Designing a Tone Mapping Algorithm for Road Visibility Experiments

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Abstract

One may wish to use computer graphics images to carry out road visibility studies but most display devices still have a limited dynamic range. In driving scenes, the human visual system may be presented with a large illumination range. Our visual system copes with the vast illumination range through adaptation. It works as a set of different band pass filters which all together make up the Contrast Sensitivity Function. Visual adaptation depends on the spatial frequency filtering characteristics. In this paper, we propose a tone mapping algorithm to compress the luminance dynamic range while reproducing the overall impression of contrast and preserving the driver's performance. To characterize the effects of local adaptation, we decompose the luminance image into a Laplacian pyramid and process the levels separately. We want the contrast perception to remain the same after the tone mapping operator has been applied. In road visibility, the Visibility Level is used as a performance index for the contrast perception. To assess our algorithm, we carried out a psychophysical experiment. We compared the visual performance of a number of observers measured when he stared at a reference scene, and when he stared at the image of this reference scene, processed by a Tone Mapping operator and displayed on a calibrated Liquid Crystal Display monitor (LCD). The reference scene is a High Dynamic Luminance image projected by a calibrated Digital Light Processing projector (DLP). The maximum luminance displayed by the DLP is 500 $cd.m^{-2}$ whereas the maximum of luminance that can be displayed by the LCD is 167 $cd.m^{-2}$. We measured the observers' visual performance with a Landolt Ring. These measures were made for 8 contrast values between the ring and the background. The break in the ring was displayed during 100 ms and we ask the subjects to indicate its position. We obtained a better preservation of the contrast perception around the perception threshold with our algorithm than with the 2 others we used for comparison.

Keywords: High dynamic range, tone mapping, visual performance, visibility level, psychophysical experiment, road visibility

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). In a daytime driving scene, the luminance can be as high as 10^5 $cd.m^{-2}$. In a night-time driving scene, the luminance can be as low as 10^{-3} $cd.m^{-2}$ and as high as 10^5 $cd.m^{-2}$ at the same time, because of the headlights of on-coming traffic. A LCD monitor is usually unable to display luminance below 10^{-1} $cd.m^{-2}$ and beyond 10^2 $cd.m^{-2}$. The CRT projectors usually used in driving simulator are even worse in displayable luminance dynamic range. Due to the size of the projection area, the maximum luminance can be as low as 10 $cd.m^{-2}$.

It is essential to compress the luminance dynamic range of images to fit the display device characteristics. An operator which maps real world luminances to target display luminances is called a tone mapping operator (TMO). It is designed to reproduce the overall impression of brightness and contrast of the real world onto limited dynamic range display devices. Because we want to use those real world luminance images to carry out road visibility studies, an appropriate TMO should preserve the visual perception of the scene. TMOs found in literature mainly deal with visual appearance issues. They are designed to reproduce the subjective impression of observers. In this paper we focus on visual performance, which is an essential aspect of road visibility. The observer is presented with a visual task which has two ways out: success or failure. Hence, we designed a TMO, which aims at preserving the observer's visual performance, and we ran psychophysical experiments based on a detection task, to evaluate our algorithm and to compare it with others from literature. Road visibility studies usually focus on low visibility situations such as rainy or foggy weather, or night-time. Here, we chose a daytime fog situation to test our tone mapping algorithm. Our goal is to validate the use of synthetic images for road visibility studies.

After a short review of TMOs and evaluation experiments from literature, we develop the tone reproduction algorithm we propose. Then we describe the psychophysical experiments we carried out to evaluate our operator. Finally the results are discussed and future work is proposed.

2 Previous work

The problem of tone reproduction is not a recent one. It was first tackled by photographers who needed to process their pictures so that they fit the visual appearance of the photographed scene. For computer graphics images, many TMOs have been proposed for compressing the dynamic range of an image so that it can be displayed effectively [Devlin et al. 2002]. There are two main categories of such operators: spatially uniform (also known as global) and spatially varying (also known as local). Global operators apply the same transformation to every pixel of the image regardless of their position in the image. Local operators apply different transformations to different parts of the image depending on their properties. Among global operators, one can mention Ward's operator [Ward 1994] which has a psycho-visual theoretical background. It

