Optik 125 (2014) 1434–1438

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Biological weight selection of multi-scale retinex via artificial bee colony algorithm

Qifu Zhang[a], Haibin Duan[a,b,*]

[a] State Key Laboratory of Virtual Reality Technology and Systems, School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, PR China
[b] Science and Technology on Aircraft Control Laboratory, Beihang University, Beijing 100191, PR China

ARTICLE INFO

Article history:
Received 13 April 2013
Accepted 1 September 2013

Keywords:
Image enhancement
Multi-scale retinex (MSR)
Artificial bee colony (ABC)
Gaussian filter

ABSTRACT

The goal of this study is to present a biological approach to weight selection in Multi-scale Retinex (MSR) using the Artificial Bee Colony (ABC) algorithm. The standard MSR assigns the same weights to the Gaussian filters with different scales and cannot ensure the optimal enhancement results in various environments. To tackle this problem, we employ ABC for weight selection to optimize the evaluation results in MSR. The optimization of weight selection compensates the defects of the scale parameters in Gaussian filters. Some examples are given to demonstrate the feasibility and potential of the approach. We report our experimental results to demonstrate the excellent performance in enhancement compared with standard MSR. The advantages of our method are systematically analyzed in detail.

1. Introduction

Image quality can be subject to various environmental factors such as relative movement, color distortion, and uneven illumination. Decrease in image quality is generally considered as the crux of observation problem for men. Computers are prone to make mistakes when dealing with low-quality images. Therefore, it is significant to restore and improve image quality for future work. Generally, the purpose of image enhancement is to improve the contrast ratio or remove noises in images [1–3]. The best-known methods of image enhancement include linear transformation, histogram equalization, histogram specification [4], homomorphic filtering, etc. The classical algorithms are easier to implement but generally have limited application areas. For instance, histogram equalization generates color distortion in images during the procedure of enhancement. Despite much progress in recent years on image enhancement, there still exist no perfect methods for all cases. In 1964 Edwin Land proposed the retinex theory on the basis of the brightness and color perception model of human visual system [5]. Retinex is a compound word comprised of retina and cortex. There is increasing evidence that complex organisms for image processing are contained in visual cortex. Retinex theory mainly contains two parts: (a) colors of objects are determined by the capability to reflect rays of light. (b) colors are not influenced by uneven illumination. The theory is mainly computational but has implications for anatomy and neuroscience. Land [5] proposed that filtered information from retina pyramidal cells is reprocessed within three independent channels. The retina–cortex system is subsequently formed by channels that remove the influence of illumination. Color perception is implemented by comparisons between intensity in three retina–cortex images. Retinex theory is applied in various researching areas to resolve problems of computer vision more specifically that of enhancement of remote sensing images, medical images and hyperspectral images. The potential for more application of retinex has yet to be explored.

Multiple algorithms have been proposed due to the absence of unified mathematic models of retinex for image enhancement. Common methods include homomorphic filtering retinex, Poisson retinex, Single-scale retinex (SSR) [6,7], etc. The retinex model modified by Land and McCann is one of the famous methods to explain the color perception mechanism of human visual system [8]. Retinex computation is performed automatically on the required signal by human visual system. SSR utilizes the Gaussian surround function of single scale for filtering and it has limited practicability in a number of cases. The goal of enhancement is reached by reducing the influence from illumination to reflection. Jobson et al. [9] integrated Gaussian filters of different spatial scales to address the drawbacks of SSR. Multi-scale retinex (MSR) succeeds in avoiding compression of dynamic range of intensity [10]. Much progress has been made to improve the standard retinex algorithm and apply retinex theory to other fields in image processing. Zhao et al. proposed a method for intrinsic image decomposition based

* Corresponding author at: State Key Laboratory of Virtual Reality Technology and Systems, School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, PR China. Tel.: +86 10 8231 7318.
E-mail address: hbduan@buaa.edu.cn (H. Duan).

