LETTER

Retinex-Based Image Enhancement with Particle Swarm Optimization and Multi-Objective Function*

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SUMMARY Multiscale retinex is one of the most popular image enhancement methods. However, its control parameters, such as Gaussian kernel sizes, gain, and offset, should be tuned carefully according to the image contents. In this letter, we propose a new method that optimizes the parameters using practical swarm optimization and multi-objective function. The method iteratively verifies the visual quality (i.e., brightness, contrast, and colorfulness) of the enhanced image using a multi-objective function while subtly adjusting the parameters. Experimental results show that the proposed method achieves better image quality qualitatively and quantitatively compared with other image enhancement methods.

key words: image enhancement, retinex algorithm, particle swarm optimization, multi-objective function

1. Introduction

Digital images are often taken in poor lighting or weather conditions, which result in unfavorable quality of image. Details, particularly in dark regions, are difficult to recognize, which has a detrimental impact on many computer vision methods such as object detection and visual tracking. Therefore, image enhancement, aiming to modify interpretability and perception of information in an image to provide improved input for computers or the human vision system, has been one of the most fundamental problems in the fields of image processing and computer vision [1].

Retinex is a nonlinear image enhancement method that simulates the lightness and color perception of the human vision system [2]. It sharpens the image details while ensuring color constancy and high dynamic range. However, the retinex method requires control parameters to be tuned and the parameters are often manually and heuristically set [3]. To automatically tune the control parameters of the retinex method, we can employ particle swarm optimization (PSO) [4] as in [3], [5] because PSO is simpler to implement, faster in comparison with other optimization methods and also ideal for non-linear problems. PSO measures its candidate solutions (control parameters) using an objective function which quantifies the quality of an enhanced image. Therefore, choosing a good objective function plays an important role in the enhancement results. Previously, we adopted an objective function that measures only the image contrast [5] as in [3]. However, the function failed to enhance the contrast in dark regions, which could lead to losing information in the background. Moreover, decrease in the colorfulness or brightness due to contrast enhancement was not considered. In this letter, we propose a multi-objective function to ensure that the contrast is enhanced while enhancing the colorfulness and brightness of the input image. This study is an extension of our previous one [5] but is different in that:

- A multi-objective function for PSO is proposed to enhance the brightness, contrast, and colorfulness of the input image.
- The study addresses the problem that the brightness or colorfulness of the input image decreases when using the objective function that focused only on enhancing the contrast.
- More extensive experiments and performance evaluation are carried out.

2. Retinex Theory

The retinex theory was introduced by Land and McCann in 1971 [6]. There have been several types of retinex methods for implementing image enhancement, such as single scale retinex (SSR), multiscale retinex (MSR), multiscale retinex with color restoration (MSRCR), and multiscale retinex with chromaticity preservation (MSRCP).

Jobson et al. [7] developed SSR, MSR, and MSRCR based on the retinex theory. SSR is a center-surrounded algorithm, where the illumination is considered by the difference between the center pixel and an average of its neighbors. The formula of SSR can be represented as:

$$R_{SSR} = \log(I_i) - \log(G \ast I_i),$$  

where $I$ is the input image, $R_{SSR}$ is the retinex output image for the $i$-th color channel, the operator $\ast$ represents the spatial convolution, and $G$ is a 2D Gaussian kernel. SSR can either provide dynamic range compression or tonal rendition, but not both simultaneously.

MSR can provide an acceptable exchange between tonal rendition and dynamic range compression. The MSR
output is specified as a weighted sum of various SSR outputs. The formula of MSR can be expressed as:

\[ R_{MSR} = \sum_{n=1}^{N} w_n [\log(I_i) - \log(G_n * I_i)], \]

where \( N \) is the number of scales, \( w_n \) is the weight associated with the \( n \)-th scale, and \( G_n \) is a 2D Gaussian kernel with a size of \( \sigma_n \).

MSRCR provides color restoration to eliminate the color distortion and gray zones that often appear in the MSR outputs of images where a certain color dominates. The MSR output is multiplied by a color restoration function \( C_i \) as follows:

\[ C_i = \beta \left[ \log(\alpha I_i) - \frac{1}{3} \sum_{i=1}^{3} I_i \right], \]

The color restoration function in MSRCR is at risk of inverting color. Color inversion can be observed in images where a certain color dominates. The MSR output is computed as in [8], as follows:

\[ A = \max \left( \frac{255}{I_{max}}, \frac{f_{cb}(R_{MSR}, p_l, p_h)}{I_{int}} \right), \]

\[ R_{MSRCP} = \eta (A_{I_i} + \epsilon), \]

where \( \eta \) and \( \epsilon \) are the gain and offset values, respectively.

