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BLIND CONTRAST RESTORATION ASSESSMENT BY GRADIENT RATIOING AT VISIBLE EDGES

NICOLAS HAUTIÈRE[1], JEAN-PHILIPPE TAREL[1], DIDIER AUBERT[2] AND ÉRIC DUMONT[1]

[1]LCPC, Division for Road Operation, Signalling and Lighting, 58 bld Lefebvre, 75732 Paris Cedex 15, France,
[2]INRETS-LCPC, Vehicle-Infrastructure-Driver Interactions Research Unit, building 824, 14 route de la Minière, 78000 Versailles, France
e-mail: nicolas.hautiere@lcpc.fr, jean-philippe.tarel@lcpc.fr, didier.aubert@inrets.fr, eric.dumont@lcpc.fr
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ABSTRACT

The contrast of outdoor images grabbed under adverse weather conditions, especially foggy weather, is altered by the scattering of daylight by atmospheric particles. As a consequence, different methods have been designed to restore the contrast of these images. However, there is a lack of methodology to assess the performances of the methods or to compare them with one another. Unlike image quality assessment or image restoration areas, there is no easy way to have a reference image, which makes the problem not straightforward to solve. In this paper, an approach is proposed which consists in computing the ratio between the gradient of the visible edges between the image before and after contrast restoration. In this way, an indicator of visibility enhancement is provided based on the concept of visibility level, commonly used in lighting engineering.

Keywords: contrast restoration, edges segmentation, visibility level, blind assessment, LIP model, advanced driver assistance system.

INTRODUCTION

The contrast of outdoor images grabbed under adverse weather conditions, especially foggy weather, is altered by the scattering of daylight by atmospheric particles (Narasimhan and Nayar, 2002). As a consequence, different methods have been designed to restore their contrast, in order to maintain the performances of video-surveillance systems (Narasimhan and Nayar, 2003) or in-vehicle vision systems (Hautière *et al.*, 2007) as good as possible. However, there is a lack of methodology to assess the performances of such methods, or to compare them with one another. Since fog effects are volumetric, fog can not be considered as a classical image noise or degradation which might be added and then removed. Consequently, compared to image quality assessment (Sheikh *et al.*, 2006) or image restoration (Guichard *et al.*, 2002) areas, there is no easy way, synthetic images from 3D models put aside, to have a reference image, which makes the problem so difficult.

In this paper, a solution is proposed. First of all, visible edges of the image before and after contrast restoration are computed. The percentage of new visible edges is computed. Then, the ratio of the gradient of the visible edges between both images is computed. Thanks to the concept of visibility level, proposed by Adrian (1989), it is shown that this ratio corresponds to the visibility enhancement produced by the restoration algorithm. Finally, based on this result, an indicator of visibility enhancement is derived.

The paper is organized as follows. First, the visibility model of Adrian (1989) is presented as well as how to use it to derive a blind contrast restoration assessment method based on visible edges ratioing. Second, the proposed methodology is applied to assess the performances of a contrast restoration method of daytime fog images grabbed using in-vehicle cameras. This method is summarized for completeness.

VISIBILITY MODEL

For non-periodic targets, visibility can be related to the (Weber) luminous contrast C, which is defined as:

$$C = \frac{\Delta L}{L_b} = \frac{L_t - L_b}{L_b} \tag{1}$$

where ΔL is the difference in luminance, between target and background, L_t is the luminance of the target, L_b is the luminance of the background.

The threshold luminance difference $\Delta L_{threshold}$ indicates a value at which a target of defined size becomes perceptible with a high probability. It depends among other things on target size and light level, decreasing with increase of light level, but leveling off and hardly changing in the photopic domain. For suprathreshold contrasts, the visibility level (VL) of a target can be quantified by the ratio:

$$VL = \frac{\text{Actual contrast}}{\text{Threshold contrast}} \tag{2}$$

At threshold, the visibility level equals one and above threshold it is greater than one. Combining (1) and (2), we have:

$$VL = \frac{C_{actual}}{C_{threshold}} = (\Delta L/L_b)_{actual} / (\Delta L/L_b)_{threshold} \quad (3)$$

As the background luminance L_b is the same for both conditions, then this equation reduces to:

$$VL = \Delta L_{actual} / \Delta L_{threshold} \quad (4)$$

In any given situation, it might be possible to measure the luminance of the target and its background, which gives ΔL_{actual}. But to estimate VL, we also need to know the value of $\Delta L_{threshold}$. This can be estimated using Adrian's empirical target visibility model (Adrian, 1989).

