

# CONTRAST SENSITIVITY FUNCTIONS FOR ROAD VISIBILITY ESTIMATION ON DIGITAL IMAGES

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## Abstract

Automotive lighting systems are designed in order to provide the driver enough visibility, day and night, whatever the weather. In road lighting practice, an object of a fixed size in a simple scene is considered as visible if the contrast between its luminance and its background luminance is higher than a threshold contrast. This ratio is denoted VL (Visibility Level). We propose a framework in order to compute the VL of objects in the road scene from an onboard camera sensor. This framework simulates edge detection by the Human Visual System in an image of the scene. Applications are proposed for automotive lighting system evaluation.

**Keywords:** Visibility Level, Computer Vision, Automotive Lighting.

## 1 Introduction

National and international standards require that automotive vehicles use lighting systems at night, in order to improve the visibility of the road environment. These systems should provide enough visibility to the drivers, in order to perform their driving task in a safe way, whatever the situation. In this paper, we present an image processing method to compute road visibility in automotive lighting systems applications.

In road lighting practice, the Visibility Level (VL) proposed by Adrian is a relevant visibility index (Adrian 1987; 1989). From experimental data (e.g. Blackwell, 1946), which gives visibility thresholds for a simple object with a homogeneous background, Adrian proposed visibility thresholds corresponding to a 50% probability of target detection. This VL is computed from two luminance measurements, for a reference standard target and for its near background. Based on Adrian's model, the VL is computed as the ratio between the actual contrast  $\Delta L/L_b$ , over the visibility threshold contrast  $\Delta L_t/L_b$ . A target is labelled as visible if the VL is above a VL threshold, called field factor, which depend on the task (in the following, the driving task).

The above methodology, using two luminance measurements, is suited for homogeneous targets, and homogeneous background. In driving situations, the road surface is heterogeneous in luminance, with implications on the VL computation (Brémond et al. 2011). Moreover, Adrian's model results from psychophysical experiments with uniform targets, which differs from actual driving situations. Another limitation of Adrian's model is that only objects smaller than  $1^\circ$  are considered.

Hautière and Dumont have proposed an image processing approach, using luminance maps, getting rid of any hypotheses about the target's shape, uniformity and about the background uniformity (Hautière & Dumont, 2007). An object in the road scene is made visible by the contrast level with respect to its background. Thus, starting from an edge detection in a luminance image of the road scene (Kohler, 1981), they proposed to rate the visibility of these edges, based on the local luminance contrast. As a result, the visibility of the edges in an image was estimated, and was related to the VL of the corresponding objects.

We propose an improvement of Hautière and Dumont's edge visibility computation, taking into account two limitations: first, they introduced an arbitrary threshold on  $\Delta L$  to label the contours as visible/not visible. Second, the edge visibility does not depend on the object's size, whereas it should. Both issues are addressed taking into account a key property of the Human Visual System (HVS), that is, its Contrast Sensitivity Function (CSF) (Campbell & Robson, 1968, Barten, 1999).

The CSF is defined in vision science literature from sine wave grating of various frequencies, displayed to observers on a uniform background. Observers have to adjust the contrast to the visibility threshold for each grating, for a range of spatial frequencies. CSF are available for various populations, normal and pathologic, photopic, mesopic and scotopic, for various age ranges, etc. (e.g. Mannos, 1974, Owsley, 1983).

