ASSESSMENT OF VISIBILITY IN COMPLEX ROAD SCENES USING DIGITAL IMAGING

Nicolas HAUTIÈRE, Eric DUMONT
Laboratoire Central des Ponts et Chaussées, Paris, France

ABSTRACT

In order to assess the impact of a lighting system on the visibility of objects in a complex road scene, a classic approach consists in selecting objects of interest to compute their luminance, the luminance of their background, and then their visibility level. Implementing this approach to analyze calibrated digital images is not easy, mostly because of the necessity to arbitrarily delimit backgrounds and to compute the luminance of non uniform regions. In this paper, we present a method to assess of visibility in digital images of complex road scenes without prior knowledge or assumption concerning the objects in the scene and their luminance, or that of their background. The idea is to use a segmentation technique to detect the edges which make the objects visible, and to compute the local contrast along these edges. The results give a clear picture of the impact of one lighting condition compared to another. In this paper, we present the image processing technique, along with sample results.

Keywords: contrast, visibility, lighting, image processing, edge detection.

1. INTRODUCTION

To study the visibility of an object with respect to the surrounding lighting conditions, the classical approach consists in estimating its contrast against its background, and comparing it with a threshold value computed with a visibility model [1]. This classic approach is based on the assumptions that the shape of the object is simple and that its background is uniform. In such conditions, measuring the luminance in two points is enough to compute the contrast, and hence the visibility level of the object.

Visibility models from the literature can be classified in two categories:

- those models which consider that an object is visible if there is a sufficient difference of luminance between this object and its background, e.g. Blackwell's model [2] or Adrian's model [3];
- those models which take into account the non-linearity of the human visual system with respect to spatial frequency, making an object visible if at least one of its spectral components is above a certain threshold, e.g. Campbell and Robson model [4].

Visibility models are usually based on psychometric experiments with optotypes on uniform backgrounds. In the real world, objects may not have simple shapes, and their background is seldom uniform. As a consequence, measuring the luminance of the object and that of the background is not a practical solution. The classic response to that problem is to use a calibrated camera, or a videophotometer, to measure the spatial distribution of luminance across the scene. However, processing the resulting images to automatically compute visibility levels is far from straightforward.

A judicious approach is to detect and segment the different objects in the scene. However, this can only be done if some information is available concerning the nature and location of the objects. When the goal is to compare different lighting situations, we claim that it is not necessary to actually detect the objects in the scene. Assuming that the presence of objects creates edges and contours in the image, we only need to assess the visibility of these features.

Hence, we developed an image processing framework which aims at computing the edges of objects in complex scenes in order to test different lighting configurations. The principle of our algorithm is to scan the image using small windows. Each window is segmented in two parts thanks to Köhler's binarization method [5]. This method finds the threshold which maximizes the difference between the two parts of the window. The pixels of the associated border form a contour.

The paper is organized as follows. First, we present our approach and describe the image processing techniques that we developed. Then, the method is illustrated in the case of a night-time road scene illuminated with different headlamps.

2. IMAGE PROCESSING FRAMEWORK

2.1. Edge detection by segmentation

Köhler's technique to binarize images finds the threshold which locally maximizes the contrast between two parts of the image [5]. Let *f* be a gray level image. A pair of pixels (x, x_1) is said to be separated by the threshold *s* if the two following conditions are met:

$$x_1 \in V_4(x) \tag{1}$$

$$\min(f(x), f(x_1)) \leq s < \max(f(x), f(x_1)) \tag{2}$$

Let $F(s)$ be the set of all pairs (x, x_1) separated by *s*. With these definitions, for every value of *s* belonging to $[0, M[$, $F(s)$ is built, where *M* is the maximum value of the gray map. For every pair belonging to $F(s)$, the local contrast $C_{x,x_1}(s)$ is computed:

$$C_{x,x_1}(s) = \min\left(\left|s - f(x)\right|, \left|s - f(x_1)\right|\right) \tag{3}$$