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where \( I_{max} \) is the image having pixel-wise maximum values among the three color channels of \( I \), \( I_{int} \) is the intensity image of \( I \), \( R_{MSR} \) is the MSR output of \( I_{int} \), and \( f_{cb}(\cdot) \) is the color balance function proposed in [9], which stretches the values of a color channel with two values representing the percentages of clipping pixels on the top and bottom side, \( p_l \) and \( p_h \) [8]. \( \eta \) and \( \epsilon \) are the gain and offset values, respectively.

3. PSO

PSO is an evolutionary computational algorithm, which imitates the bird’s social behavior and fish schooling. It optimizes a problem by iteratively attempting to improve a candidate solution using a given measure of quality [4]. Potential solutions, considered as particles in PSO, have their fitness values which are computed by an objective function (= the measure of quality) and velocities which change their positions in the problem space. The particles are guided to move toward the personal and global best solutions which are determined using the fitness values. The main process of PSO is expressed as:

\[ \begin{align*}
  v_{j+1}^k &= \omega v_{j}^k + c_1 r_1 (p_{best}^k - x_{j}^k) + c_2 r_2 (g_{best}^k - x_{j}^k), \\
  x_{j+1}^k &= x_{j}^k + v_{j+1}^k,
\end{align*} \]

where \( x_{j}^k \) and \( v_{j}^k \) represent the position and velocity of the \( j \)-th particle at the \( k \)-th iteration, respectively, \( r_1 \) and \( r_2 \) are random values in the range of \([0, 1]\), \( p_{best}^k \) is the personal best solution of the \( j \)-th particle, \( g_{best}^k \) is the global best solution, \( \omega \) is the inertia weight, and \( c_1 \) and \( c_2 \) are constants.

4. Proposed Method

MSRCP is able to enhance the image contrast while well preserving the original colors and thus has been popularly used. However, the control parameters, such as Gaussian kernel sizes, gain, and offset, has to be subtly adjusted according to the image contents. The main purpose of the proposed method is to obtain the optimal values of the parameters by using the PSO algorithm. To enhance the brightness, contrast, and colorfulness of the input image, we propose a multi-objective function, which is used as the measure of quality for the PSO algorithm.

4.1 Multi-Objective Function

The PSO algorithm employs an objective function to measure the quality of an enhanced image. The objective function used in the previous studies [3], [5] focused only enhancing the image contrast. It sometimes decreased the brightness and colorfulness of the input image, which led to losing information in the dark regions of the background. To address this problem, we propose a multi-objective function which includes three measures: brightness, contrast, and colorfulness measures.

First, to enhance the brightness of the input image, the difference between the mean intensities of the input and its enhanced images is computed. The brightness measure is expressed as:

\[ F_{BR} = \text{mean}(I_{en}) - \text{mean}(I), \]

where \( I \) and \( I_{en} \) are the input and enhanced images, respectively.

Second, to enhance the contrast of the input image, the entropy, sum of edge intensities, and number of edges are computed as in [3], [5]. The contrast measure is expressed as:

\[ F_{CT} = \log \left( \frac{\log \left( \sum_{x=1}^{W} \sum_{y=1}^{H} J(x,y) \right)}{WH} h(I_{en}) \right), \]

where \( J \) is the edge image of \( I \), which can be computed as in [10], \( f_c(\cdot) \) counts the number of pixels, whose intensity values is higher than a threshold, \( h(\cdot) \) computes the entropy of image, and \( W \) and \( H \) are the width and height of \( I \), respectively.

Third, to enhance the colorfulness of the input image, we employ the image colorfulness index proposed in [11], which reflects the richness and vividness of color. The colorfulness measure computes the difference between the colorfulness indices of the input and its enhanced images as:

\[ F_{CF} = f_c(I_{en}) - f_c(I), \]

where \( f_c(\cdot) \) computes the colorfulness index [11].

Finally, the multi-objective function linearly combines
the three measures as follows.

\[ F = k_0 F_{BR} + k_1 F_{CT} + k_2 F_{CF}. \]  

(12)

Here, \( k_0, k_1, \) and \( k_2 \) are the weighting factors of each measure, which are set experimentally depending on the input image. \( k_1 \) and \( k_2 \) are set to much smaller values (between 0 and 0.5) than \( k_0 \). Otherwise, images are likely to be over-enhanced. In this letter, we set \( k_0, k_1, \) and \( k_2 \) to 1.0, 0.4, and 0.5, respectively.