VISIBLE EDGES RATIOING

The model which has been presented in the previous section can be used to predict the visibility of objects according to their size, their contrast, the lighting conditions, the age of the observer and the observation time. However, using complex images, i.e. an image which contains several objects on a non-uniform background, it is not straightforward to calculate the value of $\Delta L_{threshold}$. Indeed, it is at least necessary to detect, segment and estimate the size of the different arbitrary objects present in the image, which still remains a challenging task in computer vision.

To solely assess the performances of a contrast restoration method, it is not necessary to achieve such a complex process. Instead, following the approach proposed in (Hautière and Dumont, 2007), it is proposed to compute, for each pixel belonging to a *visible* edge in the restored image, the following ratio r:

$$r = \mathrm{f}^{-1}(\Delta I_r) / \mathrm{f}^{-1}(\Delta I_o) \quad (5)$$

where ΔI_r denotes the gradient in the restored image, ΔI_o the gradient in the original image and f the camera response function (Grossberg and Nayar, 2004). Then, if the camera response function is assumed to be linear, which is generally the case for CCD sensors, (5) becomes simply:

$$r = \Delta I_r / \Delta I_o = \Delta L_r / \Delta L_o \quad (6)$$

r is mathematically defined because only the gradients of visible edges in the restored image are considered. However, only pixels having a minimum contrast can be restored, which ensures that ΔI_o is different from zero.

Thereafter, if an object in the image is considered, this object is composed of edges. (6) can thus be rewritten as:

$$r = (\Delta L_r / \Delta L_{threshold}) / (\Delta L_o / \Delta L_{threshold}) \quad (7)$$

where $\Delta L_{threshold}$ would be given by Adrian's model. Finally, (7) becomes:

$$r = VL_r / VL_o \quad (8)$$

where VL_r denotes the visibility level of the considered object in the restored image and VL_o the visibility level of the considered object in the original image. Consequently, the computation of r enables to compute the gain of visibility level produced by a contrast restoration method. The remaining difficulty is in detecting the visible edges in the images, and it depends on the type of images under consideration. In the following sections, this methodology is applied to images altered by daytime fog grabbed using in-vehicle cameras.

CONTRAST RESTORATION

In this section, a contrast restoration method dedicated to in-vehicle applications is presented. First, a classical model of daytime fog visual effects is recalled. Then, a contrast restoration methodology is summarized and illustrated on different road scene configurations.

VISUAL PROPERTIES OF FOG

The attenuation of luminance through the atmosphere was studied by Koschmieder (Middleton, 1952), who derived an equation relating the apparent luminance L of an object located at distance d to the luminance L_0 measured close to this object:

$$L = L_0 e^{-\beta d} + L_\infty (1 - e^{-\beta d}) \quad (9)$$

where L_∞ is the atmospheric luminance and β is the extinction coefficient of fog.

On the basis of this equation, Duntley developed a contrast attenuation law (Middleton, 1952), stating that a nearby object exhibiting contrast C_0 with the background will be perceived at distance d with the following contrast:

$$C = \left[(L - L_\infty)/L_\infty\right] e^{-\beta d} = C_0 e^{-\beta d} \quad (10)$$

