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Optimal Local Dimming Based on an Improved Shuffled Frog Leaping Algorithm

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ABSTRACT The local backlight dimming technology has recently been presented for liquid crystal displays in order to reduce the power consumption of backlight and improve the quality of the display. Therefore, exploiting the tradeoff between the image quality and power consumption has become the focus of local backlight dimming technology. This paper considers the local backlight dimming as an optimization problem, i.e., how to preserve the image quality perception with a certain low backlight power consumption. To achieve this goal, we use the swarm intelligence algorithm. Specifically, an improved shuffled frog leaping algorithm is proposed for local backlight dimming. Simulation results show that the proposed algorithm achieves the better tradeoff between power consumption and image quality when compared to other algorithms based on image parameters.

INDEX TERMS ISFLA, local backlight dimming, SI algorithm.

I. INTRODUCTION

Today, most multimedia devices such as mobile devices and desktop monitors are equipped with a Liquid Crystal (LC) panel [1]–[3]. The displayed image is formed by two elements: the backlight and the Liquid Crystal cells (LCs). As a kind of non-self-luminance device, the backlight provides the source of light for the grid of LCs that composes the pixels of the image. The preservation of image quality under various display conditions has become more and more important in the multimedia era [4]. In the traditional design of LCDs, the power consumption is appreciably large because the backlight always works at the maximum luminance level constantly regardless of the image/video signal, and thus light leakage becomes inevitable. Nowadays, Organic Light Emitting Diode (OLED) is being used in many electronic devices. It has many advantages such as high contrast range, low consumption and wide viewing angle. However, easy burn-in, low yield, low lifetime, and high cost are preventing OLEDs from completely replacing LCDs [5]–[7]. Therefore, improving the performance of LCDs is still worthy of attention. To achieve higher image quality and lower power consumption of LCDs, various technologies have been studied, including local backlight dimming technology [8]–[15], inversion methods [16], [17], and Charge Sharing (CS) methods [18]–[20]. Unlike the traditional global backlight mode, the backlight of a local dimming system consists of a two-dimensional array of LED backlight blocks, each of which illuminates a small region of LC panel and can be controlled independently. The local dimming system is as shown in Fig.1.

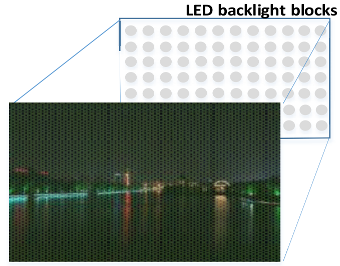

FIGURE 1. The local dimming system.

The principle of local backlight dimming is to adapt the luminance of the backlight blocks according to the image content. Some backlight blocks don't need to work at the maximum luminance level by turning down the backlight blocks behind the dark areas in the images. This way also decreases the amount of light leaking through dark pixels, so that the backlight blocks are darker behind the dark areas in the images. As for the bright areas, the reduction of light is compensated by adjusting the transmittance of the liquid crystals accordingly. With this method, we can not only save power but also maintain the quality of the displayed images. Therefore, the local backlight dimming is a promising technique to enhance the visual quality and reduce power consumption of LCDs.

For LCD-based products, 90% power consumption is attributed to backlight, and in consequence backlight power saving is considered one of the most effective ways to reduce LCD energy dissipation. Recently, exploring the trade-off between the image quality and the power consumption has become the focus of local backlight dimming technology. Several local dimming algorithms based on the parameters of input images have been proposed in [8]–[11]. The simplest ones are the average and the maximum algorithm [8]. In the average algorithm, the backlight luminance of one block is determined by the average luminance of the pixels in its illumination region. This algorithm can greatly reduce power consumption, but the perceived resolution becomes lower since the average lighting level is low. As for the maximum algorithm, the output intensity of one backlight block is set to the maximum pixel value in its illumination region. This algorithm does not produce the overflow distortion of image pixels, which effectively maintains the quality of displayed image while the power consumption is very high. The algorithm in [9] presented a mapping function to correct the difference between the maximum and the average results by using a Look-Up-Table (LUT). This method is more suitable for the overall dark image. But for the high luminance image and high contrast image, the display will be seriously distorted after dimming the backlight by this method. A comparison of the three algorithms mentioned above is shown in TABLE 1.

TABLE 1. **Comparison between several local dimming algorithms.**

Algorithm	Advantages	Disadvantages
The maximum algorithm	No overflow distortion High quality	High PC
The average algorithm	Low PC	Low perceived resolution
The LUT algorithm	Suitable for dark image	Seriously distorted for high luminance image and high contrast image

As mentioned above, local backlight dimming aims at a good compromise between image quality and power consumption. Although the above image-parameter-based algorithms operate simply, they only consider one aspect(either image quality or power consumption). Some efforts have been made to achieve the balance in recent years [12]–[15]. But these methods assure the image quality based on their own metrics in which the power consumption is not estimated.

In fact, there is always an optimal backlight luminance for each block. Therefore, the local backlight dimming can be regarded as an optimization problem, and its optimization objective is to minimize the power consumption or to minimize the distortion of the dimmed image. In [13], the local backlight dimming problem is modeled and transformed as a convex optimization problem and solved by linear programming. Compared with the algorithms whose luminance modulations are mainly based on the input image parameters, the method in [13] can get better image quality and lower power consumption. This shows that if the local backlight dimming problem is regarded as an optimization problem, an optimal scheme of luminance distribution of backlight blocks can be obtained and therefore reduces power consumption without decreasing the image quality. However, when the scale of the local dimming problem is large or its objective functions and constraints are complex, it is difficult to transform it into a convex optimization problem. Therefore, it is necessary to consider the feasibility when local dimming is considered as an optimization problem.

According to the above analysis, local backlight dimming is regarded as an optimization problem in this paper. In order to guarantee the feasibility of solving the optimization problem, the SI algorithm is applied. SI algorithms [23]–[27] are a novel class of heuristic algorithms which search for the best solution by imitating the behavior of biological populations. SI algorithms are treated as a kind of blind optimization algorithms whose optimization process can be considered as a black box [28]. They are usually applicable no matter what the objective functions and constraints are. In this paper, we did the following works:

1) In order to shorten the execution time of SI algorithm, a simplified model is built.
2) The Shuffled Frog Leaping Algorithm (SFLA) [29] which usually has better performance compared to other SI algorithms in solving discrete optimization problems [28] is utilized.

SFLA was used to solve many optimization problems in recent years. Based on the ideas such as hybrid algorithms and adaptive algorithms, some variants were proposed to improve the performance of SFLA [30]–[33]. In this paper, to further improve it, we propose an improved SFLA algorithm called ISFLA. Compared with the image-parameter algorithms, ISFLA can achieve better image quality with the same or less power consumption.

