Research on Foggy Image Enhancement Algorithm based on Improved Retinex Theory

Xiafu Lv [a], Rui Zhang [b] and Jian Chen [c]

School of Automation, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

[a]18908350829@163.com, [b]820645043@qq.com, [c]764847318@qq.com

Abstract

In order to improve the image quality in fog, this paper presents a fog-image enhancement algorithm based on adaptive guided image filter Retinex theory. Firstly convert the image from the RGB color space to the HSV color space, Then, the luminance image is estimated by adaptive guided image filter, the saturation image is linearly stretched. Finally, the image is transformed back from HSV color space to RGB color space to get the final enhanced image. Simulation results show that the improved algorithm proposed in this paper is very good for foggy image enhancement, which solves the shortcomings of traditional Retinex algorithm, the enhanced foggy image is more clear and the details are more abundant.

Keywords

Image enhancement, Retinex algorithm, Color space, Illumination estimation.

1. Introduction

Fog or haze is a common natural phenomenon, the foggy weather causes the image received by the sensor to become blurred, this is due to the presence of dust, smoke and other suspended particles in the air, which absorb and diffuse the reflected light in the scene, resulting in reduced visibility and color distortion in the scene. The existence of fog can greatly reduce the visibility of objects in the image, so that the visibility of the target is reduced, which affects the analysis and discrimination of the image content, so it becomes a lot of computer vision applications such as video surveillance, remote sensing, navigation, target identification and so on. Of the important issues. Therefore, image enhancement for single fog is still faced with great challenges.

The main purpose of foggy image enhancement is to improve the contrast and saturation of the image while maintaining the same hue. At present, the fog images are enhanced mainly by physical methods and image processing methods[1].Physical processing methods are complex and require a priori knowledge of images under the same scene in sunny days, and require physical devices, such as sensors, so they are inconvenient in practical applications[2].The fog-based image enhancement algorithm based on image processing can get rid of dependence on physical hardware devices and become the main direction of image enhancement research. At present, there are histogram equalization [3-5], wavelet transform [6], homomorphic filtering [7] and Retinex algorithm [8].The histogram equalization algorithm mainly improves the quality of the image through the detail contrast of the image, but causes the original image to be distorted. The homomorphic filtering algorithm can deal with the illumination uneven image better, but it is not effective for the fog image. Therefore, based on the human perception of the color of things, Retinex algorithm is used to enhance the fog image. The method has the characteristics of color constancy, detail enhancement, color guarantee and so on. The most common algorithms are single-scale Retinex algorithm (SSR), multi-scale Retinex algorithm (MSR) and multi-scale Retinex color restoration algorithm (MARCR).

In order to improve the enhancement effect of fog images, an improved Retinex algorithm is proposed to enhance the fog image for the traditional Retinex problem, and verified by experimental simulation.

2. Traditional Retinex Theory and Its Defects Analysis

2.1 Traditional Retinex Theory Enhancement Algorithm

Retinex theory from the color constancy theory, the theory that when the external illumination conditions have great changes, the human eye on the object color perception can still remain unchanged, showing color constancy. Retinex theory holds that an image $I(x,y)$ consists of the illumination component $L(x,y)$ and the reflection component $R(x,y)$, which can be expressed as:

$$I(x,y) = L(x,y) \times R(x,y) \tag{1}$$

In the formula (1), the irradiation component $L(x,y)$ describes the low-frequency information part of the image change slowly, and determines the dynamic range of the image pixel. The reflection component $R(x,y)$ contains most of the high-frequency detail information in the image, which determines the intrinsic nature of the image. The purpose of Retinex theory is to eliminate the radiation component, the acquisition of reflection components, in order to obtain the essence of the surface.On the formula (1) on both sides of the logarithm, can be separated from the reflection component and irradiation components, namely:

$$\log I(x,y) = \log L(x,y) + \log R(x,y) \tag{2}$$

Equation (2) shows that when the image does not depend on the influence of ambient light, the original appearance is obtained. The calculation of the illuminance component is important to obtain the estimated value of the reflected component with high frequency information.The SSR algorithm uses Gaussian filtering to estimate the illumination components $L(x,y)$ through the idea of central wrapping, namely:

$$L(x,y) = I(x,y) * F(x,y) \tag{3}$$

In formula (3), $*$ is the convolution symbol. F is the surround function, generally a Gaussian function.

$$F(x,y) = k\exp(-\frac{x^2+y^2}{\sigma^2}) \tag{4}$$

σ is the scale parameter of the Gaussian function, k is a normalization factor, which satisfies the following condition:

$$\iint F(x,y)dxdy = 1 \tag{5}$$

SSR algorithm cannot meet the details of the enhanced at the same time to achieve better color fidelity. In order to ensure the balance between the two, we introduce the MSR algorithm, the mathematical expression is as follows:

$$R_i(x,y) = \sum_{k=1}^{k} W_k\{\log I_i(x,y) - \log[F_k(x,y) * I_i(x,y)]\} \tag{6}$$

k denotes the number of encircling scales. In general, $k=3$, W_k denotes the k-th scale weighting coefficient, and $\sum_{k=1}^{k} W_k = 1$.

