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HDR Images from Photos of Car Paint with Sparkling Effect

(Bachelor Thesis)

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I hereby declare I wrote this thesis by myself, only with the help of referenced literature, under the careful supervision of my thesis advisor.

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Abstract

High dynamic range (HDR) imaging is a promising technology for a sparkling effect visualization. We investigate and propose a technique to generated HDR images of sparkling dot pattern observed on car paint from near focus photos. Our setup solves the problem of image blurring during the reconstruction process. Second part of this research is focused on visualization of car paint HDR images both, directly on HDR and LDR display. Surprisingly, our research concludes that HDR displays are not capable of sparkle visualization. On the other hand, only Mantiuk's and Reinhard's tone mapping operators showed enhanced sparkling effect on LDR monitors from all other reviewed operators in this work.

Keywords: HDR, tone mapping operator, sparkling effect, car paint

Contents

Chapter 1

Introduction

High Dynamic Range is set of techniques to capture greater dynamic range (ratio between bright and dark regions) of exposure than normal imaging technique. While with classic photo technique we can capture only limited dynamic range, HDR can be created as composition of images with various dynamic range that represents wide range of intensity found in real world.

The aim of this thesis is to present high dynamic range imaging as capturing technique of sparkling effects with focus on visualization and reproduction of sparkle appearance in car paints.

Car paint with sparkling effect contains great amount of very small particles, tiny mirrors, that in different light conditions reflect light in various intensity. Image consists of dark, bright areas and very bright dots that often cover a spherical angle less that 1° producing glow and glare effects on photo sensor and human eye. In such complex images it is often problem to compose multiple images to avoid blurring effect. The proposed device setup takes 3 images with different exposure settings to create final HDR image.

The second problem that is described and solved in this work is visualization of sparkling effect on HDR and LDR displays. By direct visualization on HDR displays we expect to get natural images including all human vision effects such as glow and glare effect produced by high illumination on human eye lens and retina. On the other hand, by visualization on LDR displays we expect to find best tone mapping operator and its parameters for sparkling visualization on conventional displays. We have selected and reviewed most common tone mapping operators in graphics community including very new operator [8]. The performed tests are summarized in the table 4.1 including results of tone mapping operators.

Best to our knowledge, we didn't find works related to HDR reconstruction of dot sparkling effect. Nevertheless, there are approaches that model the sparkling effect in a rendering algorithm such as [4], where authors explicitly modeled the sparkles by coins with successful modeling depth effect appearance. Authors in [5, 6] used random generator and Russian roulette algorithm to decide when the camera ray hits a sparkle. Multitexture approach using texture synthesis from Voronoi diagrams and tiny pyramids have been used in simulation of sparkling in aventurescent gems[13].

The camera setup with settings is described in Chapter 2. This chapter also describes the composition technique of captured photo images and the parameter setting of response curve for best sparkle capture. Chapter 3 describes tone mapping operators algorithms used to visualize sparkling effect on LDR monitors. The results are compared and concluded in chapter 4.

Chapter 2

HDR creating

Creating HDR images from car paint samples is process which consists of two main parts. The first part is digitizing car paint sample with appropriate equipment and settings so the final images have sufficient quality and characteristics. The second part describes creation of final HDR image from set of digitized images of car paint.

2.1 Capturing car paint

Creating photographs of car paint with sparkling effect with different exposure presets is very sophisticated process. Single car paint consists of layers with embedded particles. As top layer is very glossy, it could be hard to capture the scene without reflection of illuminators. Distinct feature of modern car paint is that it is orientation dependent. When turned around, different sparkles begin to sparkle. This effect is caused by random orientation of sparkles in car paint. During HDR image capturing it is needed that individual photos capture the same scene, that means the same set of sparkles should be illuminated. Otherwise the resulting image will be blurred. This can happen even when camera slightly moves by touching.

Paint particles are very small, hence I use camera with high resolution to gain high quality of each photo. To achieve very detailed photo I use macro lens and to avoid reflection of light flash from top layer, I will use macro flash. Of course a remote switch will prevent camera movements.On figure 2.1 is the whole configuration which consists of Canon 30D, Canon EF-S 60mm Macro USM lens, Canon Macro Twin Lite MT-24EX flash and remote switch, was arranged upright to car paint at a distance $10 - 15$ centimeters.

Figure 2.1: Camera configuration: Canon 30D, Canon EF-S 60mm Macro USM lens, Canon Macro Twin Lite MT-24EX flash and remote switch.

2.1.1 Camera settings

The first camera setting need to be set is aperture. With low aperture number picture is unsatisfactory, because the outer part of photo will be blurred. Sufficient setting for our purpose is $F16$. Shutter speed, second setting, is set to 1/15 sec. To simplify shooting process and avoid camera shaking, we use remote shutter and set on flash AE bracketing, begin in -2 EV with 1 EV increment. This enable us to capture 3 pictures of same scene, each with different exposure setting, particular with -2 EV, 0 EV, 2 EV, as you can see on figure 2.2. While at HDR creating is possible to use various image formats, we store photos in RAW and JPEG with resolution 8 MPix.