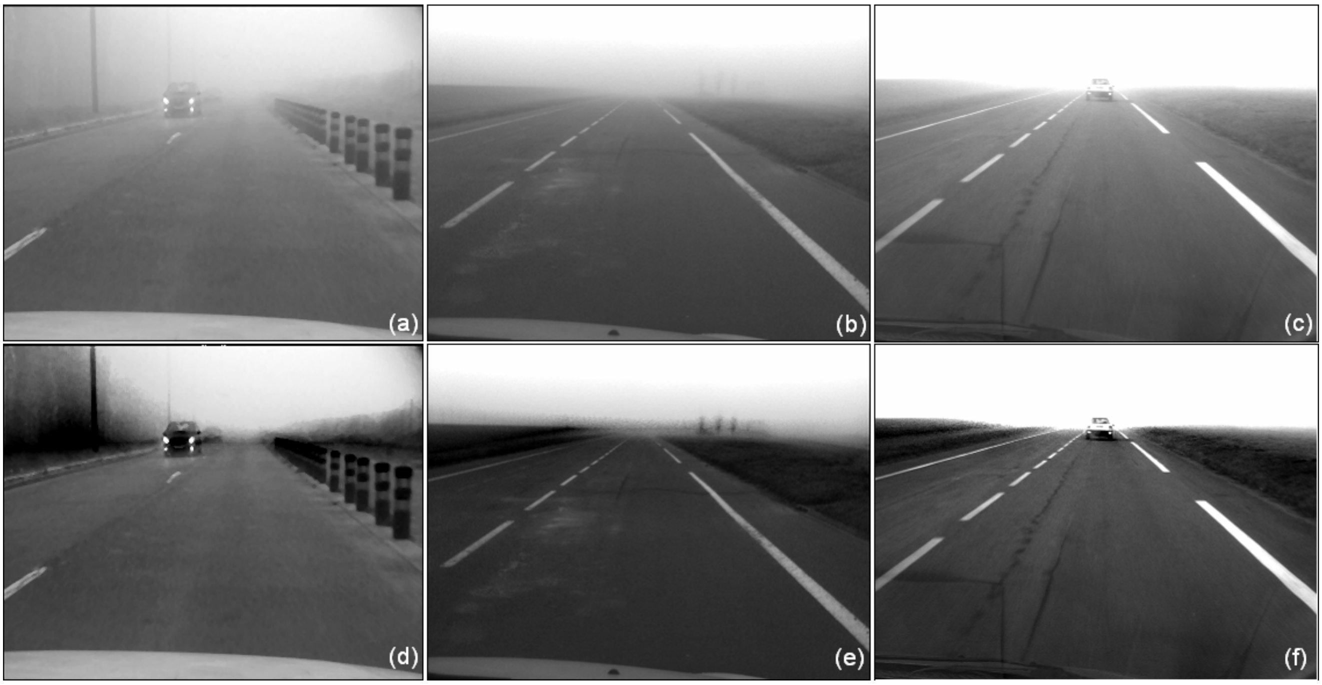

Fig. 1. *(a)(b)(c) Sample of three foggy image sequences grabbed using an in-vehicle camera, named 'Minière', 'Piste' and 'Vehicule', respectively. (d)(e)(f) Images whose contrast has been restored following the proposed methodology.*

This expression serves to base the definition of a standard dimension called "meteorological visibility distance" V_{met}, i.e. the greatest distance at which a black object ($C_0 = -1$) with a suitable size can be seen in the sky on the horizon. With the threshold contrast set at 5% (CIE, 1987), this definition yields the following expression:

$$V_{met} = -\frac{1}{\beta}\log(0.05) \simeq \frac{3}{\beta} \tag{11}$$

RESTORATION METHODOLOGY

Principle

In a foggy image, the intensity I of a pixel is the result of the camera response function f applied to (9). Assuming that f is linear, (9) becomes:

$$I = \mathrm{f}(L) = Re^{-\beta d} + A_\infty(1 - e^{-\beta d}) \tag{12}$$

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.

Hence, to restore the contrast, it is proposed to reverse (12), which becomes:

$$R = Ie^{\beta d} + A_\infty(1 - e^{\beta d}) \tag{13}$$

Assuming a flat world scene, it is possible to estimate (β, A_∞) thanks to the existence of an inflection point on the representative curve of (12) (Lavenant *et al.*, 2002; Hautière *et al.*, 2006b). Therefore, in order to be able to correctly restore the scene contrast, the remaining problem is the estimation of the depth d of the pixels.

Scene Depth Modeling

The depth distribution in a road scene can be roughly decomposed in three parts: the road surface, the sky and the surroundings. Such an heuristic model is proposed and is detailed in the following equations.

The depth d of a pixel (u, v) which does not belong to the sky region, *i.e.*whose intensity is lower than A_∞ is given by:

$$d = \min(d_1, d_2) \tag{14}$$

where d_1 models the depth of pixels belonging to the road surface, which is assumed to be a plane:

$$d_1 = \frac{\lambda}{v - v_h} \quad \text{if } v > v_h \tag{15}$$

and d_2 models the depth of verticals objects:

$$d_2 = \frac{\kappa}{\sqrt{(u-u_h)^2 + (v-v_h)^2}} \tag{16}$$

In these equations, (u_h, v_h) denotes the vanishing point position in the image, λ depends on the intrinsic and extrinsic camera parameters and $\kappa > \lambda$ controls the relative importance of the vertical world with respect to the flat world. Finally, a clipping plane at $d = \frac{\lambda}{c - v_h}$ is used to limit the depth modeling errors near the horizon line. A sample of such a scene model is given in Fig. 2.

