

Free Space Detection for Autonomous Navigation in Daytime Foggy Weather

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Abstract

Free space detection is a primary task in autonomous navigation. Unfortunately, classical approaches have difficulties in adverse weather conditions, in particular in daytime fog. In this paper, a solution is proposed thanks to a contrast restoration approach. Knowing the density of fog, the method restores the contrast of the road and, at the same time, detect the vertical objects. Indeed, these objects are falsely restored and in this way easily segmented. Some results are shown on sample images extracted from video sequences acquired from an in-vehicle camera.

1 Introduction

Free space detection is a fundamental task for autonomous vehicles, since it provides the area where the vehicle can evolve safely. In structured environments, the free space area is mainly composed of the road surface. This area is either detected based on color [3] or texture [16] segmentation, deduced from stereovision based obstacles detection [2] or is a combination of both approaches [13]. However, all these methods have difficulties in foggy weather. Indeed, the contrast is reduced with the distance, which prevents classical segmentation techniques assuming that the color or the texture of the road is constant, and obstacle detection techniques to work properly. To solve this problem, an approach consists in properly restoring the contrast of the image. Doing this, the classical free space detection techniques can then be applied to the restored image.

Methods which restore image contrast under bad weather conditions are encountered more often in the literature. Unfortunately, they can not be used on-board a moving vehicle. Indeed, some techniques require prior information about the scene [11]. Others require dedicated hardware in order to estimate the weather conditions [15]. Some techniques rely on two images with different fog intensities and exploit the atmospheric scattering to adequately restore the contrast [10]. Techniques based on polarization can also be used to reduce haziness in the image [12]. Unfortunately, they require two differently filtered images of the same scene. Finally, it is proposed in [9] to restore the contrast of more complex scenes. However, the user must manually specify a location for sky region, vanishing point and an approximation of distance

distribution in the image. Recently, different methods have been proposed which rely only on a single image as input. [6] first estimates the weather conditions and approximate a 3D geometrical model of the scene which is inferred a priori and refined during the restoration process. The method is dedicated to in-vehicle applications. In [14], image contrasts are restored by maximizing the contrasts of the direct transmission while assuming a smooth layer of airlight. [4] estimates the transmission in hazy scenes, relying on the assumption that the transmission and surface shading are locally uncorrelated. These methods are heavy to implement and run: five to seven minutes with a 600×400 image on a double Pentium 4 PC for [14] and 35 seconds with a 512×512 image on a dual core processor for [4]. Furthermore, due to their algorithmic complexity, they do not guarantee an optimal solution in a given execution time. This is quite problematic for camera-based driver-assistance systems, where such algorithms may be used as a preprocessing of images for trajectory planning.

To solely detect the free space area, we propose another approach which consists in turning the fog presence into our advantage. Based on fog density estimation, we restore the contrast of the images assuming a flat world. Doing this, the intensity of all the objects which do not respect this assumption becomes null in the restored image, which leads to a very efficient segmentation of the free space area. In a first part, we recall a well-known model of daytime fog. In a second part, we explain the principle of our contrast restoration method and explain how it is used to properly detect the free space area. Finally, experimental results are given and discussed.

2 Modelling Fog Effects in Images

2.1 Koschmieder's Law

The method proposed in this study is based on a law governing the attenuation of brightness contrast by the atmosphere. This law, derived by Koschmieder, is given by:

$$L = L_0 e^{-\beta d} + L_\infty (1 - e^{-kd}) \quad (1)$$

It relates the apparent luminance L of an object located at distance d to the luminance L_0 measured close

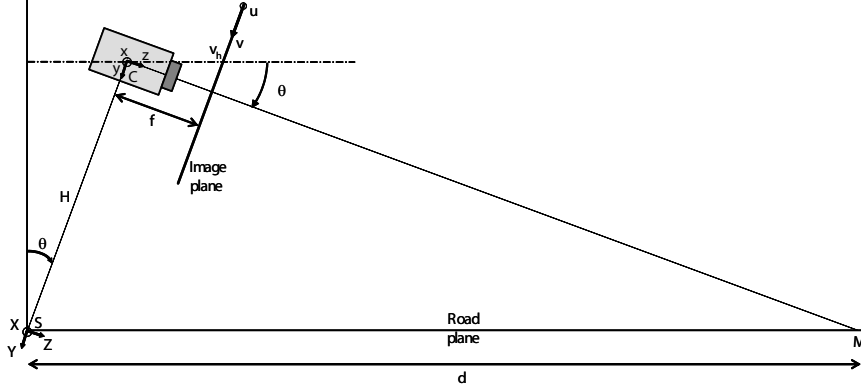


Figure 1: Modeling of the camera within its environment; it is located at a height of H in the (S, X, Y, Z) coordinate system relative to the scene. Its intrinsic parameters are its focal length f and pixel size t . θ is the angle between the optical axis of the camera and the horizontal. Within the image coordinate system, (u, v) designates the position of a pixel, (u_0, v_0) is the position of the optical center C and v_h is the vertical position of the horizon line.

