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Edge detection using ant colony optimization with novel probabilistic measures

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ABSTRACT

Edge detection is an important topic in computer vision and image processing, and has many applications in the related areas. An edge can be defined as a group of connected pixels lying between boundaries of two regions. Edge can also be defined as in binary images as the black pixels with one nearest white neighbors. An edge can be characterized as a gathering of associated pixels locating between limits of two districts. Edge can likewise be characterized as in parallel pictures as the black pixels with one closest white neighbour. An Edge is a local concept yet the limit is a worldwide idea. Edges in image contain important information and edge detection plays an important role in image processing. Therefore, over decades lots of techniques are investigated and developed for the correct detection of edge. ACO is a method based on heuristic search and it is beneficial for discrete problems. An ACO algorithm for image edge detection has been investigated. Based on tests performed on images, ACO is robust and competitive and proposed method is found to be effective, and it is independent of intensity mapping function.

Keywords: *Edge detection, ACO, Accuracy*

1. INTRODUCTION

Edge detection is an important topic in computer vision and image processing, and has many applications in the related areas. An edge can be defined as a group of connected pixels lying between boundaries of two regions. An Edge is a local concept but the boundary is a global concept. The edge pixels are the pixels whose grey levels have big difference with the gray levels of their neighbourhood pixels [1-4]. Edge detection process could be defined as the technique of extracting the edges in a digital image. It is a set of arrangements of actions with the main purpose of identifying points in an image where variations or discontinuities in intensity take place. This set of action is vital to comprehend the substance of an image [48] and with the help of these extracted edge points, we can have the important information in the field of machine vision and image analysis [5]. It goes about as a pre-processing stage for extraction of feature and object recognition [6]. It is generally used in starting phase of computer vision applications. The motivation behind recognizing sharp variations in intensity of image is to catch critical occasions and variations in the physical characteristics of the world. In normal assumptions as far as the process of image development is concerned, the reasons of intensity varies normally in correspondence to two kinds of events one is Geometric and other is Non-geometric events.

Geometric occasions comprise discontinuities in orientation of surface, discontinuities in texture, depth and colour. In the case of Non-geometric events, these have varying shadows, illumination, and inter-reflections [2]. Traditional methodologies to edge detection such as LoG operator [2], SOBEL operator [4], Prewitt operator [2], and Robert's operator [5] methods of detection are computationally costly in light of the fact that each arrangement of operations is directed for every pixel [6-8].

In typical courses, the calculation time rapidly increments with the measure of the image. Notwithstanding, the majority of the current detection procedures utilize a tremendous space for the picture edge detection of image [2]. Along these lines, without optimization the edge detection undertaking is memory and tedious An ACO constituent course of ACO has the ability of removing the demerits of typical techniques [3].

2. GENERAL BEHAVIOUR OF ACO ALGORITHM

Un-natural ant repeats visit development loop which is one-sided with the simulated pheromone trails and the heuristic data. The fundamental system at work in ACO is the disclosure of decent visits is the positive criticism done by means of the pheromone refresh by the ants. The shorter the subterranean insect's visit, the more measure of pheromone is saved by ants. This makes the ants to choose similar circular segments in the consequent cycles of the algorithm. The event of arcs with huge pheromone characteristics are additionally fortified by the system of pheromone dissipation that maintains a strategic distance from a boundless measure of pheromone and reduction the pheromone content from the arcs that infrequently get extra pheromone [3].

3. ANT COLONY OPTIMIZATION

This algorithm is influenced by sustenance searching character shown by ants [8-16] Ants as people are unsophisticated living creatures. Through some researcher's perspective, the visual sensory part of the body of these present reality ants are simple by nature and now and again they are totally visually impaired. The ants make the communication with the help of using a chemical known as pheromone. The ants impart utilizing a compound substance called pheromone. In adventure of an insect, it amasses a consistent measure of pheromone that different ants can take after. Every subterranean insect at first moves in a to some degree arbitrary design, yet when a subterranean insect experiences a pheromone trail, it must settle an issue if to make following of it or not. On the off chance that it came after the trail, the ant's own pheromone strengthens the present trail, and the development in pheromone builds the likelihood of the

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following subterranean ant choosing the way. Along these lines, the more the ants go on a way, the more alluring the way progresses toward becoming for back to back ants. Moreover, a subterranean ant utilizing a short course to a sustenance source will come back to the home sooner and, consequently, stamp its way twice, before the landing of different ants. This straight forwardly impacts the choice likelihood for the following insect withdrawing the home.