Compared with the SSR algorithm, the MSR algorithm can keep the detail enhancement better and achieve better color rendering, but the image after MSR algorithm still has color distortion. Therefore, scholars have introduced the MSRCR algorithm, the expression is:

$$R_{MSRCR_i}(x,y) = a_i(x,y)R_{MSR_i}(x,y) \tag{7}$$

$$a_i(x,y) = \log(\frac{\beta \bullet I_i(x,y)}{\sum_{k=1}^{k} i_k(x,y)}) \tag{8}$$

In the above two formulas, β is the adjustment parameter, $a_i(x,y)$ is the adjustment factor.

2.2 Defect Analysis of Retinex Algorithm

The traditional Retinex algorithm is used to enhance a fog image. SSR algorithm, MSR algorithm and MSRCR algorithm is enhanced as follows:

(a) The original image (b) SSR image (c) MSR image (d) MSRCR image

Figure. 1 Traditional Retinex algorithm to enhance the effect

According to the results of the image in Fig.1, the scene in the fog is white or gray due to the fog degradation effect，after the traditional Retinex algorithm, there will be "halo" phenomenon, color distortion is more serious, mainly due to Retinex theory, the illumination directly determines a pixel in the image can reach the dynamic range, and reflected light to determine an image the inherent nature. Therefore, the traditional Retinex algorithm is essentially equivalent to the process of high-pass filtering the image, so that the high-frequency components of the image is enhanced to filter out most of the low-frequency information, so that the content of the image information is lost. Therefore, this paper mainly aims at improving the traditional Retinex algorithm, and uses the guide filter to estimate the irradiated component to obtain high quality fog images.

3. Improved Retinex Algorithm Based on Guided Filter

The traditional Retinex algorithm has good enhancement effect on the degraded images, but there are some problems in the processing of fog images, including "halo" phenomenon, color distortion and over-enhancement in the enhancement process. In order to improve the existing problems, an improved algorithm of Retinex theory based on guided filtering is proposed in this paper. The algorithm is divided into the following steps: 1) Converts a color image from a color space to a color space. 2) The luminance image is processed by an adaptive guidance filter in the color space, and the illumination estimation image is obtained. 3) The image is transformed from color space to color space, and the final enhancement image is obtained by adaptively stretching the saturation component to improve the contrast of the image.

3.1 Color space conversion

Because the algorithm based on Retinex is based on the assumption of gray world, the enhancement process in color space is easy to cause the color distortion of the image. So we choose the color space which is closer to human visual expectation.

1) RGB color space to HSI color space

$$\begin{cases} H = \begin{cases} \theta, B \le G \\ 360^\circ - \theta, B > G \end{cases} \\ S = 1 - \dfrac{3}{R+G+B} \bullet \min(R, G, B) \\ I = \dfrac{1}{3}(R+G+B) \end{cases} \tag{9}$$

In formula (9), $\theta = \arccos\left[\dfrac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right]$, R , G and B respectively represent the three color channels of the original image. R , G , B $\in [0,1]$, H represents a hue component, $H \in [0^\circ, 360^\circ]$, S denotes the saturation component, I denotes the luminance component, and satisfies the condition S , $I \in [0,1]$.