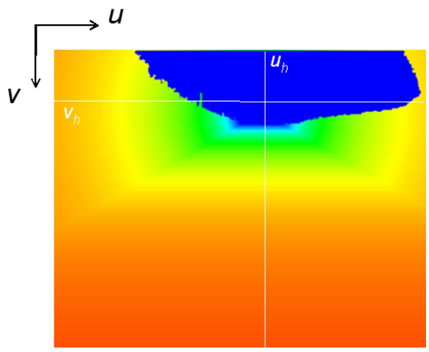

Fig. 2. *A sample of scene depth model proposed for restoring the contrast combined with (13). One can see its three components: the road plane, the vertical surroundings and the sky region (in blue). This particular model was used to obtain Fig. 1d. (u_h, v_h) denotes the position of the vanishing point in the image.*

Algorithm

To correctly restore the contrast, according to the scene model given in the previous paragraph, the remaining task consists in finding the optimal values of κ and c. To do it, one solution is to solve the following equation using Powell's method:

$$(\kappa^*, c^*) = \underset{\substack{\kappa>1 \\ c>0}}{\operatorname{argmax}} \left[Q(\kappa, c) + \kappa - c \right] \qquad (17)$$

where Q is a norm of the local normalized correlation between the original image and the restored image. Indeed, the *normalized* correlation score between the original and the restored versions of a neighborhood should remain high. A decreasing normalized correlation means that the content of the original and restored neighborhoods differ. More details about this method as well as alternate algorithms are given in (Hautière *et al.*, 2007).

The proposed algorithms have been applied to the foggy road scene images given in Fig. 1(a)(b)&(c). The outputs are given in Figs. 1(d)(e)&(f).

RESTORATION ASSESSMENT

Originally, the local contrast estimator presented in this section has been developed to estimate the visibility distance using in-vehicle cameras (Hautière *et al.*, 2006a). In this section, we show that it can also be used to assess the quality of a contrast restoration method.

Visible Edges Segmentation

Principle In order to be consistent with the definition of the meteorological visibility distance proposed by (CIE, 1987), it is enough to consider the set of edges which have a local contrast above 5% so as to obtain the visible edges under daytime foggy weather.

The LIP model (Jourlin and Pinoli, 2001) has introduced a definition of contrast well suited to digital images. In this definition, the contrast between two pixels x and y of an image f is given by:

$$C_{(x,y)}(f) = \max[f(x), f(y)] \,\triangle\!\!\!\!\!\!-\; \min[f(x), f(y)] \qquad (18)$$

where $\triangle\!\!\!\!\!\!-$ denotes LIP substraction. Naturally, this definition of contrast is consistent with the definition of contrast used in visual perception (1).

Then, the contrast associated to a border F which separates two adjacent regions follows:

$$C_F(f) = \frac{1}{\operatorname{card} V} \,\triangle\!\!\!\!\!\!\times\; \triangle\!\!\!\!\!\!+_{(x,y)\in V} C_{(x,y)}(f) \qquad (19)$$

where $\triangle\!\!\!\!\!\!\times$ and $\triangle\!\!\!\!\!\!+$ denote LIP multiplication and addition.

Implementation To implement this definition of contrast between two adjacent regions, Köhler's segmentation method has been used (Köhler, 1981). Let f be a gray level image. A couple of pixels (x,y) is said to be separated by the threshold s if two conditions are met. First, $y \in V_4(x)$. Secondly, the condition (20) is respected:

$$\min\left[f(x), f(y)\right] \le s < \max\left[f(x), f(y)\right] \qquad (20)$$

Let $F(s)$ be the set of all couples (x, y) separated by s. With these definitions, for every value of s belonging to [0,255], $F(s)$ is built. For every couple belonging to $F(s)$, the contrast $C_{x,y}(s)$ is computed:

$$C_{x,y}(s) = \min\left[\frac{|s - f(x)|}{\max(s, f(x))}, \frac{|s - f(y)|}{\max(s, f(y))}\right] \qquad (21)$$

The mean contrast (22) associated to $F(s)$ is then performed:

$$C(s) = \frac{1}{\operatorname{card} F(s)} \sum_{(x,y)\in F(s)} C_{x,y}(s) \qquad (22)$$