After some time, as more ants are fit to finish the shorter course. Hence on shorter ways pheromone gathers speedier and the more extended ways are less fortified lastly relinquished. On shorter ways Pheromone densities remain high since pheromone is set down speedier.

In the event of hunting for food, ants have a tendency to take after trails of pheromones whose concentration is greater. These trails are made by people looking for food, to show the path to others toward similar food source. The measure of pheromone is more in highly visited paths due to the fact that of the space visited by ants to acquire sources of food and come back to the home [54]. This strategy for positive input in the long run drives the ants to take after the smaller ways. It is this typical experience that empowered the advancement of the ACO meta-heuristic.

ACO plans to iteratively locate the ideal arrangement of the target issue by means of a guided search over the solution space, by building the *pheromone* data. Assume K numbers of total ants are connected to locate the ideal solution in a space χ that comprises M × N nodes, the strategy of ACO can be defined as [10].

There are two major issues in the above ACO method. These issues are, 1- the foundation of the probabilistic transition matrix $p^{(n)}$ along with the refresh of the pheromone lattice and all of which are explained below:

Initially, at the ACO n-th development-stage, the k-th ant goes to the node j from the node i as per a probabilistic action rule and it could be defined as [4]

$$p_{i,j}^{n} = \frac{\left(\tau_{i,j}^{(n-1)}\right)^{\alpha} (\eta_{i,j})^{\beta}}{\sum_{j \in \Omega_i} \left(\tau_{i,j}^{(n-1)}\right)^{\alpha} (\eta_{i,j})^{\beta}}, \quad \text{if } j \in \Omega_i \tag{1}$$

After the first step, the next step is the pheromone matrix requires be refreshed twice amid the ACO system. The principal refresh is carried out after the movement of every ant inside each development step. To be more particular, after the move of the k-th ant inside the n-th development step, the pheromone matrix is updated as [4]

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho)\tau_{i,j}^{(n-1)} + \rho\Delta_{i,j}^{k} & \text{if } (i,j) \in \text{best tour} \\ \tau_{i,j}^{(n-1)} & \text{otherwise} \end{cases}$$

In the above equation, the parameter ρ represent the *rate of evaporation*. Moreover, the *best tour* depends upon the user-defined criterion, it may be either the perfect tour discovered in the present construction-step, or the perfect solution got due to the fact that the beginning of the methodology, or a blend of both [3,10]. The update of second is carried out after the movement of *all* K ants inside each construction-step; and the pheromone matrix is updated as [3,10]

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho)\tau_{i,j}^{(n-1)} + \rho\Delta_{i,j}^{k} & \text{if } (i,j) \in \text{best tour} \\ \tau_{i,j}^{(n-1)} & \text{otherwise} \end{cases} \tag{2}$$

In the above equation, the parameter ρ represent the *rate of evaporation*. Moreover, the *best tour* depends upon the user-defined criterion, it may be either the perfect tour discovered in the present construction-step, or the perfect solution got due to the fact that the beginning of the methodology, or a blend of both [4]. The update of second is carried out after the movement of *all* K ants inside each construction-step; and the pheromone matrix is updated as [10]

$$\tau^{(n)} = (1-\psi)\tau^{(n-1)} + \psi\tau^{(0)} \tag{3}$$

here ψ represents the *pheromone decay coefficient*. It must be noted here that the ant colony system [6] caries out two update operations (i.e, (2) and (3)) for making updating of the pheromone matrix, on the other side the ant system [3] just carries one operation (i.e., (3)).

4. ACO BASED IMAGE EDGE DETECTION

In this proposed technique, number of ants proceed onward a 2-D picture, venturing starting with one pixel then onto the next to build a pheromone matrix, which decide the edge data for every pixel area in the picture to separate the edges of the picture. The development of the ants is coordinated by the nearby variety of the force values of image [3]. The procedure of Image Edge detection [10] contains the accompanying steps: in the first place is the instatement procedure. After this pheromone matrix is developed by the ACO when it additionally keeps running for N no. of iterations. Process of iterative comprises of development process and refreshes method. The latter is choice process by which edge is resolved.