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is a linear operator, very simple, which calculates a scale factor using the visual performance model of Blackwell [CIE19 1981]. It aims at preserving the threshold of perceived luminance differences while compressing the luminance range. This is a relevant approach when one wants to display scenes where visibility is an essential aspect. We can also quote Larson et al.'s algorithm [Larson et al. 1997]. They present a histogram equalisation technique for reproducing perceptually accurate tones in HDR images. They include object visibility and image contrast in their concerns. Pattanaik et al. [Pattanaik et al. 1998] proposed a local operator. They based their operator on a multiscale representation of patterns, on luminance and colour processing and adressed the problem of perception of scenes at threshold and suprathreshold levels. The multiscale approach unfortunatly introduces artefacts known as "halos". Yet it is still considered as a relevant way to tackle the tone mapping problem and solutions were proposed to minimize those artefacts [Li et al. 2005]. A further aspect to tone reproduction is time. Some operators are time dependent such as Ferwerda et al. [Ferwerda et al. 1996] and Pattanaik et al. [Pattanaik et al. 2000] operators.

Experiments have also been proposed and carried out to evaluate TMOs. Most of them were based on visual appearance. Drago et al. [Drago et al. 2003] asked their subjects to percetually judge and to indicate their preference over a panel of images processed by different TMOs. They analysed this preference data to determine a preference point in the stimulus domain they used as reference to compare algorithms. In other studies subjects were asked to rate tone mapped images. Recently, Ledda et al. [Ledda et al. 2005] proposed experiments using a HDR image as a reference scene. They compared TMOs two by two and asked the observers to choose, between two different tone mapped images, the one that was closer to the reference scene. Vienot et al. [Viénot et al. 2002] presented an evaluation paradigm using a physical reference scene and performed operator comparison with psychophysical experiments based on both visual performance and appearance.

As we already pointed out, driving scenes may generate complex images. A local TMO would be more effective than a global at dealing with such complexity. So we seek a local tone reproduction operator, that focuses on the preservation of the observer's visual performance. That means that we are mainly interested in luminance dynamic compression.

3 The Tone Mapping Operator

The general outline of our operator is cut into two parts: a vision model and image reconstruction.

3.1 Vision model

3.1.1 Theoretical background

The range of light we encounter in natural scenes is vast. Our visual system copes with this large range of illumination through adaptation. As we look from place to place in a scene our eyes adapt locally to the prevailing conditions of illumination. Yet, the adaptation is not only spatially local. In 1968, Campbell and Robson [Campbell and Robson 1968] suggest that the human visual system (HVS) works as a set of independant bandpass filters. Those filters are sensitive over a range of frequency narrower than the Contrast Sensitivity Function (CSF). The responses of the filters all together would make up the CSF. Adaptation is also local with respect to the spatial scale. In 1990, Peli [Peli 1990] suggested that an appropriate way to simulate the effects of local adaptation is to assign a contrast value to every point in the image as a function of the spatial frequency band. This may be done by pyramidal decomposition [Burt and Adelson 1983].

3.1.2 Computational model

For this spatial decomposition, we use, as Pattanaik et al. [Pattanaik et al. 1998] do, the Laplacian pyramid described by Burt and Adelson [Burt and Adelson 1983]. We first build a Gaussian pyramid using a 5×5 gaussian filter w, see table 1. Each level of the pyramid represents a low-pass image, cut at a frequency half of the one of the next higher level. The Gaussian pyramid has 7 levels to cover the sensitivity domain of the HVS. The image at level l of the pyramid, denoted as L_w^l, w for world, is computed from level $l-1$ (L_w^0 is the original image):

$$L_w^l(i,j) = \sum_{m=-2}^{2} \sum_{n=-2}^{2} w(m,n) L_w^{l-1}(2i+m, 2j+n) \quad (1)$$