Figure 2.2: Images of same car paint with different exposure setting. From left to right: -2 EV, 0 EV, 2 EV

2.1.2 HDR creation

For creating HDR images, we use the Open Source software Qtpfsgui [12], which dispose many additional options. The first advantage is capability to make HDR from different image formats. In our research we are making HDR from both formats we shoot, RAW and JPEG. To create result image properly it is important to set the exposure value for each photo to same value as it was shot (in our case it was -2 EV, 0 EV and 2 EV). Another part consists of HDR creating options, where individual options are camera response curve, weighting function and HDR creation model. Camera response curve is a curve showing the relation between amount of incoming light and image pixel values of a digital camera. When making HDR from RAW format data the response curve is linear, because RAW images contain linear sensor data. Next setting related to response curve is a Gamma parameter. The weighting function assigns a weight to all pixels (a value between 0 and 1 multiplied with the pixel value) it determines the trust of every pixel. In Qtpfsgui it is possible to set three different weighting functions: triangular, Gaussian and Plateu. Each function makes a bit different effect to final image. Last option, HDR creation model, has two possible values, Debevec model and Robertson model. We will use only Debevec's model.

At creating HDR images, we use the source photos in RAW and JPEG formats with different settings of weighting function and response curve. We compared the results from RAW and JPEG to find out which one reproduces the best sparkling effect and have the same color appearance as car paint sample. At first sight the best results has had images created with linear response curve and triangular weighting function. As best result in comparison between HDR images created from RAW and JPEG seems to be the image made from RAW. Careful investigation of HDR images from RAW data shows that various settings of weighting function and response curve have almost similar results, but we find out that darker samples had best results with different settings than brighter ones. Shown dark sample had the best result with triangular weighting function, on the other hand brighter sample best reproduces the HDR with Gaussian weighting function. As was mentioned above the response curve is set to linear when using the RAW format.

Chapter 3

Tone Mapping Operators

Tone mapping is technique used to map a set of colours to another, in this case to approximate the appearance of high dynamic range images in media with more limited dynamic range. Tone mapping operators are specific algorithms that prepare HDR images for display on LDR display devices. The goal of tone mapping in this thesis is reproducing as many image details as possible and maximize the contrast. Another information source for writing this chapter was book from Reinhard et. al, High dynamic range imaging[11]. Tone mapping operators can be divided in four main categories:

Global Operators: Compress images using an identical(nonlinear) curve for each pixel.

Local Operators: Achieve dynamic range reduction by moduling a nonlinear curve by an adaption level derived for each pixel independently by considering a local neighborhood around each pixel.

Frequency Domain Operators: Reduce dynamic range on image components selectively, based on their spatial frequency.

Gradient Domain Operators: Modify the derivative of an image to achieve dynamic range reduction.

3.1 Global Operators

Global operators are nonlinear functions based on the luminance and other global variables of the image. Such functions usually take for each pixel its value and a globally derived quantity, which map each pixel in the image in the same way. The main advantages of this operators are their simplicity and fastness. On the other side, they can cause the loss of contrast.

3.1.1 Adaptive Logarithmic Mapping for Displaying High Contrast Scenes

First global spatially uniform operator is Adaptive logarithmic mapping [2]. This algorithm is intended to imitate the human eye's response, and is useful when a true tone result is desired. At the beginning, it compute the logarithmic average of the scene based on luminance values for all pixels and, using this value and the external parameter "bias", it creates a non-linear logarithmic function that is applied to each pixel separately, without considering the neighboring pixels.

Algorithm

The operator effectively applies a logarithmic compression to the input luminance values, but the base of the logarithm is adjusted according to each pixel's radiance. The luminance values are interpolated from $\log_2(L_w)$ and $\log_{10}(L_w)$, allowing contrast and detail preservation in dark and medium luminance regions while still compressing light regions by larger amounts. A logarithmic function of arbitrary *base* may be constructed from logarithmic functions with a given base, as follows:

$$\log_{base} = \frac{\log(x)}{\log(base)} \tag{3.1}$$

To smoothly interpolate between different logarithmic bases, authors use Perlin and Hoffert's bias function:

$$bias_b(t) = t^{\frac{\log(b)}{\log(0.5)}} \tag{3.2}$$

where b is "bias" user parameter. The final tone mapping function, which is used to compute a displaying value L_d for each pixel is defined:

$$L_d = \frac{L_{d,max} \cdot 0.01}{\log_{10}(L_{w,max})} \cdot \frac{\log(L_w + 1)}{\log\left(2 + 8\left(\left(\frac{L_w}{L_{w,max}}\right)^{\frac{\log(b)}{\log(0.5)}}\right)\right)} \tag{3.3}$$

where $L_{d,max}$ is the maximum display luminance and appropriate value is $100cd/m^2$, $L_{w,max}$ is maximum luminance in the scene, L_w is luminance of pixel and b is "bias" user parameter. The constants 2 and 8 bound the chosen logarithmic base between 2 and 10 in Equation 3.1.

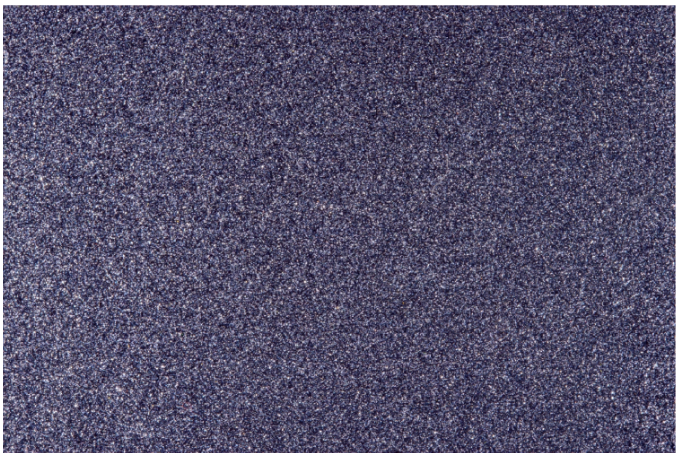

Figure 3.1: Tone mapped image generated with adaptive logarithmic mapping. Only one parameter "bias" was set on 0.85.