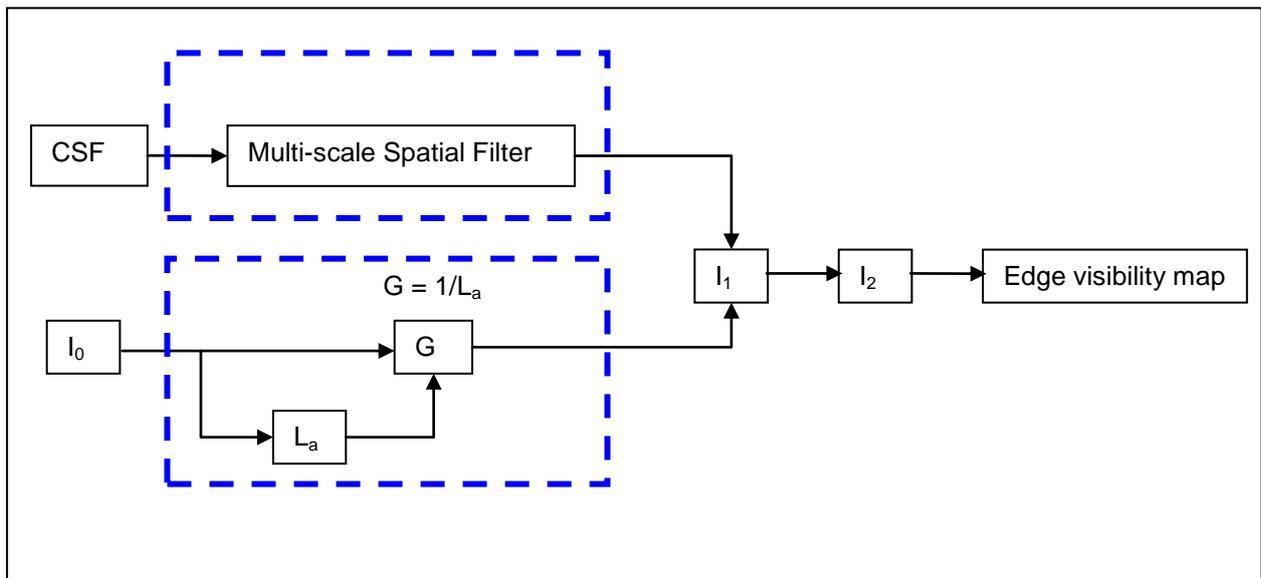
Using the computer vision approach of edge detection, we have designed a set of spatial filters (Difference of Gaussian, DoG) which mimic the HVS. From a given CSF, we compute a collection of DoG filters, which weighted sum has the same property, in the spatial domain, as the CSF in the frequency domain.

The result of these filters allows detecting the edges in a way which is equivalent to a convolution with the human CSF. Thus, any CSF can be simulated as input, and our results simulates the visibility of object's edges for the population (or condition) simulated with the selected CSF. The next step of the algorithm is the computation of the VL on the visible edges, which also uses the output of the DoG filters.

## 2 Model

The proposed model takes a luminance image as input, and computes the edges and edge visibility for the objects in the image. For this, the model detects the object's edges with the multi-scale spatial filter (DoG filters) and computes the VL along these edges (Fig.1).

The model is split into two algorithms. The first one searches the set of spatial filters (Differences of Gaussian) in order to simulate the vision of a given CSF, taken from the literature in vision science. Secondly, the adaptation luminance is taken into account through a normalization of the input image.



**Figure 1.** Unified framework of the proposed model

To take into account the adaptation luminance, we considered Weber's law, which states that visual performance depends on the contrast of an object with respect to its background, not on the absolute difference value. To express this from an image processing point of view, the input image is normalized.

For this, we assume that the adaptation luminance is similar to the mean luminance of the input image. We set the inverse of the adaptation luminance as a Gain feedback, which applies on the input image  $I_0$  to produce image  $I_1$  (see Fig. 1). Then, the Vision model is applied to  $I_1$ .

One interesting point with this normalization step is that using input images from a linear camera sensor is a fair compromise, even if no luminance calibration is available. Indeed, usual cameras use an automatic gain which is similar to the proposed simulation of the luminance adaptation.

The Vision model is issued from vision science literature. From a physiological point of view, the activity of ganglion cells of an observer is modified when he detects a target. These LGN cells have

corresponding receptive fields in the retina. Each receptive field is divided into two regions: a central region and a peripheral region. Their antagonist activity can create configurations either ON/OFF (center ON and periphery OFF) or OFF/ON. When a receptive field is excited, the neural response of the ganglion cell can be represented by a Differential of Gaussian (DoG) (Enroth-Cugell & Robson, 1966). Moreover, the size of these receptive fields varies, so that HVS can be considered as a multiscale analyzer (Campbell & Robson, 1968). The CSF does not model as a single frequency filter but as a multitude of filters, each corresponding to the response of a cell type.

