Designing a Tone Mapping Algorithm for Road Visibility Experiments

Justine Grave*
Laboratoire Central des Ponts et Chaussées, Paris
Laboratoire d'InfoRmatique en Image et Systèmes d'information, Lyon
Roland Brémond†
Laboratoire Central des Ponts et Chaussées, Paris

Abstract

In this paper, we propose a tone mapping operator based on a multiscale representation pattern and on thresholds of detection contrast computed for local adaptation luminances. The vision model, combined to a display model, compresses the luminance range of the image to fit the dynamic range of the display device. Our goal is to match our perceptions of the scene at detection threshold levels. This operator has been evaluated as regards its capacity to maintain visual performances, by means of a psychophysical experiment which involves a Landolt ring on a non uniform background image. The luminance histogram is that of a daytime road scene and all semantic clues have been removed. The experiment shows that our algorithm gives good results, especially for contrasts close to the threshold value. Those results prove that computer graphics images can be used for road visibility experiment in driving simulators or in psychovisual experiments.

Keywords: Tone Mapping, Visual performance, Psychophysical experiment, Road visibility studies

1 Introduction

Road visibility studies can take strong benefit from the use of computer graphics images, through driving simulation and psychovisual experiments. Unfortunately, the visual environment of the driver is far more complex than any display device is able to render (luminance dynamic range, luminance values, color gamut, color values).

The purpose of tone mapping algorithms is to cope with the luminance limitations of display devices. In this paper, we propose a tone mapping algorithm designed for road visibility psychovisual studies (it should be extended to any visibility studies). This algorithm is validated through a psychometric experiment. We compare the visual performances of a panel of subjects measured first with a high luminance scene and then with this scene tone mapped to fit the low luminance dynamic of a specific display device. The test is a detection task, using a Landolt ring. Therefore, the visual performances involve contrast sensitivity and visual acuity.

Road visibility studies usually focus on low visibility situations such as rainy or foggy weather, or nighttime. In this paper, we choose a daytime fog situation to test our tone mapping algorithm. We aim to validite the use of synthetic images for road visibility studies.

*e-mail: justine.grave@lcpc.fr
†e-mail:roland.bremond@lcpc.fr

2 Algorithm

The algorithm is based on the operator of Pattanaik et al. [Pattanaik et al. 1998] which is the most complete as concerns vision models. That operator uses a pyramidal decomposition of the image and models the behavior of the human visual system (at least at the low levels of vision), then inverses the vision model according to the specific characteristics of the display device, see figure 1.

Hence, the tone mapping algorithm dramatically depends, in its results, on the display device. The algorithm and the display cannot be evaluated separatly (see section 3).

Our Algorithm differs from Pattanaik et al. in two ways. First, as the main issue in road visibility is contrast sensitivity, we restrict the algorithm to luminance mapping whereas Pattanaik et al. consider other phenomena such as color and glare. Secondly, as we are mainly interested in visual performances, we only base our algorithm on data from Blackwell [CIE19 1981], whereas Pattanaik et al. also use suprathreshold data.

2.1 Vision model

Physiological and psychological data indicate that the retinal image is processed by visual mechanisms which are sensitive to different scales of patterns. The responses of those mechanisms have the same characteristics as bandpass filters in the spatial frequency domain. These mechanisms are sensitive to different range of spatial frequencies and the Contrast Sensitivity Function (CSF) is the envelope of their sensitivities [Wilson 1991].

Starting from this retinal model, Pattanak et al. build a pyramidal decomposition of the image. Each level of the pyramid corresponds to a passband filtering. This pyramidal decomposition follows the Laplacian pyramid model [Burt and Adelson 1983]: level l of the pyramid (image L_l) is obtained by the convolution of level $l-1$ with a Gaussian filter. The size of L_{l-1} is four times the size of L_l, which makes necessary to expand L_l to build a contrast image $C_l^{\mathrm{w}}(i,j)$ for level l:

$$C_l^{\mathrm{w}}(i,j) = L_{l-1}(i,j) - L_l^{expand}(i,j) \quad (1)$$

The restrictions we explained earlier lead us to use Blackwell data [CIE19 1981] to compute threshold data. Ferwerda [Ferwerda et al. 1996] uses these data to make tvi (threshold versus intensity) functions, for cones and for rods. Larson [Larson et al. 1997] combines the two functions into a set of equations giving the contrast threshold for different ranges of adaptation luminance. These functions are called Just Noticeable Difference (JND). The detection task is linked to contrast perception through the Visibility Level

