parameters that are used to adjust the function to obtain larger fitness value in the enhanced image.

The proposed approach utilizes the ABC algorithm to find the optimal values for the variables α and β. In other words, the ABC algorithm only needs to determine the values of two parameters. Fig. 1 illustrates the image transformation function (1) with different parameters. When we need to enhance the dark image, we can set a smaller α value than β. On the other hand, we can set a greater α value than β to enhance the bright image. The artificial bees are moving to search for the optimal α and β values to enhance the image contrast based on the fitness function, which is defined as (2) in next section in details.

3.2.2. Fitness function

The fitness function is the objective evaluation criterion to automatically measure the quality of the produced image. It is critical to determine the quality of the enhanced image. Intuitively, compared with the original image, the enhanced image is desired to have more number of edges, a higher intensity of the edges and a higher contrast. Motivated by this, a new fitness function is proposed to contain four performance measures: (i). sum of edge intensities; (ii). number of edge pixels; (iii). entropy of the image; and (iv). image contrast.

More specifically, given the original image, the proposed approach will enhance the image to produce a enhanced version of the image (denoted as I_e) according to the following fitness function

$$F(I_e) = \log(\log(S(I_e)))\cdot E(I_e)\cdot H(I_e)\cdot C(I_e), \tag{2}$$

where the detailed mathematical definitions is described as follows.

The first term $S(I_e)$ in the proposed fitness function (2) represents the sum of edge intensities of the image. The enhanced image is desired to have larger value than the original low-contrast image. It can be obtained by first applying the image edge detector (e.g., Canny edge detector [29]), followed by calculating the summation of intensities of edge pixels.

The second term $E(I_e)$ in the proposed fitness function (2) represents the number of edge pixels of the enhanced image. The enhanced image is desired to be sharper, that means it has more edge pixels, than the original low-contrast image. It can be calculated by counting the number of pixels whose intensity value is above a threshold in the Canny edge image.

The third term $H(I_e)$ in the proposed fitness function (2) represents the entropy value of the enhanced image, which is defined as

$$H(I_e) = \sum_{i=0}^{255} h_i \log_2(h_i), \tag{3}$$

in which h_i is the probability of occurrence of the i-th intensity value of the image.

The fourth term $C(I_e)$ in the proposed fitness function (2) represents the contrast value of the enhanced image. The enhanced image is desired to yield larger contrast than the original input image. The contrast at a gray-scale image pixel should be expressed as the ratio of the local change and the local average [30]. The contrast of the whole image is evaluated by considering local contrast of non-overlapping image blocks as

$$C(I_e) = \sum_{i=1}^{N_B} C(B_i), \tag{4}$$

where B_i represents the i-th image block, N_B is the total number of image blocks. For each image block, the local band limited contrast value $C(B_i)$ is calculated over all contrast measure at each pixel location (r,c) of the image block B_i as

$$C(B_i) = \sum_{(r,c)\in B_i} C(r,c) = \sum_{(r,c)\in B_i} \frac{I_e(r,c)\otimes F_b}{I_e(r,c)\otimes F_l}, \tag{5}$$

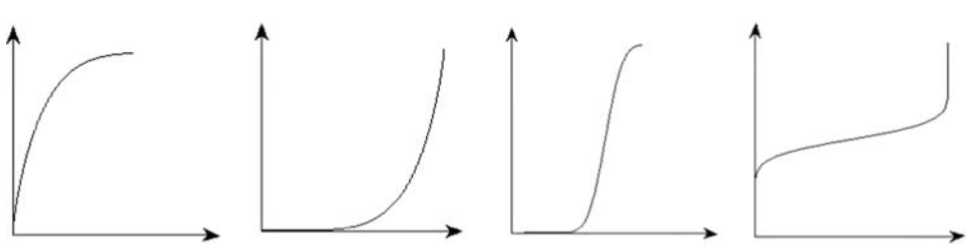

Fig. 1. Examples of the image transformation function (1) with different parameters: (a) the dull part is stretched; (b) the bright part is stretched; (c) the middle part is stretched and both ends are compressed; (d) both ends are stretched and the middle part is compressed.

in which $\otimes$ is the convolution operator, F_b is a band pass filter and F_l is a low pass filter. Furthermore, F_b and F_l are two Gaussian functions differ in terms of their sigma values σ_1, σ_2 as $\sigma_1 = \frac{L\times\max\{M,N\}}{v^2}$, and $\sigma_2 = L \times \sigma_1$, $v \in [0, \pi]$ is the frequency at which the pass band of the underlying band pass filter peaks, M and N is the dimension of the image in terms of number of rows and columns. After the contrast value for each image block is calculated, its value is set to be a binary value. If the image block contrast falls into an interval, its label is set to be 0; on the other hand, it will be set to be 1, which indicates that it yields bad contrast in this image block. The contrast value for the whole image is furthermore normalized into the interval [0, 1].

