LETTER

A Hybrid Retinex-Based Algorithm for UAV-Taken Image Enhancement

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SUMMARY A hybrid Retinex-based image enhancement algorithm is proposed to improve the quality of images captured by unmanned aerial vehicles (UAVs) in this paper. Hyperparameters of the employed multi-scale Retinex with chromaticity preservation (MSRCP) model are automatically tuned via a two-phase evolutionary computing algorithm. In the two-phase optimization algorithm, the Rao-2 algorithm is applied to performing the global search and a solution is obtained by maximizing the objective function. Next, the Nelder-Mead simplex method is used to improve the solution via local search. Real UAV-taken images of bad quality are collected to verify the performance of the proposed algorithm. Meanwhile, four famous image enhancement algorithms, Multi-Scale Retinex, Multi-Scale Retinex with Color Restoration, Automated Multi-Scale Retinex, and MSRCP are utilized as benchmarking methods. Meanwhile, two commonly used evolutionary computing algorithms, particle swarm optimization and flower pollination algorithm, are considered to verify the efficiency of the proposed method in tuning parameters of the MSRCP model. Experimental results demonstrate that the proposed method achieves the best performance compared with benchmarks and thus the proposed method is applicable for real UAV-based applications.

key words: image enhancement, multiscale Retinex, Rao algorithm, evolutionary computing

1. Introduction

Recent advances in unmanned aerial vehicle (UAV) technologies have facilitated their applications in various domains, such as infrastructure surface inspection, remote rescue, and farm pest control. Since many UAV-based applications rely on UAV-taken images, related image processing algorithms are highly desired. External factors, including insufficient light and bad weather conditions, can induce UAV-taken images with poor qualities [1]. As a consequence, the performance of computer vision algorithms for different tasks, such as object detection, object tracking and semantic segmentation, may be affected. Image enhancement algorithms can improve the quality and information content of originally collected images. Therefore, it is of great importance to develop suitable image enhancement algorithms for UAV-taken images [2].

In literature, Retinex-based image enhancement meth-

ods are widely applied. The Retinex theory is based on lightness and color perception of human vision, proposed by Land and McCann in 1971 [3], [4]. Retinex-based methods can sharpen image details and maintain color constancy with the high dynamic range [5]. However, controlling parameters are often included in Retinex-based methods and these parameters need to be manually determined. Therefore, the robustness of Retinex-based methods cannot be guaranteed for different images. To address this issue, automated parameter tuning methods were proposed to improve the performance of Retinex-based methods. Since parameter tuning of Retinex-based models can be regarded as a non-convex optimization problem, different evolutionary computing algorithms were employed. Hanumantharaju *et al.* [5] and Matin *et al.* [2] applied the particle swarm optimization (PSO) into parameter optimization of Retinex-based methods. Mohamed *et al.* [6] utilized flower pollination algorithm (FPA) to search the best weight of Gaussian filter for multiscale Retinex (MSR) algorithm. However, the applied evolutionary computing algorithms usually contain algorithm-specific parameters and tuning these introduced parameters requires more computational cost.

To overcome this limitation, a hybrid Retinex-based algorithm is proposed for the enhancement of UAV-taken images. In the proposed method, an improved Rao-2 algorithm is incorporated to automatically tune the controlling parameters of the multi-scale Retinex with chromaticity preservation (MSRCP) model. An optimization problem to maximize the contrast enhancement-based contrast changed image quality measure (CEIQ) value of images is formulated. To obtain the best solutions (parameter settings), two search phases, global search and local search, are included in the improved Rao-2 algorithm. Rao-2 algorithm proposed by Rao [7] is employed to conduct the global search. Candidate solutions are iteratively updated based on random interaction between the best and worst solutions and no algorithm-specific parameters needs to be defined. Next, the Nelder-Mead (NM) simplex algorithm [8], [9] is utilized to further improve the solutions obtained by Rao-2 algorithm. The combination of the Rao-2 and simplex algorithms can enhance the exploration and exploitation abilities of the optimization algorithm simultaneously. To validate the performance of the proposed method, real collected UAV-taken images with bad illumination conditions are utilized and four Retinex-based methods, MSR [10], multiscale Retinex with color restoration (MSRCR) [11], automated multiscale

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Retinex (AMSR) [12] and MSRCR [13], are employed as benchmarking algorithms. Besides, the proposed method is compared with PSO and FPA in tuning parameters of the MSRCR model.