2) HSI color space to RGB color space

when $0^\circ \le H \le 120^\circ$,

$$\begin{cases} R = I \bullet \left[1 + \frac{S \bullet \cos H}{\cos(60^\circ - H)}\right] \\ G = 3I - (R - B) \\ B = I(1 - S) \end{cases} \tag{10}$$

when $120^\circ \le H \le 240^\circ$,

$$\begin{cases} H = H - 120^\circ \\ R = I(1 - S) \\ G = I(1 + \frac{S \bullet \cos H}{\cos(60^\circ - H)}) \\ B = 3I - (R + G) \end{cases} \tag{11}$$

when $240^\circ \le H \le 360^\circ$,

$$\begin{cases} H = H - 240^\circ \\ R = 3I - (R + G) \\ G = I(1 - S) \\ B = I(1 + \frac{S \bullet \cos H}{\cos(60^\circ - H)}) \end{cases} \tag{12}$$

3.2 Estimation of illuminance components based on adaptive bootstrap filtering

For the problem of illumination component estimation, the common improvement is to use the bilateral filter which preserves the edge instead of Gaussian filter as the center surround function to estimate the illumination component. Although the bilateral filtering can preserve the detail information while smoothing, the time complexity Higher. The traditional time complexity of bilateral filtering is $O(Nr^2)$, where r is the radius of the filter window and N is the number of pixels in the image. In this paper, we use the linear guidance filter with smoothing and preserving function to estimate the illuminance components. The filtering is based on the least squares method and is filtered through the box filter and integrated image technique to ensure that the time complexity is only $O(N)$ and the execution speed and filtering window Size-independent, compared with the use of bilateral filtering to estimate the efficiency of illumination components higher. Reflective components based on guided filtering are solved as follows:

$$R(x,y) = \log I(x,y) - \log[I(x,y) * F(x,y)] \tag{13}$$

In that formula, $R(x,y)$ represents the reflection component under the logarithm, $I(x,y)$ represents the luminance image of the original image, $F(x,y)$ denotes a bootstrap filter function, which may be expressed as a local linear model:

$$q_i = a_k I_i + b_k, \quad \forall i \in w_k \tag{14}$$

k, i is the pixel of the image, a and b are constants, w_k is the rectangular window with k as the center, I is the guide image, q is the output image.

In order to find the optimal solution of the linear coefficient (a_k, b_k), to minimize the difference between q and the filter input p, the cost function in the equivalent minimization window w_k is:

$$E(a_k - b_k) = \sum_{i \in w_k} ((a_k I_i + b_k - p_i) + \varepsilon a_k^2) \tag{15}$$

ε is a regularization parameter, in order to prevent a too large, linear coefficients a_k and b_k can be solved by:

$$\begin{cases} a_k = \dfrac{\frac{1}{|w|}\sum_{i \in w_k} I_i p_i - \mu_k \bar{p}_k}{\sigma^2{}_k + \varepsilon} \\ b_k = p_k - a_k \mu_k \end{cases} \tag{16}$$

μ_k and σ_k^2 are the mean and variance of the leading image I in the window w_k, $|w|$ is the number of pixels in the window w, ε is the regularization parameter, which is used to balance the smoothing and edge preserving degree, the bigger the value, the better the smoothness , the edge retention is poorer.

Since the same regularization factor ε is applied to different windows, the difference between the pixels in different windows is not taken into account. For regions with large texture changes and rich edge information, a smaller regularization factor ε is needed to punish the larger a_k in the linear model. For regions with a smooth gray-scale transition, larger regularization is needed Factor ε is penalized to obtain a smaller approximation error. Therefore, this paper proposes an adaptive regularization factor according to the difference between image information to enhance the robustness of the image. The cost function is rewritten as follows:

$$E(a_k,b_k)=\sum_{i\in w_k}((a_k I_i+b_k-p_i)+\frac{\varepsilon}{\varphi_G(i)}a_k) \tag{17}$$

$\varphi_G(i)$ is the definition of the variance weighting factor, the expression is:

$$\phi_G(i')=\frac{1}{N}\sum_{i=1}^{N}\frac{(\frac{\sigma^2_{G,\rho}(i')+v_1}{\mu_{G,\rho}(i')+v_2})\zeta}{(\frac{\sigma^2_{G,\rho}(i)+v_1}{\mu_{G,\rho}(i)+v_2})\zeta} \tag{18}$$

G is the leading image, the current central pixel is i', $\sigma^2{}_{G,\rho}(i')$ and $\mu^2{}_{G,\rho}(i')$ are the variance and mean value of G in the 3×3 neighborhood of the center pixel, N is the total number of pixels of the image, i is all pixels of the image, v_1, v_2 and ζ are three constants, the value of v_1 is $(0.001*256)^2$, the value of v_2 is 10^{-9}, and ζ is 0.75 in this paper.

