Dehazing Of Single Nighttime Haze Image using Superpixel Method

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Abstract - *The open air pictures captured in harsh climate are corrupted due to the nearness of fog, mist, rain and so on. Pictures of scenes captured in lousy climate have destitute contrasts and colors. This might also cause problem in spotting the objects within the captured murky images. Due to murkiness there may be trouble to numerous computer vision application because it diminishes the perceivability of the scene. Picture de-hazing is one of the essential imperative inspect variety in picture preparing. Cloudiness is genuinely an Climatic effect.*

In this paper a novel super-pixel based single image haze removal algorithm with a neural network method is proposed for nighttime haze image. The input nighttime haze image is first decomposed into a glow image and glow-loose nighttime haze picture the usage of their relative smoothness. A super pixel based approach is then brought to compute the price of atmospheric light and dark channel for each pixel in the glow free haze image. The transmission map is decomposed from the darkish channel of the glow-unfastened haze photo by means of the weighted guided photograph filter. Since super-pixels normally adhere to the limits of gadgets well, a smaller nearby window size may be selected. In addition to this the gathered images (the hazy images) will input to a neural network that will increase the quality of the output image that the actual image we want to get.

Key words: **Nighttime image haze removal, Glow decomposition, Morphological artifacts, Super-pixel segmentation, Weighted guided image filtering**

1. INTRODUCTION

In real life, natural phenomena (inclusive of rain, haze, snow etc)can lead to degradation of outdoor images. Because in these environments, massive amount of particle floating in the atmosphere, mild propagation within the atmosphere will be suffering from these floating particles. In the sector of computer vision image de-hazing has a much broader demand. From the perspective of image processing, it may provide pretreatment for some visual algorithms. Besides from the practical factor of view, it plays an important role in military system and civil system [1]. Haze free images makes the scene look more practical and provide more useful information. Therefore the studies of image de-hazing has critical practical importance and development prospect.

There were many haze removal techniques which are primarily based on the optical model developed for day time haze images. At present, the most widely bodily model is a linear equation such as transmission and atmospheric light. According to the version, day time de-hazing technique want to estimate the atmospheric mild and transmission map. Many classic strategies use additional information or multiple photographs to do away with haze from the haze snapshot. For example Schechner et al. [2] proposed a novel technique of using images with different polarizer orientation to de-hazing. Lai et al. [3] proposed an interesting technique to derive the most beneficial transmission map at once from the sunlight hours haze image version. In [4], a quick algorithm for single image de-hazing is proposed based totally on linear transformation with the aid of assuming that a linear relationship existence inside the minimal channel between the hazy image and the haze-free image. On top of dark channel prior, He et al. introduced a simple method to study single image haze elimination in [5]. The dark channel prior is based on a commentary that most nearby patches in haze-free scene images include a few pixels that have very low intensities in at the least one coloration channel. Many dark channel prior based totally haze removal algorithms were delivered since then [7][8]. The dark channel earlier based totally methods usually work well, but the dark channel earlier has limitations. For example, morphological artifacts are an issue for the darkish channel previous while the preliminary transmission map is computed use of the dark channel earlier [5]. A simple edge retaining decomposition based totally framework changed into proposed for single image haze removal in [9]. Simplified dark channel of the haze image is decomposed into a base layer and a element layer via the weighted guided image filter (WGIF) in [11], and the transmission map is expected from the base layer. Image enhancement based techniques also are applied to the image de-hazing, for example [12][13][14].

Even though these techniques generally carry out well for daylight hours haze image shots, they are now not properly ready to correct nighttime scenes due to varying imaging conditions such as active light assets or glow effects. Due to existence of active light assets, for example, avenue lighting et al, and their related glow, the version of daytime haze images are now not applicable to the midnight haze image. Recently, several interesting methods have been emerged to decorate nighttime haze images [15][16][17][20]. Pei and Lee [15] introduced a method primarily based the color transfer processing. The colorings of a nighttime haze image had been mapped to those of a daytime haze image. Then, a dark channel prior primarily based set of rules was supplied to estimate the transmission map. A post-processing step become also furnished to improve the insufficient brightness and coffee overall evaluation of haze-free image. Due to the coloration transfer, even though their approach has the dependable de-hazing quality, the shade of the complete haze free image looks unnatural. Zhang et al [16] proposed a new photo model which accounted for various illumination. First, the mild intensity became estimated and enhanced to achieve an illumination balanced result, then, they expected the shade traits of the incident light, finally, they used the darkish channel previous to cast off the haze.