The rest of the paper is organized as follows: In section II, the related work of local backlight dimming and the method to regard the local backlight dimming as an optimization problem are described. In Section III, the optimization problem model of local backlight dimming is built and simplified. In section IV, IFSLA algorithm is proposed. In section V, the experimental results are given. Finally, we conclude our work in section VI.

II. PREVIOUS WORK

A. RELEVANT KNOWLEDGE ABOUT LOCAL BACKLIGHT DIMMING

In order to optimize local backlight dimming, the display characteristics of LCD screen are taken into account. The basic concepts are the transmittance [13], the ratio of light that an LC pixel lets through [34], and the local luminance level of the backlight [35]. In a local backlight dimming LCD screen, the observed pixel luminance $y_i^{'}$ at pixel i can be ideally expressed as the product of the backlight luminance b_i and the attenuation coefficient a_i as Equation.(1).

$$y_i^{'} = a_i \cdot b_i \tag{1}$$

If $b_i = 0$, there is no light behind the pixel, and if $b_i = 1$, the light intensity is at the maximal level. Similarly, the full backlight goes through the LC if $a_i = 1$, and the light is fully blocked if $a_i = 0$. However, in practice, light can't be completely blocked because of the leakage [15].

In the local dimming system, the LED backlight array is much sparser than LC cells. Thus, each LED block needs to cover an area of at least thousands of pixels. The backlight luminance b_i of ith pixel will be calculated based on the luminance of the nearby LED backlight blocks [10], [36]. The calculation is shown as Equation. (2).

$$b_i = \sum_{i=1}^{N} h_{i,j} \cdot r_j \tag{2}$$

where N is the number of LED backlight blocks in the local backlight dimming LCD system. Coefficient $h_{i,j}$ models the attenuation of the light from the jth LED backlight blocks at pixel i, and r_j is the luminance intensity of jth LED backlight block.

B. OPTIMIZING THE LOCAL BACKLIGHT DIMMING

In the local backlight dimming technology, there are two main factors: power consumption and image quality. A good local backlight dimming algorithm should be able to obtain the best image quality when the power consumption is below a certain value, or obtain the lowest power consumption when the image quality is better than a certain criterion. Therefore, the local backlight dimming can be regarded as an optimization problem whose objective is to minimize the power consumption or to minimize the distortion of an image after local dimming. Assuming that there are $M \times N$ backlight blocks and the range of the backlight luminance value of each block is [0, 255]. The number of the possible backlight blocks luminance distribution schemes will be $256^{M \times N}$ and each schemes correspond to a power consumption and image quality. It is certain that there are one or more schemes that can get the best image quality among the schemes whose power consumption is less than or equal to a certain value, and vice versa. Therefore, extracting backlight luminance of each block is to find the optimal backlight blocks luminance distribution scheme under certain constrains.

Supposing that the image quality is expressed as Q and the power consumption is expressed asPC. If the objective of the local backlight dimming is to get the best image quality when the power consumption is less than or equal to a certain value, the problem can be described as Equation. (3).

$$\begin{aligned} &\max: \ Q \\ &s.t.: \ PC \leq P_{limit} \end{aligned} \tag{3}$$

where P_{limit} is the constraint value of power consumption.

On the contrary, supposing that the objective of the local backlight dimming is to get the lowest power consumption while the dimmed image achieves a certain image quality, the problem can be described as Equation. (4).

$$\begin{aligned} &\min: \ PC \\ &s.t.: \ Q \geq Q_{limit} \end{aligned} \tag{4}$$

where Q_{limit} is the constraint value of image quality.

SI algorithms have excellent adaptive ability, they are easy to be applied no matter what the objective functions and the constraints are. Therefore, When SI algorithms are used to solve Equation. (3) and Equation. (4), the computational complexity is the same. For simplicity, this paper takes the image quality as the optimization objective while the power consumption is considered as the constraint.

III. BUILDING AND SIMPLIFYING THE MODEL

A. THE OPTIMIZATION PROBLEM MODEL OF LOCAL BACKLIGHT DIMMING

In this paper, the objective of local backlight dimming is to obtain the best image quality under a certain power constraint, so the objective function should be able to evaluate image quality. Because Peak Signal to Noise Ratio (PSNR) can indicate the degree of image distortion stemming from backlight dimming, it is used to evaluate the image quality. The formula for calculating $PSNR$ is represented as Equation. (5). The greater the $PSNR$, the better the image quality.

$$\begin{cases} PSNR = 10 \cdot \log_{10}(\frac{255^2}{MSE}) \\ MSE = \frac{1}{H \times W} \sum\limits_{i=1}^{H} \sum\limits_{j=1}^{W} (Y_{i,j}^{'} - Y_{i,j}) \end{cases} \tag{5}$$

where H and W are the height and width of the input image, $Y_{i,j}$ and $Y_{i,j}^{'}$ are the luminance of $(i,j)\,th$ pixel before and after local dimming, respectively.

On the other hand, the power consumption is considered as the constraint. The power consumption can be calculated by Equation. (6).

$$PC = \frac{\frac{1}{M \times N} \sum\limits_{i=1}^{M} \sum\limits_{j=1}^{N} BL_{i,j}}{BL_{full}} \times 100\% \tag{6}$$

where $BL_{i,j}$ is the backlight luminance of $(i,j)\,th$ block, BL_{full} is the backlight luminance when the backlight source is fully lit, usually $BL_{full} = 255$. Equation. (6) is a calculation method of power consumption proposed in [37].

The actual power consumption is related to the luminance of backlight, the higher the luminance of backlight, the higher the power consumption. Therefore, it is a positive correlation between PC calculated by equation(6) and the actual power consumption.

The optimization problem model of local backlight dimming is shown in Equation. (7).

$$\begin{aligned} \max : f(x) &= PSNR \\ s.t.\ PC &\leq P_{limit} \end{aligned} \tag{7}$$

B. SIMPLIFYING THE OPTIMIZATION PROBLEM

SI algorithms usually generate a set of initial solutions at random, and then update the set of initial solutions by multiple iterations to search for the optimal solution. In the iterative process, the value of the objective function needs to be calculated to evaluate the quality of each updated solution. Since the solutions are updated for many times, the amount of computation of the objective function will be huge.

In order to reduce the amount of computation, the above model is further simplified in this paper. The first step is sampling the input image before performing the optimization, and the size of the input image $H \times W$ is reduced to $h \times w$ where $h = H/10$ and $w = W/10$.The second step is simplifying the objective function. In this step, MSE instead of $PSNR$ is used as objective function and $1/(h \times w)$ is omitted for calculating MSE. The simplified objective function is shown in Equation. (8).

$$f'(x) = \sum_{i=1}^{h} \sum_{j=1}^{w} \left(y'_{i,j} - y_{i,j} \right)^2 \tag{8}$$

According to the model of local backlight dimming in Section II, the simplified model is shown as Equation. (9).

$$\begin{aligned} \min : f'(x) &= \sum_{i=1}^{h} \sum_{j=1}^{w} \left(y'_{i,j} - y_{i,j} \right)^2 \\ s.t.\ PC &\leq P_{limit} \end{aligned} \tag{9}$$

where $y_{i,j}$ and $y'_{i,j}$ are the luminance of $(i,j)\ th$ pixel before and after dimming.

