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Removing fog from traffic image sequence

Li Nan[1] Lu Xiaobo[2]

([1] School of Transportation, Southeast University, Nanjing 210096, China)

([2] School of Automation, Southeast University, Nanjing 210096, China)

Abstract: Aiming at removing fog from traffic images, a distance field is built according to the characteristics of traffic images, and a novel parameter estimation method based on the traffic image sequence is proposed. The fog model is derived from atmospheric scattering models. The direction of the distance field is parallel to the center line of the road, which increases along a line from the observer to the horizon, and the normalization is carried out to improve the distribution of the distance field model. After parameter initialization, the variations of the average gray values of reference regions are taken as the determining conditions to adjust the parameters. Finally, restorations are made by the fog model. Experimental results show that the proposed method can effectively remove fog from traffic images.

Key words: traffic images; fog; distance field; depth of field; physical model

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Weather conditions are important factors for many applications of computer vision such as surveillance, intelligent vehicles, outdoor object recognition, etc. As a typical weather phenomenon, fog strongly influences the quality of traffic images. Therefore, removing fog from traffic images is a necessary task.

It is well known that the conventional space invariant filtering techniques fail to adequately remove fog from images. So many other methods have begun to raise concerns, such as the method based on wavelet fusion[1], the method using optimal normal distribution[2], etc. Recently, the physics-based method has been demonstrated to be effective. But the earlier physics-based methods usually used predicted weather information which is often unreliable. Oakley et al. [3-4] described a physics-based method to restore scene contrast without using predicted weather information. However, the depth of field (DOF) is assumed to be known beforehand, which is difficult to be determined.

In order to improve this method, Narasimhan and Nayar[5] analyzed color variations in scenes under different weather conditions based on the dichromatic atmospheric scattering model. They computed the complete 3D structure and recovered clear day scene color from two or more bad weather images[6-7]. The changes in intensities of scene points under different weather conditions provided simple constraints to detect depth discontinuities in the scene. Hautiere et al. [8] proposed a method concerning traffic images, which took the scene structure into account. However, the maximum DOF was mainly estimated by a priori sensor calibration, and the horizon line was set above its actual position. Huang[9] proposed a method according to the exponential relationship between the degradation and depths of the scene points. Dong et al. [10] suggested a simple depth-cueing to make restoration.

The maximum DOFs of the above methods are inaccurate because of the visual deviations. A priori sensor calibration was used for precise estimation in Ref. [8]. The DOF is complex, which takes the camera's position into account, and causes a deviation between the actual distance and the perceived distance in the image. Researchers set the position of the horizon line above its actual position to reduce this deviation, but this operation may lead to another deviation.

To deal with the problems mentioned above, this paper builds a distance field and proposes a novel parameter estimation method for traffic images.

1 Atmospheric Scattering Models

Generally, atmospheric scattering is a complex process which is influenced by many factors. Attenuation and airlight are two of them, which is the focus in modeling the weather degradation.

The attenuation model describes the way that light gets attenuated as it traverses from a scene point to the observer, and the airlight model quantifies how a column of atmosphere acts as a light source by reflecting environmental illumination towards an observer. The attenuation model $\boldsymbol{B}_{\mathrm{dt}}(\boldsymbol{d}, \lambda)$ and the airlight model $\boldsymbol{B}_{\mathrm{a}}(\boldsymbol{d}, \lambda)$ are described as[7]

$$\boldsymbol{B}_{\mathrm{dt}}(\boldsymbol{d}, \lambda) = \frac{\boldsymbol{B}_{\infty}(\lambda)\boldsymbol{r}(\lambda)\mathrm{e}^{-\beta(\lambda)\boldsymbol{d}}}{\boldsymbol{d}^2} \tag{1}$$

$$\boldsymbol{B}_{\mathrm{a}}(\boldsymbol{d}, \lambda) = \boldsymbol{B}_{\infty}(\lambda)(1 - \mathrm{e}^{-\beta(\lambda)\boldsymbol{d}}) \tag{2}$$

where $\boldsymbol{d}$ is the DOF; λ is the wavelength; $\beta(\lambda)$ represents the scattering coefficient of the atmosphere to scatter light in all directions; $\beta(\lambda)\boldsymbol{d}$ represents the optical DOF point; $\boldsymbol{B}_{\infty}(\lambda)$ is the horizon brightness; $\boldsymbol{r}(\lambda)$ describes the reflectance properties and the sky aperture at the scene point.