The main contribution of this paper is a new type of haze elimination algorithm using the concept of super-pixel. Compared with the patch based totally methods, the super-pixel can be used to reduce morphologic artifacts because of the patch. This is due to the fact that the super-pixel can adhere to boundaries of items within the haze image well. As such, the radius of the WGIF may be reduced. Subsequently, more exceptional details may be preserved. In addition, the proposed super-pixel based totally technique has more chance to correctly estimate the transmission maps for all pixels I white gadgets nearby a digital camera than algorithms in [9][17] and [25]. In other words, the proposed method provides a technique to a challenging problem on the estimation of transmission maps for pixels in white items close by the digital camera. The rest of this paper is organized as preliminary knowledge, procedure of nighttime single image haze removal, experimental results and conclusion.

2. PRELIMINARY KNOWLEDGE

Since the WGIF and the SLIC might be implemented in the proposed method, the relevant expertise on them are summarized in this section.

2.1. Weighted Guided Image Filter

Denote the guidance photograph as I, the filtering output as Z, and the input photograph as X. The pictures I and X can be identical. Z is thought to be a linear remodel of I in a window Ω_k focused at the pixel p, and the radius of the window Ω_k is r

$$Z(p) = a_k I(p)+b_k, \forall p \in \Omega_k, \quad (1)$$

Wherein the price of (a_k,b_k) can be computed by means of minimizing the following cost function in the window Ω_k.

$$E(a_k,b_k) = \sum p\in\Omega k \left((a_k I(p)+b_k - X_p)^2 + \lambda_{ak}{}^2\right), \quad (2)$$

And λ is a regularization parameter penalizing large a_k. Since, halo artifacts may appear on some edges, an edge-conscious weighting is introduced and incorporated into the GIF to form the WGIF. The edge-aware weighting $\Gamma_I(k)$ is :

$$E(ak,bk) = \sum p\in\Omega k \left((ak\, I(p)+bk - X(p))2 + \lambda\, \Gamma I(k)\, a\, 2\, k\right), \quad (3)$$

The solutions of ak and bk are given as:

$$a_k = \mu_I \odot X,r\,(k) - \mu_{I,r}(k)\mu X,r(k)\ \sigma\ 2\ I,r\,(k) + \lambda\, \Gamma I\,(k)\,, \quad (4)$$

$$b_k = \mu X,r(k) - ak\mu_{I,r}(k) \quad (5)$$

2.2 Super-pixel Segmentation Via The SLIC

A super-pixel is a small region composed by a sequence of pixels with adjacent positions, similar shade, similar brightness, similar texture and different characteristics. The SLIC (Simple Linear Iterative Clustering) is a common approach of the super pixel segmentation. This method can phase pixels quick and simply, besides, it may perceive barriers better. The color images are converted into a five-dimensional feature vectors V = [l,a,b,x,y] in CIELAB color area and XY coordinate. Where, [l,a,b] suggests the color of pixel, [x,y] shows the placement of pixel. It is a distance measurement standard for five-dimensional characteristic vectors, and a neighborhood clustering procedure for photo pixels. SLIC set of rules can generate compact and about uniform super-pixels. Besides, t has a high overall evaluation in terms of speed, contour preserving and hyper pixel shape, and the segmentation impact is in keeping with people's expectation. The metric of SLIC is given as:

$$d_{lab} = \sqrt{\ } (l(p)-l(p'))^2 + (a(p)-a(p'))^2 + (b(p)-b(p'))^2 \quad (6)$$

$$d_{xy} = \sqrt{\ } (x(p)- x(p'))^2 + (y(p)-y(p'))^2 \quad (7)$$

$$D_s = \sqrt{\ } (\ dlab\ Nlab\ )^2 + (\ dxy\ Nxy\ )^2 \quad (8)$$

where, d_{lab} represents color distance; d_{xy} represents spatial distance; p and p′ are two pixels; $N_{xy} = \sqrt{\ } K\ N$, where K is called the total number of pixels, N is the number of the super pixels; N_{lab} varies with special images, however it is normally a set value. The super-pixels normally can pick out obstacles better. So, it is able to be expected that the concept of super-pixel may be used to reduce the morphological artifacts within the single image haze removal.