3.1.2 Dynamic Range Reduction Inspired by Photoreceptor Physiology

Dynamic range reduction [9] operator is a relatively simple algorithm with only minimum processing on the original image. Authors adapt a computational model of photoreceptor behavior to help solve the tone reproduction problem.

Algorithm

Authors employed a model of photoreceptor adaptation, which can be described as the receptor's automatic adjustment to the general level of illumination. The following formulation is practical for the purpose of tone reproduction:

$$V = \frac{I}{I + \sigma(I_a)} \tag{3.4}$$

where V is photoreceptor response, I is photoreceptor input and σ is the semi-saturation constant(which is a function of the receptor's adaptation level I_a). For practical purposes, the semi-saturation constant may be computed from the adaptation value I_a as follows:

$$\sigma(I_a) = (fI)^m \tag{3.5}$$

where f and m are user parameters. The scale factor f can initially be estimated as 1. A reasonable initial estimate for m may be derived from image measures such as the minimum(L_{min}), maximum(L_{max}), and average luminance(L_{av}), as follows:

$$\begin{aligned} m &= 0.3 + 0.7k^{1.4} \\ k &= \frac{L_{max} - L_{av}}{L_{max} - L_{min}} \end{aligned} \tag{3.6}$$

where luminance is specified as:

$$L = 0.2125I_r + 0.7154I_g + 0.0721I_b \tag{3.7}$$

The exponent m is used to steer overall impression of contrast.

Equation 3.4 is applied to each red, green and blue channels separately, because it is similar to photoreceptor behavior, in which each of the three different cone types is thought to operate largely independently. Strong color casts may be removed by interpolating between the luminance value L of the pixel and the red, green and blue intensity values of each pixel $I_{r|g|b}$. This produces a different adaptation level I_a for each pixel individually:

$$I_a = cI_{r|g|b} + (1 - c)L \tag{3.8}$$

where amount of color correction is controlled by the weight factor c which is also called chromatic adaptation. No color correction is applied if c equals 0 and if c equals 1 is achieved a von Kries style of color correction.

Sometimes is good to control whether the pixel adaptation is based on the pixel intensity itself, or on global averages:

$$I_a = aI_{r|g|b} + (1 - a)I^{av}_{r|g|b} \tag{3.9}$$

where a is light adaptation and interpolates between the pixel intensity $I_{r|g|b}$ and the average channel intensity $I^{av}_{r|g|b}$. When a equals 1, adaptation is based on the pixel intensity, and if a equals 0, the adaptation is global.

Light adaptation and chromatic adaptation may be combined by bilinear interpolation, as follows:

$$\begin{aligned} I_a^{local} &= cI_{r|g|b} + (1-c)L \\ I_a^{global} &= cI^{av}_{r|g|b} + (1-c)L^{av} \\ I_a &= aI_a^{local} + (1-a)I_a^{global} \end{aligned} \tag{3.10}$$

Figure 3.2: Reinhard's dynamic range reduction produced with brightness set on -10, chromatic adaptation set on 1 and light adaptation set on 1.

3.2 Local Operators

In local operator's nonlinear functions are parameters changed in each pixel, according to its luminance value, as well as to the luminance values of a set of neighboring pixels. That mean the effect of the algorithm changes in each pixel according to the local features of the image. This algorithms are more complicated than global operator's, but they can provide best performance, since the human vision is mainly sensitive to local contrast.

3.2.1 A Tone Mapping Algorithm for High Contrast Images

Next operator is a tone mapping algorithm for high contrast images [1]. The operator is performed in three steps. First, it estimates the local adaptation luminance at each point in the image. Then, a simple function is applied to these values to compress them into the required display range. Since important image details can be lost during this process, algorithm reintroduces details in the final pass over the image. Ashikhmin's operator is aimed at preserving local contrast, which is defined as:

$$c(x,y) = \frac{L(x,y)}{L_a(x,y)} - 1 \tag{3.11}$$

where L is pixel luminance and L_a is local adaptation level. Final mapping to the display luminance is defined as:

$$L_d(x,y) = TM(L_a(x,y))\frac{L(x,y)}{L_a(x,y)} \tag{3.12}$$

where $TM(L)$ is tone mapping function.

Local adaptation level

The local adaptation level of the pixel is a Gaussian weighted average of the pixel values taken over some neighborhood. It is very important to choose the neighborhood as large as possible without crossing sharp luminance gradients. To compute if a pixel neighborhood contains any large gradients is used band-limited local contrast lc:

$$lc(s,x,y) = \frac{G_s(L)(x,y) - G_{2s}(L)(x,y)}{G_s(L)(x,y)} \tag{3.13}$$

where $G_s(L)$ represents the result of applying gaussian filter of width s to the input image. If the difference of $G_s(L)(x,y)$ and $G_{2s}(L)(x,y)$ is close to 0, no sharp gradients occurred in the pixel's neighborhood. For each pixel is chosen the smallest scale s_t from range 1 to 10, for which $lc(s_t,x,y)$ exceeds a user-specified threshold t. Default value of this threshold is 0.5. While scale s_t is the size of a locally uniform neighborhood, the local adaptation level L_a is G_{s_t}