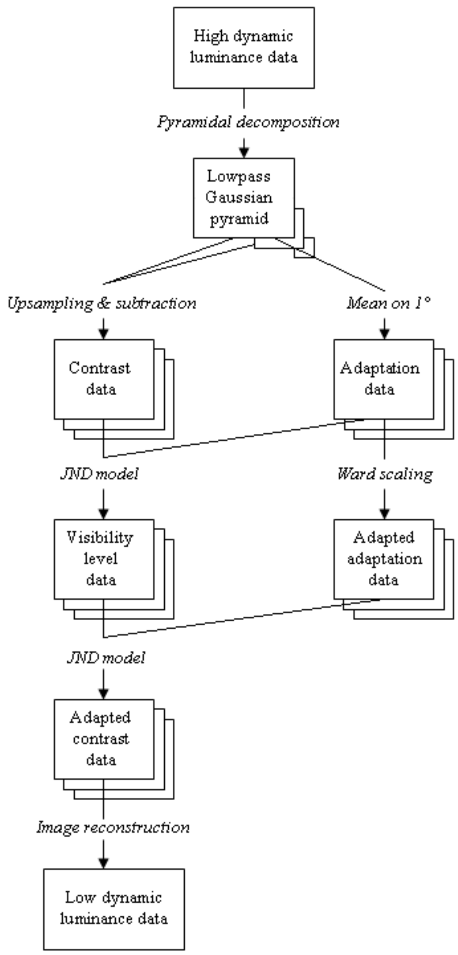

Figure 1: Flow-chart of our Tone reproduction operator.

(VL) which is defined in road lighting applications as $V = \Delta L/\Delta L_t$, where ΔL is the actual luminance contrast and ΔL_t is the JND for a given adaptation luminance, see figure 2.

Adaptation luminance range	log10 of JND
$\log10(L_a) < -3.94$	-2.86
$-3.94 \leq \log10(L_a) < -1.44$	$(0.405\log10(L_a)+1.6)^{2.18} - 2.86$
$-1.44 \leq \log10(L_a) < -0.0184$	$\log10(L_a) - 0.395$
$-0.0184 \leq \log10(L_a) < 1.9$	$(0.249\log10(L_a)+0.65)^{2.7} - 0.72$
$\log10(L_a) \geq 1.9$	$\log10(L_a) - 1.255$

Figure 2: Just Noticeable Difference for different ranges of adaptation luminance.

The way we compute the adaptation data also differs from that of Pattanaik et al. We take into account known data about the visual field (around 1 degree according to Moon and Spencer [Moon and Spencer 1945]). This implies that the computational model depends on the distance between the observer and the display device.

The VL image at each level l contains at every pixel the modelized visibility level of the corresponding pixel in the original image for the frequency range of level l.

So the VL image at level l is computed as follows:

$$V_l(i,j) = \frac{C_l^{\mathrm{w}}(i,j)}{\Delta L_t(L_l^{\mathrm{aw}}(i,j))} \tag{2}$$

where $V_l(i,j)$ is the VL for pixel (i,j) at level l, $C_l^{\mathrm{w}}(i,j)$ the contrast and $L_l^{\mathrm{aw}}(i,j)$, the local adaptation luminance.

2.2 Image reconstruction

To build a displayable image, the characteristics of the device used for display such as maximum and minimum displayable luminances need to be specified.