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http://dx.doi.org/10.1016/j.ijleo.2013.09.019

on retinex and texture analysis [11]. Chen et al. utilized the region-based retinex for the enhancement of electronic portal images [12]. Parthasarathy and Sankaran [13] developed an automated MSR that obtains parameter values to enhance images; it can be used for color restoration. Shukri et al. applied a modified MSR for motion-blurred iris images to minimize the intra-individual variations [14].

Our research attempts to improve MSR by optimizing weight selection of different Gaussian filters for illumination estimation. Of special interest to us here are techniques on the basis of intelligence optimization algorithms. Swarm-intelligence optimization is a novel class of bio-inspired methods and has been widely used in solving problems of computer vision [15,16]. The methods have strong global searching capability and obtain a wide range of applications in the field of function optimization, path planning and combinatorial optimization [17–21]. The artificial bee colony (ABC) algorithm is a popular swarm-intelligence-based algorithm proposed by Karaboga in 2005 [22]. ABC simulates the biological mechanism of bee groups seeking for optimal food sources. In this design we propose a method to optimize the weight selection for Gaussian filters of MSR using ABC. The results show that our proposed method outperforms the standard MSR, and is comparable to the state-of-the-art optimization methods in various kinds of cases.

The remainder of this paper is organized as follows: We begin with the description of MSR model in Section 2. Our modified method using ABC is presented in detail in Section 3, and its efficient implementation is discussed in Section 4. The conclusion is represented in Section 5.

2. MSR

There exist two classes of approach for image enhancement: space domain approach and frequency domain approach [23]. Retinex is considered to belong to the latter. Images are composed of two parts, namely, the reflectance image and the illuminance image. The reflectance image determines intrinsic properties and the illuminance image determines dynamic range [6,9]. The intensity of point (x,y) can be presented as:

$$I(x, y) = R(x, y) \cdot L(x, y) \tag{1}$$

where $L(x,y)$ is the irradiance that falls on point (x,y) on the surface and $R(x,y)$ represents the reflectance of the image. Eq. (1) can be presented by taking the logarithm as

$$\log[R(x, y)] = \log\ I(x, y) - \log[G(x, y) \times I(x, y)] \tag{2}$$

where $G(x,y)$ is the low-pass filter that estimates the illuminance image. MSR concept includes the application of multiple Gaussian filters with different weights based on the equations given as:

$$O_i(x, y) = \sum_{n=1}^{N} \omega_n \{\log\ I_i(x, y) - \log[F_n(x, y) \times I_i(x, y)]\} \tag{3}$$

$$F_n(x, y) = Ke^{-(x^2+y^2)/\sigma_n^2}, \quad \iint F_n(x, y)dxdy = 1$$

where ω_n represents weight value for the nth scale, and $F_n(x,y)$ is the Gaussian filter function with scale parameter σ_n. Fig. 1 shows the process of MSR. We generally use small-scale, middle-scale and large-scale Gaussian filters to implement MSR.

The weights for three scales in Fig. 1 are given the same numerical value of 1/3. However, this simplification cannot achieve the optimal results for enhancement in various scenes. Our main work concentrates on selecting the weights using ABC algorithm to compensate the defects of MSR.

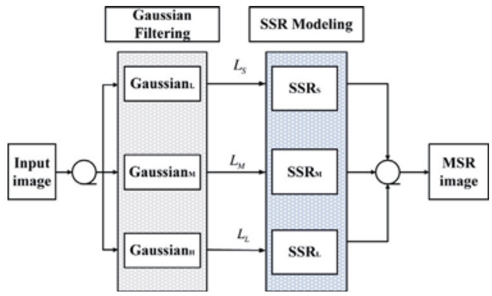

Fig. 1. Flow chart of MSR.