Tone mapping function

To construct the tone mapping function $TM(L)$, Ashikhmin introduces the notion of perceptual capacity of a range of luminance values. As a scaling factor for a small range of luminance values ΔL can be used human sensitivity to luminance changes, which is given by threshold versus intensity(TVI) functions. Perceptual importance of a just noticeable difference is independent of the absolute luminance value for which it is computed. For a range of world luminance values between 0 and L, perceptual capacity $C(L)$ is defined as:

$$C(L) = \int_0^L \frac{dx}{TVI(x)} \tag{3.14}$$

The perceptual capacity of a world luminance range from L_1 to L_2 is simply $C(L_2) - C(L_1)$. The TVI function is approximated by four linear segments(in log-log space), thus the perceptual capacity function becomes:

$$C(L) = \begin{cases} L/0.0014 & \text{if } L < 0.0034 \\ 2.4483 + \log(L/0.0034)/0.4027 & \text{if } 0.0034 \leq L < 1 \\ 16.5630 + (L-1)/0.4027 & \text{if } 1 \leq L < 7.2444 \\ 32.0693 + \log(L/7.2444)/0.0556 & \text{otherwise} \end{cases} \tag{3.15}$$

The final tone mapping function is defined as:

$$TM(L) = L_{d,max} \frac{C(L) - C(L_{min})}{C(L_{max}) - C(L_{min})} \tag{3.16}$$

where $L_{d,max}$ is the maximum displayable luminance and L_{min} and L_{max} are minimum and maximum luminance values.

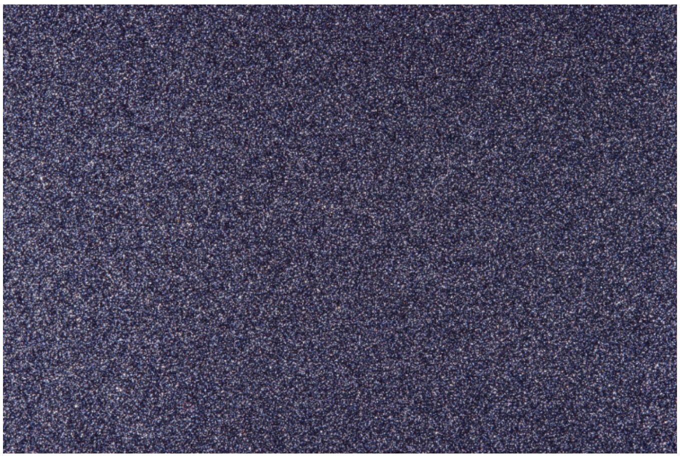

Figure 3.3: Ashikhmin's tone mapping algorithm with local contrast threshold set to 0.5.

3.2.2 Photographic Tone Reproduction for Digital Images(Reinhard)

Another operator from Reinhard is a Photographic tone reproduction for Digital Images[10]. For this algorithm development is used the basic conceptual framework of the Zone System to manage choices in tone reproduction. First of all, a linear scaling is applied to image. Then is applied automatic dodging-and-burning to accomplish dynamic range compression.

Linear scaling

Like many other tone-reproduction operators, Reinhard et al. view the log average luminance $\overline{L}_w$ as a useful approximation of a scene's key, which is an indicator of how light or dark the overall impression of scene is. The quantity $\overline{L}_w$ is computed by:

$$\overline{L}_w(x,y) = \frac{1}{N} exp\left(\sum_{x,y} \log(\delta + L_w(x,y))\right) \tag{3.17}$$

where N is the total number of pixels in the image, δ is a small value to avoid the singularity that occurs if black pixels are present in the image and L_w is "world" luminance for pixel (x, y). For average-key scenes, $\overline{L}_w$ is mapped to 18% of the display range, but in case of this thesis, $\overline{L}_w$ is mapped to 2% of the display range because the overall impression of the scene is dark. The initial scaling is then given by equation:

$$L(x,y) = \frac{a}{\overline{L}_w} L_w(x,y) \tag{3.18}$$

where a is a user parameter defining the value which $\overline{L}_w$ is mapped to. The main problem with equation 3.18 is that many scenes have a predominantly average dynamic range with a few high luminance regions near highlights. In modern photography are used transfer functions that predominantly compress high luminance values. This may be modeled with this compressive function:

$$L_d(x,y) = \frac{L(x,y)}{1 + L(x,y)} \tag{3.19}$$

This function scales small values linearly, whereas higher luminance values are compressed by larger amounts. This formulation is guaranteed to bring all luminance values within displayable range. But equation 3.19 can be extended to allow high luminance values to burn out in a controllable fashion:

$$L_d(x,y) = \frac{L(x,y)\left(1 + \frac{L(x,y)}{L_{white}^2}\right)}{1 + L(x,y)} \tag{3.20}$$

where L_{white} is the smallest luminance that will be mapped to pure white. By default is L_{white} set to the maximum luminance in the scene. This equation is reasonable global tone mapping operator. However, it may be modified to become a local tone mapping operator by applying dodging-and-burning algorithm.

Automatic dodging-and-burning

Dodging and burning is a printing technique where some light is withheld from a portion of the print during development (dodging), or more light is added to that region (burning). This may bring up selected dark regions, or bring down selected light regions.

In traditional dodging and burning, the area that receives a different exposure from the remainder of the print is bounded by sharp contrast. This is a key observation that should be reproduced by an automatic dodge-and-burn algorithm.