To address the local optimum problem of the ABC algorithm, we can ensure the randomness of parameters so as to minimize the possibility of local optimum. First, the proposed method only needs to optimize two parameters, which is conducive to avoid local optimum. Second, when we perform the image enhancement experiment, we set some constraints based on the luminance difference among the images. To be more specific, when we need to enhance the dark image, we can set a smaller α value than β. On the other hand, we can set a greater α value than β to enhance the bright image. This step can improve the computational efficiency of the algorithm.

3.2.3. Summary of the proposed approach

The objective of the proposed approach is to guide the artificial bees moving to search for the optimal parameters (defined in (1)) according to the new fitness function (defined in (2)). The implementation of the proposed is summarized as follows.

- Initialization: In this step, the population is initialized. All food sources are considered as solution vectors to the optimization problem. Since the purpose of the proposed approach is to find the optimal parameters α and β in (1), the initial solution is composed of N variables of two dimensions to be optimized in order to maximize the objective function. These solution vectors are initially generated as

$$X_i^0 = \{\alpha_i^0, \beta_i^0\}, \tag{6}$$

$$\alpha_i^0 = \alpha_l + rand(0, 1) \times (\alpha_u - \alpha_l), \tag{7}$$

$$\beta_i^0 = \beta_l + rand(0, 1) \times (\beta_u - \beta_l), \tag{8}$$

  where $i = 1, 2, \ldots, N$ and N is the total number of possible solutions, $[\alpha_l, \alpha_u]$ and $[\beta_l, \beta_u]$ are the lower and upper bounds of the parameters α and β, respectively.
- Employed bee stage: At each iteration step n, each employed bee determines a new solution X_i^{n+1} in the neighborhood of its currently associated solution X_i^n as

$$X_i^{n+1} = X_i^n + \phi(X_i^n - X_j^n), \tag{9}$$

  where j is a randomly chosen index, and ϕ is a random number within the range of $[-1, 1]$. If the fitness value (determined by (2)) of the newly generated solution X_i^{n+1} is better than that of its currently associated solution X_i^n, then the employed bee moves to this new food source while abandoning the old one, using a greedy selection approach; otherwise, it remains at its old solution.
- Onlooker bee stage: After all employed bees have completed their works, each onlooker bee selects a solution according to its fitness value using the roulette wheel selection method as

$$P(X_i^n) = F(X_i^n)/\Sigma_{i=1}^N F(X_i^n), \tag{10}$$

  where $F(\cdot)$ is the fitness of solution X_i^n calculated using (2), and N is the total number of solutions.
- Scout stage: If the fitness value of the certain solution has not been improved for a given number of generations, a new solution is generated using the same equation of the initialization step (6).
- Stop Condition: When the number of iterations reaches its maximum, the best so far gotten parameters are to be used for enhancing the input image. We can stop the iteration when the fitness value is converged. We can record and evaluate the variance of the fitness data. If it is less than a very small number, the fitness value can be considered as converged so that the iteration can be stopped.

4. Experimental results

4.1. Experimental setup

The proposed approach is compared with conventional image contrast enhancement approaches using the standard Kodak test image dataset [31]. This dataset contains of 24 color images. Each color image is first converted into gray-scale image, which serves as the ground truth in our experiment for performance evaluation. The contrast of these gray-scale images are further adjusted using *GNU Image Manipulation Program* (GIMP) [32] to generate both low-contrast and high-contrast images. These generated images are applied using various image contrast enhancement methods to reconstruct the enhanced image, which is further compared with the ground truth image for performance evaluation.