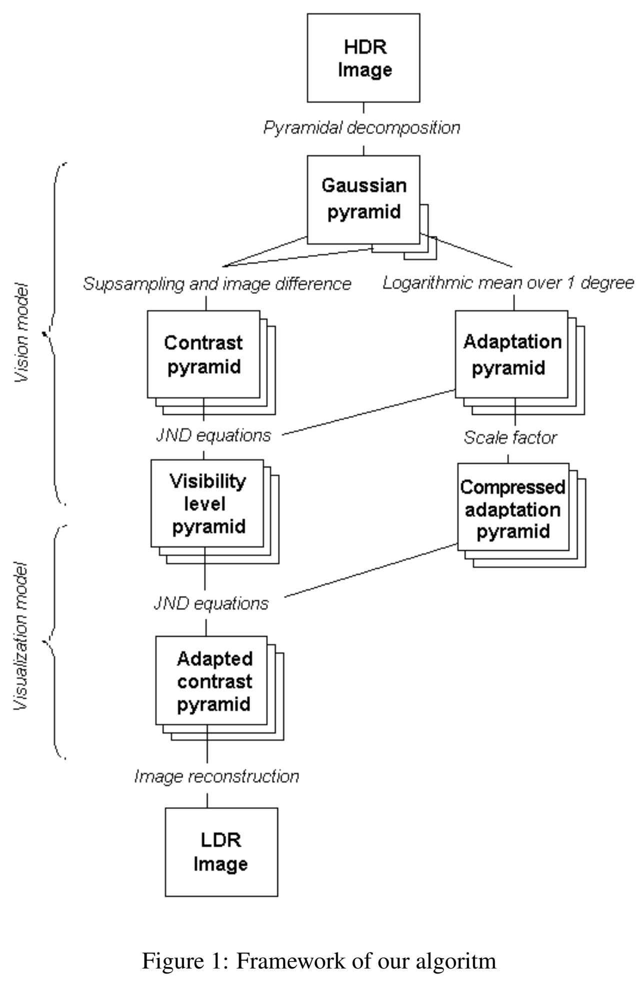

Figure 1: Framework of our algoritm

The filtering process downsamples the image. To calculate a pyramid of difference-of-Gaussian images, we take the image at level l, L_w^l, and we subtract the image at level $l+1$ which has been upsam-

0.0025	0.0125	0.02	0.0125	0.0025
0.0125	0.0625	0.1	0.0625	0.0125
0.02	0.1	0.16	0.1	0.02
0.0125	0.0625	0.1	0.0625	0.0125
0.0025	0.0125	0.02	0.0125	0.0025

Table 1: 5×5 gaussian filter, w, used to build the Laplacian pyramid

pled by bilinear interpolation, denoted $L_{wExpand}^{l+1}$:

$$C_w^l(i,j) = L_w^l(i,j) - L_{wExpand}^{l+1}(i,j) \tag{2}$$

This results in a 7 levels pyramid, the first 6 levels are band-pass images and the last higher level is a low-pass image. We denote C_w^l the band-pass images and in what follows we call them contrast images.

We aim at preserving the contrast perception, which means that the observer should perceive in the same way both the contrast of a pixel in the HDR image and the contrast of the same pixel in the processed and displayed image. To quantify the contrast perception, considering visual performance, we use the Visibility Level (VL), defined in road visibility [Adrian 1991]:

$$V^l(i,j) = \frac{C_w^l(i,j)}{\Delta L_t(L_{aw}^l(i,j))} \tag{3}$$

where V^l is the image of VL values at level l, ΔL_t is the perception threshold of luminance difference which depends on an adaptation luminance denoted L_{aw}^l.

To compute the contrast threshold ΔL_t, we use sensitivity functions also called Just Noticeable Difference (JND) [Larson et al. 1997], which connect the adaptation luminance (AL) to the minimum detectable luminance change. In our case, the AL values are reckoned from the $L_{wExpand}^{l+1}$ images. We use the same definition for AL as Ward [Ward 1994] and we consider that the visual adaptation is mainly achieved in foveal vision, which as a field of around 1 degree. So we compute the logarithmic mean of luminance over 1 degree in the visual field. To accelerate the computation, we calculate AL values every 0.5 degree. The AL values at pixel (i,j) is computed from the 4 closest values using bilinear interpolation.

3.2 Image reconstruction for display

The VL images are used to compute new contrast images C_d^l, d for display, adapted to the display device characteristics on which we will display the rebuilt image. The new contrast images are computed using equation 3 and the JND:

$$C_d^l(i,j) = V^l(i,j).\Delta L_t(L_{ad}^l(i,j)) \tag{4}$$

New adaptation images L_{ad}^l are computed from the old ones L_{aw}^l, using a scale factor k [Ward 1994] and the display device characteristics. If the AL values are included in the display device luminance range, there is no need to modify them. So the scale factor is clipped to 1 (see equation 6).

$$L_{ad}^l(i,j) = k.L_{aw}^l(i,j) \tag{5}$$

$$k = Min\left(\left[\frac{1.219 + ((L_{dmax} - L_{dmin})/2)^{0.4}}{1.219 + (L_a^l)^{0.4}}\right]^{2.5}, 1\right) \tag{6}$$

L_{dmax} and L_{dmin} are the extreme luminances that can be displayed by the device and L_a^l is the logarithmic mean of the luminances in image L_{wa}^l.