For each pixel, it is necessary to find the largest surrounding area that does not contain any sharp contrasts. Contrast measures frequently use a center-surround function which is often implemented by subtracting two Gaussian blurred images. For the same pixel in the center are computed two Gaussian-weighted averages over smaller(center) and larger(surround) areas and compared to each other. If there is no significant contrasts in the pixel's neighborhood, the difference of these two Gaussians will be close to 0. On the other side, if there is a contrast edge that overlaps the surround but not the center Gaussian the two averages will be significantly different. This function is constructed using circularly symmetric Gaussian profiles of the form:

$$R_i(x, y, s) = \frac{1}{\pi(\alpha_i s)^2} exp\left(-\frac{x^2 + y^2}{(\alpha_i s)^2}\right) \tag{3.21}$$

These profiles operate at different scales s and at image positions (x, y). If Gaussian-blurred image at scale s is given by

$$V_i(x, y, s) = L(x, y) \otimes R_i(x, y, s), \tag{3.22}$$

the center-surround mechanism at that scale is computed with

$$V(x, y, s) = \frac{V_1(x, y, s) - V_2(x, y, s)}{2^{\phi} a/s^2 + V_1(x, y, s)} \tag{3.23}$$

where ϕ is sharpening parameter, a is key value and center V_1 and surround V_2 responses are derived from equations 3.21 and 3.22. The $2^{\phi}a/s^2$ term prevents V from becoming too large for small values of V. In equation 3.23 V_1 represents *center* average and V_2 represents *surround* average at the scale s. To find the largest surrounding area around pixel with relatively low contrast, it is necessary to look for the largest scale s_m for which difference of Gaussians remains below the threshold:

$$|V(x, y, s_m)| < \epsilon \tag{3.24}$$

where ϵ is threshold. For this scale $V_1(x, y, s_m)$(center) may be taken as a local average. Therefore, local operator that implements a computational model of dodging-and-burning can be converted from global operator of equation 3.19 by replacing L with V_1 in the denominator:

$$L_d(x, y) = \frac{L(x, y)}{1 + V_1(x, y, s_m(x, y))} \tag{3.25}$$

The luminance of a dark pixel in a relatively bright region will satisfy $L < V_1$, so this operator will decrease the display luminance L_d , thereby increasing the contrast at that pixel. This is akin to photographic "dodging". Similarly, a pixel in a relatively dark region will be compressed less, and is thus "burned". In either case the pixel's contrast relative to the surrounding area is increased.

Figure 3.4: Image generated with Photographic tone reproduction, where key value was 0.02 and $\phi = 1$.

3.3 Frequently Domain Operators

3.3.1 Fast Bilateral Filtering for the Display of High-Dynamic-Range Images

Fast bilateral filtering [3] is very popular tone mapping operator, because it produces most realistic images from HDR of classic outdoor scenes. This operator reduces the contrast while preserving detail. It is based on a two-scale decomposition of the image into a base layer, encoding large-scale variations, and a detail layer. Result in our testing on samples with sparkling effect was quite good as you can see on figure 3.5.

Bilateral filtering

Bilateral filtering is an edge-preserving smoothing operator that effectively blurs an image but keeps sharp edges intact. Image smoothed with bilateral filter is called base layer and the result of dividing input image with this smoothed is called detail layer. After applying bilateral filter, dynamic range is reduced by scaling base layer to a user-specified contrast. The amount of compression is defined by user parameter called *base contrast*, which default and sufficient value is 5. Computation of bilateral filtering implemented directly in image space is relatively expensive, therefore Durand and Dorsey introduce computation, which yielding an approximate solution that in practice is indistinguishable from accurate spatial processing:

$$\begin{aligned}
D_j^{smooth}(x,y) &= \tfrac{1}{k_j(x,y)} \textstyle\sum_u \sum_v b_j(x,y,u,v) D(x-u, y-v) \\
k_j(x,y) &= \textstyle\sum_u \sum_v b_j(x,y,u,v) \\
b_j(x,y,u,v) &= f\left(\sqrt{(x-u)^2 + (y-v)^2}\right) g(D(x-u, y-v) - D_j)
\end{aligned} \tag{3.26}$$

where D_j form a quantized set of possible values for pixel (x,y). The final output for this pixel is a linear combination of the output of the two smoothed values D_j^{smooth} and D_{j+1}^{smooth}. These two values are chosen such that D_j and D_{j+1} are the closest two values to the input density D of pixel (x, y). Two another user parameters are spatial kernel sigma and range kernel sigma, which are deviations of Gaussian $f()$ and $g()$.

Figure 3.5: Fast bilateral filtering with default parameters: "spatial kernel sigma = 8", "range kernel sigma = 0.4", "base contrast = 5".

3.4 Gradient Domain Operators

3.4.1 Gradient Domain High Dynamic Range Compression

First gradient domain operator we tried was one from Fattal et al.[7]. We believed in local enhancement of sparkle luminance according to sharp gradient changes near the sparkle. The algorithm manipulates the gradient field of the luminance image by attenuating the magnitudes of large gradients. Smaller details are amplified thus becoming more evident. User parameters for this operator are α and β, which are described in *Gradient attenuation function* section. We used default value of parameter α, which was 0.1. Default value of parameter β is 0.8, but with this value resulting image has the blurred areas.Figure 3.6 shows the tone mapped HDR image and Figure 3.7 the marked blurred area with red line.

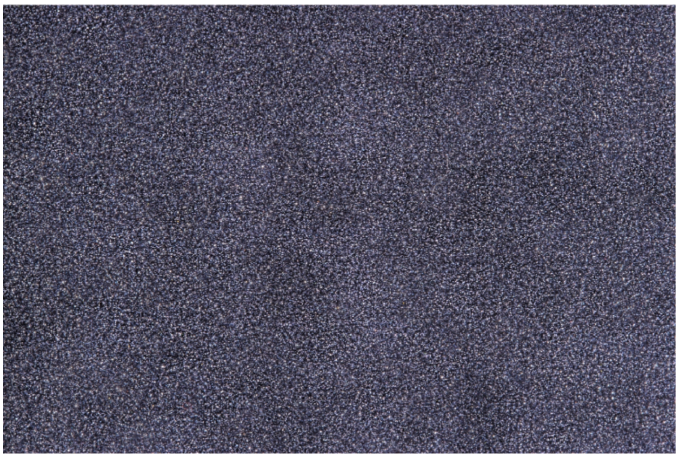

Figure 3.6: Tone mapped HDR image with gradient domain operator. Parameter $\alpha = 0.1$, $\beta = 0.883$.