The grayness of an image in fog weather can be denoted by

$$\boldsymbol{B} = \boldsymbol{B}_{\mathrm{dt}}(\boldsymbol{d}, \lambda) + \boldsymbol{B}_{\mathrm{a}}(\boldsymbol{d}, \lambda) = \frac{\boldsymbol{B}_{\infty}(\lambda)\boldsymbol{r}(\lambda)\mathrm{e}^{-\beta(\lambda)\boldsymbol{d}}}{\boldsymbol{d}^2} + \boldsymbol{B}_{\infty}(\lambda)(1 - \mathrm{e}^{-\beta(\lambda)\boldsymbol{d}}) = \boldsymbol{I}_{\infty}\boldsymbol{\rho}\mathrm{e}^{-\beta d} + \boldsymbol{I}_{\infty}(1 - \mathrm{e}^{-\beta d}) \tag{3}$$

where $\boldsymbol{I}_{\infty}$ is termed as sky intensity; $\boldsymbol{\rho}$ is the normalized radiance of the scene point; $\boldsymbol{B}$ is the degraded image in fog weather.

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Biographies: Li Nan (1982—), male, graduate; Lu Xiaobo (corresponding author), male, doctor, professor, xblu@seu.edu.cn.

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Furthermore, given $\boldsymbol{Z} = \boldsymbol{I}_\infty \boldsymbol{\rho}$, we obtain

$$\boldsymbol{B} = Z\mathrm{e}^{-\beta d} - \boldsymbol{I}_\infty (1 - \mathrm{e}^{-\beta d}) \tag{4}$$

where $\boldsymbol{Z}$ is the radiance of the scene point on a clear day, and the goal of restoration is to estimate $\boldsymbol{Z}$.

However, the scattering coefficient β and the distance $\boldsymbol{d}$ are difficult to obtain. As the sky intensity in fog weather is similar to that on clear days, the fog condition is to lessen the $|\boldsymbol{B} - \boldsymbol{I}_\infty|$, so $|\boldsymbol{B} - \boldsymbol{I}_\infty|$ can be seen as the indicator of attenuation. A modified equation of Eq. (4) can be described as

$$\boldsymbol{Z} = \mathrm{e}^{kl}(\boldsymbol{B} - \boldsymbol{I}_\infty) + \boldsymbol{I}_\infty \tag{5}$$

where $k = \beta n$ controls the variation of visibility, which reflects the fog density; $\boldsymbol{l} = \boldsymbol{d}/n$ is the normalized DOF, and n is the normalized coefficient.

The qualitative analysis curves between visibility and k are shown in Fig. 1. The visibility declines slowly in the close scene, and it varies fast in the distant scene. We set $k = \boldsymbol{l}$ by experience, which is not discussed in this paper.

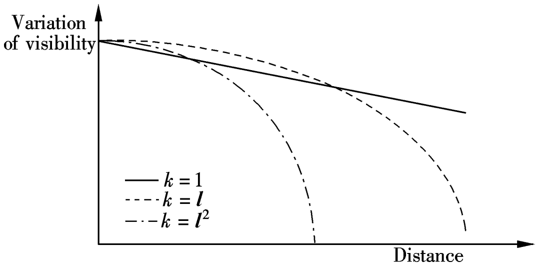

Fig. 1 Qualitative analysis between visibility and k

The normalized DOF $\boldsymbol{l}$ controls the extension of fog and it can be indicated by the distance field.

2 Distance Field Modeling

In this section, we build a distance field and propose a parameter estimation method.

2.1 The distance field

Unlike other images, the vision of the traffic image is often near the center line of the road. We mark the traffic image according to this character, as shown in Fig. 2(a).

From Fig. 2(a), we observe that the DOF increases gradually from the observer line to the horizon line along the direction of the center line. Even though there exists an angle between the traffic flow line and the center line, the distance between the vehicle line and the horizon line is not influenced. $\boldsymbol{l}$ is normalized to the range of [0, 1], which can improve the distribution of the distance field. We set the distance in the horizon line equal to 1 and the observer line to 0. The normalized distance field can be formulated as

$$\boldsymbol{l}(i,j) = 1 - \frac{i - i_0}{\max(i - i_0)} \qquad 0 \leqslant i \leqslant i_M \tag{6}$$

where i_0 is the vertical coordinate of horizon line $\boldsymbol{O}_{i=i_0}$; i_M is the vertical coordinate of the observer line; $M \times N$ is the image size.