The rest of this paper is organized as follows. The problem formulation and the proposed method are presented in Sect. 2. In Sect. 3, the experiments and analyses are discussed. Finally, Sect. 4 makes the conclusion.

2. Method

Land and McCann proposed Retinex theory imitating the human visual system in 1971 [4]. In Retinex theory, a given image S is recognized as a reflection image R with multiplicative noise. In order to restore the real reflection image of object like the human visual system, it needs to reasonably eliminate or reduce the influence of noise. Therefore, the reflection image R can be estimated as Eq. (1).

$$R_{SSR_i} = \log(S_i) - \log(G_k * S_i) \quad (1)$$

where S is the input image, G is a Gaussian filter, and R is the output image. Since only one scale transformation is implemented, it is also called single scale Retinex (SSR).

However, since the noise information extracted by single scale transformation is limited, dynamic range compression and contrast enhancement of the enhanced image derived by SSR are hard to achieve good results at the same time. In order to address this limitation, MSR was developed. It can maintain the color tone of the image while being compressed in the dynamic range. The output of MSR is described as the weighted sum of different SSRs as (2).

$$R_{MSR_i} = \sum_{k=1}^N w_k [\log(S_i) - \log(G_k * S_i)] \quad (2)$$

where N is the number of scales, w_k is the weight of the k -th scale transformation, and G_k is a Gaussian filter with a scale size of σ_k . The scale parameter c_k has a significant impact on the output image. Generally, N is set to 3 which represents three scales transformation, high scale, middle scale and low scale, and w_k is set to 1/3 for synthesizing multi-scale noise fairly.

MSRCR was proposed by Jiang *et al.* [14] for solving color distortion problem existing in SSR and MSR. On the basic of MSR, MSRCR introduced a color restoration factor Q to reduce the color distortion derived from contrast enhancement in the local area of the image, described as (3) and (4).

$$Q_i = \beta [\log(\alpha S_i) - \log(\sum_{i=1}^3 S_i)] \quad (3)$$

$$R_{MSRCR_i} = g(Q_i R_{MSR_i} + \varepsilon) \quad (4)$$

where i -th band of the color of restoration function (CRF). β is a gain constant, α controls color intensity, g and ε are the values of gain and offset respectively.

However, color restoration in MSRCR has the risk of inverting colors. The color restoration problem may lead to pixels with values near 0 jump to 255 or those with values near 255 down to 0. A possible way to solve this problem is that use Multi-scale Retinex with chromaticity preservation (MSRCP) to attain color balance. The formula of MSRCP can be represented as (5) and (6).

$$A = \min \left\{ \frac{255}{\max(S_{Ri}, S_{Gi}, S_{Bi})}, \frac{f_{cb}(R_{MSR_{int}}, p_t, p_b)}{S_{int}} \right\} \quad (5)$$

$$R_{MSRCP_i} = A \cdot S_i \quad (6)$$

where S_{Ri} , S_{Gi} , S_{Bi} are three colors channels of the input image S , S_{int} is the intensity image of input and $R_{MSR_{int}}$ is the MSR output of S_{int} . The f_{cb} is a color balance function, it extends the values of a color channel with two values, the percentages of clipping pixels on the top (p_t) and the percentages of clipping pixels on the bottom (p_b). However, MSRCP introduces too many adjustable parameters while solving the color quality problem, which increases the complexity of this algorithm. Therefore, this algorithm is not friendly to manual operation in real applications. To find appropriate parameters in different image scenarios, an optimization problem is formulated as (7).

$$\begin{aligned} \max_{\sigma_1, \sigma_2, \sigma_3, p_t, p_b} \quad & \text{CEIQ} [f_{MSRCP}(S | \sigma_1, \sigma_2, \sigma_3, p_t, p_b)] \\ \text{s.t.} \quad & 0 \leq \sigma_1 \leq 50 \\ & 51 \leq \sigma_2 \leq 100 \\ & 101 \leq \sigma_3 \leq 255 \\ & 0.01 \leq p_t \leq 0.05 \\ & 0.95 \leq p_b \leq 0.99 \end{aligned} \quad (7)$$

where S is the input image, σ_1 , σ_2 , σ_3 , p_t , and p_b are controlling parameters of MSRCP function, CEIQ is contrast enhancement-based contrast changed image quality measure.