Algorithm

First of all is computed density image $H(x, y) = \log(L(x, y))$ from input image L, from which is then computed gradient field $\bigtriangledown H(x, y)$ as follows:

$$\bigtriangledown H(x, y) = (D(x+1, y) - D(x, y), D(x, y+1) - D(x, y)) \tag{3.27}$$

The gradient field is then attenuated by multiplying each gradient with a gradient attenuation function $\Phi(x, y)$, which is described in section below, resulting in a compressed gradient field $G(x, y)$, as follows:

$$G(x, y) = \bigtriangledown H(x, y)\Phi(x, y) \tag{3.28}$$

To obtain compressed dynamic range image I, Fattal searched for this image I whose gradient is the closest to G in the least square sense. Image I is constructed by solving the Poisson equation:

$$\bigtriangledown^2 I = div\ G \tag{3.29}$$

where $\bigtriangledown^2$ is Laplatian operator $\bigtriangledown^2 I = \frac{\delta^2 I}{\delta x^2} + \frac{\delta^2 I}{\delta y^2}$ and $div\ G$ is the divergence of the vector field G, defined as $dvi\ G = \frac{\delta G_x}{\delta x} + \frac{\delta G_y}{\delta y}$.

Gradient attenuation function

From a density image H is constructed a Gaussian pyramid $H_0, H_1, \ldots, H_d$, where H_0 is the full resolution HDR image and H_d is coarsest level in the pyramid with the resolution at least 32 by 32. At each level k are computed the gradients using central differences:

$$\bigtriangledown H_k = \left(\frac{H_k(x+1,y) - H_k(x-1,y)}{2^{k+1}}, \frac{H_k(x,y+1) - H_k(x,y-1)}{2^{k+1}} \right). \tag{3.30}$$

At each level k for each pixel a scaling factor $\varphi_k(x,y)$ is determined based on the magnitude of the gradient, as follows:

$$\varphi_k(x,y) = \frac{\alpha}{|| \bigtriangledown H_k(x,y)||} \left(\frac{|| \bigtriangledown H_k(x,y)||}{\alpha} \right)^{\beta}. \tag{3.31}$$

This scale factor features 2 user parameters, α and β. Parameter α is the threshold, with the meaning the details whose luminance derivative is less than α are amplified, those whose derivative is greater than α are decreased. Second parameter β expresses how much the algorithm will be effective. Setting $\beta = 1$, the algorithm will perform no operation on the HDR, and there will be only a linear shrink of the dynamics. Decreasing β will increase the effectiveness of the algorithm, in other words you will increase the compression of the dynamics making the details much more evident. The full resolution gradient attenuation function $\Phi(x,y)$ can now be constructed by considering the coarsest level first and then propagating partial values in top-down fashion, as follows:

$$\begin{aligned} \Phi_d(x,y) &= \varphi_d(x,y) \\ \Phi_k(x,y) &= L(\Phi_{k+1})(x,y)\varphi_k(x,y) \\ \Phi(x,y) &= \Phi_0(x,y) \end{aligned} \tag{3.32}$$

where $\Phi_k(x,y)$ is the partially accumulated scale factor at level k, and $L()$ is an upsampling operator with linear interpolation.

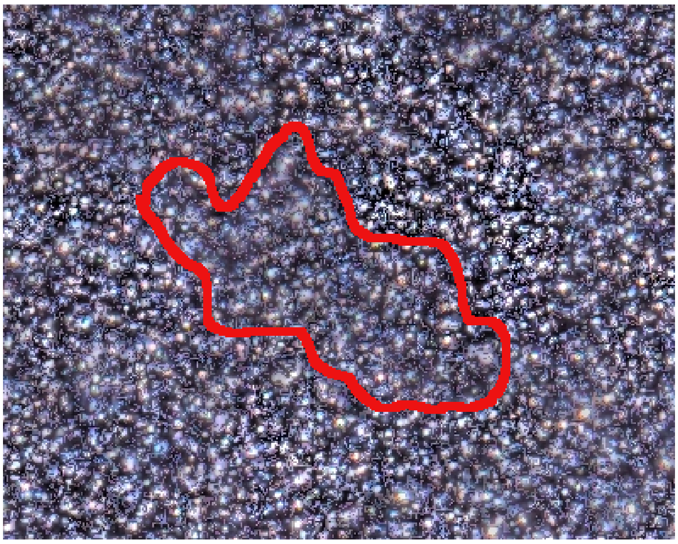

Figure 3.7: Detail of the blurred area in tone mapped image with gradient domain operator.