The last level of the pyramid being a low-pass imag, is scaled with the factor k of equation 6.

The image is reconstructed, following the inverse process of the pyramidal decomposition. The last level is upsampled by bilinear interpolation and added to the next lower level. The result is upsampled and added to the next lower level and so on until the image is rebuilt. We finally apply a display device model to convert luminance values into addressing values. The device model is a table which maps displayed luminance to 8-bit numeric values [CIE122 1996].

Figures 1 is a framework of our algorithm. Figure 2 illustrates the different steps of the process in a 3 level pyramid. Figures 3, 4 and 5 show images processed by different TMOs. We cannot judge or compare the TMOs based on those images because they have been calculated to be displayed on a specific display device and because we cannot show the HDR image. At this stage of our work, we need to evaluate our algorithm with an objective method.

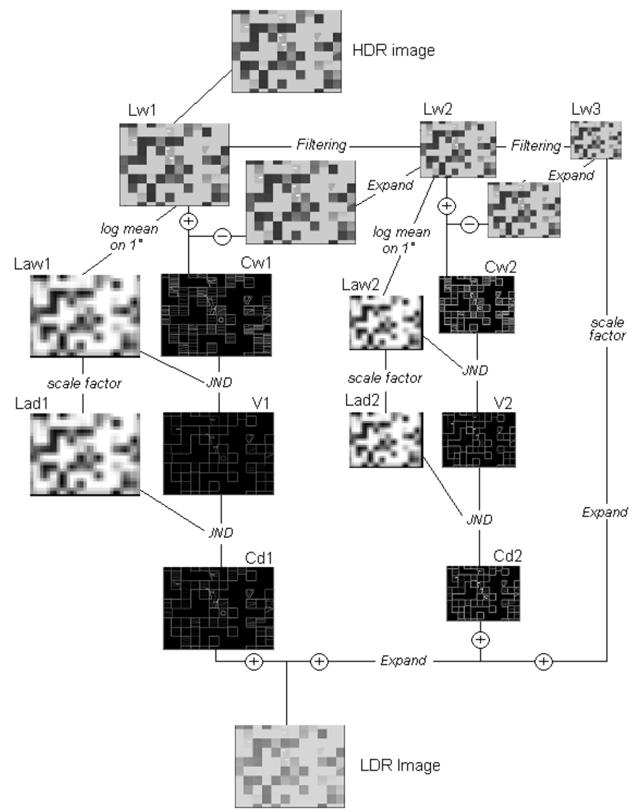

Figure 2: Example of a 3 level pyramid

4 The evaluation

The general principle of the experiments that will enable us to evaluate our TMO coupled with a display device [Grave and Brémond 2005] is to compare the observer's visual performance measured in two display configurations. First when the observer is looking at

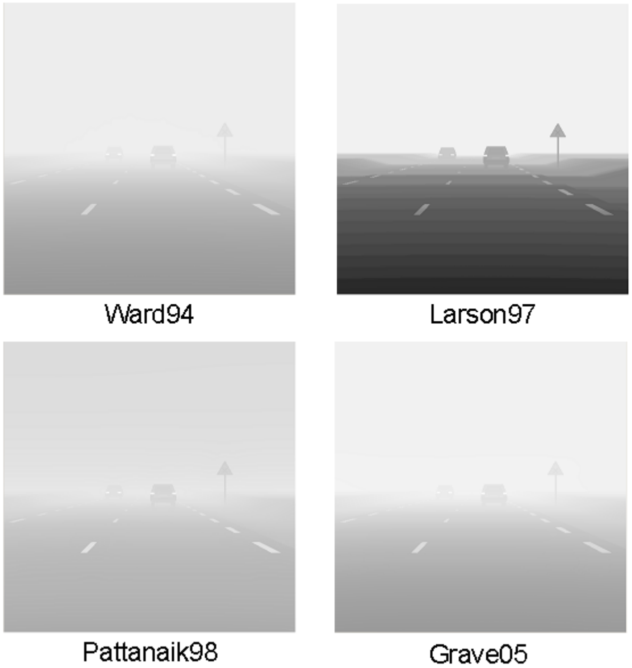

Figure 3: Synthetic image of a foggy daytime driving scene processed by four TMOs, $Lmax = 1000\ cd.m^{-2}$ and $Lmin = 114.65\ cd.m^{-2}$

a reference scene, which is, in our case, a HDR image. Secondly when we show the tone mapped scene on a LDR display device [Viénot et al. 2002] (figure 6); we call this configuration the comparison scene. The performance differences between the reference scene and the comparison scene are measured and compared for different TMOs, our operator and three other that were chosen for our investigations: Ward's [Ward 1994], Larson et al.'s [Larson et al. 1997] and Pattanaik et al.'s [Pattanaik et al. 1998].