IV. USING ISFLA FOR LOCAL BACKLIGHT DIMMING

A. SFLA

SFLA [29] is a novel SI algorithm which searches for optimal solutions by imitating the foraging behavior of frog population. In [28], different SI algorithms are used to solve the discrete optimization problems and the results show that SFLA has the best performance. In SFLA, the position of each frog in the population corresponds to a solution, the leaping of frogs will change their positions to search for better solutions. First, SFLA randomly generates some initial solutions (frog positions) according to the number of frogs, and then update the initial solutions with many iterations. Once the algorithm is terminated, the optimal solution in the population is used as the output solution.

Each iteration of SFLA mainly consists of three steps: grouping, leaping and shuffling. Supposing that the number of frogs is M, and the number of groups is N. In the grouping process, the M frogs in the population are sorted according to their fitness values, and then the sorted solutions will be divided into N groups. The first frog will be assigned to the first group, the second frog will be assigned to the second group. When the Nth frog is assigned to the Nth group, the $(N+1)\,th$ frog will be assigned to the first group and so on. In the process of leaping, the frog whose position is the worst in the group should leap toward the frog whose position is the optimal in the group or leap toward the frog whose position is the optimal in the population. If a better position is found after leaping, the original position will be replaced by the better one. It can be seen from the leaping process that the SFLA only update the groups' worst solutions in each iteration. In the shuffling process, all groups' frogs are shuffled together and getting ready for the next iteration.

B. ISFLA

When SFLA is applied to local backlight dimming, there are two disadvantages:

1) THE WAY OF GENERATING INITIAL SOLUTIONS

The SFLA randomly generate a set of initial solutions, and then update the initial solutions to get better solutions. According to the analysis in section II. If there are $M \times N$ blocks, the number of possible solutions are $256^{M \times N}$, the solution space becomes extremely large. Beyond that, the quality of the initial solutions will be poor if the initial solutions are generated randomly. When the algorithm is running in a large solution space and the initial solutions' quality is poor, it is difficult to obtain high quality solutions. In this case, the algorithm execution time may be very long and the quality of the final output solution may be poor.

2) THE SEARCH INTERVAL OF SOLUTIONS

The range of backlight luminance value is [0, 255], so the search interval of solutions is usually set to [0, 255]. In fact, there is a certain correlation between the pixels' gray levels and the backlight luminance. Serious distortion may occur in some image regions after local dimming if the search interval is not limited according to this correlation. For example, when the search interval is [0, 255], the solution obtained within this interval might be 1. in that case, the backlight luminance value will be set to 1. Assuming that there is an image region whose pixel levels are all higher than 200 and the backlight luminance of this region is 1, it is likely that the pixels with high gray level will be seriously distorted.

Considering the disadvantages mentioned above, cycle optimization is introduced in ISFLA. In each cycle, a certain number of iterations are performed. When the maximum iteration number is reached in one cycle, this cycle will end and the next cycle begins. When the quality of the optimal solution obtained in one cycle is not improved compared with the optimal solution in the previous cycle, the whole

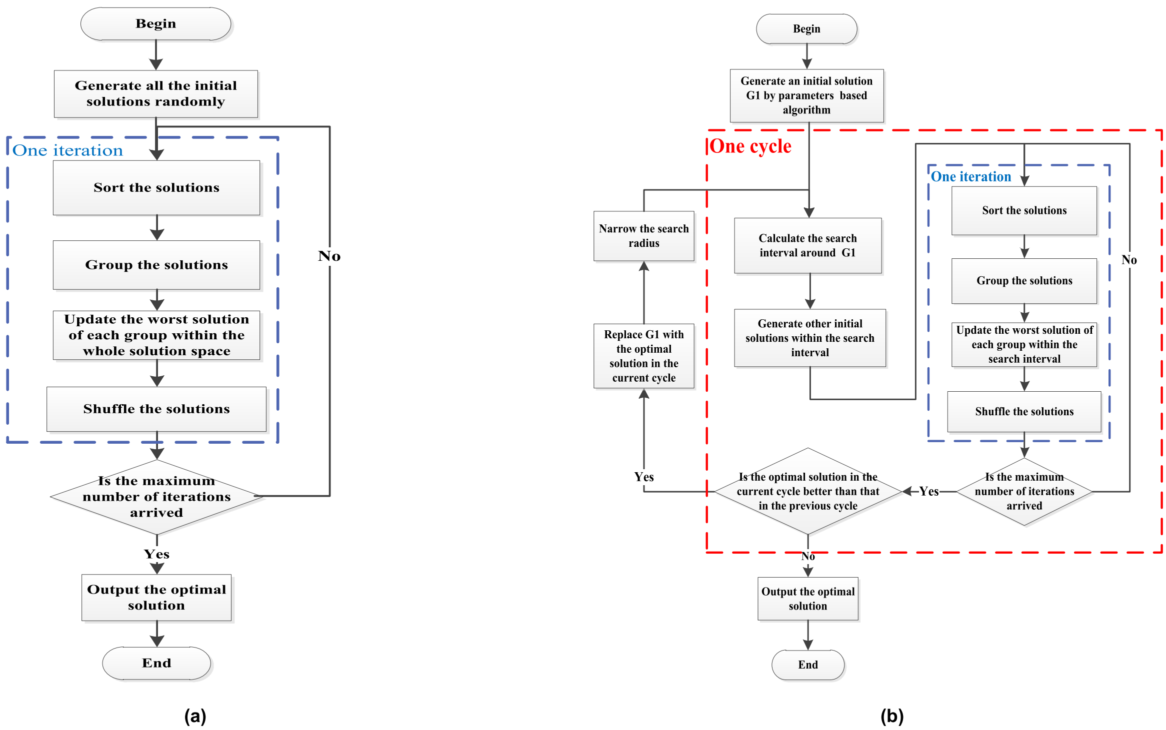

FIGURE 2. **The flow charts of SFLA and ISFLA. (a) SFLA. (b) ISFLA.**

algorithm is terminated and the optimal solution found during the process of the algorithm is the output solution. The specific steps of one cycle of ISFLA are described as follows:

1) Generating the first initial solution. The first cycle's first initial solution should be generated by an existing algorithm based on image parameters such as the maximum algorithm and the average algorithm. Other cycle's first initial solution is generated based on the method proposed in step (5).
2) Obtaining the search interval of this cycle. The first initial solution will be set as the center of the search interval, the lower and upper bounds are obtained by subtracting the interval radius from the center and adding the interval radius to the center, respectively.
3) Generating other initial solutions of this cycle. Other initial solutions will be generated randomly in the search interval determined in step (2).
4) Starting the iterative updating of this cycle. The search for new solutions should be done within the search interval obtained in step (2).
5) After the end of this cycle, the optimal solution of this cycle is taken as the first initial solution of the next cycle and the next cycle starts.