3.4.2 A Perceptual Framework for Contrast Processing of High Dynamic Range Images(Mantiuk)

The last operator is a Perceptual framework for contrast processing [8]. Images are processed in a visual response space, in which contrast values directly correlate with their visibility in an image. This framework involves a transformation of an image from luminance space to a pyramid of low-pass contrast images and then to the visual response space. After modifying response values, the transformation is reversed to produce the resulting image. The overview of this framework is shown in Figure 3.8. The final image of car paint is on figure 3.9

Contrast discrimination

Contrast detection and contrast discrimination is very important perceptual characteristics of eye because is used to derive this contrast processing framework. Contrast detection threshold is the smallest visible contrast of a stimulus presented on a uniform field. The contrast discrimination thresh-

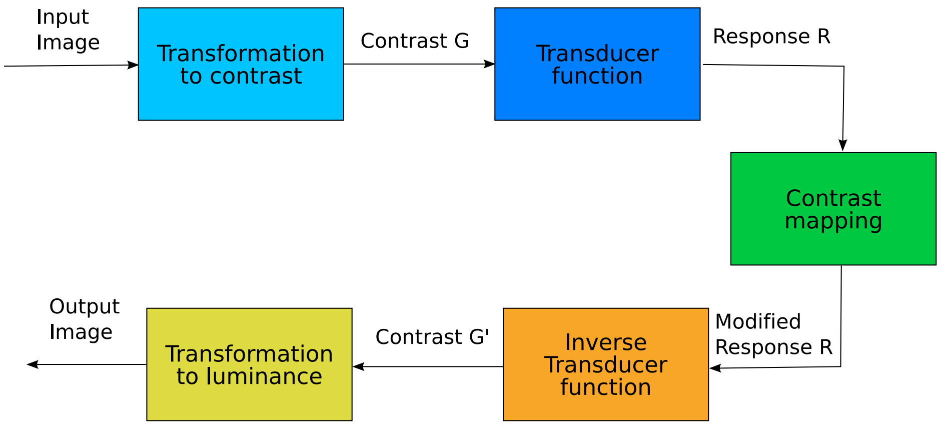

Figure 3.8: Data flow in the framework of the perceptual contrast processing.

old is the smallest visible difference between two nearly identical signals. A stimulus can be considered supra-threshold when its contrast is significantly above the detection threshold and when the contrast is lower or very close to the detection threshold, a stimulus is considered threshold. Contrast discrimination is associated with the supra-threshold characteristics of the human visual system(HVS). The function of contrast discrimination for contrast G is defined:

$$\Delta G(G) = 0.0405 \cdot G^{0.6628} + 0.00042435 \cdot G^{-0.38072} \tag{3.33}$$

Transform Luminance and Contrast

In this section is explained a method of transforming the complex images from luminance to physical contrast and vice-versa. To a simple stimulus is applicable several contrast definitions, but for measure the contrast in complex scenes is used a difference between selected levels of a Gaussian pyramid. But this approach tends to introduce halo artifacts at sharp edges when it is modified. To avoid this problem, authors introduce a low-pass measure of contrast using a logarithmic ratio G as the measure of contrast between a pixel and one of its neighbors at a particular level, k, of a Gaussian pyramid:

$$G_{i,j}^k = \log_{10}(L_i^k / L_j^k) \tag{3.34}$$

where L_I^k and L_j^k are luminance values for neighboring pixels i and j. There are two or more $G_{i,j}^k$ measures for a single pixel i depending on how many neighbor pixels are used. For tone mapping operations on complex images are sufficient two nearest neighbors.

For transforming luminance to contrast is used equation 3.34, in next part of this section is explained the inverse operation which restores an image from the modified contrast values $\hat{G}$. The problem is that there is probably no image that would match such contrast values. Authors look instead for images which have contrast values very close to $\hat{G}$. This can by done by the minimization of distance between a set of contrast values $\hat{G}$ and G, which is the contrast of the actual image. This can be written as a minimization of function:

$$f(x_1^1, x_2^1, \ldots, x_N^1) = \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j \in \phi_i} p_{i,j}^k (G_{i,j}^k - \hat{G}_{i,j}^k)^2 \tag{3.35}$$

where ϕ_i is set of the neighbors of the pixel i, N is total number of pixels, K is total number of levels in a Gaussian pyramid and $p_{i,j}^k$ is a constant weighting factor, which can be used to control a mismatch between the desired contrast and the contrast resulting from the solution of optimization problem. This constant is defined as:

$$p_{i,j}^k = \begin{cases} \Delta G^{-1}(\hat{G}_{i,j}^k) & \text{if } \hat{G}_{i,j}^k \geq 0.001 \\ \Delta G^{-1}(0.001) & \text{otherwise,} \end{cases} \tag{3.36}$$

where ΔG^{-1} is an inverse of the contrast discrimination function from equation 3.33 and the second condition avoids division by 0 for very low contrast.

Transducer Function

Next step in this framework is transforming from a given physical contrast to the visual response space. This transformation is done because final image processing is done on the response rather than on the physical contrast. For this purpose is derived a transducer function that would predict the response of the HVS for the full range of contrast.

Derived transducer function $T(G) = R$ is based on assumption that the value of the response R should change by one unit for each Just Noticeable Difference(JND) both for threshold and supra-threshold stimuli. To simplify the case of threshold stimuli, authors assumed that:

$$T(0) = 0 \quad \text{and} \quad T(G_{threshold}) = 1 \tag{3.37}$$

or

$$T^{-1}(0) = 0 \quad \text{and} \quad T^{-1}(1) = G_{threshold} \tag{3.38}$$

for the inverse transducer function $T^{-1}(R) = G$. For a supra-threshold stimulus the response function T is approximated by its first derivative:

$$\Delta T \approx \frac{dT(G)}{dG} \Delta G(G) = 1 \tag{3.39}$$

where $\Delta G(G)$ is the discrimination function form equation 3.33. The above equation can be solved by solving numerically the equivalent differential equation:

$$\frac{dT^{-1}(R)}{dR} = \Delta G(T^{-1}(R)) \tag{3.40}$$

for the inverse response function $T^{-1}(R) = G$ and for the boundary condition from equation 3.38. G is a non-negative logarithmic ratio and R is the response of the HVS. Finding the function T is straightforward, because the function T^{-1} is strictly monotonic.