To address the above-mentioned optimization problem and obtain the best solutions, two search phases, global search and local search, are performed. In the global search phase, Rao-2 algorithm is utilized to search the best solutions on a large solution space. This algorithm has advantages such as simple operation, fast searching speed, and no algorithm-specific parameters. The update strategy of Rao-2 algorithm is defined as Eqs. (8) and (9):

$$\begin{aligned} P'_{j,k,i} = & P_{j,k,i} + r_{1,j,i}(P_{j,best,i} - P_{j,worst,i}) \\ & + r_{2,j,i}(|P_{j,k,i} \text{ or } P_{j,l,i}| - |P_{j,l,i} \text{ or } P_{j,k,i}|) \end{aligned} \quad (8)$$

$$P_{k,i+1} = \begin{cases} P'_{k,i}, & \text{if } f(P'_{k,i}) \geq f(P_{k,i}) \\ P_{k,i}, & \text{if } f(P'_{k,i}) < f(P_{k,i}) \end{cases} \quad (9)$$

where $P_{j,best,i}$ is the best candidate of j -th variable and $P_{j,worst,i}$ is the worst candidate of j -th variable for during the i -th iteration. $P'_{j,k,i}$ is updated result of $P_{j,k,i}$, $r_{1,j,i}$ and $r_{2,j,i}$ are two random numbers of the j -th variable during the i -th iteration, with their value in the range $[0, 1]$, and $f(P_{k,i})$ is fitness value derived by candidate solution $P_{k,i}$.

Though Rao-2 has a fast-searching speed, its searching precision is not high enough. Therefore, on the basis of result of Rao-2, Nelder-Mead method [9] is employed for it has a good local search capability. This method can readjust the simplex according to the local behavior. The detailed steps of Nelder-Mead method are described as follow:

(1) Initialization

Initialize randomly to generate $n + 1$ vertices within their acceptable range. Calculate the value of objective function and the simplex constraint of each vertex, then order them as $f(x_1) \leq f(x_2) \leq \dots \leq f(x_{n+1})$.

(2) Reflection

Compute the reflection point x_r as (10):

$$x_{\text{refl}} = \bar{x} + \eta(\bar{x} - x_{\text{high}}) \quad (10)$$

(3) Expansion

In order to expand the search space in the same direction, the position of vertices is updated as (11).

$$x_{\text{exp}} = \varepsilon x_{\text{refl}} + (1 - \varepsilon) x_{\text{cent}} \quad (11)$$

where x_{cent} is the center of the simplex without x_{high} in minimization case. If $f(x_{\text{exp}}) < f(x_{\text{refl}})$, x_{high} is replaced by x_{exp} ; Otherwise, x_{high} is replaced by x_{refl} ; Then go to step 6.

(4) Contraction Execute a contraction between $\bar{x}$ and the better one of x_{n+1} and x_{refl} , if $f(x_n) \leq f(x_r) < f(x_{n+1})$, calculate the outside contraction as (12):

$$x_{ci} = \bar{x} + \theta(x_{\text{refl}} - \bar{x}) \quad (12)$$

Once x_{con} is obtained, if $f(x_{ci}) \leq f(x_{\text{refl}})$, then replace x_{n+1} with x_{con} and go to Step6; Otherwise, go to the step 5. If $f(x_r) \geq f(x_{n+1})$, compute the inside contraction based on (13):

$$x_{cj} = \bar{x} + \theta(x_{n+1} - \bar{x}) \quad (13)$$

After getting x_{cj} , if $f(x_{cj}) \geq f(x_{n+1})$, then replace x_{n+1} with x_{cj} and go to Step6, otherwise go to step 5.

(5) Shrinkage If contraction failed, shrink all vertices of the simplex as (14):

$$x_i = \lambda x_i + (1 - \lambda)x_{\text{low}} \quad (14)$$

(6) If the termination criterion is satisfied, the algorithm will be exited. Otherwise, repeat from Step 3.

The main optimization process of the hybrid optimization algorithm is expressed as Algorithm 1.

3. Case Study

To verify the performance of proposed method, 20 images captured by the UAV (model: DJI Mavic Pro) for wind turbine inspection are utilized. The images are taken under the backlight or bad illumination conditions, and example images are shown in Fig. 1.