Initialization process

In this procedure for a picture I of size M ×N is taken as input information which functions as an solution space for the manufactured ants. The K quantities of ants are haphazardly moved over the entire picture with the end goal that the each pixel of the picture is seen as a node. The constant is allotted to every, which is the underlying estimation of each part of the pheromone matrix. The initial value of each component of the pheromone matrix $\tau^{(0)}$ is set to be a constant.

Construction Process

One ant is irregularly chosen at the *n*-th construction-step from the above-discussed whole *K* ants, and this ant will continuously move on the image for *L* movement-steps. This ant moves to its neighboring node (*i*, *j*) as per the transition probability that is

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$$p^{n}_{(l,m)(i,j)} = \frac{\left(\tau^{(n-1)}_{i,j}\right)^{\alpha} \left(\eta_{i,j}\right)^{\beta}}{\sum_{i,j \in \Omega_{(l,m)}} \left(\tau^{(n-1)}_{i,j}\right)^{\alpha} \left(\eta_{i,j}\right)^{\beta}}, \qquad (4)$$

In the above equation, $\tau^{(n-1)}_{i,j}$ is defined as the pheromone value of the node (i, j), the parameter $\Omega_{(l,m)}$ represents the neighborhood nodes of the node (l,m), the parameter $\eta_{i,j}$ defines the heuristic information at the node (i, j). The effect of the pheromone matrix and the heuristic matrix, is represented by the constants α and β respectively.

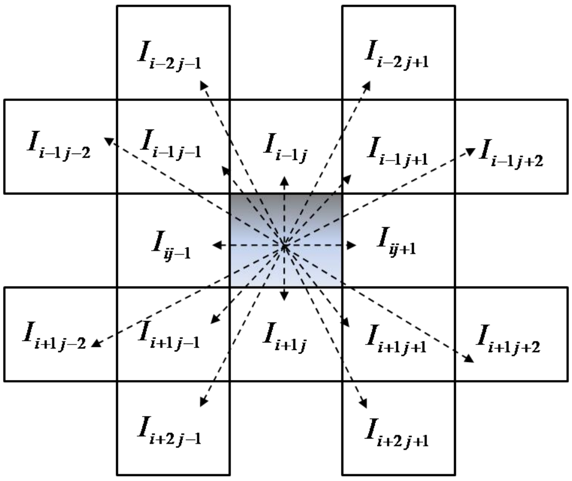

Figure 1: A local configuration at the pixel position $I_{i,j}$ for computing the variation $V_c(I_{i,j})$. The pixel $I_{i,j}$ is marked as gray square

The procedure comprises two vital issues and these are given beneath: The main issue is the heuristic data $\eta_{i,j}$ which can be determined by the local insights of the picture which relies on upon inner clique c. The local statistics at the pixel area (i, j) is figured as takes after [3]

$$\eta_{i,j} = \frac{1}{Z} V_c(i, j) \qquad (5)$$

Now, here the parameter Z represents a normalization factor, means the capacity of a neighborhood gathering of pixels c which is called coterie [10]. Determines the power estimation of a pixel at a location (i,j) of a picture I and is given with the help of the below equation

$$Z = \sum_{i=1:M} \sum_{j=1:N} V_c(i, j) \qquad (6)$$

The parameter Z defines a normalization factor, while $I_{i,j}$ represents the measure of intensity of the pixel at the (i, j) position of the image I, the function $V_c(i, j)$ is a function of a local group of pixels (known as the *clique*), and its estimation relies on the changes in intensity values of image of the clique c (as illustrated in Figure 1). All the more particularly, for the pixel $I_{i,j}$ under consideration, the function $V_c(i, j)$ is

$$\begin{aligned} V_c(I_{i,j}) = f\big(& \left|I_{i-2,j-1} - I_{i+2,j+1}\right| + \left|I_{i-2,j+1} - I_{i+2,j-1}\right| \\ & + \left|I_{i-1,j-2} - I_{i+1,j+2}\right| + \left|I_{i-1,j-1} - I_{i+1,j+1}\right| \\ & + \left|I_{i-1,j} - I_{i+1,j}\right| + \left|I_{i-1,j+1} - I_{i-1,j-1}\right| \\ & + \left|I_{i-1,j+2} - I_{i-1,j-2}\right| + \left|I_{i,j-1} - I_{i,j+1}\right| \big) \end{aligned} \qquad (7)$$