Because the first initial solution of the first cycle is generated according to image parameters, the quality of this initial solution in ISFLA is usually higher than the initial solution randomly generated. At the same time, generating other initial solutions around the first initial solution is also beneficial to improve the quality of the initial solutions, and these high quality initial solutions are beneficial to reduce the execution time and improve the quality of the output solution. Besides, the algorithm based on image parameters can effectively guarantee the correlation between the backlight luminance and the pixels' gray levels. Therefore, it can avoid serious distortion of some image blocks.

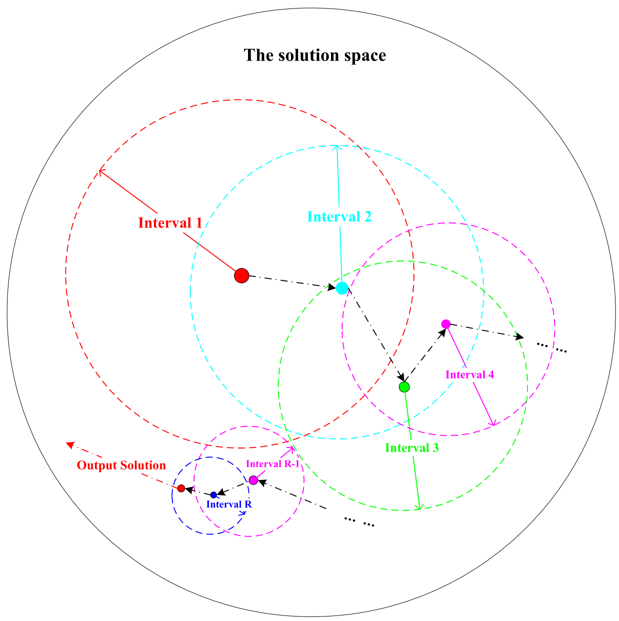

FIGURE 3. **The diagrammatic sketch of ISFLA algorithm process.**

In addition, in the searching process, the quality of the early solutions is relatively poor and they are far from the optimal

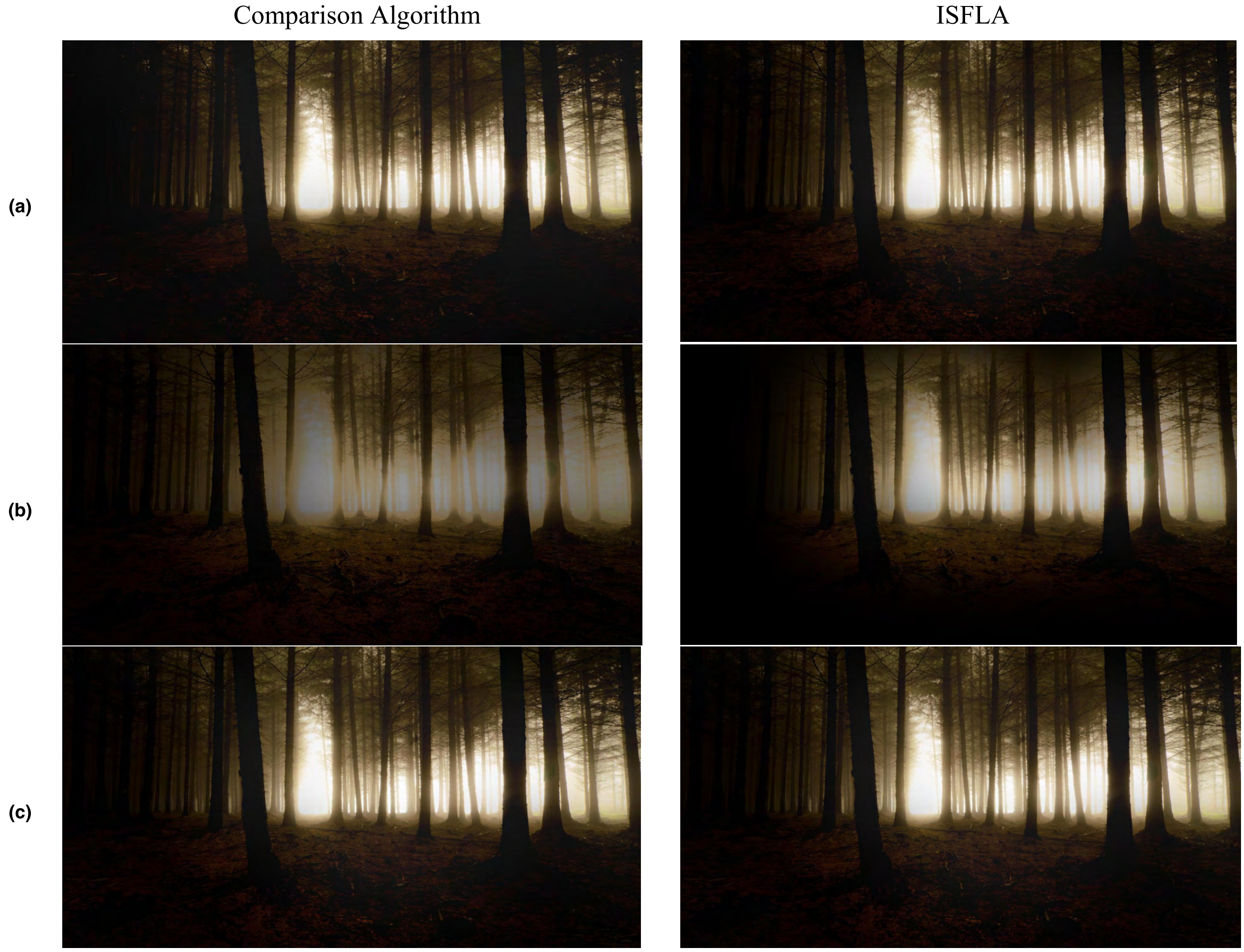

FIGURE 4. Low luminance image. (a) comparison between the maximum algorithm and the proposed algorithm. (b) comparison between the average algorithm and the proposed algorithm. (c) comparison between the LUT algorithm and the proposed algorithm.

solution, so the search interval should be extended. While in the later stage, the solutions' quality is relatively high and they are usually close to the optimal solution, so the search interval should be narrowed. Therefore, in ISFLA, the search interval is gradually narrowed as the algorithm is running.