3.3 Linear Tension Saturation Component

During the process of image acquisition, the illuminance of each image is different due to the different external environment. It is necessary to stretch the saturation component S in the process of image enhancement. Therefore, in order to adaptively adapt the saturation component S of the low illuminance image to a better condition, an adaptive stretching algorithm for the saturation component S is proposed. The expression is as follows:

$$S'=(1+e^{\frac{M_V}{\max(R,G,B)+\min(R,G,B)}})\bullet S \tag{19}$$

S denotes the saturation component of the original image, S' denotes the saturation of the linearly stretched image, M_V denotes the mean of the original image, and $\max(R,G,B)$ and $\min(R,G,B)$ denote the maximum and minimum values of the three color components of the images R, G and B, respectively.

4. Experimental Simulation and Analysis

In order to verify the effectiveness of this algorithm, the experiment was carried out on the MATLAB platform (CPU Intel dual-core frequency 2.5GHz), and the size of the experimental image was chosen to be 320 ×240.The experiment will be validated from subjective visual effect and objective quality evaluation. This paper compares the traditional single-scale Retinex algorithm (SSR), the multi-scale Retinex algorithm (MSR) and the multi-scale Retinex algorithm with color fidelity (MSRCR). Through a large number of experiments, the relevant parameters are set as follows:

1) The algorithm of this paper: (guidance filter parameter) $r=4,\varepsilon=0.01$;

2) Single-scale Retinex algorithm: $\sigma=80$;

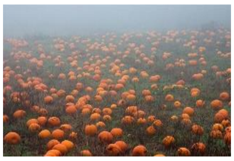
3) Multi-scale Retinex algorithm: (three Gaussian scale parameters) $\sigma_1=15,\sigma_2=80,\sigma_3=250$;

4) Retinex algorithm for color restoration: $\sigma_1=15,\sigma_2=80,\sigma_3=250$; Color recovery function $G_M=192$, $b_M=-30,\alpha_M=125,\beta_M=46$.

4.1 Results of Simulation

In this paper, we use the standard deviation, information entropy, clarity and other indicators to enhance the image of the objective evaluation (Figure. 2, Figure. 3).

Experiment 1:



(a)original image (b)SSR (c)MSR


(d)MSRCR (e)this paper algorithm

Figure. 2 image enhancement experiment 1

Experiment 2:



(a)original image (b)SSR (c)MSR


(d)MSRCR (e) this paper algorithm

Figure. 3 image enhancement experiment 2

4.2 Results of Objective Evaluation (Table 1 and Table 2).

Table 1 Comparison of objective evaluation results in experiment 1

	Standard deviation	Clarity	information entropy
original image	52.1568	10.9323	7.6673
SSR	41.9484	7.4598	4.3574
MSR	53.0088	12.6600	7.7074
MSRCR	29.7045	8.1903	6.5227
this paper algorithm	62.3091	24.6747	7.9822

Table 2 Comparison of objective evaluation results in experiment 2

	Standard deviation	Clarity	information entropy
original image	22.0918	4.2059	6.4249
SSR	17.1595	3.6510	4.0037
MSR	33.6530	6.6621	7.0622
MSRCR	17.8988	6.2035	6.1145
this paper algorithm	30.5955	11.6561	7.1182

4.3 Analysis of Algorithmic Data

(1) In the aspect of clarity, we can see from the experiment 1 that the clarity of the algorithm is 3.13 times, 1.68 times and 2.85 times of SSR, MSR and MSRCR respectively. It can be seen from experiment 2 that the clarity of this algorithm is 3.94 times, 1.08 times and 1.15 times of SSR, MSR and MSRCR, respectively. It can be shown that the enhanced image is clearer and the details are richer.

(2) In terms of information entropy, the information entropy of the image enhanced by this algorithm is obviously higher than the three methods. Experiment 1 shows that the information entropy of this algorithm is 1.81 times, 1.05 times and 1.21 times of SSR, MSR and MSRCR algorithm. Experiment 2 shows that the proposed algorithm is 1.97 times, 0.95 times and 1.06 times as high as that of SSR, MSR and MSRCR, and the information entropy of the enhanced image is obviously higher than that of the original image. It is shown that the details of the image enhanced by this algorithm are richer and the effect is better.

5. Conclusion

In this paper, we focus on the shortcomings of the traditional Retinex algorithm, and propose an improved fog-image enhancement method based on the Retinex algorithm. In this paper, Adaptive Boot Filter is introduced into Retinex algorithm. Firstly, the color space is transformed from RGB color space to HSI color space. Then, the illuminance component of the image is estimated by adaptive bootstrapping filter. Saturation component to obtain a final enhanced image. The experimental results show that the final image enhancement is superior to the traditional Retinex algorithm, the de-fog effect is better, and the details of the image are more obvious.

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