In order to find out the function f(·) in (7), the four functions mentioned below are considered in this work;

$$f(x) = \lambda x \quad \text{for } x \geq 0$$

$$f(x) = \lambda x^2 \quad \text{for } x \geq 0$$

$$f(x) = \begin{cases} \sin\left(\dfrac{\pi x}{2\lambda}\right) & 0 \leq x \leq \lambda \\ 0 & \text{otherwise} \end{cases}$$

$$f(x) = \begin{cases} \dfrac{\pi x \sin\left(\dfrac{\pi x}{\lambda}\right)}{\lambda} & 0 \leq x \leq \lambda \\ 0 & \text{otherwise} \end{cases} \qquad (8)$$

The parameter λ defined in the functions (8)-(11) modifies the functions' respective shapes. The second problem is to find out the acceptable range of the ant's movement (i.e., $\Omega_{(l,m)}$ in (4)) at the position (l,m). In this paper, the 8-connectivity neighbourhood, as demonstrated in Figure 2 is considered.

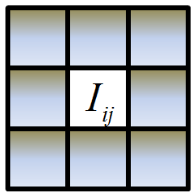

Figure 2: Various neighbourhoods (marked as gray regions) of the pixel $I_{i,j}$: 8-connectivity neighbourhood.

Update Process

In the update process, we update the pheromone matrix after the two operations of updation. The initial update is performed after the mobility of every ant in every development step. Every block of building of pheromone matrix is altered as provided in equation (6):

$$\tau^{(n-1)}_{i,j} = \begin{cases} (1-\rho)\tau^{(n-1)}_{i,j} + \rho \Delta^{k}_{i,j} & \text{if } (i,j) \in \text{visited current ant} \\ \tau^{(n-1)}_{i,j} & \text{otherwise} \end{cases} \qquad (9)$$

At this point, the parameter ρ represents the rate of evaporation of pheromone that relies on the measure of user choice, is estimated by the heuristic matrix.

We carry out the second update after the movement of the whole ants in each construction-step as in the equation given below:

$$\tau^{(n)} = (1-\psi)\tau^{(n-1)} + \psi \tau^{(0)} \qquad (10)$$

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Now, the parameter ψ represent the pheromone decay coefficient expands the look for the consequent ants by diminishing the pheromone level on the traversed edges. Along these lines it gives a chance to the consequent ants to create fundamental arrangements. Consequently, the probability of reiteration turns out to be more improbable in a similar iteration [10].

Decision process

In this progression, a binary decision is made at each pixel location to find out whether it is edge or not, by making application a threshold T on the last pheromone matrix τ (N). We propose the above-discussed T in this research article to be adaptively estimated on the basis of the technique created in [16]

We chose the initial threshold $T^{(0)}$ as the pheromone matrix mean value . After this, the entries of the pheromone matrix is ordered into two classifications as per the standard that its value is not more than $T^{(0)}$ or bigger than $T^{(0)}$. At that point the latest threshold is registered as the average of two mean values of all of the above two classes. The discussed procedure is rehashed till the point the threshold value doesn't vary any more (as far as a user- characterized tolerance). We can define the above iterative technique as.

Step 1: Initialize $T^{(0)}$ as

$$T^{(0)} = \frac{\sum_{i=1:M} \sum_{j=1:N} \tau_{i,j}^{(N)}}{MN}$$

and set the iteration index as $l = 0$.