The experiments are carried out in a dedicated room at the LCPC. The room is painted black and has no window so that we can control the illumination and reproduce the experimental condition at any time. We chose to compare the visual performance of the observer with a reference scene (a contrast ratio of 1000 : 1 and a maximum displayable luminance of 500 $cd.m^{-2}$) and with the same scene processed with a TMO and displayed on a LCD screen (a contrast ratio of 400 : 1 and a maximum displayable luminance of 167 $cd.m^{-2}$).

4.1 The reference scene

The reference scene needs two display devices to project the image on a screen. A first image is projected by a Digital Light Processing videoprojector (DLP) in the center of the screen. The (DLP) has been calibrated [CIE122 1996], which means that we measured with a photometer the displayed luminance corresponding to an addressing value. A second image is projected with a overhead projector for the peripheral vision (see figure 7).

4.2 The comparison scene

The configuration we chose for the comparison scene is very close to the configuration of the reference scene. The image is processed

Figure 4: Picture, taken with a calibrated digital camera, of an urban scene in the evening, processed by four TMOs, $Lmax = 478\ cd.m^{-2}$ and $Lmin = 0\ cd.m^{-2}$

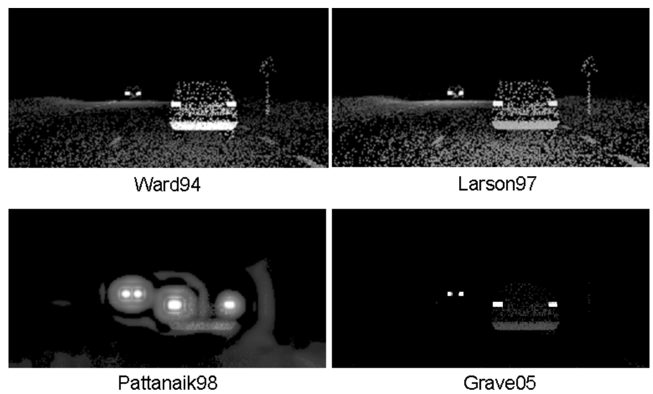

Figure 5: Synthetic image of a night-time driving scene processed by four TMOs, $Lmax = 16180.9\ cd.m^{-2}$ and $Lmin = 0\ cd.m^{-2}$

by a TMO and displayed on a calibrated LCD [CIE122 1996]. The image projected by the overhead projector is dimmed with a neutral filter and projected on a polystyrene screen, in which the LCD is inserted. The filtering process decrease the projected luminance for the peripheric vision with a amplitude similar to what sustained the luminance of the image displayed on the LCD.

4.3 The performance task

We chose the danger detection as a relevant visual task for driving. This task is related to performance indexes. We decided to measure visual performance with a Landolt ring. This greatly simplifies the visual task we are interested in but it leads to a fundamental aspect of that task and it is often used for road visibility and road lighting studies [Adrian 2003]. The broken ring of Landolt is the simplest optotype. An optotype is a visuel test which leads to a certain point to form recognition. This test is already complex and the detection of the gap depends on several parameters (see figure 8):

- the time during which the gap is shown

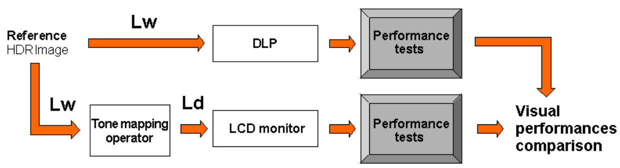

Figure 6: General principle of the evaluation experiment

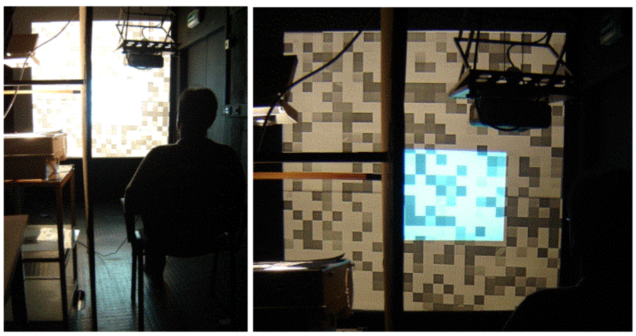

Figure 7: The reference scene in the CLOVIS room

- the background luminance L_b
- the size of the gap e (minute of angle). The custom is to characterize the gap by the visual acuity $V = \frac{1}{e}$
- the contrast (defined as Weber fraction) between the background luminance L_b and the ring luminance L_t, $C = \frac{L_b - L_t}{L_b} = \frac{\Delta L}{L_b}$
- the position of the gap (which has 4 or 8 different positions)