to this object at a time when the atmosphere has an extinction coefficient β . L_∞ denotes the atmospheric luminance. On the basis of this equation, Duntley developed a contrast attenuation law [8], stating that a nearby object exhibiting contrast C_0 with the background will be perceived at distance d with the following contrast:

$$C = [(L_0 - L_\infty) / L_\infty] e^{-\beta d} = C_0 e^{-\beta d} \quad (2)$$

This expression serves as a base to define a standard dimension called "meteorological visibility distance" V_{met} , i.e. the greatest distance at which a black object ($C_0 = -1$) of a suitable dimension can be seen in the sky on the horizon, with the threshold contrast set at 5% [1]. It is thus a standard dimension that characterizes the opacity of a fog layer. This definition yields the following expression:

$$V_{met} = -1/\beta \log(0.05) \simeq 3/\beta \quad (3)$$

3 Camera

In this section, a method to compute the extinction coefficient β using a single camera behind the vehicle windshield is recalled from [7].

3.1 Flat World Hypothesis

In the image plane, the position of a pixel is given by its (u, v) coordinates. The coordinates of the optical center projection in the image are designated by (u_0, v_0) . In Fig. 1, H denotes the height of the camera, θ the angle between the optical axis of the camera and the horizontal, and v_h the horizon line. The intrinsic parameters of the camera are its focal length f , and the horizontal size t_{pu} and vertical size t_{pv} of a pixel. We have also made use herein of $\alpha_u = \frac{f}{t_{pu}}$ and $\alpha_v = \frac{f}{t_{pv}}$, and have typically considered: $\alpha_u \approx \alpha_v = \alpha$. The hypothesis of a flat road is adopted, which makes it possible to associate a distance d with each line v of the image:

$$d = \frac{\lambda}{v - v_h} \text{ if } v > v_h, \text{ where } \lambda = H\alpha / \cos \theta \quad (4)$$

3.2 Camera Response

Let us denote f the camera response function, assumed to be linear, which models the mapping from scene luminance to image intensity by the imaging system, including optic as well as electronic parts. In a foggy scene, the intensity I of a pixel is the result of f applied to (1):

$$I = f(L) = R e^{-\beta d} + A_\infty (1 - e^{-\beta d}) \quad (5)$$

where R is the intrinsic intensity of the pixel, i.e. the intensity corresponding to the intrinsic luminance value of the corresponding scene point and A_∞ is the background sky intensity.

3.3 Recovery of Fog Parameters

Following a variable change from d to v based on (4), (5) thus becomes:

$$I = A_\infty + (R - A_\infty) e^{-\beta \frac{\lambda}{v - v_h}} \quad (6)$$

By twice taking the derivative of I with respect to v , one obtains the following:

$$\frac{d^2 I}{dv^2} = \beta \varphi(v) e^{-\beta \frac{\lambda}{v - v_h}} \left(\frac{\beta \lambda}{v - v_h} - 2 \right) \quad (7)$$

where $\varphi(v) = \frac{\lambda(R - A_\infty)}{(v - v_h)^3}$. The equation $\frac{d^2 I}{dv^2} = 0$ has two solutions. The solution $\beta = 0$ is of no interest. The only useful solution is given in (8):

$$\beta = 2(v_i - v_h) / \lambda \quad (8)$$

where v_i denotes the position of the inflection point of $I(v)$. In this manner, the parameter β of Koschmieder's law is obtained once v_i is known. Finally, thanks to v_i , v_h and β values, the values of the other parameters of (5) are deduced through use of I_i and $\frac{dI}{dv}|_{v=v_i}$, which are respectively the values of the function I and its derivative in $v = v_i$:

$$R = I_i - (1 - e^{-\beta d_i}) \frac{(v_i - v_h)}{2e^{-\beta d_i}} \frac{dI}{dv}|_{v=v_i} \quad (9)$$

$$A_\infty = I_i + \frac{(v_i - v_h)}{2} \frac{dI}{dv}|_{v=v_i} \quad (10)$$

where R is the intrinsic intensity of the road surface.

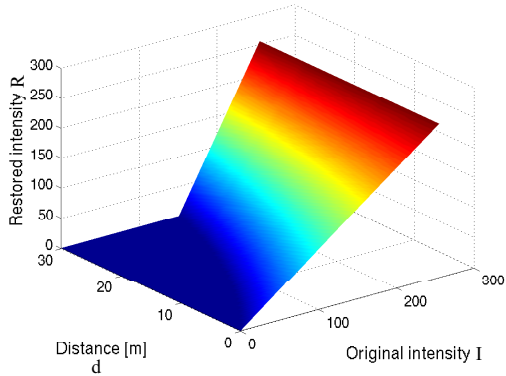


Figure 2: 3D plot of the corrected contrast restoration function (13) for $\beta = 0.05$ and $A_\infty = 255$. One can see that objects intensity may become null after contrast restoration.

