ADAPTIVE IMAGE CONTRAST ENHANCEMENT USING ARTIFICIAL BEE COLONY OPTIMIZATION

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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 multiple 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.

***Index Terms*—** Image contrast enhancement; Artificial bee colony algorithm;

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, 2]. A widely used image enhancement method in the spatial domain is called histogram equalization [3]. 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]. Image transformation function can be also combined with evolutionary algorithms [6–8] to process low-quality images. These evolutionary algorithms are utilized to search for the optimal mapping of the grey levels of the input image into new grey levels, so that the image contrast is enhanced.

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 multiple-objective optimization problem [9]. The ABC algorithm provides 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). Yimit *et al.* [10] exploits a grayscale transformation function using local gray-level distribution in the neighborhood of each pixel of the image. Draa and Bouaziz [11] proposes to find the optimal image solution based on a new grey-level mapping technique and a new image quality measure. Joshi and Prakash [12] proposes to incorporate the direction constraints into the conventional ABC algorithm so that artificial bees can move adaptively to obtain better solution. Bhandari *et al.* uses the ABC algorithm to learn the parameters of the adaptive wavelet-domain thresholding function required for optimal image contrast enhancement [13].

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

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approaches [10–13].

- First, a new multiple 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 image quality. 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.

- 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. To overcome this issue, the proposed approach exploits a parametric image enhancement method, more specifically, the *Incomplete Beta Function* (IBF) [14], which has been proven to be effective in image contrast enhancement. The solution space has a smaller size compared with that of image intensity levels for all pixels in the image.

The rest of this paper is organized as follows. An ABC-based image contrast enhancement approach is proposed in Section 2 and then evaluated in Section 3 in extensive experiments. Finally, Section 4 concludes this paper.

2. PROPOSED ABC-BASED IMAGE CONTRAST ENHANCEMENT APPROACH

2.1. Motivation 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 [9]. These artificial bees move in a search space and choose food sources, which are possible solutions to the target optimization problem.

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.

2.2. Proposed image contrast enhancement approach

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 challenges will be addressed in following sections in details.

2.2.1. 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 [15, 16]. 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 [14], 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

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

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. 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.

2.2.2. 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 (denoted as I_s), 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

$$F(I_e) = \log(\log(S(I_e))) \cdot E(I_e) \cdot H(I_e) \cdot C(I_e), \qquad (2)$$

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), 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

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

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. The contrast of the whole image is evaluated by considering local contrast of non-overlapping image blocks as

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

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

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

in which $\bigotimes$ 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.

2.2.3. *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 order to find the optimal parameters α and β in (1), the solution vectors are initially generated as

$$X_i^0 = \{\alpha_i^0, \beta_i^0\}, \qquad (6)$$

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

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

  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.

- 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

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

  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 solution while abandoning the old one; otherwise, it remains at its old solution.

- A solution is selected according to its fitness value using the roulette wheel selection method as

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

  where $F(\cdot)$ is the fitness of solution X_i^n calculated using (2), and N is the total number of solutions.

- 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).

- When the number of iterations reaches its maximum, the best so far gotten parameters are to be used for enhancing the input image.

3. EXPERIMENTAL RESULTS

The proposed approach is compared with conventional image contrast enhancement approaches using Kodak test image dataset [17]. Each color image is first converted into gray-scale image, which serves as the ground truth in our experiments for performance evaluation. The contrast of these gray-scale images are adjusted using *GNU Image Manipulation Program* (GIMP) [18] to generate both low-contrast and high-contrast images. These generated images are applied using various image contrast enhancement methods to produce 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 [6–8]; and (iii). ABC-based image contrast enhancement approaches [11, 12]. The performance evaluation is conducted using four image quality criterions, including: (i). *Peak Signal-to-Noise Ratio* (PSNR); (ii). *Structural Similarity Index Measure* (SSIM) [19]; (iii). *Information Fidelity Criterion* (IFC) [20]; (iv). *Visual Signal to Noise Ratio* (VSNR) [21]. 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.

Experiment is conducted to evaluate the image enhancement performance of the proposed approach. Various enhanced images of four test images $Zebra$, $Liftingbody$, Boy, and $Lena$ are presented in Figure 1. Furthermore, the performance averaged over the whole Kodak test image dataset is presented in Table 1. As seen from these Figure and Table, the proposed approach outperforms the conventional image enhancement approaches by achieving the best image visual quality and the best objective performance.

4. CONCLUSIONS

An ABC-based image contrast enhancement approach has been proposed in this paper, by exploiting a new multiple objective image contrast fitness function. In addition, the proposed approach utilizes a parametric transformation function image enhancement method. 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.

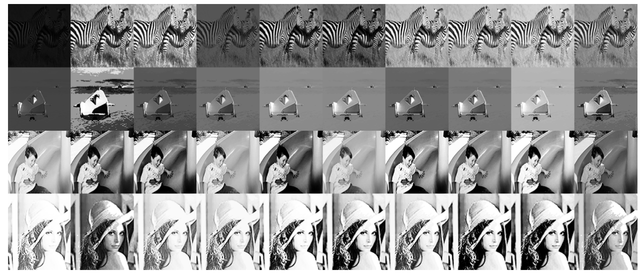

Fig. 1. The visual quality performance comparison of enhanced image obtained by various image enhancement approaches. The first column is the input image. The 2-nd to the 8-th columns are results of Ref. [3–8, 11, 12], respectively. The last column is the result of the proposed approach. From top to bottom, the test images are $Zebra$, $Liftingbody$, Boy, and $Lena$, respectively.