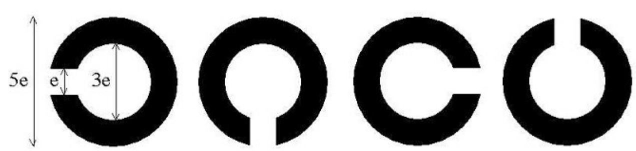

Figure 8: Description of the Landolt ring for the performance test

We show the ring on a square with a uniform luminance. The ring and the square are called "the test". We also add visual noise (see paragraph 4.4). To correctly insert the test in the peripheral image, we chose L_b to be equal to the adaptation luminance of the noise image.

In the experiments we set several paramaters:

- the gap is shown during 100 ms,
- L_b is equal to the adaptation luminance computed with the Moon and Spencer [Moon and Spencer 1945] method, assuming the gaze is centered on the ring,
- the size of the gap is set to $e = 8$ minute of angle, which fits with a visual acuity $V = 0.13$ (calculated with the scene geometry and the observer's position).

Two parameters may vary:

- the contrast is positive and takes 8 different values from a value that is under the perception threshold to a value that is easily detected
- the gap can be at 4 different positions (see figure 8)

4.4 The peripheral image

The function of the peripheral image is to adapt the observer's vision to a luminance high enough to limit his eyestrain. The performance test is a Landolt ring on a uniform square. The image into which the test is inserted is chosen to qualify for:

- a luminance histogram close to the one of a driving scene with specific visibility conditions. The results presented here are obtained with a daytime driving scene with fog [Dumont and Cavallo 2004] (see figure 9),
- the absence of semantic to limit the cognitive aspect of the visual environment.

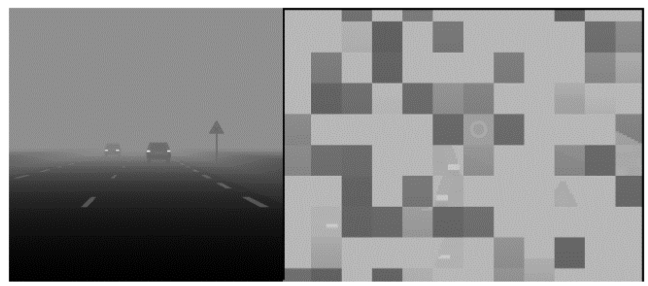

Figure 9: Image used to make the visual noise into which is inserted the performance test (left) and the test image with the performance test in its center (right)

To make the noise image, a HDR image of a simulated driving scene [Dumont and Cavallo 2004] is first clipped to 500 $cd.m^{-2}$ (since it is the maximum luminance we can display with the video projector that displays the HDR image). The image is divided into blocks, the same size as the performance test. The blocks are mixed randomly to remove the semantics while preserving the luminance histogram.

4.5 The experimental protocole

For every test, we display during 1 s an image with a full ring. Then, for 100 ms, the gap in the ring is displayed at one of the 4 possible positions (see figure 8). The observer indicates on a gamepad the position of the gap he has perceived. We ask the observer to give an answer whether or not he thinks he has seen the gap. The answer is recorded and the next test is displayed. We did the experiment twice: first with 9 observers and then with 4 observers. Among the 9 observers, 3 were women and 6 were men. 5 of them were between 20 and 35 years and 4 between 35 and 50. Among the 4 observers, 3 were men and 1 was a woman. 2 of them were between 20 and 35 years and 2 between 35 and 50. Every observer sat 3 m from the screen where the HDR image was projected and 1.5 m from the LCD monitor, to preserve the angular size of a pixel. We showed 136 tests for the reference scene and for each of the TMO we tested.