4 Free Space Detection Method

4.1 Restoration Principle

In this section, we describe a simple method to restore scene contrast from an image of a foggy scene. Let us consider a pixel with known depth d . Its intensity I is given by (5). (A_∞, β) characterizes the weather condition and is estimated thanks to section 3.3. Consequently, R can be estimated directly for all scene points from:

$$R = Ie^{\beta d} + A_\infty(1 - e^{\beta d}) \quad (11)$$

This equation means that an object exhibiting a contrast C in the original image will have the following contrast C_r with respect to the background sky in the restored image:

$$C_r = \frac{(R - A_\infty)}{A_\infty} = \frac{(I - A_\infty)}{A_\infty} e^{\beta d} = C e^{\beta d} \quad (12)$$

We thus have a method which restore the contrast exponentially. Unfortunately, R is negative for certain values of (I, d) . In such cases, we propose to set these values to 0. The restoration equation becomes finally:

$$R = \max \left[0, Ie^{\beta d} + A_\infty(1 - e^{\beta d}) \right] \quad (13)$$

We plotted this function for a certain range of (I, d) values in Fig. 2. To properly restore the scene contrast, the remaining problem is the estimation of the depth d of each pixel.

4.2 Flat World Restoration

[6] proposed a complex 3D model of a road scene to restore the contrast. The proposed model is relevant for most road scenes but it is not enough generic to handle all traffic scenes configurations. In a first step, we propose to use a quite opposite scheme, which consists in only assuming that the road is flat. The distance of a pixel in the image is thus given by (4). Only bigger distances are clipped using a parameter c .

The distance d_c of a pixel $P(i, j)$ is thus expressed by:

$$d_c(i \in [0, N[, j \in [0, M[) = \begin{cases} \frac{\lambda}{j - v_h} & \text{if } N > j > c \\ \frac{\lambda}{c - v_h} & \text{if } 0 \leq j \leq c \end{cases} \quad (14)$$

where $N \times M$ denotes the size of the image. c is used to set the maximum distance used for the contrast restoration. It makes sense to set the position of this clipping plane equal to the meteorological visibility distance. Indeed, no pixel has a contrast above 5% further than V_{met} . Consequently, the structure of the scene is unknown beyond this distance. Using (3) and (8), we thus set:

$$c = (2v_i + v_h)/3 \quad (15)$$

By using (14) in (13), the contrast of objects belonging to the road plane is correctly restored.

4.3 Free Space Detection

Conversely, the contrast of vertical objects of the scene (other vehicles, trees...) is falsely restored since their distance in the scene is largely overestimated. Consequently, according to (13), their intensity becomes null in the restored image. This is an inconvenient of this method, which was mitigated in [5] by underestimating the value of the horizon line. However, this inconvenient can be turned into our advantage. Thus, by detecting the pixels whose intensity is null after contrast restoration, we easily segment the vertical objects in front of the vehicle and then segment the free space area accordingly by looking for the biggest connected component in front of the vehicle. To improve the results of this last step, a morphological opening of the connected component may be performed.

4.4 Experimental Results

Some results are shown in Fig. 3. The segmented vertical objects are overlaid in red and the segmented free space area is overlaid in green. The proposed method allows to obtain quite good results, even if some minor improvements could be made on the segmentation of curbs and very bright objects. The quality of these results can be compared with color based or stereovision approaches. The good point in our method is that we only use one gray level image. However, it only works in daytime foggy weather. The classical methods and the proposed one are thus complementary. On one side, the fog detection method is sensitive both to the inhomogeneity of the fog and the presence of big objects in front of the vehicle (see [7] for more details). On the other side, the segmentation method is not sensitive to the inhomogeneity of fog and can be applied to other weather conditions such as rainy weather. A rainy weather image is shown in the bottom right of Fig. 3. The remaining critical point of the method is the setting of the pitch angle of the vehicle. From a hardware point of view, the computation of the fog density takes less than 40 ms in C++ using a 2.4 GHz Intel Core 2 Duo PC on 1/4 PAL images. On the same hardware platform, the free space detection takes less than 20 ms. Such a computation time is obtained using a few look-up-tables.



Figure 3: Free space detection of the road scene. First and third columns: original images. Second and fourth columns: results of vertical objects segmentation in overlaid red and free space area in overlaid green. The figure at the bottom-right shows a test using a rainy weather image (in this case, β is set manually).

5 Conclusion

In this paper, a solution is proposed to detect the free space area in foggy road scenes thanks to a contrast restoration approach. Knowing approximately the density of fog, the proposed method is able to restore the contrast of the road and at the same time to segment the vertical objects. Indeed, these objects are falsely restored and in this way easily segmented. Some results are shown on sample images extracted from video sequences acquired from an in-vehicle camera. The computation time is negligible which allows an easy implementation in complement to classical free space extraction techniques.

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