3. NIGHTTIME SINGLE IMAGE HAZE REMOVAL

In this section, first provide information on the model of nighttime haze images. Based on this version, the glow is eliminated from the input photograph thereby the glow-free haze image is obtained. The model of the glow-loose haze photo is similar with the version of sunlight hours haze picture except that the atmospheric light is spatially varying inside the nighttime haze photograph. It is thus predicted that existing dark channel based algorithm for sunlight hours haze removal may be prolonged to address nighttime haze image. Based on this observation, a super-pixel based haze elimination algorithm is offered for the glow-free nighttime haze images.

3.1 Modelling Of A Nighttime Haze Image

Since the light source best from the sun, the sunlight hours images are not stricken by other light sources. In the daylight hours haze image de-hazing algorithm, the model is generally used as;

$$X_c(p) = Z_c(p)t(p) + A_c(1-t(p)) \quad (9)$$

When a photo is captured at night, light sources especially come from road lighting fixtures and car lighting etc. These lights aren't international uniform, thus; the glow is present inside the image. The glow is an atmospheric point spread function (APSF). Inspired by this, the complete nighttime haze scenes by adding the glow version into the daylight haze picture model:

$$X_c(p) = Z_c(p)t(p)+ A_c(1-t(p))+ A_a * APSF \quad (10)$$

In which $c\in\{r,g,b\}$ represents coloration channel index, X_c shows discovered nighttime images. Z_c represents the scene radiance vector. T is the transmission map and indicates the elements of light that penetrates via the haze. A_c represents atmospheric light which is not always globally uniform any longer. A_a indicates active light sources, that the intensity is convolved with APSF. So that it will get the scene radiance vector, this is, the haze free image Z, the glow (that is A_a*APSF) are decomposed from the input photograph ($X_c(p)$), and the atmospheric light A_c and the transmission map t are estimated.

3.2 Glow Removal from the Input Image

From the unprocessed images, we can see that glow can reduce the visibility of the photograph or may be make a few objects unseen. In order to attain an excellent visual image, the glow should be eliminated from the input photograph. For simplicity, the equation (10) can be written as:

$$X_c(p) = J_c(p)+G_c(p) \quad (11)$$

Where, $J_c(p) = Z_c(p)t(p) + A_c(1\text{-}t(p))$, we name it a glow free nighttime haze image, and $G_c(p) = A_a$* APSF, it's far a glow photograph. From the equation (12), the glow elimination can be seemed as a layer separation problem. The objective function for glow layer separation may be described as follow:

$$E(J) = \sum p\,(\rho(J(p) * f_{1,2}) + \lambda_1((X(p)- J(p)) * f_3)^2)$$

$$s.t. 0 \le J(p) \le X(p) \quad (12)$$

$$\sum J_r(p) = \sum p\, J_g(p) = \sum p\, J_b(p)$$

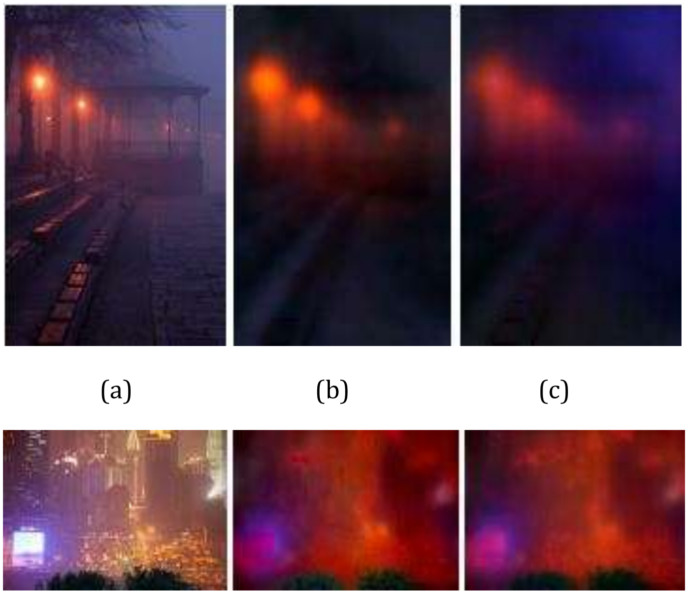
Where, f_{12} is the 2-route first spinoff filters. f_3 is the second order Laplacian filter out and the operator $*$ denotes convolution. $\rho(\mu) = \min(\mu 2,\tau)$ is a robust characteristic which preserves large gradients of the input photo X within the closing nighttime haze layer [17]. For simplicity, we outline $F^jL = L * f_i$ then the objective function can be rewritten as;