Fig. 1 Example images used in our experiment.

Fig. 2 Enhancement results of different methods

Four benchmarking algorithms, MSR [11], MSRCR [12], AMSR [13], MSRCP [14] are considered, and their controlling parameters are set according to [2]. In addition, PSO and FPA algorithms are also used to tune parameters of the MSRCP model. A PC with Intel Core i3-9100@3.60GHz CPU and 16GB RAM is used to implement the considered algorithms based on Python 3.6 and Windows 10.

Algorithm 1 Hybrid optimization algorithm

Input: Population size N , Max iterations M .

Output: The optimum solution P_{best}^*

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1: for  $k := 1$  to  $N$  do
2:   Initialize  $P_k$ 
3: end for
4: Get the best solution  $P_{\text{best}}$  and the worst solution  $P_{\text{worst}}$ .
5: Set  $i = 1$ 
6: while termination criterion not satisfied do
7:   Get  $P'_{j,k,i}$  according to (8).
8:   Update  $P_k$  according to (9).
9:   Update the best solution  $P_{\text{best}}$  and the worst solution  $P_{\text{worst}}$ .
10:  Set  $i = i + 1$ 
11: end while
12: Update  $P_{\text{best}}$  via Nelder-Mead algorithm to  $P_{\text{best}}^*$ 
13: return  $P_{\text{best}}^*$ 

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To intuitively demonstrate the enhancement performance of the proposed method, a sample image is selected and the enhancement results via using different methods are provide in Fig. 2. As shown, the enhanced image of MSR has obvious color distortion. Compared with MSR, AMSR and MSRCR achieve better performance and the image contrast is significantly improved. However, a certain degree of color distortion is still observed. The color of the enhanced image of MSRCP is close to the reality, but the excessive contrast increase causes the detail loss. In contrast, the proposed method yields the best performance and the advantages includes: 1) the contrast is greatly enhanced; 2) image

Table 1 Average CEIQ, MDM and BIQME values of different image enhancement methods

	MSR	AMSR	MSRCR	MSRCP	Proposed
CEIQ	2.84774	3.27126	3.22431	3.239915	3.4075
MDM	0.895195	0.91175	0.91206	0.91122	0.93324
BIQME	0.43690	0.53353	0.53781	0.54680	0.57928

Table 2 Comparison among PSO, FPA and the proposed method

	Time (s)	CEIQ
PSO	4705.4412	3.3898
FPA	5070.3422	3.3549
Proposed	542.4760	3.4075

details are mostly retained; 3) the image color looks more natural.

In order to better evaluate the quality of enhanced images, three commonly used image quality metrics, Blind Image Quality Measure of Enhanced images (BIQME) [15], contrast enhancement-based contrast changed image quality measure (CEIQ) [16], and Minkowski Distance-based Metric (MDM) [17]. Average values of each metric for the images are listed in Table 1. In the comparison among the three evolutionary computing algorithms, both the CEIQ value and the execution time are recorded in Table 2 for each algorithm. Both of the population size and the number of iterations are set to 10 for a fair comparison. Meanwhile, the algorithm-specific parameters of PSO and FPA are optimized using grid search with eight configurations considered.

As shown in Table 1, the proposed method dominates the compared methods in terms of the highest CEIQ, MDM and BIQME values, which indicates that the proposed method can improve the overall image quality with contrast distortion avoided. Table 2 shows the proposed method is more efficient and effective in tuning parameters of the MSRCP model. Thus, the proposed method is promising for real UAV-taken image enhancement tasks.

4. Conclusion

A novel Retinex-based image enhancement method was proposed to improve the quality of UAV-taken images in this paper. The proposed method was based on the MSRCP model and its controlling parameters were tuned using the two-phase optimization algorithm. The Rao-2 algorithm were used for the global search while the NM algorithm were responsible for the local search. 10 UAV-taken images with bad quality were employed to assess the performance of the proposed method. Meanwhile, the proposed method was benchmarked with MSR, MSRCR, AMSR and MSRCP algorithms. In the comparative study, the proposed method outperformed the other methods with the largest average CEIQ, MDM, and BIQME values. It is feasible to apply the proposed algorithm in real UAV-based applications. However, only a limited number of images are considered in this study. In the future work, more UAV-taken images will be collected and enhanced by using the proposed method.

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