The distance field $\boldsymbol{l}(i, j)$ with one parameter i_0 is built. Next, we estimate i_0.

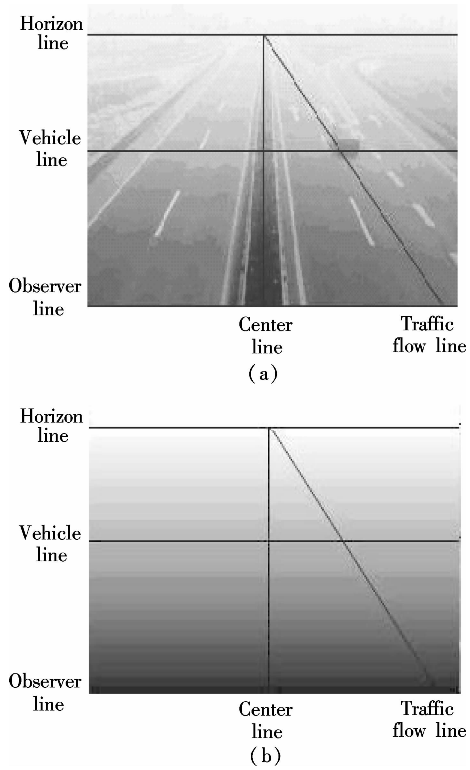

Fig. 2 Distance field of fog image. (a) Fog image; (b) Distance field

2.2 Parameter estimation

In the modeling of the distance field, many studies underestimate the precision of the horizon line position. They usually take the vanishing line instead of the actual horizon line, which is estimated by eye, so there exist some deviations. In this section, we propose a novel parameter estimation method.

The grayness of the moving vehicle varies gradually in fog weather. If restoration is made by the ideal distance field, the grays of the vehicle in different frames tend to be the same. Contrary to the above case, if the distance field is inaccurate, these grays will be different.

First, we assume that there are W successive images in the same scene $\boldsymbol{Z}_1, \boldsymbol{Z}_2, \ldots, \boldsymbol{Z}_W$, and their sizes are $M \times N$. Suppose that the reference regions $\boldsymbol{E}_1$, $\boldsymbol{E}_2$, ..., $\boldsymbol{E}_W$ are the same region of the vehicle in different frames. Taking $\boldsymbol{E}_1$ and $\boldsymbol{E}_2$ for examples, the observed horizon lines are supposed to be estimated by eye, which associate the air with the ground in fog, and the horizon lines in both images are the same. A distance field is built as shown in Fig. 3.

Because of the inaccuracy of eye measurement, there is a deviation $\Delta l > 0$ between the observed horizon line and the actual horizon line. Therefore, the actual distance of the vehicle line is $l_{1\mathrm{v}} = l'_{1\mathrm{v}} + \Delta l$, and the matrix of the distance field is $\boldsymbol{l}_1 = \boldsymbol{l}'_1 + \Delta \boldsymbol{l}$, where

$$\Delta \boldsymbol{l} = \begin{bmatrix} \Delta l & \Delta l & \ldots & \Delta l \\ \Delta l & \Delta l & \ldots & \Delta l \\ \vdots & \vdots & & \vdots \\ \Delta l & \Delta l & \ldots & \Delta l \end{bmatrix}_{M \times N} \tag{7}$$

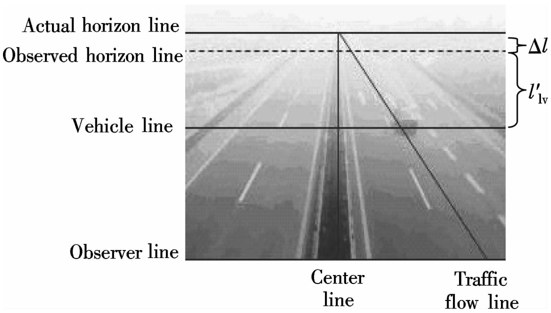

Fig. 3 Analysis of distance field

Substituting $\boldsymbol{l}'_1$ into Eq. (5), we can obtain

$$\boldsymbol{R}'_1 = \mathrm{e}^{(l_1')^2}(\boldsymbol{E}_1 - \boldsymbol{I}_\infty) + \boldsymbol{I}_\infty \tag{8}$$

where $\boldsymbol{R}'_1$ is the estimation of $\boldsymbol{R}_1$.