The proposed approach is compared with other eight approaches including: (i). conventional histogram-based image contrast enhancement approaches [3–5]; (ii). evolutionary-based image contrast enhancement approaches [7–9]; and (iii). ABC-based image contrast enhancement approaches [21,22].

The performance evaluation is conducted using five image quality criterions, including: (i). *Peak Signal-to-Noise Ratio* (PSNR); (ii). *Structural Similarity Index Measure* (SSIM) [33]; (iii). *Information Fidelity Criterion* (IFC) [34]; (iv). *Visual Information Fidelity* (VIF) [35] and (v). *Visual Signal to Noise Ratio* (VSNR) [36]. All of these criterions have been widely used in the image contrast enhancement area for conducting performance evaluation of various image contrast enhancement approaches.

The parameters of the proposed approach are set as follows. The number of artificial bees is set to be 50, the number of maximum iterations is set to be 50, the upper limit of nectar amount not updated is set to be 5. Both the lower bounds α_l, β_l and upper bounds α_u, β_u of the parameters α and β are set to be 0 and 10, respectively. The same parameter setting is applied for all test images, since the proposed approach is fairly robust to the choice of the parameters used.

4.2. Performance evaluation

The first experiment is to evaluate the image enhancement performance of the proposed approach. The input image and the enhanced images of four test images *Zebra*, *Liftingbody*, *Boy*, and *Lena* are presented in Fig. 2. The detailed performance of these four test images are reported in Tables 1, 2. Furthermore, the performance averaged over the whole Kodak test image dataset is presented in Table 3. As seen from these Figure and Tables, the proposed approach outperforms the conventional image enhancement approaches by achieving the best image visual quality and the best objective performance. Furthermore, an additional experiment has been conducted to compare the proposed approach with few recent image contrast enhancement approaches [37–40] using selected images from MIT-Adobe FiveK database [41]. The performance comparison is presented in Fig. 3 and Table 4, where the proposed approach outperforms the conventional image enhancement approaches by achieving the best image visual quality and the best objective performance.

The second experiment is to the proposed approach using the conventional fitness function with that of using new fitness function. The performance evaluation is conducted using *Boy* and *Lena* images,