To simulate this, we have implemented a weighted sum of DoG (or SdoG) in order to mimic a given CSF, such as:

$$SDoG(I) = \sum_k \omega_k [G_{\sigma_{k+}} - G_{\sigma_{k-}}](I) \quad (1)$$

Where  $I$  is the input image,  $G_{\sigma}$  is the normalized Gaussian operator with standard deviation  $\sigma_+$  (center) and  $\sigma_-$  (periphery) such as  $\sigma_- = \lambda \sigma_+$ .  $\omega$  is the DoG's weight. We use  $\lambda = 3$  in the following. Tab. 1 shows the filters coefficients computed from Barten's CSF ( $L_a = 100 \text{ cd/m}^2$ ).

**Table 1.** Composition of the DoG filters

	DoG <sub>1</sub>	DoG <sub>2</sub>	DoG <sub>3</sub>	DoG <sub>4</sub>	DoG <sub>5</sub>	DoG <sub>6</sub>
Frequency (cpd)	2.90	7.70	1.00	0.40	1.50	0.10
$\sigma_+$ (cpd)	0.25	0.10	0.74	1.85	0.49	7.41
$\omega$	393.20	169.26	134.46	45.83	22.98	17.21

By applying the SDoG to the input image  $I_1$ , we obtain image  $I_2$  which shows zero-crossings (Marr & Hildreth, 1980). The visible edges are determined from zero-crossings in  $I_2$  and the edge value is set to its visibility, which is also computed from the SDoG.

### 3 Applications

We demonstrate the benefits of our approach with two applications, both in the field of automotive lighting. First, the comparative approach, proposed by Hautière and Dumont (Hautière and Dumont, 2007) is improved. Second, we show that our model allows simulating an Automotive Lighting Systems performance for drivers with impaired vision.

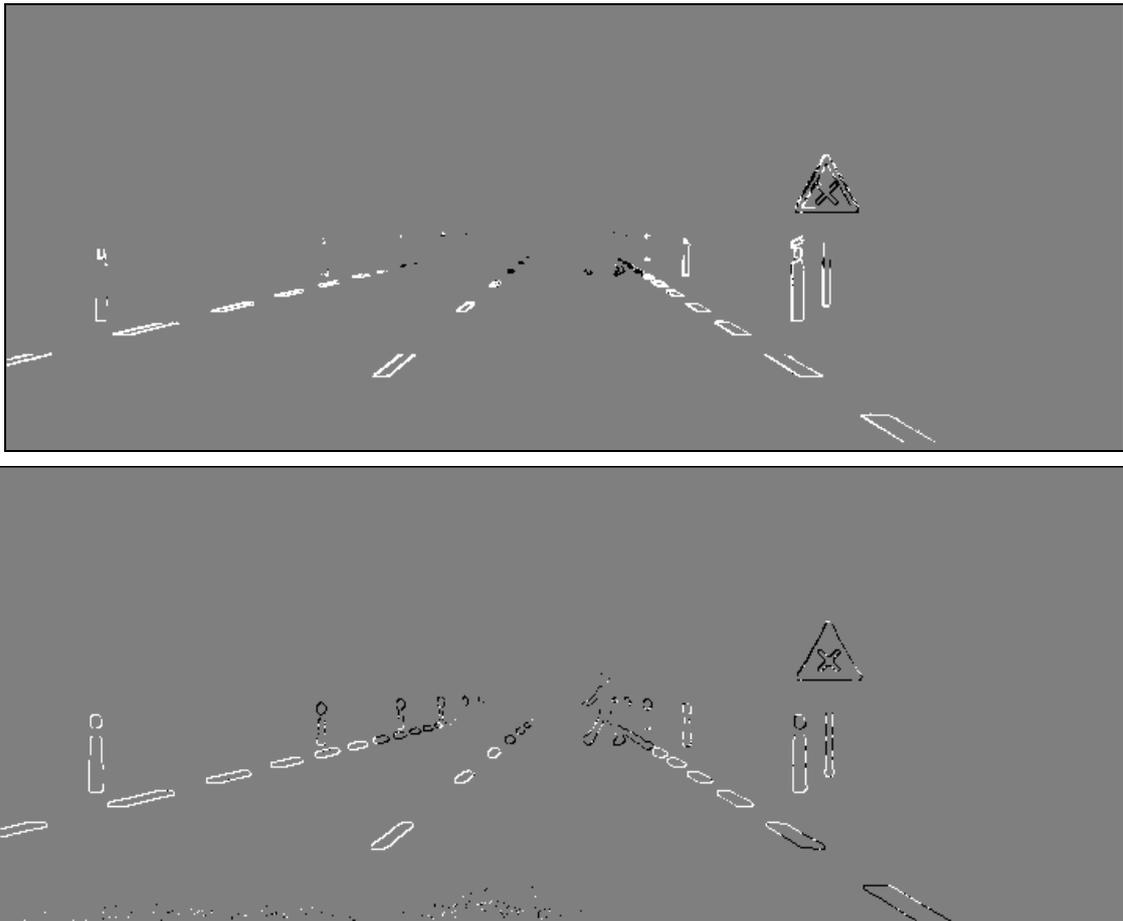
In order to estimate the road visibility at night, Hautière and Dumont (Hautière and Dumont, 2007) proposed to compute the edge visibility in the scene, then the ratio between these visibilities, for a headlamp system A and for a headlamps system B. In the following, we follow their framework and show the improvement which result from our new model.