To further illustrate the proposed algorithm, the flow charts of SFLA and ISFLA are shown in Fig.2.

Fig. 3 briefly describes the algorithmic process where Interval i present the search interval in the ith cycle, the central point in Interval 1 is the initial solution generated by the existing algorithm based on image parameters and the central point in Interval j $(j > 1)$ is the optimal solution obtained in the $(j-1)$ th cycle.

The pseudo code of the ISFLA is shown in appendix, where $rand$ is a random value between 0 and 1, λ is a coefficient between 0 and 1.

V. SIMULATION RESULTS AND DISCUSSIONS

A. COMPARISONS BETWEEN ISFLA AND PARAMETERS-BASED ALGORITHMS

To evaluate the performance of ISFLA, we compare ISFLA against several known backlight local dimming algorithms based on image parameters (including the maximum algorithm, the average algorithm [5], and the LUT algorithm [6]). Four different types of images (low luminance image, high luminance image, low contrast ratio image and high contrast ratio image) are used as test samples. The resolution of the test images is 1920×1080. All the test images are divided into 7×5 blocks for local dimming control. The solution of the comparison algorithm is taken as the first initial solution of ISFLA and the constraint value P_{limit} is set to equal to the power consumption PC of the comparison algorithm. This method of setting P_{limit} can ensure thePC of the output solution of ISFLA is equal to or lower than the comparison algorithm.

The simulation experiments are conducted with the MATLAB R2010b. Fig. 4-7 present the representative simulation results and each figure corresponds to one test image.

It can be seen from Fig. 4-7 that the image distortion of the average algorithm is significantly larger than other comparison algorithms. The maximum algorithm reproduces good details in bright regions but tends to have visible artifacts in dark regions. The visual quality of images processed by the LUT algorithm is better than the average algorithm. However, we find that for the images processed by this

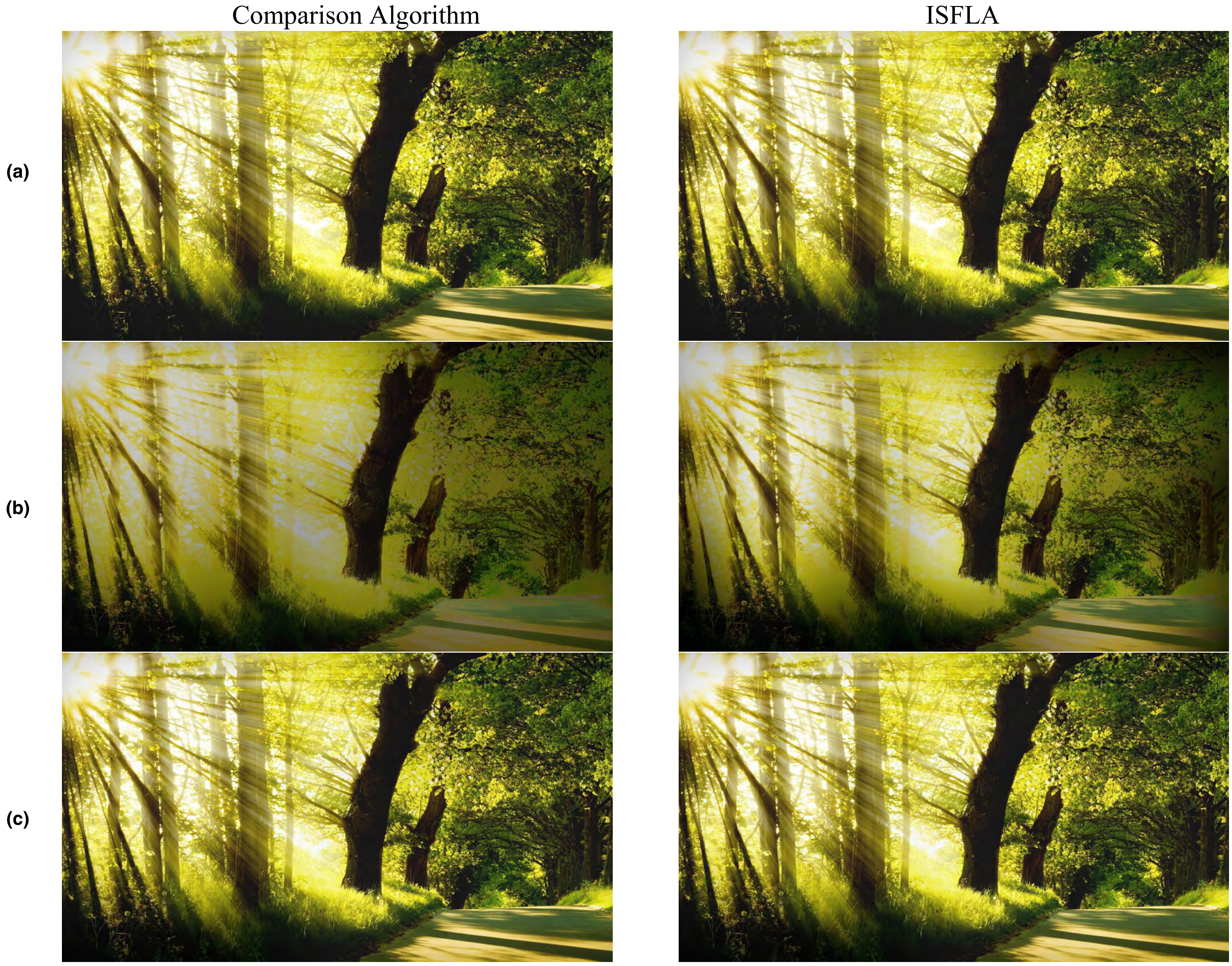

FIGURE 5. High luminance image. (a) comparison between the maximum algorithm and the proposed algorithm. (b) comparison between the average algorithm and the proposed algorithm. (c) comparison between the LUT algorithm and the proposed algorithm.

algorithm, clipping artifacts appear at the bright pixels in dark regions. In other words, the LUT algorithm can reproduce good details in bright regions but tend to have visible artifacts in dark regions. On the contrary, the proposed algorithm ISFLA can effectively reduce the image distortion and preserve the image detail no matter what type of image. Especially compared with the average algorithm, the quality of the image processed by the proposed algorithm is remarkably improved when their power consumption is the same.

TABLE 2 shows the comparison between ISFLA and the comparison algorithms in terms of *PSNR* and *PC*.