$$E(J) = \sum p\,(\rho(F^{1,2}\, J(p)) + \lambda_1(F^3\, J(p)- F^3\, X(p))^2\,) \quad (13)$$

According to the method [23], with a view to pass the F^jL time period outdoor the $\rho(\cdot)$ function, a weight β is delivered to the goal function, the brand new objective function may be written as;

$$E(J) = \sum p\,(\beta(F^{1,2}\, J(p)-g^{1,2})^2 +\rho(g^{1,2})$$

$$+ \lambda_1(F^3\, J(p)- F^3\, X(p))^2\,) \quad (14)$$



(a) (b) (c)

(d) (e) (f)

Fig.1: (a,d) two nighttime haze pictures; (b,e) glow pix with the aid of the method[23]; (c,f) glow photographs by the proposed algorithm. The glow pictures produced with the aid of the proposed set of rules are smoother.

It can be validated that the above solution is an approximated solution at the same time as the provided solution within the equation (16) is an precise one. Therefore, our output is more correct than the output in [23]. The Fig.1 indicates separated glow picture with the aid of the algorithm in [23] and the proposed set of rules. Clearly, the glow's element in (c,f) is greater meticulous and non-stop than (b,e). Therefore, the proposed glow decomposition method is higher than the technique in [23].Since the input image consists of a glow picture and a glow-loose haze photo the procedure of glow decomposition directly impacts the composition of glow-free image, thereby

(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Fig. 2: (a,f) two haze images; (b,g) glow images by the method [23]; (c,h) glow-free haze images by the method [23]; (d,i) glow images by the proposed algorithm; (e,j) glow-free haze images by the proposed algorithm. There are more details in the glow-free haze images by the proposed algorithm

affecting the high-quality of de-hazed picture. The Fig.2 shows the glow images and glow-loose images by means of the Li's algorithm and the proposed algorithm. It may be visible from the Fig.2 (c)(e) that the glow may be removed better through our algorithm, and from the Fig.2 (h)(j) that the glow unfastened haze photographs are toward the nature scene.

3.3 Atmospheric Light Estimation

After the glow being removed from the input image, a glow-free nighttime haze image is finded. In order to repair the haze-free photo, the atmospheric light A_c and the transmission map t is need to be estimated. Since the models of a daytime haze image are almost the same besides for the atmospheric light, it is able to be expected that some existing method of daytime haze image de-hazing can be carried out to removal the haze from the glow-free nighttime haze image. The atmospheric light is always appeared as the brightest shade within the daylight haze image. However, due to the presence of the light sources, the atmospheric light is not always global uniform inside the glow-free nighttime haze image. According to the photograph formation model, the picture $Z_c(p)$ is a produce of illumination and reflectance components:

$$Z_c(p) = A_c(p)R_c(p) \tag{15}$$

where $R_c(p)$ is the reflectance component. The glow-free nightime haze image is then represented as:

$$X_c(p) = A_c(p)R_c(p)t(p) + A_c(p)(1-t(p)) \tag{16}$$

the components $A_c(p)$ and $t(p)$ are assumed to be constant in a local window of p. It can then be derived that

$$\max_{p'\in\Omega(p)} \{X_c(p')\} = A_c(p) \max_{p'\in\Omega(p)} \{R_c(p')\}t(p)+ A_c(p)(1-t(p)) \tag{17}$$