3. MSR biological weights selection based on ABC

3.1. ABC

ABC was inspired by the phenomenon that bees dance to transmit the information about food sources. The algorithm was initially applied to solve the extremum problems of continuous multi-peak functions. ABC has been utilized in various research areas including workshop scheduling and robot path planning as a novel heuristic bionic intelligent optimization algorithm. Generally ABC composes of three basic parts: food sources, employed foragers and unemployed foragers. Food sources correspond to the possible solutions within the scope of solution space in mathematic problems. The values of food sources are subject to various factors such as viability of the source and proximity to the hive. Employed foragers are linked with specific food sources that are currently exploited. They return to the hive and unload nectar after recording the source location and gathering nectar rapidly. Employed foragers may abandon the previous source when the food source is exhausted and turn into followers, or they may dance to recruit mates in the hive. They may continue to forage alone with no followers as the third choice. Unemployed foragers can be classified into two types: scouts and onlookers. The scouts search for new food sources without any prior knowledge. The onlookers seek for food on the basis of information obtained from the dance of employed foragers.

All the bees act as scouts with no prior knowledge at the beginning. The choices they make are decided by the revenue degree obtained from random search according to the following principle: Bees turn into leaders if their incomes rank higher than the threshold, otherwise they become followers. The leaders recruit more partners and keep on gathering. Bees abandon the food sources and continue searching if their incomes are relatively lower. The bees set for searching new sources when it fails to find better sources. In a word, ABC is concerned with seeking out the optimal value of fitness function by simulating the searching strategy of bees.

3.2. ABC-based MSR

The retinex theory makes better performances in image enhancement compared with other methods. The center/surround operation of the standard MSR is especially effective for fog removal and night vision. However, standard MSR may not achieve optimal results for image enhancement due to the same weight values assigned to the Gaussian filters with different scales. The choice of weight values is supposed to be within reasonable limits. This traditional difficulty in MSR has limited its application in vision enhancement. Our work attempts to apply ABC to the selection of weights for optimization.

The weight values are given randomly within the range of (0, 1) as the initial food sources. The values are subject to:

$$\omega_L + \omega_M + \omega_S = 1 \tag{4}$$

where ω_S, ω_M and ω_L respectively represent the weights for Gaussian filters with small scale, middle scale and large scale. Our goal is to achieve the optimal enhancement by weight selection using the artificial bee colony searching strategy. It is noticeable that the calculation of contrast ratio can be difficult due to the subjectivity of evaluation for image quality. For our research we used the following equation to evaluate the quality of images:

$$C = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} f^2(x, y) - \left[\frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} f(x, y) \right]^2 \tag{5}$$

where M and N are the size of images. However, the information of image details is ignored in Eq. (5). We combined both contrast ratio and the entropy of brightness to achieve the fitness function. The entropy of brightness H in images is calculated by:

$$\begin{aligned} grad(x, y) &= 4f(x, y) - [f(x-1, y) + f(x+1, y) \\ &\quad + f(x, y+1) + f(x, y-1)] \end{aligned} \tag{6}$$

$$H = \sum \frac{grad(x, y)[1 + grad(x, y)]}{m} \tag{7}$$

where $grad(x,y)$ represents the gradient of point (x,y). The fitness function is defined as $-C$ and the optimal enhancement can be achieved when $-C$ reaches the minimum. The entropy of brightness reflects the frequency of changes in gray scale and can be used to represent image details.

$$\text{Fitness} = \lambda_1 \times C + \lambda_2 \times H \tag{8}$$

where λ_1 and λ_2 are the weights for contrast ratio and entropy respectively. Additionally, it is noticeable that our proposed algorithm spends more processing time compared with the state-of-the-art methods due to iterations in ABC. The flow chart of weight selection using ABC is shown with Fig. 2.