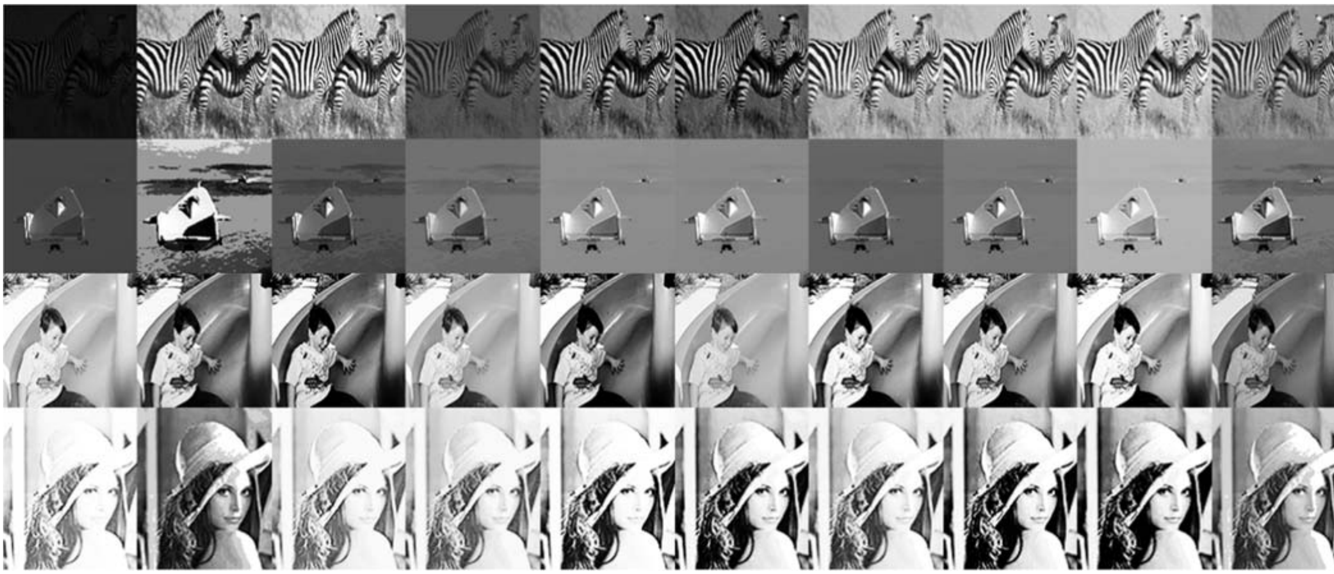

Fig. 2. The visual quality performance comparison of enhanced image obtained by various image enhancement approaches. The first column is the input image. The 2-nd to the 8-th columns are results of Ref. [3–5,7–9,21,22], respectively. The last column is the result of the proposed approach. From top to bottom, the test images are *Zebra*, *Liftingbody*, *Boy*, and *Lena*, respectively.

Table 1
The performance evaluation of various image contrast enhancement approaches using test images *Zebra* and *Liftingbody*. A larger value indicates better image quality.

Test image	Method	PSNR	SSIM [33]	IFC [34]	VIF [35]	VSNR [36]
Zebra	Ref. [3]	16.46	0.82	3.59	0.39	22.24
	Ref. [4]	16.51	0.84	4.02	0.43	22.33
	Ref. [5]	14.49	0.65	3.00	0.31	18.29
	Ref. [7]	13.71	0.81	3.94	0.42	16.74
	Ref. [8]	16.56	0.87	4.43	0.47	22.44
	Ref. [9]	17.07	0.88	4.38	0.46	23.45
	Ref. [21]	16.27	0.87	4.28	0.45	21.86
	Ref. [22]	14.41	0.84	4.11	0.43	18.13
	Proposed approach	23.02	0.93	5.10	0.49	35.36
Liftingbody	Ref. [3]	14.98	0.67	1.90	0.37	18.10
	Ref. [4]	14.78	0.70	2.01	0.33	17.70
	Ref. [5]	20.62	0.77	2.29	0.36	29.38
	Ref. [7]	21.36	0.82	2.07	0.28	30.85
	Ref. [8]	20.26	0.80	2.05	0.28	28.67
	Ref. [9]	18.82	0.80	2.04	0.27	25.79
	Ref. [21]	23.30	0.83	2.10	0.29	34.75
	Ref. [22]	12.79	0.70	1.77	0.26	13.73
	Proposed approach	23.98	0.92	2.73	0.47	36.11

and the performance is compared in Table 5. As seen from this Table, the proposed approach utilizes the proposed new fitness function significantly outperforms that using conventional fitness function.

The third experiment is to compare the histogram of the input image and that of the enhanced image, in order to evaluate the performance of image contrast enhancement. The histograms are compared in Fig. 4, where one can see that the proposed approach is able to adjust the histogram and enhance the image contrast. Furthermore, in order to quantitatively evaluate the image histogram after applying image enhancement, a histogram variance measure is proposed as follows. First, the gray scales of the image [0, 255] are equally split into four intervals. Then, the number of pixels that fall into each interval is counted, followed by calculating the variance of these four numbers. A smaller variance value indicates better image contrast quality. As seen in Table 6, the proposed approach is able to enhance the image histogram contrast.

The last experiment is to evaluate the execution time of the

Table 2
The performance evaluation of various image contrast enhancement approaches using test images *Boy* and *Lena*. A larger value indicates better image quality.

Test image	Method	PSNR	SSIM [33]	IFC [34]	VIF [35]	VSNR [36]
Boy	Ref. [3]	17.15	0.85	3.48	0.59	22.41
	Ref. [4]	16.78	0.84	3.85	0.61	21.68
	Ref. [5]	12.57	0.88	4.92	0.64	13.27
	Ref. [7]	14.61	0.84	4.91	0.69	17.35
	Ref. [8]	15.50	0.85	5.09	0.71	19.12
	Ref. [9]	13.77	0.83	4.39	0.64	17.32
	Ref. [21]	16.93	0.89	5.76	0.76	21.99
	Ref. [22]	12.88	0.79	4.05	0.62	13.87
	Proposed approach	17.18	0.92	6.21	0.79	22.48
Lena	Ref. [3]	19.80	0.97	4.63	0.57	31.89
	Ref. [4]	11.71	0.84	2.56	0.29	15.70
	Ref. [5]	12.97	0.88	2.81	0.32	18.22
	Ref. [7]	20.81	0.96	4.64	0.57	33.89
	Ref. [8]	13.19	0.86	2.52	0.31	18.67
	Ref. [9]	14.39	0.91	3.07	0.37	21.05
	Ref. [21]	16.35	0.90	3.36	0.42	24.99
	Ref. [22]	16.75	0.90	3.41	0.44	25.78
	Proposed approach	23.97	0.98	4.76	0.57	40.22

Table 3
The performance evaluation of various image contrast enhancement approaches using the whole Kodak image dataset [31]. A larger value indicates better image quality.