5 Results

We consider an average observer whose visual performance are computed by averaging the visual performance of 9 (or 4) observers. Those visual performance are shown in figure 10. We can compare the visual performance measured with the reference scene (HDR image) and those measured with the image processed by our TMO. For a better comparison of the performance, we calculate an estimation of the margins of error around the reference values of the rate of the correct answers, for each contrast. We consider that for a certain contrast c, the tests are realisations of a random variable, the expectation of which is the performance of the average observer p_c. Let us denote X_c, a random variable that follows the Bernouilli distribution. X_c can take 2 values, 1 if the answer is correct (with the probability p_c) and 0 if it is wrong (with the probability $q_c = 1 - p_c$). Let us denote Y_c, a random variable corresponding to the number of correct answers for contrast c (17 for each of the 9 observers). Y_c follows a binomial distribution with parameters $n = 153$ and p_c. The Bienaymé-Tchebychev inequality gives:

$$P(|E(Y_c) - Y_c| \geq \varepsilon_c) \leq \frac{V(Y_c)}{\varepsilon_c^2} \tag{7}$$

If we denote $\alpha = \frac{V(Y_c)}{\varepsilon_c^2}$, then $\varepsilon_c = \sqrt{\frac{V(Y_c)}{\alpha}}$. We denote $F_c^n = E(Y_c)/n$, the rate of correct answers. We know that $E(Y_c) = n.p_c$ and $V(Y_c) = n.p_c.(1-p_c)$ (Binomial distribution properties). So $E(F_c^n) = p_c$ and $V(F_c^n) = p_c.(1-p_c)/n$. We want $\varepsilon_c = \sqrt{\frac{p_c.(1-p_c)}{n.\alpha}}$ such that:

$$\begin{array}{l} P(|F_c^n - p_c| \geq \varepsilon_c) \leq \alpha \\ \Leftrightarrow P[(F_c^n - \varepsilon_c) \leq p_c \leq (F_c^n + \varepsilon_c)] \geq (1-\alpha) \end{array} \tag{8}$$

If we choose $\alpha = 0.1$, which is the same as looking for a margin of error (+ or - ε_c around the value of F_c^n) which gather together 90 percents of the values that F_c^n can take. We can estimate the values of ε_c with $\sqrt{\frac{p_c.(1-p_c)}{n0.1}}$ (see table 2).

Estimation of p_c	Estimation of ε_c
0.2876	0.1157
0.5621	0.1268
0.4967	0.1278
0.7124	0.1157
0.8824	0.0824
0.9150	0.0713
0.9379	0.0617
0.9673	0.0455

Table 2: Estimated margins of error with $n = 153$ and $\alpha = 0.1$

Figure 10 shows the visual performance measured with the reference scene and the margins of error estimated for the reference. The performance values measured with the images processed by our TMO are mostly within the margins of error except for contrast 0.034 which seems to be an absurd value of the reference.

6 Discussion

The plot at the top of figure 11 shows the average visual performance calculated over 9 observers, and compares our operator to two other TMOs ([Ward 1994] and [Larson et al. 1997]). The plot at the bottom of figure 11 shows the average visual performance

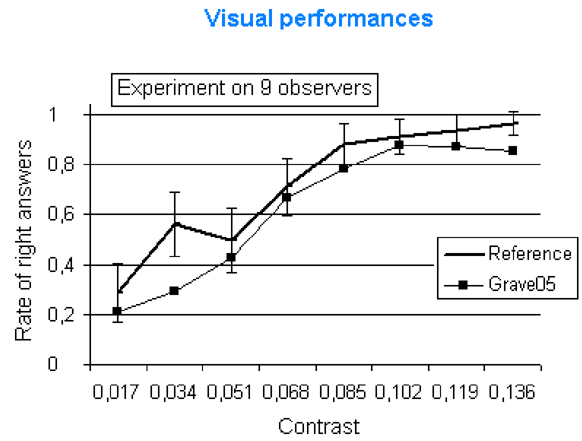

Figure 10: Visual performance measured with the reference scene and with the image processed by our TMO.

calculated over only 4 observers (because we had less time to organize the tests) and compare our operator to three other TMOs ([Ward 1994] [Larson et al. 1997] and [Pattanaik et al. 1998]). The results of the experiments, for a luminance distribution that is similar to a daytime driving situation with fog, showed the TMO we propose gives better results than those obtained with the TMO proposed by Ward, Larson et al. and Pattanaik et al., considering visual performance around the threshold value of contrast.