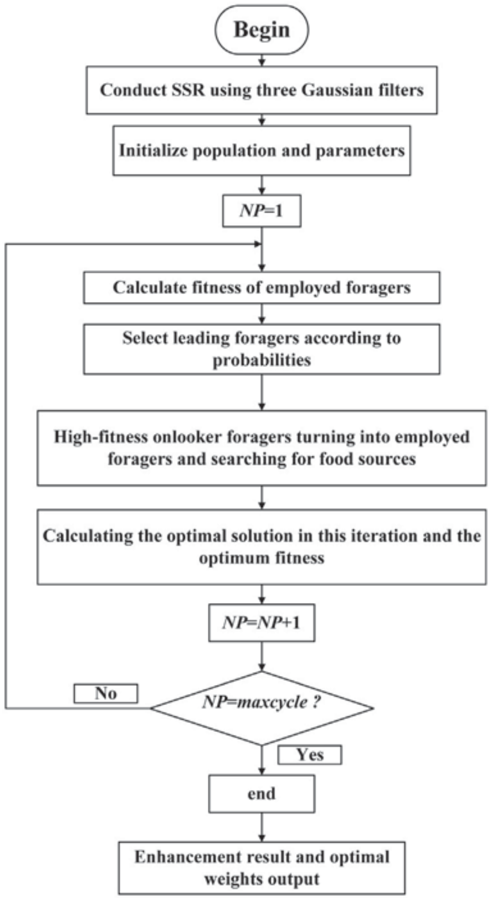

Fig. 2. Flow chart of MSR biological weight selection based on ABC.

4. Experimental results and discussion

To demonstrate the effectiveness of the modified bio-inspired mechanism, we conducted series of comparative simulations using our method and the standard MSR. We also adopted Particle Swarm Optimization algorithm as another approach to implement our comparison. The simulations are based on the case of dim environments to evaluate the ability of our proposed method for defogging and improving the contrast ratio. The Gaussian filters that were used in MSR and our proposed biological algorithm share the same scale parameters as follows:

$$\sigma_L = 53.38, \quad \sigma_M = 1458, \quad \sigma_S = 13,944.5$$

The scale parameters were obtained from previous experimental results. Figs. 3–5 present the results of the modified method compared with standard MSR and PSO-MSR. The iteration curves are given as well. The parameters for ABC were set to the following values: The total number of bees is 20, where employed foragers and unemployed foragers share half the population respectively. The maximum of iteration is 50. The procedure of simulation was implemented in Matlab 2012b and executed by the computer with 2.0 GHZ CPU, 4 GB memory, and operation system of Windows 7.

Fig. 3 shows the performance of our ABC-based MSR (ABC-MSR) on the 256×192 image compared with the standard MSR and PSO-based MSR (PSO-MSR). The standard MSR fails to present the edges of the building and the background of the sky appears absolutely white. The image quality is obviously better in Fig. 3(d) using the ABC weight selection. The details of image can be seen more clearly and the variations in density of background are presented. PSO-MSR and ABC-MSR present almost the same enhancement

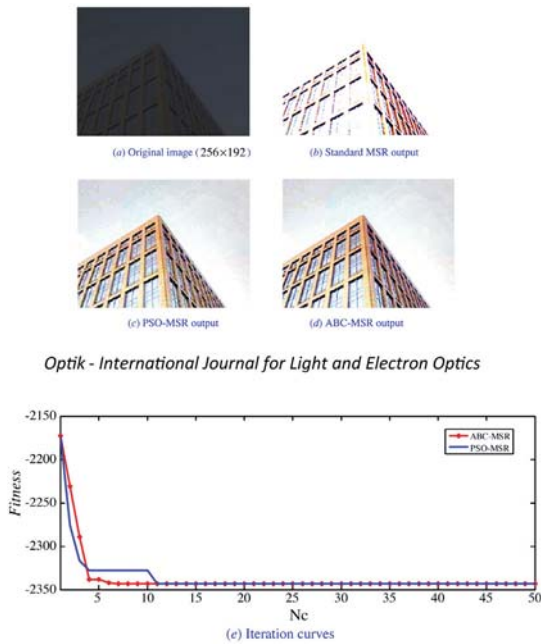

Fig. 3. Comparison results of the MSR algorithms in Scene 1. (a) Original image (256×192). (b) Standard MSR output. (c) PSO-MSR output. (d) ABC-MSR output. (e) Iteration curves.