It can be seen in TABLE 2, compared with the other algorithms, for the low luminance image, the *PSNRs* of ISFLA have been improved by 9.48%, 30.86%, and 33.78%, for the high luminance image, the *PSNRs* of ISFLA have been improved by 0.13%, 12.98% and 17.74%. The *PSNR* improved degree of the low luminance image is higher than that of the high luminance image. For the low contrast ratio image, the *PSNRs* of ISFLA have been improved by 12.09%, 18.62% and 34.04%, and for the high contrast ratio image, the *PSNRs* of ISFLA have been increased by 8.52%, 16.99% and 14.35%. The *PSNR* improved degree of the low contrast ratio image is higher than that of the high contrast ratio image. The above results show that ISFLA can effectively improve the *PSNR* of the images, especially for low luminance images and low contrast ratio images.

In addition, it can be seen in table 2 that higher *PSNR* usually correspond to higher *PC*for the same image. Therefore, after ISFLA, *PC* usually reach the constraint value P_{limit} to get the highest *PSNR*. Because the *PC*of the comparison algorithm is taken as the $P_{limit}$of ISFLA, the*PC*of ISFLA is in most cases equal to that of the comparison algorithm. But as shown in table 2, in some cases, the *PC* of ISFLA is lower than the comparison algorithm. For example, in Fig. 4, Fig. 5 and Fig. 7, the *PCs*of the maximum algorithm are 63.06%, 100% and 72.53%, while the *PCs* of ISFLA are 42.60%, 98.90% and 61.46%. These results illustrate that not all the reducing of the power consumption will bring the worse image quality, instead, it may improve image quality sometimes. For example, reducing the backlight luminance

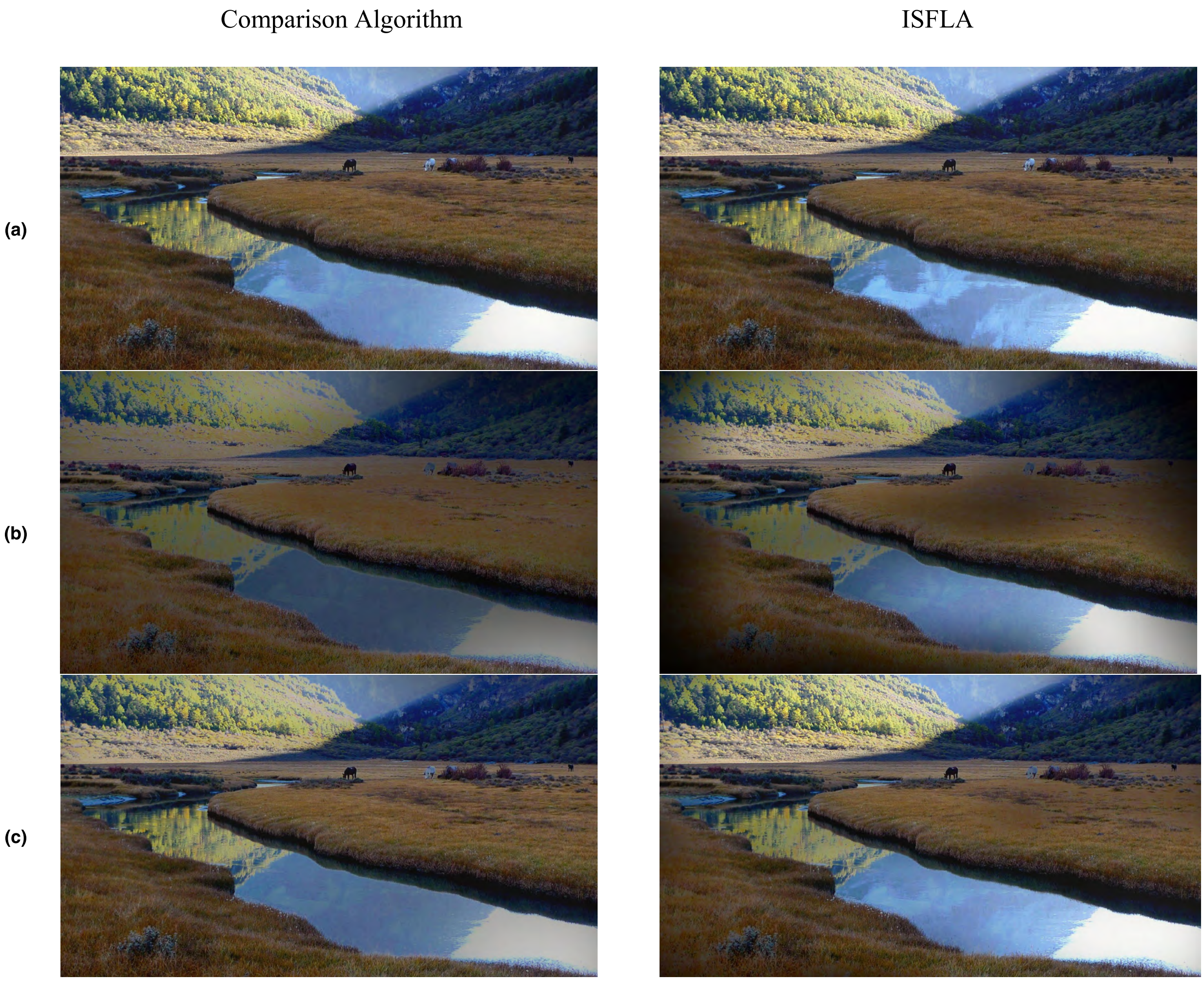

FIGURE 6. Low contrast ratio image. (a) comparison between the maximum algorithm and the proposed algorithm. (b) comparison between the average algorithm and the proposed algorithm. (c) comparison between the LUT algorithm and the proposed algorithm.

TABLE 2. Comparison of PC and PSNR between different local dimming algorithms.

Fig.	Evaluation index	Maximum	ISFLA	**Improve**	Average	ISFLA	**Improve**	LUT	ISFLA	**Improve**
4	$PC(\%)$	63.06	42.60	**32.45%**	20.27	20.26	**0.05%**	41.70	41.49	**0.50%**
	$PSNR(dB)$	30.90	33.83	**9.48%**	18.63	24.38	**30.86%**	25.28	33.82	**33.78%**
5	$PC(\%)$	100	98.90	**1.10%**	51.90	51.90	**0**	76.07	76.07	**0**
	$PSNR(dB)$	30.22	30.26	**0.13%**	15.79	17.84	**12.98%**	22.55	26.55	**17.74%**
6	$PC(\%)$	84.12	84.12	**0**	37.20	37.20	**0**	60.73	60.72	**0.02%**
	$PSNR(dB)$	28.46	31.90	**12.09%**	14.07	16.69	**18.62%**	19.83	26.58	**34.04%**
7	$PC(\%)$	72.53	61.46	**15.26%**	28.19	28.19	**0**	50.38	50.38	**0**
	$PSNR(dB)$	30.62	33.23	**8.52%**	19.84	23.21	**16.99%**	28.78	32.91	**14.35%**

behind a image's dark regions can reduce the power consumption of the backlight, at the same time, the image quality will also be improved because this dimming method would decrease the amount of light leaking and enhance the image contrast ratio.