Using the following maximum reflectance prior [24],

$$\max_{p'\in\Omega(p)} \{R_c(p')\} = 1 \tag{18}$$

it can be derived that

$$A_c(p) = \max_{p'\in\Omega(p)} \{X_c(p')\}. \tag{19}$$

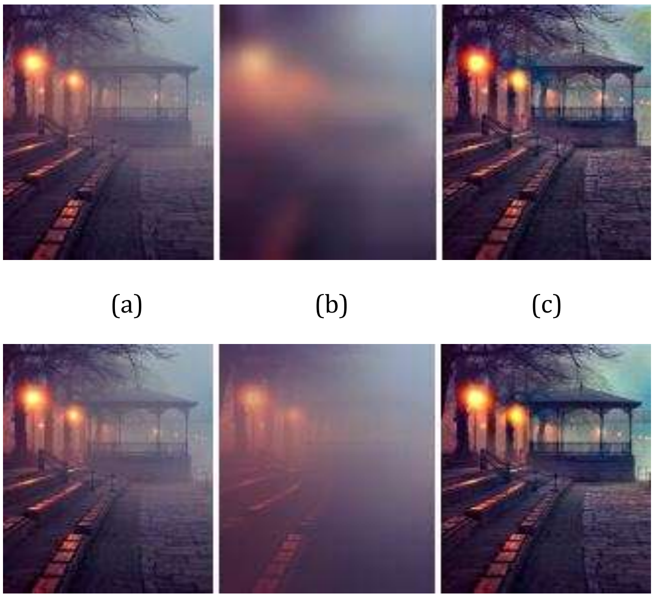
(a) (b) (c)

Fig. 3: (a) a glow-free haze image; (b) an initial atmospheric light image; (c) a refined atmospheric light image. There are morphological artifacts in the initial atmospheric light image and they are removed by the WGIF.

On the premise of the feature of super-pixel, the atmospheric light more risk to be uniform in each super-pixel. Hence, the glow free nighttime haze image J_c is decomposed into N super-pixels in place of a grid of small areas in [17]. The brightest pixel within the i^{th} super-pixel and it is assigned to all the pixels inside the super-pixel to make up the preliminary atmospheric light $IA_c(p)$. Even though the morphological artifacts are reduced the usage of the super-pixels, there are still visible morphological artifacts. WGIF can be followed to remove the morphological artifacts. The

WGIF can be followed to remove the morphological artifacts in order to get the clean global atmospheric light $A_c(p)$.

The photos to be filtered are $IA_c(p)$ and the guidance images are the color components of the glow-free nighttime haze images $J_c(p)$.



(a) (b) (c)

(d) (e) (f)

Fig.4: (a),(d) are the equal glow-free haze image by way of the proposed method; (b),(c) respectively is an atmospheric light image, de-hazed image via the method [17]; (e),(f) respectively is an atmospheric light image, de-hazed image by means of the proposed method.

3.4 Transmission Map Estimation

After getting the atmospheric light, the transmission map is estimated to recover the scene radiance. Here the concept of DehazeNet is used to estimate the transmission map. DehazeNet is an give up-to-end system. It without delay learns and estimates the mapping relations among hazy image patches and their medium transmissions. This is completed through special design of its deep architecture to encompass established image de-hazing principles. I propose a novel nonlinear activation feature in DehazeNet, clled Bilateral Rectified Linear Unit (BReLU).

BReLU is a singular activation characteristic that is beneficial for image recovery and reconstruction. BReLU extends Rectified Linear Unit(ReLU) and demonstrates its importance in obtaining accurate image recuperation. Technically BReLU uses the bilateral Restraint to lessen search space and enhance convergence. I establish connections between components of DehazeNet and those assumptions/priors used in existing dehazing method, and explain that DehazeNet improves over these strategies by automatically gaining knowledge of all these additives from give up to quit. Neural network (DehazeNet) net are designed to implement four sequential operations for Medium transmission estimation, namely, feature extraction, multi- scale mapping, local extremum, and nonlinear regression are represented in Fig.5.

1) Feature Extraction: Feature extraction is performed by the usage of the convolution layer of nueral network. The input image can be filtered with different kinds of filters. So we can maintain the vital info and can do away with the unwanted details. Convolution is performed by the usage of 5 filters of length 3X5.

2) Multi- Scale Mapping: Here we can filter with different filters having different scales like 4X3, 4X5, 4X7. Then we can analyze the details clearly.

3) Local Extremum: When the last two steps are completed, we get a lot of filtered images. Local extremum is the process of selecting the most important values from these filtered images.