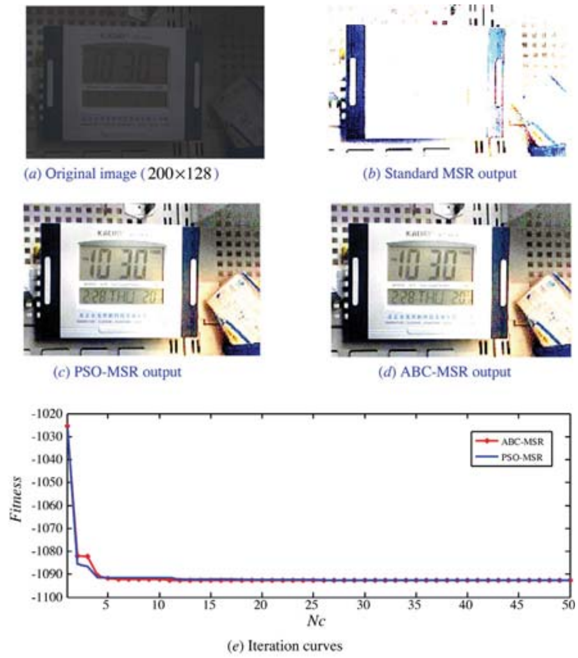

Fig. 4. Comparison results of the MSR algorithms in Scene 2. (a) Original image (200 × 128). (b) Standard MSR output. (c) PSO-MSR output. (d) ABC-MSR output. (e) Iteration curves.

results according to Fig. 3(c and d). However, Fig. 3(e) indicates that the convergence velocity of ABC-MSR is obviously faster than PSO-MSR. For Case 2, Fig. 4 gives the evaluation results of both algorithms for the 200 × 128 image of the indoor scene. Numbers in the electronic clock appear more visible in Fig. 4(d) in our enhanced image. The result in Fig. 4(b) loses much detail due to the

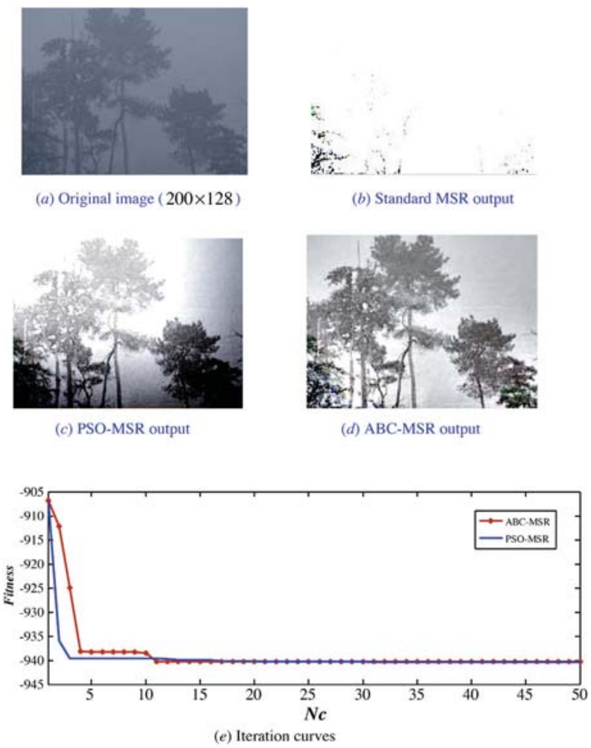

Fig. 5. Comparison results of the MSR algorithms in Scene 3. (a) Original image (200 × 128). (b) Standard MSR output. (c) PSO-MSR output. (d) ABC-MSR output. (e) Iteration curves.