It should also be noted that different initial solutions would lead to different $PSNR$ and PC. That is mainly because the values of P_{limit} which are equal to the PC of the initial solutions are different. In addition, initial solutions with different quality would also influence the quality of the output solutions.

FIGURE 7. **High contrast ratio image. (a) comparison between the maximum algorithm and the proposed algorithm. (b) comparison between the average algorithm and the proposed algorithm. (c) comparison between the LUT algorithm and the proposed algorithm.**

B. COMPARISON BETWEEN ISFLA AND SFLA

To further analyze the performance, ISFLA is compared with the original SFLA. The updating process of a SI algorithm is to generate new solutions to replace the original solutions repeatedly. When a new solution is generated, it should be evaluated by the fitness function. Because many new solutions are invalid, in order to get a valid solution to replace the original one, usually a large number of new solutions are required to be generated. For SFLA and ISFLA, the generation and evaluations of new solutions take up most of the computational cost. The computational complexity of the two algorithms for generating and evaluating a new solution is basically the same. So the running time of the two algorithms is almost the same under the same number of evaluations. The number of evaluations of the two algorithms is set to be 500000 and the two algorithms run under the same P_{limit} to process the four test images. Fig.8 gives the representative simulation results. TABLE 3 shows the comparison between SFLA and ISFLA in terms ofPC and $PSNR$.

TABLE 3. **Comparison of PC and PSNR between SFLA and ISFL.**

Images	Evaluation index	SFLA	ISFLA	**Improve**
Low luminance	$PC(\%)$	41.70	41.58	**0.29%**
	$PSNR(dB)$	29.31	33.82	**15.39%**
High luminance	$PC(\%)$	74.58	76.06	**-1.98%**
	$PSNR(dB)$	26.53	30.90	**16.47%**
Low contrast ratio	$PC(\%)$	60.72	60.72	**0**
	$PSNR(dB)$	22.76	26.55	**16.65%**
High contrast ratio	$PC(\%)$	50.36	50.38	**-0.04%**
	$PSNR(dB)$	29.54	32.83	**11.14%**

It can be seen from be seen from Fig. 8, ISFLA can obtain the image with higher quality under the same number of evaluations. It should be noted that the region circled by the red line in Fig. 8 (d) is seriously distorted.

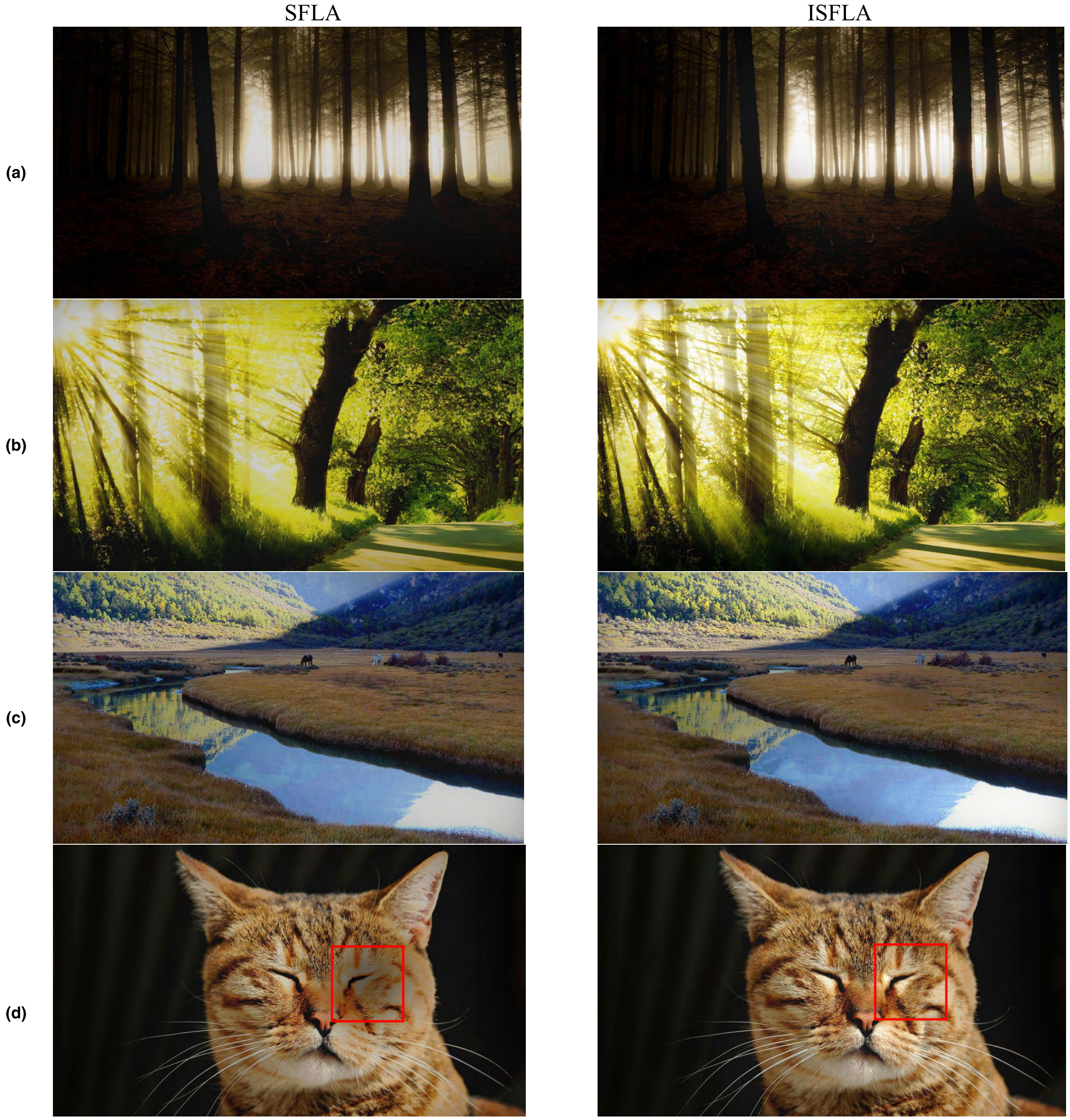

FIGURE 8. Comparison between SFLA and ISFLA. (a) Low luminance image. (b)High luminance image. (c) Low contrast ratio image. (d) High contrast ratio image.

This result shows one of the SFLA's disadvantages mentioned in section III. Because the search interval of SFLA is [0,255], the circled region with high pixel levels is set with a low backlight luminance. Serious distortion could be perceived.