4.2 Tuning the MSRCP Parameters Using the PSO

This section describes how the proposed method iteratively tunes the MSRCP parameters in Eq. (6) using the PSO algorithm. Given \( N, w_1, w_2, \) and \( w_3 \) are preset to 3, 1/3, 1/3, and 1/3, respectively in Eq. (2), the MSRCP parameters includes the Gaussian kernel sizes (\( \sigma_1, \sigma_2, \) and \( \sigma_3 \)), gain (\( \eta \)), offset (\( \epsilon \)), and clipping percentages (\( p_t \) and \( p_b \)). Thus, the dimension of each particle is set to 7. During the optimization, the available range of each parameter is set as follows:

- \( \sigma_1 \in [0, 50] \)
- \( \sigma_2 \in [51, 100] \)
- \( \sigma_3 \in [101, 255] \)
- \( \eta \in [0, 30] \)
- \( \epsilon \in [-15, 15] \)
- \( p_t \in [1, 5] \)
- \( p_b \in [1, 5] \)

Both the number of particles and iterations are set to 30 to produce satisfactory results.

The PSO steps for obtaining the optimal MSRCP parameters are as follows:

i. Initialize the particles with random position and velocity within the available range.
ii. Initialize the number of iterations with 0.
iii. Generate enhanced images and compute the fitness values for every particle using Eqs. (6) and (12), respectively.
iv. Compare the fitness value of each particle with that of its \( p_{\text{best}} \); if the fitness value of a particle is higher than the \( p'_{\text{best}} \) value, then the particle becomes \( p_{\text{best}} \).
v. Compare the fitness value of each particle with that of \( g_{\text{best}} \); if the fitness value of a particle is higher than the \( g'_{\text{best}} \) value, then the particle becomes \( g_{\text{best}} \).
vi. Update particles’ velocity and position using Eqs. (7) and (8).

vii. Repeat the steps iii to vii until the number of iterations reaches the maximum value.

5. Experimental Results and Discussion

For the experiment, we used 20 images with low light conditions and poor quality from different datasets including images used in [12]–[14] (Fig. 1). The proposed method were compared with four conventional image enhancement methods, i.e. MSR [7], aMSRCR [15], AGCWD [16], and MSRCP-PSO [5], in subjective and objective aspects. All the methods were implemented and verified with C++ on a PC with 3.20 GHz CPU and 32 GB RAM.

5.1 Visual Assessment

Figure 2 shows the enhancement results of different methods. MSR did not produce acceptable results; the enhanced images look unnatural and color distortion is obviously visible. aMSRCR improved the contrast; more details are visible in the enhanced images. However, aMSRCR also yielded significant color distortion. Compared to MSR and aMSRCR, AGCWD had better performance; the color of enhanced images looks more natural. However, some dark regions were under-enhanced and some bright regions were over-enhanced. MSRCP-PSO, our previous method, well enhanced images both in dark and right regions without color distortion. However, the method, which is only based on these measures, is not able to produce satisfactory results.
PSNR), which can be used as a measure for color distortion caused by image enhancement. Therefore, the proposed method could successfully enhance the contrast while preserving or enhancing the colorfulness and brightness of the input image; most details in the dark regions are visible and the enhanced images look more natural.

5.2 Quantitative Evaluation

Quantitative evaluation of contrast enhancement is not an easy task, because there is no a standard criterion for quantifying the improved perception. Thus, in this letter, we first adopted three measures which have been popularly used in the literature: feature similarity index (FSIM) [17], contrast enhancement based contrast-changed image quality measure (CEIQ) [18], and patch-based contrast quality index (PCQI) [19]. As shown in Fig. 3, the proposed method achieved the highest score for CEIQ and PCQI, which indicates that the proposed method most effectively improved the overall image quality. For FSIM, however, AGCWD scored higher than the proposed method. This may be because AGCWD, which is based on histogram equalization, better preserves structure information of the input image than the other retinex-based methods.

Then, we also computed the peak signal-to-noise ratio (PSNR) [20], which can be used as a measure for color distortion caused by image enhancement. Table 1 shows the average PSNR values of each method. As expected, aMSRCR, MSRC-PSO, and the proposed method achieved higher PSNR values than the others, due to their color restoration or chromaticity preservation functionality. Among them, the proposed method achieved the highest PSNR value, which will be because the multi-objective function allowed the color distortion to be further minimized.

6. Conclusion

In this letter, a new retinex-based image enhancement method that optimized the MSRCP parameters using the PSO algorithm was presented. For the optimization, a multi-objective function was proposed to measure the image quality in terms of brightness, contrast, and colorfulness. The proposed method outperformed the conventional image enhancement methods in both visual and quantitative evaluation. Especially, the method allowed the enhanced images to look more natural and vivid by preserving or enhancing the colorfulness and brightness of the input images.

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