7 Conclusion and further works

We propose a new tone mapping algorithm, designed for a detection task, for road visibility and road lighting studies. Our main objective is to preserve the observer's visual performance despite the luminance dynamic range compression of images. To evaluate our algorithm and to check that it fulfills this condition, we carried out a psychophysical experiment in order to compare visual performance measured with a reference scene, a HDR image, and with a comparison scene. The comparison scene was made of the reference scene tone mapped and displayed on a LDR display device. Even if we had few subjects, the results seem to show that our TMO best preserves the visual performances, for a daytime driving situation, around the threshold of the visual perception, compared to some of the TMOs from literature we chose for our investigation.

We want now to widen the validation of our TMO to other driving visibility conditions such as urban, night-time and evening scenes. In night-time scenes, we are confronted with other display problems than only luminance dynamic range compression. First, most luminance values are under the lower luminance most devices can display (under 0.5 $cd.m^{-2}$). Secondly, in that low luminance range, because of the display device quantification, two luminance values with noticeable difference may be associated to the same addressing value. This is not taken into account in our algorithm. For that purpose, there are two stages in our operator we could improve. The first stage is the compression of the adaptation luminances. We force the scale factor to be lower or equal to 1. If for night-time or evening scenes, the scale factor is allowed of being over 1, the contrasts will be intensified so that some of them will be perceived in the LDR image. We should also use other characteristics of the display device beyond the minimum and maximum displayable lu-

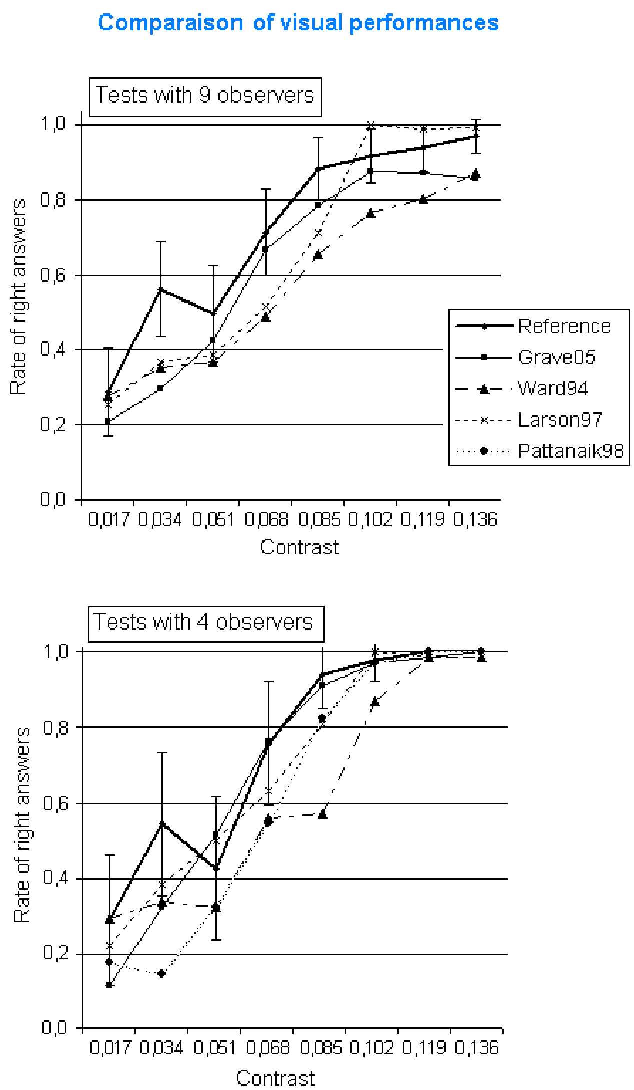

Figure 11: Comparison of visual performance measured with 9 observers in the graph at the top of the figure and with 4 observers in the graph at the bottom of the figure for 4 different TMOs.

minance values. Achievable visibility levels is something we want to take into consideration. This is our work in process.

Three other aspects of our work may lead to further improvements. First, we should add glare effect, in particular in night-time scenes, implementing Spencer et al. glare model [Spencer et al. 1995]. Secondly, we want to compare our algorithm to Reinhard et al. TMO [Reinhard et al. 2002] which appears to be effective despite the lack of vision model [Ledda et al. 2005]. Finally, we want to test our TMO on display devices which has the same characteristics as driving simulators, which have very low luminance dynamic range.

And in the long term, we want to introduce a dynamic aspect which is one of the important characteristics of the driving task.

8 Acknowledgments

We would like to thank the participants for taking part of the experimental study. We would also like to thank Eric Dumont, Jean-Philippe Farrugia, Bernard Péroche and Françoise Viénot for their help in the progress of this work.

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