4) Nonlinear Regression: Non-linear regression is the last step. It is the process of selecting the most important values and getting the output. When it does, we get a transmission map. After getting the atmospheric light, the transmission map is estimated to recover the scene radiance.

3.5 Recovery of the Scene Radiance

The haze-free image $Z_c(p)$ can be recovered the use of equation (20). It is worth nothing that the value of t_p is close to zero, $Z_c(p)t(p)$ is also near to zero. In this situation, if the haze free image is restored, the noise inside the haze free image will be substantially amplified. Thus a lower sure t_m which was added to constrain t_p can lessen the noise. The value of the t_m is decided by way of the denses of the haze. Its value is decided on as 0.2 if the haze is not heavy, 0.375 otherwise. The final image is restored as

$$Z_c(p) = J_c(p) - A_c(p) \max(t(p), t_m) + A_c(p) \qquad (20)$$

It is well worth nothing that the proposed edition mechanism of t_m is coarse and pleasant of de-hazed images may want to be advanced through a finer choice of t_m with appreciate to special haze levels.

4. Experimental Results

Here I compare proposed algorithm with the daylight hours haze elimination algorithms in [5] and four nighttime haze elimination algorithms in [16][17] and [24].

4.1 Comparison Among Different Haze Removal Algorithm

For comparison, the results the use of dehazing algorithms in [5], [16], [17], [20], [24] and proposed algorithm are shown within the Fig.14. He's approach in [5] is a classical set of rules for daytime haze images. It is not always surprised that it is not appropriate to put off the haze from

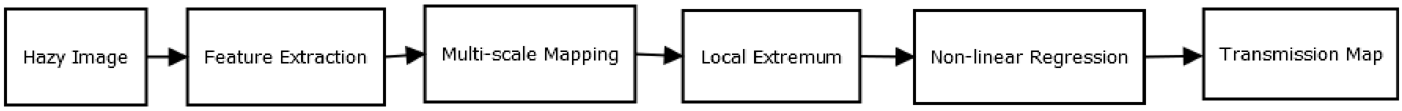


Fig. 5 The architecture of DehazeNet. DehazeNet conceptually consists of four sequential operations (feature extraction, multi-scale mapping, local extremum and non-linear regression).