Step 2: *Make the* separation of the pheromone matrix $\tau^{(N)}$ into two class making use of $T^{(l)}$, here the first class comprises entries of τ that have not more values than $T^{(l)}$, on the other hand the second class comprises the left over entries of τ . After this, make the calculation of the mean of all of the above two classes through

$$m_L^{(l)} = \frac{\sum_{i=1:M} \sum_{j=1:N} g_{T^{(l)}}^{L} \tau_{i,j}^{(N)}}{\sum_{i=1:M} \sum_{j=1:N} h_{T^{(l)}}^{L} \tau_{i,j}^{(N)}}$$

$$m_U^{(l)} = \frac{\sum_{i=1:M} \sum_{j=1:N} g_{T^{(l)}}^{U} \tau_{i,j}^{(N)}}{\sum_{i=1:M} \sum_{j=1:N} h_{T^{(l)}}^{U} \tau_{i,j}^{(N)}}$$

Where,

$$g_{T^{(l)}}^{L} = \begin{cases} x & x \le T^{(l)} \\ 0 & \text{otherwise} \end{cases}$$

$$h_{T^{(l)}}^{L} = \begin{cases} 1 & x \le T^{(l)} \\ 0 & \text{otherwise} \end{cases}$$

$$g_{T^{(l)}}^{U} = \begin{cases} x & x \ge T^{(l)} \\ 0 & \text{otherwise} \end{cases}$$

$$h_{T^{(l)}}^{U} = \begin{cases} 1 & x \ge T^{(l)} \\ 0 & \text{otherwise} \end{cases}$$

Step 3: Set the iteration index $l = l + 1$, and update the threshold as

$$T^{(l)} = \frac{m_L^{(l)} + m_U^{(l)}}{2}$$

Step 4: In the case of $\left| T^{l} - T^{(l-1)} \right| > \varepsilon$, then go to *Step 2*; else, the iteration method is terminated and we make a binary decision on each pixel position (i, j) in order to find out if it is edge (i.e., $E_{i,j} = 1$) or not (i.e., $E_{i,j} = 0$), on the basis of criterion

$$E_{i,j} = \begin{cases} 1 & \tau_{i,j}^{(N)} \ge T^{(l)} \\ 0 & \text{otherwise} \end{cases}$$

5. PROPOSED METHOD

In this method we have only used derivative and maximum derivative which contribute to edge is considered. Here we have not used any intensity mapping function as we define

$$V_c(I_{i,j}) = \frac{1}{I_{\max}} \max \begin{bmatrix} \left| I_{i-2,j-1} - I_{i+2,j+1} \right| + \left| I_{i-2,j+1} - I_{i+2,j-1} \right| \\ + \left| I_{i-1,j-2} - I_{i+1,j+2} \right| + \left| I_{i-1,j-1} - I_{i+1,j+1} \right| \\ + \left| I_{i-1,j} - I_{i+1,j} \right| + \left| I_{i-1,j+1} - I_{i-1,j-1} \right| \\ + \left| I_{i-1,j+2} - I_{i-1,j-2} \right| + \left| I_{i,j-1} - I_{i,j+1} \right| \end{bmatrix}$$

where, I_{max} is the maximum intensity

6. RESULTS

Experiments are conducted using BSD images as in previous paper. Furthermore, various parameters of the proposed approach are set as follows.

$K = \left\lfloor \sqrt{MN} \right\rfloor$: the total number of ants, where the function $\lfloor x \rfloor$ represents the highest integer value that is smaller than or equals to x.

$\tau_{init} = 0.0001$: the initial value of each component of the pheromone matrix.

α = 1: the weighting factor of the pheromone information

β = 0.1: the weighting factor of the heuristic information.

• Ω = 8-connectivity neighbourhood: the permissible ant's movement.

λ = 10: the adjusting factor of the functions.

ρ = 0.1: the evaporation rate.

L = 40: total number of ant's movement-steps within each construction-step.

ψ = 0.05: the pheromone decay coefficient.

ε = 0.1: the user-defined tolerance value used in the decision process of the proposed method.