Table 1. The performance evaluation of various image contrast enhancement approaches using the whole Kodak image dataset [17]. A larger value indicates better image quality.

Method	PSNR	SSIM [19]	IFC [20]	VSNR [21]
Ref. [3]	16.26	0.79	4.26	20.17
Ref. [4]	19.88	0.87	4.60	27.42
Ref. [5]	17.78	0.72	4.55	23.21
Ref. [6]	18.87	0.88	4.62	25.40
Ref. [7]	15.46	0.86	4.35	28.08
Ref. [8]	19.84	0.91	4.62	27.33
Ref. [11]	13.56	0.85	4.26	26.77
Ref. [12]	13.79	0.86	4.30	28.24
Proposed	24.66	0.95	5.72	29.98

5. REFERENCES

[1] K. Gu, G. Zhai, W. Lin, and M. Liu, "The analysis of image contrast: From quality assessment to automatic enhancement," *IEEE Trans. on Cybernetics*, vol. 46, no. 1, pp. 284–297, Jan 2016.

[2] J. Tian and K.-K. Ma, "A survey on super-resolution imaging," *Signal, Image and Video Processing*, vol. 5, no. 3, pp. 329–342, Sept. 2011.

[3] K. Santhi and R. W. Banu, "Adaptive contrast enhancement using modified histogram equalization," *Optik - International Journal for Light and Electron Optics*, vol. 126, no. 19, pp. 1809 – 1814, Oct. 2015.

[4] H.-J. Kim, J.-M Lee, J.-A. Lee, S.-G. Oh, and W.-Y. Kim, *Contrast Enhancement Using Adaptively Modified Histogram Equalization*, pp. 1150–1158, Springer Berlin Heidelberg, Berlin, Heidelberg, 2006.

[5] S. Poddar, S. Tewary, D. Sharma, V. Karar, A. Ghosh,

and S.K. Pal, "Non-parametric modified histogram equalisation for contrast enhancement," *IET Image Processing*, vol. 7, no. 7, pp. 641–652, 2013.

[6] S. Hashemi, S. Kiani, N. Noroozi, and M. E. Moghaddam, "An image contrast enhancement method based on genetic algorithm," *Pattern Recognition Letters*, vol. 31, no. 13, pp. 1816 – 1824, Oct. 2010.

[7] S. Agrawal and R. Panda, "An efficient algorithm for gray level image enhancement using cuckoo search," in *Int. Conf. on Swarm, Evolutionary, and Memetic Computing*, Berlin, Heidelberg, 2012, pp. 82–89, Springer-Verlag.

[8] Q. Gao, D. Chen, G. Zeng, and K. He, "Image enhancement technique based on improved PSO algorithm," in *IEEE Int. Conf. on Industrial Electronics and Applications*, Jun. 2011, pp. 234–238.

[9] B. Akay and D. Karaboga, "A survey on the applications of artificial bee colony in signal, image, and video processing," *Signal, Image and Video Processing*, vol. 9, no. 4, pp. 967–990, May 2015.

[10] A. Yimit., Y. Hagihara, T. Miyoshi, and Y. Hagihara, "Automatic image enhancement by artificial bee colony algorithm," in *Int. Conf. on Graphic and Image Processing*, 2012, pp. 1–5.

[11] A. Draa and A. Bouaziz, "An artificial bee colony algorithm for image contrast enhancement," *Swarm and Evolutionary Computation*, vol. 16, pp. 69–84, Jun. 2014.

[12] P. Joshi and S. Prakash, "An efficient technique for image contrast enhancement using artificial bee colony," in *IEEE Int. Conf. on Identity, Security and Behavior Analysis*, Hong Kong, Mar. 2015, pp. 1–6.

[13] A. K. Bhandari, V. Soni, A. Kumar, and G. K. Singh, "Artificial bee colony-based satellite image contrast and brightness enhancement technique using DWT-SVD," *International Journal of Remote Sensing*, vol. 35, no. 5, pp. 1601–1624, 2014.

[14] J. D. Tubbs, "A note on parametric image enhancement," *Pattern Recognition*, vol. 20, no. 6, pp. 617–621, 1987.

[15] F. Russo, "Piecewise linear model-based image enhancement," *EURASIP Journal on Advances in Signal Processing*, vol. 2004, 2004, 983173.

[16] Z. Ling, Y. Liang, Y. Wang, H. Shen, and X. Lu, "Adaptive extended piecewise histogram equalisation for dark image enhancement," *IET Image Processing*, vol. 9, no. 11, pp. 1012–1019, 2015.

[17] "Kodak lossless true color image suite," http://r0k.us/graphics/kodak/.

[18] "GNU image manipulation program," https://www.gimp.org/.

[19] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Trans. on Image Processing*, vol. 13, no. 4, pp. 600–612, Apr. 2004.

[20] H. R. Sheikh, A. C. Bovik, and G. de Veciana, "An information fidelity criterion for image quality assessment using natural scene statistics," *IEEE Trans. on Image Processing*, vol. 14, no. 12, pp. 2117–2128, Dec 2005.

[21] D. M. Chandler and S. S. Hemami, "VSNR: A wavelet-based visual signal-to-noise ratio for natural images," *IEEE Trans. on Image Processing*, vol. 16, no. 9, pp. 2284–2298, Sept 2007.