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

$$C(s) = \frac{1}{\mathrm{card}(F(s))} \sum_{(x,x_1) \in F(s)} C_{x,x_1}(s) \tag{4}$$

The threshold which leads to the highest mean contrast along the associated edge $F(s_0)$ verifies the following condition:

$$s_0 = \underset{s \in [0,M[}{\mathrm{argmax}}\, C(s) \tag{5}$$

Instead of using this method to binarize the image, we use it to measure the contrast locally: the evaluated contrast between either side of the local edge $F(s_0)$ is equal to $2C(s_0)$. We propose some algorithmic optimizations of this method in [6].

2.2. Application to luminance maps

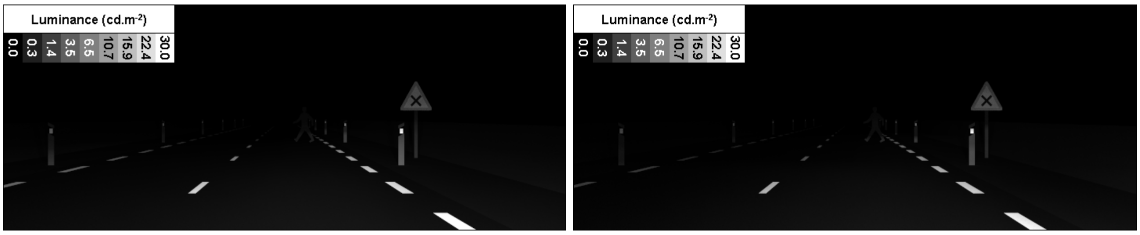
Let us now consider a luminance map, instead of gray levels. If it has been acquired with a *n*-bit digital videophotometer, then applying the presented edge detection method is quite straightforward. If it has been computed using a physically-based computer graphics technique, we need to convert the floating point values into *n*-bit digital values before applying the segmentation. Once the edges have been detected, the digital values can be converted back into luminance.

In the end, we get a distribution of contrast (luminance difference) along local edges. A visibility model based on Weber's law may then be applied to find those edges which are visible, or different luminance maps of one road scene in different lighting conditions may be compared.

3. SAMPLE RESULTS

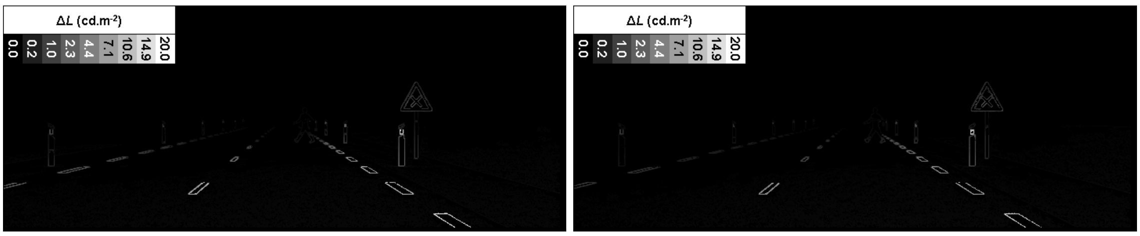
For the sake of demonstration, let us consider the following practical situation, which may be of interest to automotive engineers: a passenger car on a two-lane highway at night, with the low-beam headlamps providing the only illumination. The idea is to compare two pairs of low-beam headlamps, A and B. There is a sign on the right side of the road 30 meters ahead announcing an intersection, and a pedestrian crossing the road 50 meters ahead. Aside from these two “objects”, the impact of the headlamps can be assessed from the contrast of retro-reflective markings on the pavement, and retro-reflective delineators on both sides of the road.