N = 4: total number of construction-steps

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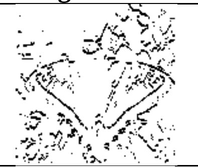
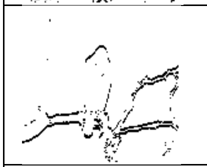
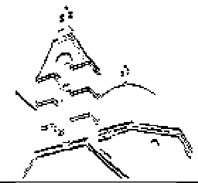
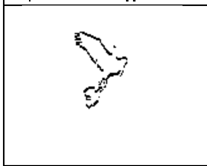
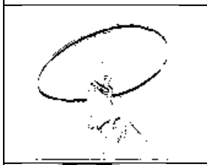
Proposed Method Images	Old Results	Proposed Method
	Min=87.86658 Max=**90.71638**	89.05698
	Min=91.25178 Max=93.67599	**95.04619**
	Min=91.72918 Max=93.67599	**93.81799**
	Min=96.79459 Max=97.35259	**98.23920**
	Min=93.57059 Max=**96.14359**	95.88319
	Min=93.14279 Max=**97.18519**	95.38719

Figure 3: Comparison of various images Accuracy (All methods)

The comparison of accuracy of various methods is shown in Figure 3, and images in first column are defined as 1 to 6. Here, for image 1 with old method maximum accuracy is 90.71638 while with proposed method 1 and 2 accuracy is 88.07118 and 89.05698 respectively. Here, for image 2 with old method maximum accuracy is 93.67599 while with proposed method 1 and 2 accuracy is 91.31998 and 95.04619 respectively. Similar data for other images are also shown. With old method accuracy for image 1, 5 and 6 is better in comparison to other images, and for rest of the images 2, 3 and 4 accuracy results is better for proposed method 2.

In Figure 4, images are compared with all the methods. In the first column ground truth images are shown for all six images. With old method, boundary edges are better recognized, with proposed method minor details are more easily recognized.

Ground Truth Image	Old Method	Proposed Method 2

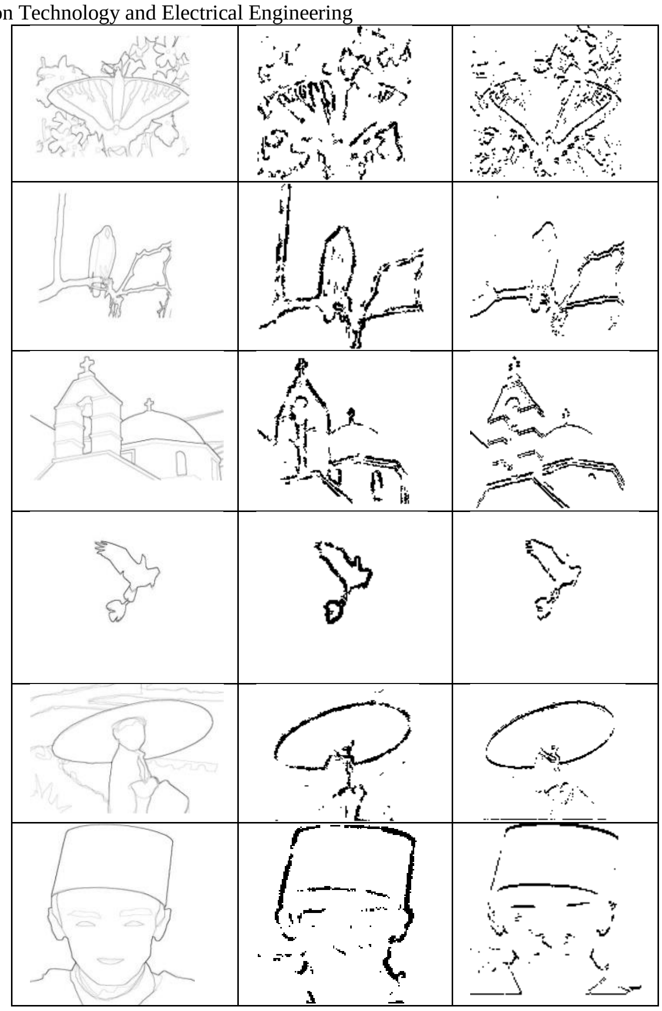


Figure 4: Comparison of various images (All methods)

7. CONCUSIONS

Edges in image contain important information and edge detection plays an important role in image processing. Therefore, over decades lots of techniques are investigated and developed for the correct detection of edge. ACO is a method based on heuristic search and it is beneficial for discrete problems.

An ACO algorithm for image edge detection has been investigated. Based on tests performed on images, ACO is robust and competitive and proposed method is found to be effective, and it is independent of intensity mapping function.

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