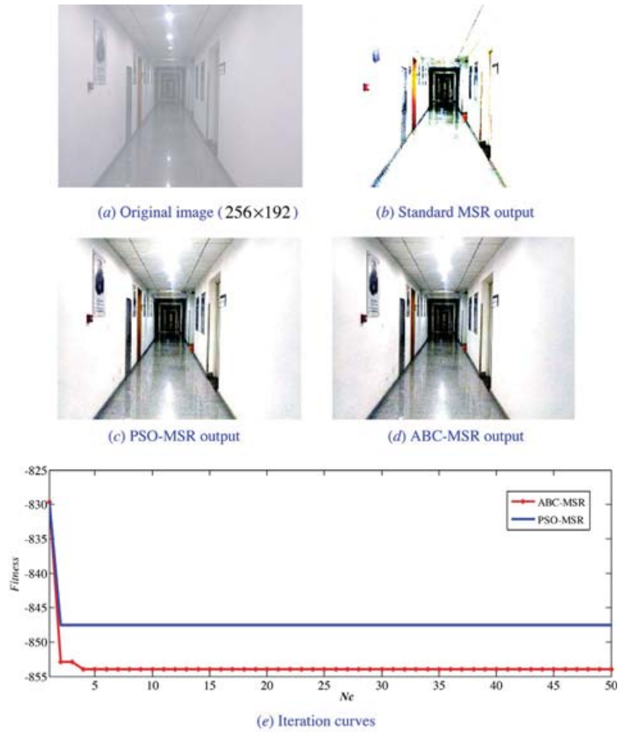

Fig. 6. Comparison results of the MSR algorithms in Scene 4. (a) Original image (256 × 192). (b) Standard MSR output. (c) PSO-MSR output. (d) ABC-MSR output. (e) Iteration curves.

inappropriate parameter assignment. PSO-MSR and ABC-MSR present better enhancement in Fig. 4(c and d). Nevertheless, ABC-MSR converges to the optimal value with less iteration in Fig. 4(e). The original image in Fig. 5(a) was taken outdoors after sunset. As can be seen, the trees are almost invisible after enhancement by the standard MSR in Fig. 5(b). Fig. 5(c and d) shows ABC-MSR present better evaluation results as the upper parts of PSO-MSR output appear less visible. Besides, the iteration curve of ABC-MSR presents a faster converging rate than PSO-MSR.

To further support the notion that the ABC-MSR exceeds the standard MSR in feasibility, another comparative simulation in the scene with excessive intensity is implemented in Fig. 6. Serious color distortion exists in the standard MSR output as is seen in Fig. 6(b). PSO-MSR and ABC-MSR increase the image quality obviously in Fig. 6(c and d). ABC-MSR achieves better optimal value according to the iteration curves in Fig. 6(e). Our method succeeds in illuminating the dim scene and preserving details. As observed from the results, our proposed algorithm shows better performances in the four scenes. The fitness function introduced in Eq. (8) is multiplied by −1 as the value for evaluation in four iteration curves. The curves are able to converge to the minimum in less than 30 iterations. Standard MSR needs to adjust its scale parameters according to the variations of environments to achieve better enhancement. We use ABC searching strategy to reach the same goals by optimizing the fitness values adaptively and compensate the defects of the standard MSR.

5. Conclusions

This paper proposes a biological weight selection strategy for MSR using the ABC algorithm. Some comparative simulations were conducted to demonstrate the significant advantages of the modified ABC-MSR in image enhancement in contrast with the standard MSR. The improved MSR makes excellent performances by weight optimization of Gaussian filters without adjusting the scale parameters to various environments. The bio-inspired methods, such as particle swarm optimization, bio-geography optimization, differential evolution are also novel approaches to solve such complicated problems. Our future work will focus on the acceleration of our modified MSR algorithm, and also focus on the modified MSR applications in Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), Unmanned Surface Vehicles (USVs), and Unmanned Underwater Vehicles (UUVs).

Acknowledgements

This work was partially supported by Natural Science Foundation of China (NSFC) under grant #61333004, #61273054 and #60975072, National Key Basic Research Program of China under grant #2014CB046401, National Magnetic Confinement Fusion Research Program of China under grant #2012GB102006, Program for New Century Excellent Talents in University of China under grant #NCET-10-0021, Top-Notch Young Talents Program of China, and Aeronautical Foundation of China under grant #20135851042.

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