**Figure 2.** Luminance maps of a road scene lit by two automotive lighting systems. Monte-Carlo simulation, after Dumont (1999).

Night driving is mostly concerned with the mesopic range, so that we have tuned our edge visibility simulator to Barten's mesopic CSF (Barten, 1999). As an output, we get a map of the road objects' edges, with the visibility of these edges for a human observer. Using the same input images as in Hautière & Dumont (2007), we have computed the edge visibility with a vision model which is closer to human vision than they did: we take into account the CSF, and the output of our model gives absolute

visibility value, while they computed relative values, and had to select an arbitrary threshold. It was interesting, then, to see if these differences in the vision model would result in differences in the edge visibility.



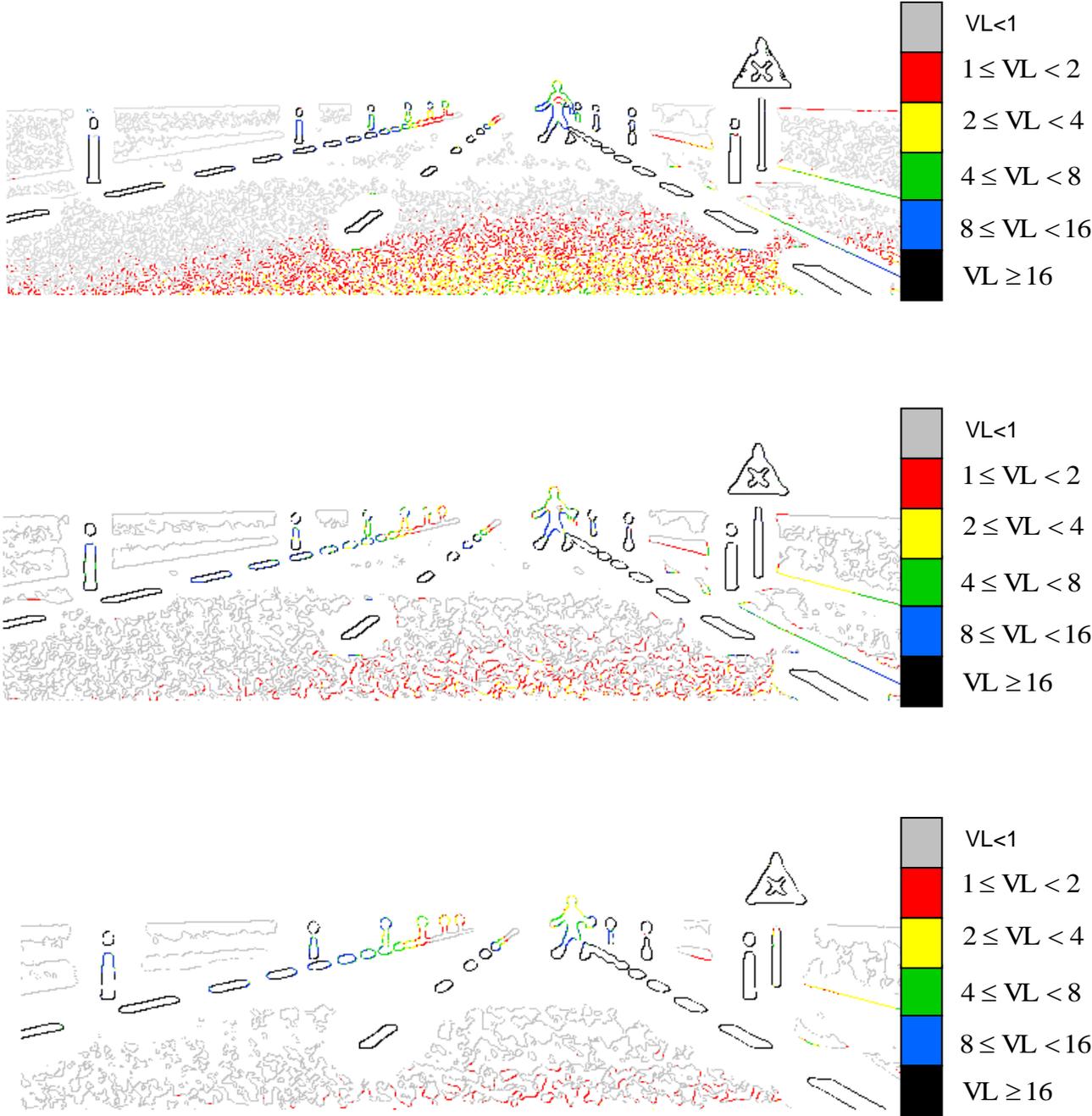
**Figure 3.** Automotive lighting comparison: Hautière's method (top) and the proposed framework (bottom). Object's edges with a better visibility with headlamps A are in white, edges with a better visibility with headlamps B are in black.