The best threshold s_0 verifies the following condition:

$$s_0 = \underset{s\in[0,255[}{\operatorname{argmax}} C(s) \qquad (23)$$

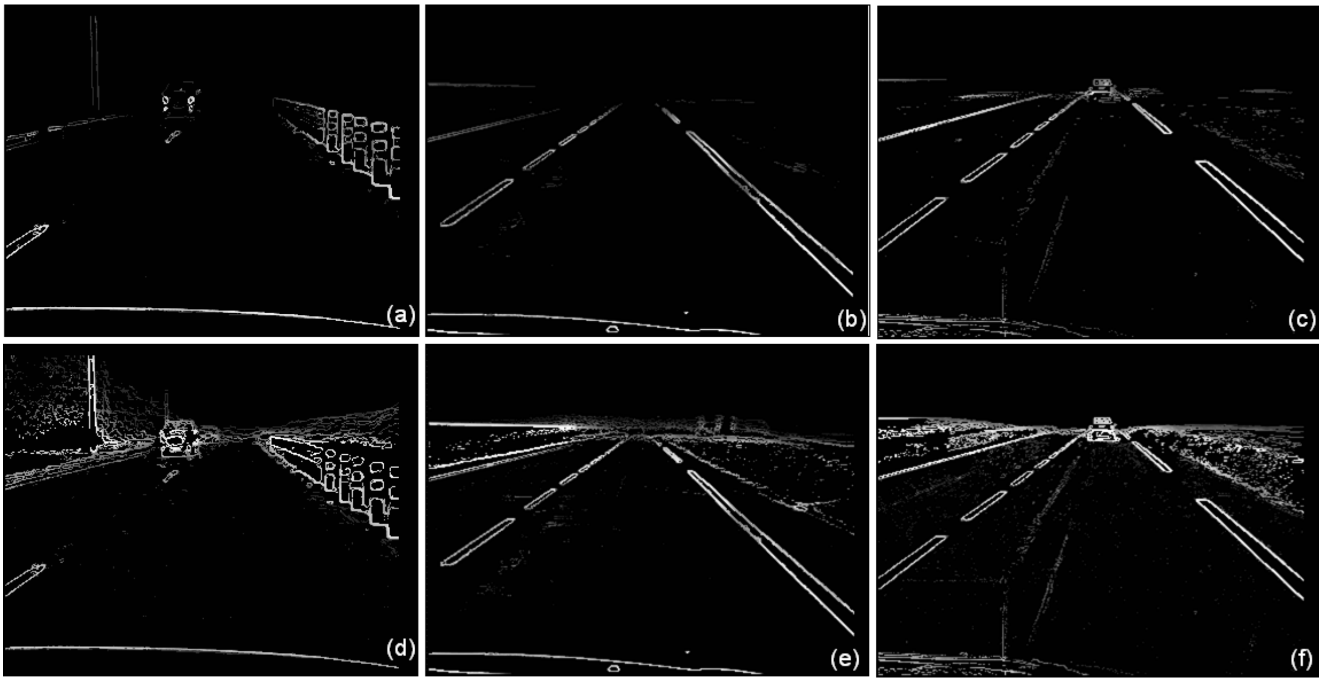

Fig. 3. *Computation of local contrasts above 5%, assumed to be the visible edges by daytime fog, in the images of Fig. 1.*

It is the threshold which has the best mean contrast along the associated border $F(s_0)$. Instead of using this method to binarize images, we use it to measure the contrast locally. The evaluated contrast equals $2C(s_0)$ along the associated border $F(s_0)$. Finally, if $2C(s_0) > 5\%$, $F(s_0)$ is considered to be a visible edge. Details about the implementation of this method can be found in (Hautière *et al.*, 2006a).

The proposed algorithm has been applied to the images given in Fig. 1. The results are given in Fig. 3.

Descriptors

n_o and n_r denote the cardinal numbers of the set of visible edges in the original image I_o, respectively in the contrast restored image I_r. The latter set is denoted $\wp_r$. First of all, we propose to compute e, the percentage of new visible edges in I_r:

$$e = \frac{n_r - n_o}{n_o} \tag{24}$$

The value of e evaluates the ability of the method to restore edges which were not visible in I_o but are in I_r.