Figure 1 shows the luminance maps resulting from the illumination of this road scene by the tested headlamps, computed with PROF, the Monte Carlo light tracing software developed by the LCPC. The simulated horizontal field of vision is 30°. These luminance maps were digitized to 14-bit level maps, and processed with the presented edge detection algorithm. The resulting local edge contrast maps were converted back to luminance difference maps, which are shown in Figure 2. Then, at every pixel presenting a local edge with a contrast above 0.05 cd.m^{-2}, the ratio between the contrast resulting from headlamps A and B was computed. Assuming both illumination systems yield the same adaptation, the ratio between contrasts is equivalent to the ratio between visibility levels. Hence, in Figure 3, we get a picture of the features of the scene which are made more visible by either system.



(A) (B)

Figure 1. Luminance maps in the field of vision of a driver on a 2-lane highway at night, simulated with two different pairs of low-beam headlamps.



(A) (B)

Figure 2. Local edge contrast maps computed with the presented technique.

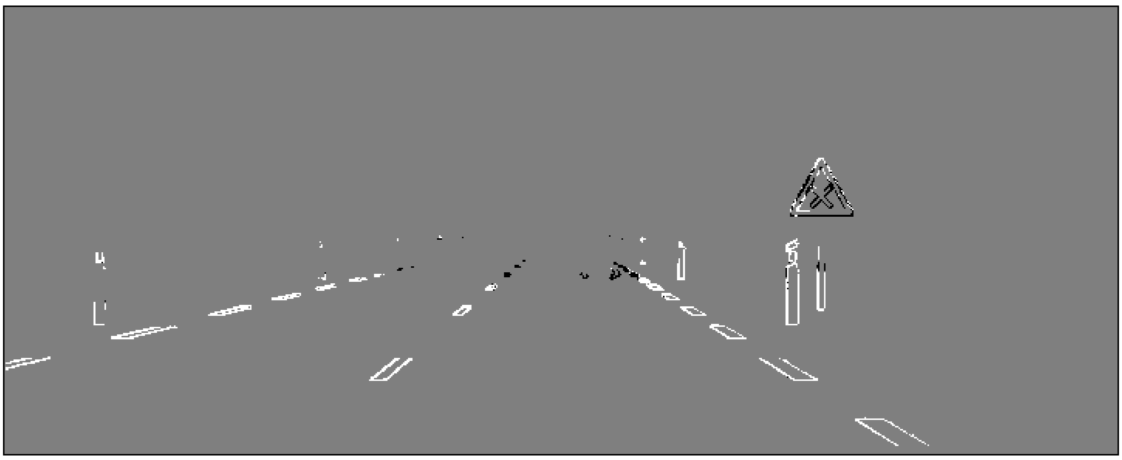


Figure 3. Comparative assessment: edges best contrasted with headlamps A are in white, while edges best contrasted with headlamps B are in black.

From the results, it appears that headlamps A bring the highest visibility to the markings and the delineators up to a distance of 50 meters, while the pedestrian (or at least his feet) and the sign, as well as the markings beyond 50 meters, are most visible when the scene is illuminated with headlamps B.

4. CONCLUSION

In this paper, we have presented a method to compute the contrast along the local edges in the digital luminance map of a complex road scene. Assuming a constant adaptation luminance, the resulting contrast map is proportional to a map of visibility levels, and thus can be used to compare the impact of different road or automotive lighting systems. The advantage of the method lies in its ability to automatically extract visibility information without having to solve the problem of computing the luminance of heterogeneous objects and backgrounds.

A potential improvement of the presented method would be to make it multi-scale. Thus, we would have something close to a visual differences predictor [7], only it would predict visible features instead of visible differences, making it possible to rate lighting systems using digital imaging.

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Authors:

Nicolas Hautière – Laboratoire Central des Ponts et Chaussées
58 boulevard Lefebvre 75732 Paris Cedex 15 France
Phone: +33(0)1 4043 6519 – Fax: +33(0)1 4043 5499 – E-mail: nicolas.hautiere@lcpc.fr

Eric Dumont – Laboratoire Central des Ponts et Chaussées
58 boulevard Lefebvre 75732 Paris Cedex 15 France
Phone: +33(0)1 4043 5349 – Fax: +33(0)1 4043 5499 – E-mail: eric.dumont@lcpc.fr