The VL images are converted into contrast images, using the same JND equations with new adaptation luminance values. These adaptation values are computed through a scale factor [Ward 1994] using the display characteristics as follows:

$$L_l^{\mathrm{ad}}(i,j) = kL_l^{\mathrm{aw}}(i,j) \tag{3}$$

with

$$k = \left[\frac{1.219 + (L_{\mathrm{dmax}}/2)^{0.4}}{1.219 + (L_l^{\mathrm{aw}}(i,j))^{0.4}}\right]^{2.5} \tag{4}$$

hence the displayed contrast is:

$$C_l^{\mathrm{d}}(i,j) = V_l(i,j).\Delta L_t(L_l^{\mathrm{ad}}(i,j)) \tag{5}$$

The final image is built by agregating all pyramid levels into a low luminance range image which can be displayed on the device. The model of the device is used to convert luminances into RGB data. This model is a Look Up Table (LUT) obtained with the calibration method described in the publication 122 of the CIE [CIE122 1996].

3 Experimental Method

An experimentation has been designed in order to assess the quality of our algorithm, on a LCD display device, for a visual performance task. At the moment, the evaluation only concerns daytime fog environments. The experimental method is adapted from [McNamara et al. 1998]. We compare the visual performances of 9 subjects measured with a reference scene (with high luminances, up to 1000 cd.m^{-2}) and with a simulated and tone mapped scene displayed on a low luminance range LCD screen (up to 200 cd.m^{-2}).

The visual task was chosen comparable with a danger detection task and associated to a performance index. We chose to measure the visual performance. This task is simplified but fundamental for the visual driving task. The test is a Landolt ring on a background of uniform luminance usually used for visual performance evaluation [CIE19 1981]. The image surrounding the test is a road image in daytime fog, computed with a photometric model of fog effects on road vision [Dumont and Cavallo 2004].

We decided to avoid any semantic clue, in order to limit the cognitive aspect of the visual environment. To make the background image, a luminance image of the driving scene is cut into blocks which are mixed randomly like a jigsaw. Thus the new image has the same luminance histogram as the former but the semantic information is removed, see figure 3. We want to decorrelate the test from the comprehension of the image which could sidestep the results.

We fixed some of the parameters of the test such as:

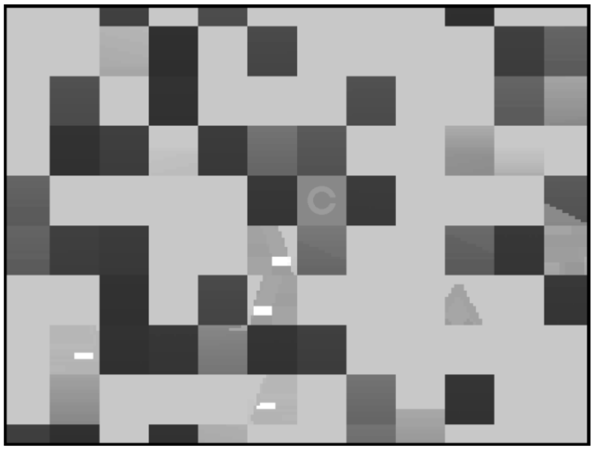

Figure 3: Reference image displayed by a video projector

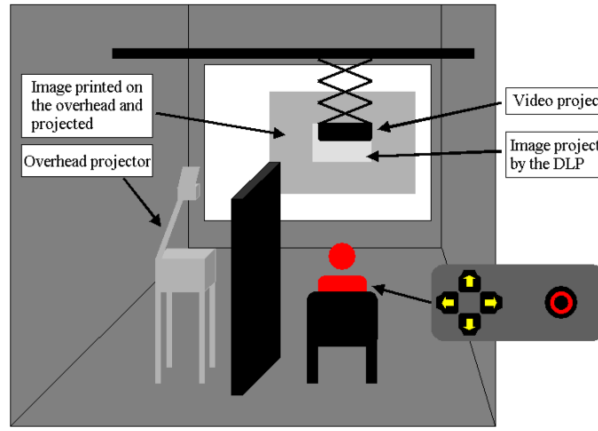

Figure 4: Experimental setup for the reference scene.

- **the presentation time** of the gap, fixed to 100 ms;
- **the background luminance**, calculated like the adaptation luminance defined by Moon and Spencer [Moon and Spencer 1945];
- **the angular size of the gap** fixed to 0.13 degree.