Fig. 3 shows Visible Edge Maps (VEM) computed from the same luminance images as input (see Fig. 2): a road scene seen with two automotive lighting systems. Two striking results appear. From Hautière's results, the "white" ALS outperforms the black one almost everywhere, except on the road sign. Using our vision model, it appears that the "black" ALS is also better than the white one to detect the road marking far away from the car, and more importantly, for the detection of the pedestrian, 50 meters in front of the driver. This makes our new algorithm an improved tool for the a priori evaluation of road lighting systems.

Another application of the proposed model is presented in Fig. 4. In the previous example, we proposed to compare the visibility for various lighting systems. Now, we propose to compare the road visibility for various drivers. This may contribute to the design of specific lighting systems (or lighting modes) for drivers with impaired vision, and may also be included in the specifications of new lighting systems.

In the example in Fig. 4, the visibility of a road scene is compared between drivers of 20, 60 and 80 years old, based on published data about the changes in the CSF with age (Owsley et al., 1993). Indeed, drivers do not have the same visual performance, and it may be interesting to know, for the system designer, what is the system performance for a specific population. Of course, the proposed framework could also be applied to the visibility simulation of people with impaired vision due to a specific pathology, providing that data are available to simulate the CSF impairment due to this pathology.

In Fig. 4, we find as expected two main features. First, the visibility of any edge (or object) lowers with age. This can be seen by comparing the visibility distance, at a given threshold, between the 3 images, for the delineators or for the lane marking. Second, the drivers are less sensitive to high spatial frequencies with age, which can be seen from the road surface texture, as well as from the object's shape, which includes less detail with age.



**Figure 4.** Visibility Edge Maps (VEM) of the same road scene, computed for 20 years old (top), 60 years old (middle) and 80 years old drivers (bottom).

## 4 Conclusion

We have proposed a unified framework which computes the visibility of any object in a complex road scene, from an image taken from an onboard sensor. The VL computation is based on a reference model of the HVS, the Contrast Sensitivity Function. The approach improves previous methods in Computer Vision based on edge detection techniques (Hautière & Dumont, 2007). The output is a visibility map of the edges in the scene. The framework allows to simulate any CSF, which leads to a number of applications, either by tuning the CSF to a specific situation (e.g. mesopic vision in the case of night driving) or comparing two populations (e.g. young vs. older drivers). Unlike Adrian's photometric concept of the VL, no hypothesis is made either on the object's size, or on their background uniformity.

Improvements are expected from the proposed computer vision tool for automotive lighting design and Advanced Driving Assistance Systems (ADAS). Also, existing methods for the diagnosis of road visibility on rural networks (Brémond et al., 2007) could be improved by the proposed model.

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