$\boldsymbol{E}_2$ can be treated as $\boldsymbol{E}_1$, and we can obtain

$$\boldsymbol{R}'_2 = \mathrm{e}^{(l_2')^2}(\boldsymbol{E}_2 - \boldsymbol{I}_\infty) + \boldsymbol{I}_\infty \tag{9}$$

Under ideal conditions, the real radiance $\boldsymbol{R}_1 = \boldsymbol{R}_2$, and we can deduce that

$$\mathrm{e}^{(l_1' + \Delta l)^2}(\boldsymbol{E}_1 - \boldsymbol{I}_\infty) + \boldsymbol{I}_\infty = \mathrm{e}^{(l_2' + \Delta l)^2}(\boldsymbol{E}_2 - \boldsymbol{I}_\infty) + \boldsymbol{I}_\infty$$

$$\frac{\mathrm{e}^{(l_1' + \Delta l)^2}}{\mathrm{e}^{(l_2' + \Delta l)^2}} = \frac{\boldsymbol{E}_2 - \boldsymbol{I}_\infty}{\boldsymbol{E}_1 - \boldsymbol{I}_\infty}, \quad \mathrm{e}^{(l_1' + \Delta l)^2 - (l_2' + \Delta l)^2} = \frac{\boldsymbol{E}_2 - \boldsymbol{I}_\infty}{\boldsymbol{E}_1 - \boldsymbol{I}_\infty}$$

that is

$$\frac{\mathrm{e}^{(l_1')^2 - (l_2')^2}}{\mathrm{e}^{2\Delta l(l_1' - l_2')}} = \frac{\boldsymbol{E}_2 - \boldsymbol{I}_\infty}{\boldsymbol{E}_1 - \boldsymbol{I}_\infty} \tag{10}$$

Then we calculate $\boldsymbol{R}'_1 - \boldsymbol{R}'_2$,

$$\boldsymbol{R}'_1 - \boldsymbol{R}'_2 = \mathrm{e}^{(l_1')^2}(\boldsymbol{E}_1 - \boldsymbol{I}_\infty) - \mathrm{e}^{(l_2')^2}(\boldsymbol{E}_2 - \boldsymbol{I}_\infty) \tag{11}$$

Substituting Eq. (10) into Eq. (11), we can obtain

$$\boldsymbol{R}'_1 - \boldsymbol{R}'_2 = \mathrm{e}^{(l_2')^2}(\boldsymbol{E}_2 - \boldsymbol{I}_\infty)\frac{\mathrm{e}^{(l_1')^2}(\boldsymbol{E}_1 - \boldsymbol{I}_\infty)}{\mathrm{e}^{(l_2')^2}(\boldsymbol{E}_2 - \boldsymbol{I}_\infty)} = \mathrm{e}^{(l_2')^2}(\boldsymbol{E}_2 - \boldsymbol{I}_\infty)\left(\frac{1}{\mathrm{e}^{2\Delta l(l_1' - l_2')}} - 1\right) \tag{12}$$

Assume that R'_1, R'_2, E'_1, E'_2 and I_∞ are the average values of $\boldsymbol{R}'_1$, $\boldsymbol{R}'_2$, $\boldsymbol{E}'_1$, $\boldsymbol{E}'_2$ and $\boldsymbol{I}_\infty$, respectively.

As $0 < \dfrac{1}{\mathrm{e}^{2\Delta(l_1' - l_2')}} - 1 < 1$, we can obtain

$$R'_1 - R'_2 < \mathrm{e}^{(l_2')^2}(E_2 - I_\infty) = R'_2 - I_\infty \tag{13}$$

The inequality (13) is the determinate condition of $\Delta l > 0$. Under real conditions, restoration is influenced by some factors such as reflected light, dust, noise, etc. So a group of calculations, $R'_1 - R'_2$, $R'_2 - R'_3$, …, $R'_{W-1} - R'_W$, $R'_2 - I_\infty$, $R'_3 - I_\infty$, …, $R'_W - I_\infty$, can be taken to weaken these influences, if they satisfy

$$(R'_1 - R'_2) + (R'_2 - R'_3) + \ldots + (R'_{W-1} - R'_W) < (R'_2 - I_\infty) + (R'_3 - I_\infty) + \ldots + (R'_W - I_\infty)$$

that is

$$R'_1 - R'_W < (R'_2 - I_\infty) + (R'_3 - I_\infty) + \ldots + (R'_W - I_\infty) \tag{14}$$