Method	PSNR	SSIM [33]	IFC [34]	VIF [35]	VSNR [36]
Ref. [3]	16.26	0.79	4.26	0.41	20.17
Ref. [4]	19.88	0.87	4.60	0.51	27.42
Ref. [5]	17.78	0.72	4.55	0.63	23.21
Ref. [7]	18.87	0.88	4.62	0.51	25.40
Ref. [8]	15.46	0.86	4.35	0.52	28.08
Ref. [9]	19.84	0.91	4.62	0.53	27.33
Ref. [21]	13.56	0.85	4.26	0.60	26.77
Ref. [22]	13.79	0.86	4.30	0.69	28.24
Proposed approach	24.66	0.95	5.72	0.75	29.98

Fig. 3. The comparison of images and their respective reconstructed images using MIT-Adobe FiveK Dataset [41]: (a) original ground-truth image; (b) simulated degraded images; (c)-(f): reconstructed images of [37–40], respectively; (g): proposed approach.

Table 4
The performance evaluation of various image contrast enhancement approaches using MIT-Adobe FiveK Dataset [41]. A larger value indicates better image quality.

Method	PSNR	SSIM [33]	IFC [34]	VIF [35]	VSNR [36]
Ref. [37]	15.36	0.51	3.13	0.33	17.62
Ref. [38]	20.69	0.77	3.84	0.41	19.44
Ref. [39]	17.93	0.62	2.74	0.37	20.60
Ref. [40]	19.17	0.55	2.91	0.30	19.26
Proposed approach	21.07	0.84	3.79	0.45	22.08

Table 5
The performance evaluation of the proposed approach using conventional fitness function with that of using new fitness function. A larger value indicates better image quality.

Test image	Fitness function	PSNR	SSIM [33]	IFC [34]	VIF [35]	VSNR [36]
Boy	Without (4)	10.14	0.78	3.96	0.53	8.40
	With (4)	17.18	0.92	6.21	0.79	22.48
Lena	Without (4)	15.80	0.91	3.31	0.41	23.88
	With (4)	23.97	0.98	4.76	0.57	40.22

proposed approach. It is implemented using *Matlab* programming language. The number of colony is set to be 100, the number of iteration is set to be 100, the threshold of nectar amount not updated is set be 5. It is run on a PC with a Intel Core™ i5 CPU 3.2 GHz and an 8 GB RAM. The proposed approach is compared with those using swarm intelligent methods [7–9,21,22]. The execution time of various approaches are reported in Table 7, where one can see that the proposed approach is faster than conventional approaches, due to the fact that the proposed approach searches for the optimal parameters of image transformation function rather than the optimal image intensity values in the whole image intensity space. Note that the proposed approach could be furthermore optimized using the parallel ABC approach [42] or the implementation on GPU [43] to accelerate its execution time.

5. Conclusions

An image contrast enhancement approach has been proposed in this paper by exploiting the ABC algorithm. The proposed approach develops a new objective image contrast fitness function by incorpor-