Table 3 shows that compared with SFLA, ISFLA significantly improves the *PSNR* of images under the similar power consumption.

Based on the objective function value $f^{'}(x)$ (as shown in equation. (9)) calculated after different number of evaluations, we can get the descending curves of the two algorithms. Fig. 9 shows the descending curves of the two algorithms when they are used to process the high luminance image.

It can be seen from Fig.9 (a), the quality of the initial solutions of SFLA is quite poor. Although it has a fast descending speed in the early stage, the quality of the solutions after a large number of evaluations are still much worse than the quality of initial solutions of ISFLA. This proves another SFLA's disadvantage mentioned in section III - initial solutions with poor quality will prevent SFLA from finding solutions with high quality. Fig.9 (b) shows the descending curve of ISFLA clearly. It can be seen that although the

Algorithm 1 The Pseudo Code of ISFLA

```
num_population = M, num_group = N, max_num_iteration = Q, num_cycle = 1, interval_radius = R;  /* Initialize basic parameters including the number of frogs in the population, the number of groups, the maximum number of iterations, the sequence number of the current cycle and the initial search radius */
G_1 = run_traditional_algorithm();  /* Get an initial solution G_1 by the existing algorithm which is based on image parameters.*/
do
  L_bound = G_1 − interval_radius; /* Calculate the lower bound of the search interval */
  U_bound = G_1 + interval_radius; /* Calculate the upper bound of the search interval */
  for i = 2 : M
    G_i = get_initial_solutions (interval);  /* Randomly generate other initial solutions G_i within the search interval */
  end for
  fit_calculate (each_solution);  /* Calculate the fitness value of each solution */
  sort();  /* Sort all solutions based on fitness values */
  group();  /* Group the solutions */
  for num_iteration = 1 : Q/*Start the iterative optimization in one cycle*/
      for j = 1 : N
        G_j,temp = G_j,worst + rand × (G_j,best − G_j,worst);  /* The worst frog G_j,worst in the jth group leaps toward the best frog G_j,best in the jth group to get a new solution G_j,temp*/
          Fit_j,temp = fit_calculate (G_j,temp);  /* Get the fitness value of G_j,temp*/
        if(isValid (G_j,temp) &&Fit_j,temp < Fit_j,worst)
          G_j,worst = G_j,temp; /* If solution G_j,temp is valid and it's fitness is better than solution G_j,worst, replace G_j,worst with G_j,temp*/
        else
          G_j,temp = G_j,worst + rand × (G_best − G_j,worst); /* The worst frog G_j,worst in the jth group leaps toward the best frog G_best in the population to get a new solution G_j,temp*/
            Fit_j,temp = fit_calculate (G_j,temp);
          if (isValid (G_j,temp) &&Fit_j,temp < Fit_i,worst)
            G_j,worst = G_j,temp;
          else
            G_j,temp = random_frog (interval);  /* Generate a solution G_j,temp randomly within the search interval */
                while(!isValid (G_j,temp))
                  G_j,temp = random_frog (interval); /* If G_j,temp is not valid, regenerate it randomly within the search interval */
            end while
            G_j,worst = G_j,temp; /*Replace G_j,worst with G_j,temp*/
          end if
        end if
      end for
    shuffle();  /* Shuffle all the frogs */
    sort();
    group();
  end for /*End the iterative optimization in one cycle*/
  best_solution (num_cycle) = get_optimal_solution();  /* Get the optimal solution best_solution(num_cycle)in the current cycle*/
  Fit_best (num_cycle) = Fit_calculate (best_solution (num_cycle)); /* Get the fitness value of best_solution (num_cycle)*/
  G_1 = best_solution (num_cycle);  /* Set the current optimal solution as an initial solution of the next cycle*/
  num_cycle = num_cycle + 1;/* Update num*_cycle/
  interval_radius = λ × interval_radius;  /* Narrow the search radius */
while (num_cycle < 3||Fit_best (num_cycle − 1) < Fit_best (num_cycle − 2)); /* If the optimal solution in the current cycle is better the optimal solution in the last cycle, start the next cycle*/
output (best_solution (num_cycle − 2)) ;  /* Output the solution */
```

quality of the initial solutions is high, ISFLA can also keep a fast descending speed. After about 300000 evaluations, the curve tends to be stable. It means the solutions obtained now have a certain high quality and can be used as the output solution. But after 300000 evaluations, the solution of SFLA is still poor and its curve still keeps declining. It means

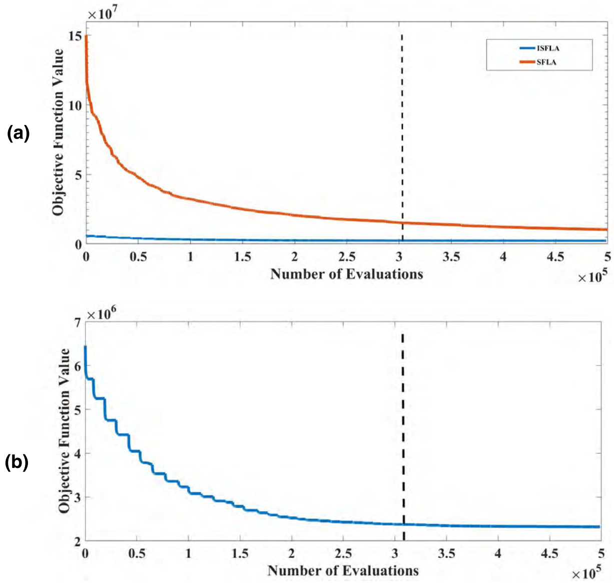

FIGURE 9. Descending curves of SFLA and ISFLA. (a) Comparison between descending curves of SFLA and ISFLA. (b) Descending curve of ISFLA.

there is still a lot of time required by SFLA to get a high quality solution. Therefore, compared with SFLA, ISFLA can get higher quality solutions with much less running time. In another words, ISFLA effectively reduces the amount of computation of the original algorithm.

VI. CONCLUSION

In this paper, local backlight dimming is regarded as an optimization problem and SI algorithm with strong adaptability is selected to solve the problem. The optimization problem model is built and simplified, the ISFLA is applied. Compared with SFLA, the algorithm performance of ISFLA is significantly improved. Compared with the algorithms which based on image parameters, the proposed algorithm can get better image quality with the same or lower power consumption. In addition, although we have simplified the optimization problem model and improved the algorithm to reduce the algorithm execution time, the algorithm execution time is still a bit long. So future work needs to be done to reduce the execution time of the proposed algorithm.

APPENDIX
THE PSEUDO CODE OF ISFLA

See Algorithm 1.

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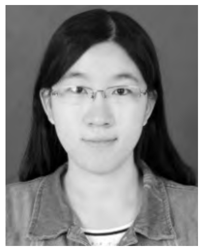

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