In complement, we propose to compute $\bar{r}$, the geometric mean of the ratios of VL defined by (8). The value of $\bar{r}$ expresses the quality of the contrast restoration by the proposed method. Contrary to (24), this descriptor takes into account not visible and visible edges in I_o:

$$\bar{r} = \exp\left[\frac{1}{n_r}\sum_{P_i \in \wp_r} \log r_i\right] \tag{25}$$

For the method here summarized, the value of r for each visible edge in I_r has been computed and is shown in Fig. 4 using false colors. The main point to notice is that the visibility enhancement is bigger for distant objects than for close objects, as expected. Then, descriptors (24) and (25) have been computed for the images in Fig. 1 and for the results of a more classical histogram stretching algorithm. The results are given in Tab. 1. As expected, the proposed method performs better than the histogram stretching, which is a spatially invariant filter contrary to our method.

	(a)		(b)	
	e	$\bar{r}$	e	$\bar{r}$
Minière	1.4	2.6	0.25	1.1
Piste	1.1	1.8	0.33	1.3
Vehicule	1.6	1.7	0.4	1.1

Table 1. *Quantitative evaluation of two contrast restoration methods applied to the images in Fig. 1abc using the descriptors (24) and (25): (a) algorithm here summarized; (b) classical histogram stretching.*

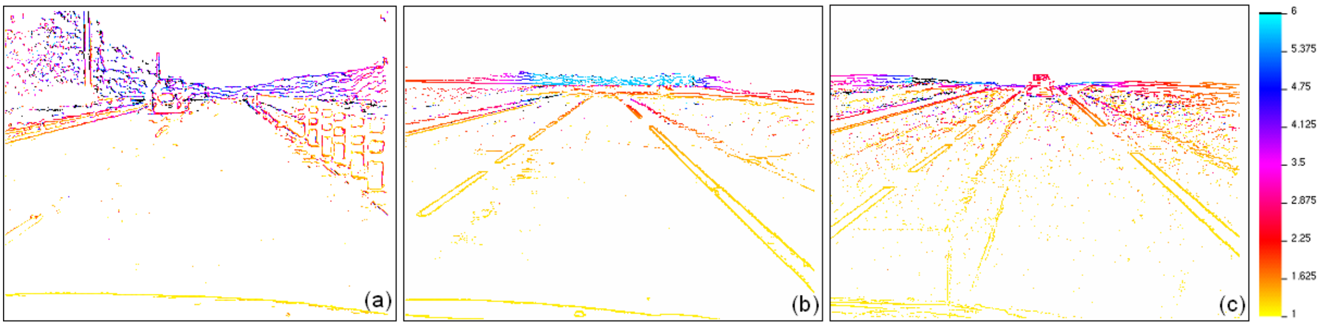

Fig. 4. *Map of r values computed on the pairs of images of Fig. 1 using false colors. Each pixel shows the enhancement of visibility level induced by the contrast restoration algorithm here summarized.*

DISCUSSION AND PERSPECTIVES

The proposed methodology allows to assess the performances of contrast restoration methods based on visual descriptors. However, it does not rate the fidelity of the contrast restoration method. It measures only the enhancement of visibility of existing objects in the scene. To achieve such an objective, the same scene with and without fog must be grabbed, which can be done using synthetic images. Notice that the proposed method is not able to assess the creation of visual artefacts.

Thereafter, it would be interesting to apply the proposed methodology to other types of contrast degraded images, such as night-fog images grabbed using in-vehicle cameras. Indeed, such images are very poorly contrasted. Thanks to the dynamic range maximization given in (Jourlin and Pinoli, 2001), it is possible to improve the visibility in such images. Köhler's method can also be used to detect visible edges in night images based on a DCT transform and a Contrast Sensitivity Function (CSF) of the human visual system (Hautière and Aubert, 2006). It should thus be possible to assess in the same way the performances of the range maximization algorithm.

CONCLUSION

In this paper, the problem of the assessment of contrast restoration algorithms of weather-degraded images has been raised. A solution based on visible edges ratioing has been proposed, which computes, for each pixel belonging to a visible object in the restored image, the visibility level (VL) enhancement produced by the algorithm. This method has been applied to daytime fog images grabbed onboard a moving vehicle. In this context, the visible edges are assumed to be the pixels having a local contrast above 5%. An operator based on a segmentation algorithm has been proposed to extract such pixels and has been used to assess the performance of contrast restoration algorithms. A contrast restoration algorithm is summarized. It is based on a photometric model of fog and consists in inverting this model with a depth distribution of the scene inferred. Finally, we propose three descriptors of the enhancement visibility: a map of VL enhancement for each pair of foggy and restored images, the geometric mean of VL enhancement and the percentage of new visible edges.

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