If inequality (14) is satisfied, we can determine $\Delta l > 0$. Contrary to the above case, the determining condition $\Delta l < 0$ can be described as

$$R'_1 - R'_W > (R'_2 - I_\infty) + (R'_3 - I_\infty) + \ldots + (R'_W - I_\infty) \tag{15}$$

Terms (14) and (15) are the determining conditions for convergence. Removing fog from traffic image sequences can be summarized as follows:

1) Parameter initialization Suppose that the observed horizon line $\boldsymbol{O}'_{i=i_0}$ associates the air with the ground by eye. The unit of the iteration step size s is pixel. The initial deviation $\Delta l' = 0$; and the reference regions $\boldsymbol{E}_1$, $\boldsymbol{E}_2$, …, $\boldsymbol{E}_W$ are selected at the same region of the same vehicle in different frames.

2) Iteration process Estimate sequence $\boldsymbol{R}'_1$, $\boldsymbol{R}'_2$, …, $\boldsymbol{R}'_W$ by Eq. (5); and calculate $R'_1 - R'_W$ and $(R'_2 - I_\infty) + (R'_3 - I_\infty) + \ldots + (R'_W - I_\infty)$.

3) Judgement of convergence If (14) and $R'_1 - R'_W \neq 0$ are satisfied, set $\Delta l' = \Delta l' - s$ and update step 2) until $R'_1 - R'_W \leqslant m$, where m is a small constant. If (15) and $R'_1 - R'_W \neq 0$ are satisfied, set $\Delta l' = \Delta l' + s$ and update step 2) until $R'_1 - R'_W \leqslant m$. The final horizon line is $\boldsymbol{O}'_{i=i_0+\Delta l'}$.

4) Distance field building Build the distance field $\boldsymbol{l}(i,j)$ by Eq. (6) according to $\boldsymbol{O}'_{i=i_0+\Delta l'}$ calculated by step 3);

5) Restoration Make restoration by Eq. (5) according to $\boldsymbol{l}(i,j)$ calculated by step 4).

3 Experiment

Some experiments are performed to test the proposed method. The experiments are processed on both synthetic and real data.

3.1 Synthetic experiments

A clear traffic image sequence is given. Four images of the image sequence are taken as the object images, and their sizes are 257×448. First, we locate the horizon line $\boldsymbol{O}_{i=32}$ and build the distance field, and then we add fog to the four images by the distance field. The degradation process is shown in Fig. 4.

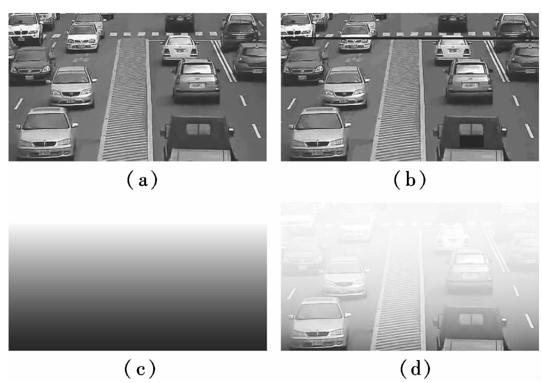

Fig. 4 Fog degradation process. (a) Clear image; (b) The horizon line (black line in the image) and the reference region (black square region on the truck); (c) The distance field; (d) Fog degraded image

We assume that the deviation step size $s = 1$. The histogram equalization method and the method in Ref. [8] are also used for comparisons. The results are shown in Fig. 5. The assumed horizon line is supposed to be above the actual horizon line in Ref. [8], which is shown in Fig. 5(a).

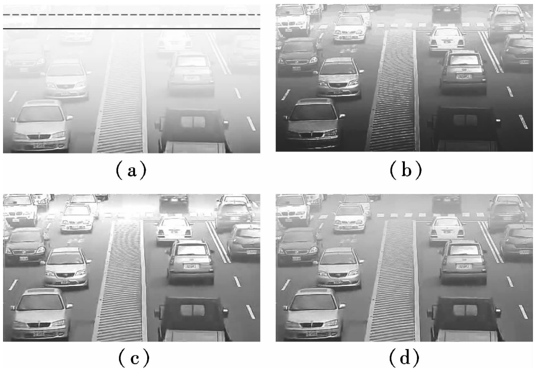

Fig. 5 Restoration result. (a) Initial horizon line (solid line is the actual horizon line, dash line is the assumed horizon line in Ref. [8]); (b) The result of the histogram equalization method; (c) The result of the method in Ref. [8]; (d) The result of the proposed method

The result of the histogram equalization method is shown in Fig. 5(b), which is too dark in the close scene and too light in the distant scene. The result of the method in Ref.[8] is shown in Fig. 5(c). We notice that the distance field is more diffused, and the restoration in close and medium scenes are weaker. Fig. 5(d) is the result of the proposed method, from which we can see the best effects in close, medium and distant scenes.