The variable parameters are:

- **the position** of the gap, which can take 4 different positions (right, top, left, bottom);
- **the contrast** between the background L_b and the ring L_t luminances, which takes 8 values sampled from values detected with difficulty and to easily detected ones.

4 Image Comparison Experiment

The reference scene is generated with two projectors, in order to achieve high luminance values, see figure 4. The central part of the image is projected on the center of the screen by a video projector (DLP NEC LT 1065, 2100 ANSI lumen) which has been calibrated [CIE122 1996]. This image is 1024 by 768 pixels on 70 by 54 cm^2 so that the angular size of a pixel is 0.013 degree. We can thus display luminances up to 1000 cd.m^{-2}. The rest of the image is projected by an overhead projector (PROLITE 250/400, max power 300W).

The low luminance scene configuration is similar to that of the reference. The central image is tone mapped and displayed on a LCD (1701 NEC, 17"), calibrated as well [CIE122 1996]. The rest of the image is again projected by the overhead projector on a polystyrene screen after having been scaled down to keep the same ratio of the average luminance with the central image as in the reference.

We use the Presentation software [Presentation] in order to control the display and to record the answers given by the observers with a gamepad. 17 tests were carried out for each of the 8 contrast values, with 9 observers. The subjects were instructed to indicate the position of the gap, even when they had not seen it.

5 Results

The data gathered through this experiment cannot lead to a significative statistical analysis for each person. We rather consider an average observer whose visual performances are shown in figure 5. We can compare the performances obtained with the reference scene with those obtained with the scene processed by our algorithm.

To compare the results of our algorithm to those of the reference, we compute an estimate of the margin of error of the reference values for each contrast. We consider each answer, for contrast c, as a realization of a random process which follows the Bernouilli distribution, with the probability p_c. We consider X_c the number of good answers within the 153 tests for contrast c. X_c follows the binomial distribution, with parameters $n = 153$ and p_c. The Bienaymé-Tchebychev inequality gives:

$$P(|E(X_c)/n - p_c| \geq \varepsilon_c) \leq 0.05$$

with

$$\varepsilon_c = \sqrt{\frac{p_c(1-p_c)}{0.05n}}$$

We are looking for the values of ε_c, the uncertainty around the experimental values which gather 95 percent of the data. Figure 5 shows the reference visual performance values, with the estimated margin of error, and the values we obtained with our algorithm. These values are mostly inside the uncertainty range, except at contrast 0.034 where the reference value seems aberrant.

6 Discussion

We used the same experimental method, with the same observers and with the same reference images to measure visual performances obtained with two other tone mapping operators: the operator of Ward [Ward 1994] and the one of Larson [Larson et al. 1997]. The operator of Ward is linear. It uses the experimental data of Blackwell on thresholds of detection contrast to compute a luminance scale factor. It is designed to measure visual performance. The method of Larson et al. [Larson et al. 1997] is a compression and

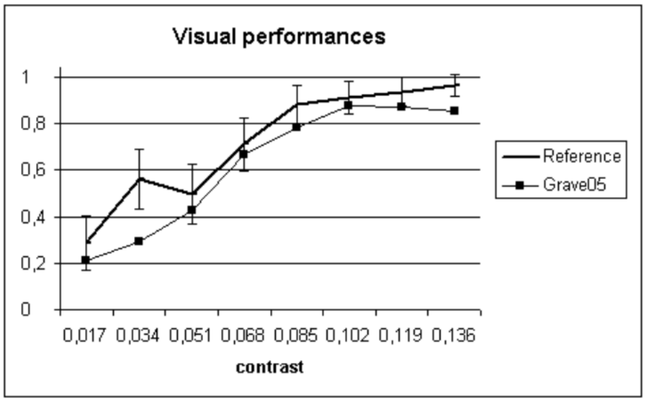

Figure 5: Average visual performances over 9 observers.

equalization of the luminance histogram, using JND functions. It focuses on object visibility and image contrast. We did not implement the part of the algorithm which considers the viewer's dependent response, that is to say glare, acuity and chromatic sensitivity. That way, it suits visual performance measures as well. Figure 6 compares the visual performances obtained with our algorithm, that of Ward and that of Larson et al., with the reference.