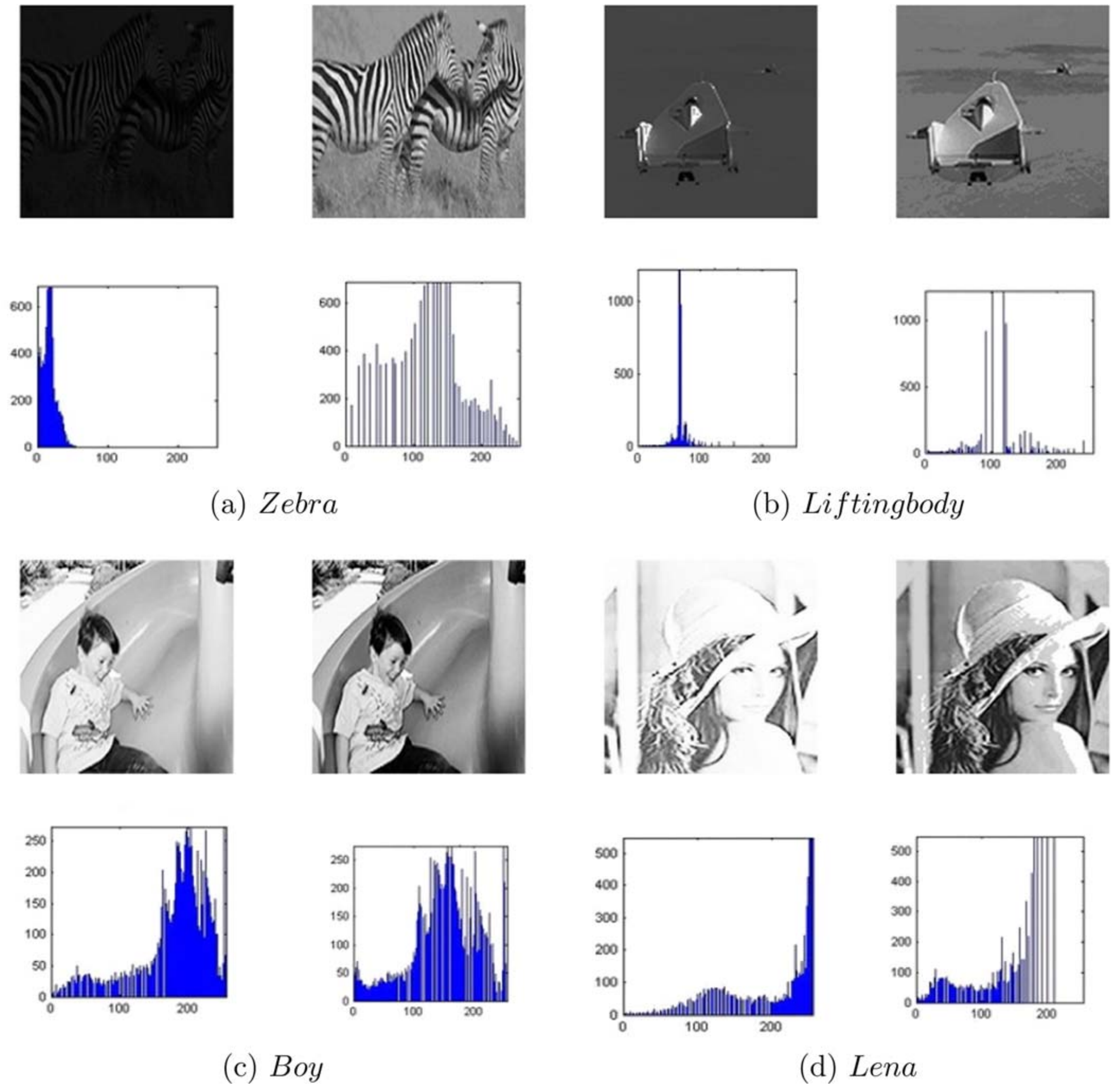

Fig. 4. The comparison of images and their respective histograms. The first and the third columns present the original input image, and the second and the fourth columns present the enhanced images.

Table 6
The histogram variance performance comparison between the original image and the enhanced image using the proposed image enhancement approach. A smaller value indicates better image quality.

Image	*Zebra*	*Liftingbody*	*Boy*	*Lena*
Input image	9.36	8.73	8.40	8.40
Enhanced image	8.49	8.68	8.22	7.68

Table 7
The execution time performance (in s) evaluation of various image contrast enhancement approaches.

Ref. [7]	Ref. [8]	Ref. [9]	Ref. [21]	Ref. [22]	Proposed approach
1992.47	2102.87	2072.65	1920.25	2460.58	885.73

ating a new image contrast measure. In addition, the proposed approach utilizes a parametric transformation function for performing image contrast enhancement. This is faster and more efficient than conventional approaches that need to search for optimal image pixel intensities levels. The proposed approach is able to achieve better enhanced images in terms of both visual quality and objective performance measure, as verified in extensive experimental results.

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