An indicator PSNR can be used to measure the performance, and it is defined by

$$\mathrm{PSNR} = 10\lg \frac{1}{\mathrm{MSE}} \tag{16}$$

$$\mathrm{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(\boldsymbol{R} - \boldsymbol{R}')^2 \tag{17}$$

where $\boldsymbol{R}'$ is the estimation of $\boldsymbol{R}$. The comparison of the PSNR of different methods is shown in Tab. 1

Tab. 1 Comparison of the PSNR of different methods

Method	The histogram equalization method	The method in Ref. [8]	The proposed method
PSNR	24.601 8	29.578 8	35.875 1

3.2 Real data experiments

Real data experiments are conducted to further test the proposed method. A real traffic video in heavy fog is extracted. Three images, whose sizes are 161×241 pixels, are taken as the object images, and they are shown in Fig. 6.

Fig. 6 Real traffic images in heavy fog

The experiments are also performed by three methods: the histogram equalization method, the method in Ref. [8] and the proposed method. The black square region on top of the bus is taken as the reference region in the proposed method. The results are shown in Fig. 7.

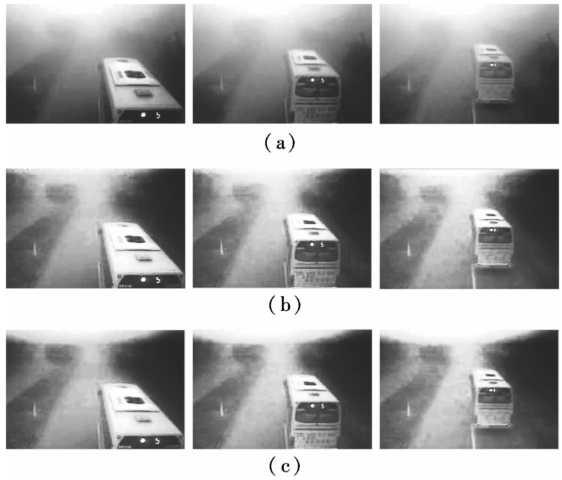

Fig. 7 Restoration results. (a) The results of the histogram equalization method; (b) The results of the method in Ref. [8]; (c) The results of the proposed method

Fig. 7(a) shows the results of the histogram equalization method. Note that the restored images are too dark in the close scenes and too light in the distant scenes. Fig. 7(b) and Fig. 7(c) are the results of the method in Ref. [8] and the proposed method, respectively. We can see that the distant scenes in Fig. 7(b) are lighter than those in Fig. 7(c). It is obvious that the proposed method outperforms the histogram equalization method and the method in Ref.[8].

From the synthetic experiments and the real data experiments, we can conclude that the proposed distance field and parameter estimation are effective, which have better performance in removing fog from traffic image sequences.

4 Conclusion

Fog weather affects the quality of traffic images seriously. In this paper, a distance field is built, and a novel parameter estimation method is proposed to remove fog from traffic image sequences. Based on the characteristic of traffic images, a distance field with one parameter is built, which avoids the deviation due to the complexity of multi-parameters, and a novel parameter estimation method by sequence traffic images is proposed, which is more precise. Experimental results show that the proposed method can effectively remove fog from traffic images.

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序列交通图像去雾

李　楠[1]　　路小波[2]

([1] 东南大学交通学院,南京 210096)
([2] 东南大学自动化学院,南京 210096)

摘要:为了消除交通图像中的雾,根据交通图像的特点建立了一种距离场并提出了一种新颖的基于序列交通图像的参数估计方法. 首先,基于大气散射模型推导出雾模糊模型,将距离场的方向平行于道路中线,距离场沿观察者到地平线的方向递增,并进行归一化处理改善距离场的分布特性;然后,对参数进行初始化,并以参考区域的平均灰度变化作为判定条件,对参数进行调整;最后,根据雾模糊模型实施复原. 实验结果表明,所提方法能够对交通图像中的雾进行有效去除.

关键词:交通图像;雾;距离场;景深;物理模型
中图分类号:TP391