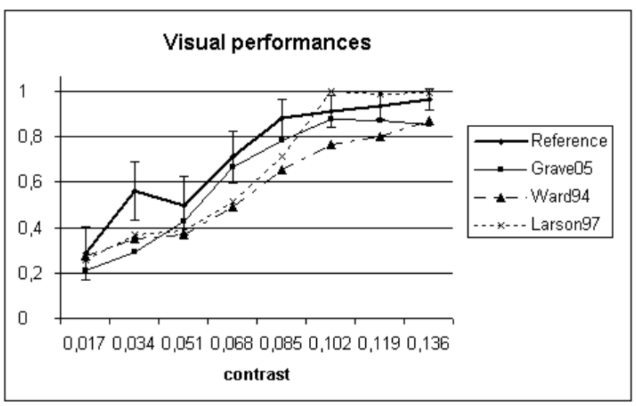

Figure 6: Comparison of average visual performances for 9 subjects, measured with 3 tone mapping operators and with the reference.

We note that the algorithm we propose gives the best results for contrasts close to the threshold. Yet this comparison is only relevant for daytime fog visibility condition and for a LCD display device. We should extend the evaluation to other conditions of visibility, especially nighttime. Nevertheless, these results are hopeful and allow to use computer graphics images for visibility studies on a LCD device, in daytime and with foggy weather.

7 Future work

The next step of our work is to evaluate and adapt if necessary our algorithm for nighttime traffic conditions of visibility. In particular, we would like to introduce glare effects which turn to be very disturbing at night.

If the detection of static objects is classicaly used in experimental paradigms, the detection of moving objects, in particular in peripheral vision, is a visual task for which we would like to validate our algorithm so that it should be relevant for the whole detection task while driving.

References

BURT, P. J., AND ADELSON, E. H. 1983. The laplacian pyramid as a compact image code. *IEEE Transactions on Communications 31*, 4 (April), 532–540.

CIE122. 1996. The relationship between digital and colorimetric data for computer-controlled crt displays. *CIE Publication, report 122*.

CIE19. 1981. An analytic model for describing the influence of lighting parameters upon visual performance. *CIE Publication, report 19/2.1*.

DUMONT, E., AND CAVALLO, V. 2004. Extended photometric model of fog effects on road vision. *Transportation Research Record*, 77–81.

FERWERDA, J. A., PATTANAIK, S. N., SHIRLEY, P., AND GREENBERG, D. P. 1996. A model of visual adaptation for realistic image synthesis. In *Proceedings of ACM SIGGRAPH '96*, 249–258.

LARSON, G. W., RUSHMEIER, H., AND PIATKO, C. 1997. A visibility matching tone reproduction operator for high dynamic range scenes. *EEE Transactions on Visualization and Compter Graphics* (Dec), 291–306.

MCNAMARA, A., CHALMERS, A., TROSCIANKO, T., AND REINHARD, E. 1998. Fidelity of graphics reconstructions: A psychophysical investigation. In *Proceedings of the 9th Eurographics Rendering Workshop*, Springer Verlag, 237–246.

MOON, P., AND SPENCER, D. 1945. The visual effect of non-uniform surrounds. *Journal of the Optical Society of America 35*, 3, 233–248.

PATTANAIK, S. N., FERWERDA, J. A., FAIRCHILD, M. D., AND GREENBERG, D. P. 1998. Multiscale model of adaptation and spatial vision for realistic image display. In *Proc. SIGGRAPH '98*, 287–298.

PRESENTATION. http://nbs.neuro-bs.com/presentation.

WARD, G. 1994. A contrast-based scalefactor for luminance display. In *Graphics Gems IV*, Academic Press, Boston, 415–421.

WILSON, H. 1991. Psychophysical models of spatial vision and hyperacuity. In *Spatial Vision*, D. Regan, vol. 10, 64–81. Vision and Visual Dysfunction.