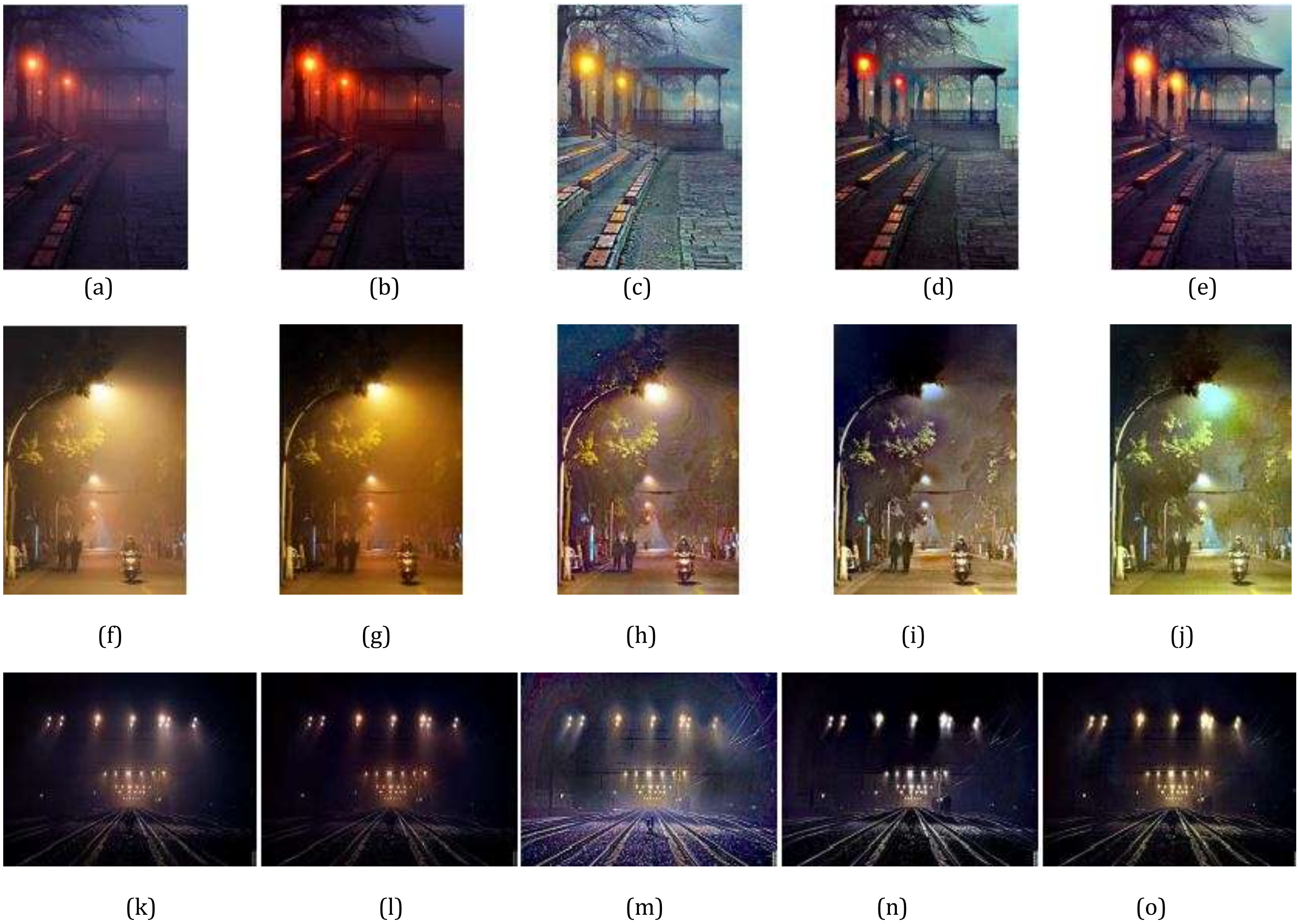


Fig.6: (a,f,k) haze images; (b,g,l) dehazed images by the method in [5]; (c,h,m) dehazed images by method [6]; (d,I,n) dehazed images by the method in [17]; (e,j,o) dehazed images by proposed algorithm.

nighttime haze image. Only part of haze can be removed via this method and the glow nonetheless exists in the final pictures. The techniques in [16] and [17] are designed for images, there are visible halo artifacts and noise is amplified within the de-hazed snap shots as illustrated in the Fig.6 (h),(m) glow around the mild sources. The method in [16] was improved in [24].

Neither the algorithm in [20] nor the set of rules in [24] addressed the glow artifacts. As such, the glow artifacts are grater visible within the de-hazed images by way of the algorithms in [20] and [24]. It is well worth nothing that a bigger t_m is selected in the equation (20) to keep away from amplifying noise in the sky regions. On the other hand, excellent details can also be smoothed through the proposed algorithm. It is desired to layout a finer t_m for the proposed set of rules. In spite of our algorithm works nicely in de-hazing of nighttime haze image, there are still some deficiencies. For example, the haze removal image appears darker than the input image. Fortunately, this problem may be addressed using a single image brightening algorithm in [26].

The running time of the proposed algorithm is barely longer because of segment the glow-free image into super-pixels. The approach in [17] works better than the method [16]. Unfortunately, noise is likewise amplified and halo artifacts nevertheless exists inside the final images. The set of rules in [17] money owned that the atmospheric light is locally regular in a grid of small area. However, this is not continually true. On the other hand, according to capabilities of the super-pixels, it's far more likely that the atmospheric mild is regular within the super-pixel.

5. CONCLUSION

This paper presented a novel super-pixel based nighttime haze image de-hazing set of rules. The proposed set of rules can eliminate the glow and the haze higher than the state-of-the art methods. Local exceptional details are also preserved better, and the color distortion and halo artifacts are glaringly reduced. As such, the haze-loose image is in the direction of a nature scene. On the alternative hand, because segmentation of glow-free nighttime haze images into super-pixels is required with the aid of the proposed algorithm, the running time and the complexity are increased. It is known that the existing single image haze elimination algorithms suffer from amplifying noise inside the sky region. This problem could be addressed by means of deciding on a finer adaptive t_m inside the equation (20). This problem can be studied in future research.

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