Contrast Mapping

This framework contains two tone mapping methods, Contrast mapping and Contrast equalization(histogram equalization), but the first one has better results with car's paint, therefore I describe only this method in this thesis.

Contrast mapping is trying to fit to the dynamic range of the display so that no information is lost, instead of make images look realistic and natural.

Since the response $R^k_{i,j}$ is perceptually linearized, contrast reduction can be achieved by multiplying the response values by a constant l:

$$\hat{R}^k_{i,j} = R^k_{i,j} \cdot l \tag{3.41}$$

where l is between 0 and 1. This is the same as lowering the maximum contrast that can be achieved by the destination display. Since the contrast response R is perceptually linearized, scaling effectively enhances low physical contrast W , for which we are the most sensitive, and compresses large contrast magnitudes, for which the sensitivity is much lower.

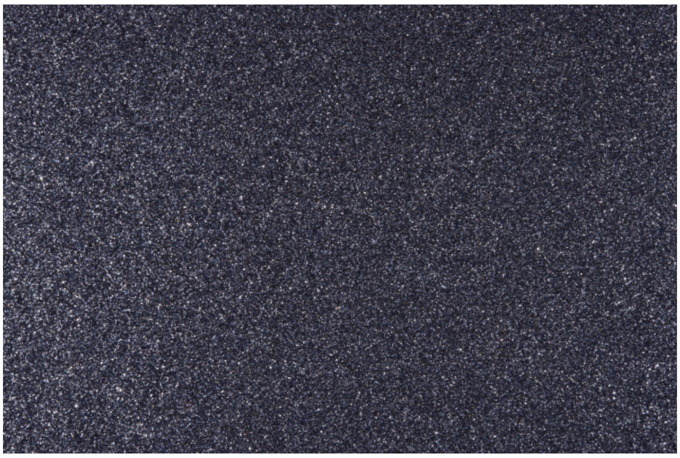

Figure 3.9: Tone mapped image with perceptual framework for contrast processing. Contrast factor set on 1 and saturation factor on 1.9.

Chapter 4

Comparison

After generating HDR image and applying individual tone mapping operators the visual comparison with original sample is needed. To see all the visual information that HDR image could interpret, we observer the HDR images of car paints with strong sparkling on HDR monitor. We use the BRIGHTSIDE^{TM} HDR display for this project. It is a 18-inch LED-based HDR monitor, and its luminance range is $0.05 - 3000 \ \ cd/m^2$. By limiting its maximum and minimum luminance values, we can simulate the broad range of conventional displays. We found out that the image was brighter and also highlight got much brighter comparing to conventional monitors. Unfortunately, there was still not enough dynamic range to see details in the highlight and sparkles. We could not get to the point that the image looked well exposed and highlight looked realistic. Regarding this findings, we compared results from tone mapping operators with car paint sample and the summary of this comparison is in table 4.1.

operator	summary
Fattal	On Figure 3.6 is result of this operator, which isn't good enough for sparkling effect, because of blurred areas on whole image, which is shown in detail on Figure 3.7
Drago	This operator does not enhance the details comparing to other parts of the image. Result shown on figure 3.1 was blurred and even the color shift occurred comparing to the original sample.
Ashikhmin	Images produced from this operator shown on Figure 3.3 was sharp enough, but the dynamic range and color didn't match the original.
Durand	Color and sharpness was very good with this operator as we can see on Figure 3.5. Most of the sparkles had medium lightness, that is insufficient for our purpose.
Reinhard 2005	Resulting image color was almost gray-scale (figure 3.2) with this operator and its default parameters brightness, chromatic adaptation and light adaptation. By changing the parameters we couldn't reproduce the image color matching the sample paint. On the other side, the sparkling effect on this image was very good.
Reinhard 2002	This algorithm is simple and produces very good results on our image sets. Color representation is better than in previous operators and sparkling effect is one of the best. Generated picture is shown on Figure 3.4.
Mantiuk	This is one of the proper operators for tone mapping the images with sparkling effect. Color appearance matches the original and images poses a bit less sharpness.

Table 4.1: Comparison of tone mapping operators on sparkling images

Chapter 5

Conclusion

In this work we have presented another method for sparkling effect reconstruction from photos and visualization of produced HDR images. We have found out that displaying generated images on HDR monitor was not the best choice and our expectation were false. Referring to table 4.1 Reinhard's Dynamic Range Reproduction [10] and Mantiuk's Perceptual Framework [8] were selected as the best operators for visualization of HDR images with included sparkling effect, particularly the car paints captured by our photographic setup.

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List of Figures

Abstrakt

High dynamic range (HDR) imaging je sľubná technológia na vizualizáciu trblietivého efektu. V tejto práci skúmame a navrhujeme techniky na generovanie HDR obrázkov z fotiek automobilových lakov ktoré obsahujú trblietivé vzorkovanie. Vďaka vhodnej voľbe a nastavení snímacích zariadení sme zabránili vygenerovaniu neostrých HDR obrázkov. Druhá časť tejto práce sa zameriava hlavne na vizualizáciu HDR obrázkov automobilových lakov na HDR ako aj LDR monitore. Na správne zobrazenie na LDR monitoroch je potrebné výstupným HDR obrázkom upraviť dynamický rozsah pomocou tzv. tone mapping operátorov. Pri skúmaní sme prišli k záveru, že HDR displeje nie sú vhodné na vizualizáciu trblietivého efektu. Na druhej strane, zo skúmaných tone mapping operátorov iba Mantiukov a Reinhardov operátor umožňuje zobraziť zvýšený trblietivý efekt na LDR monitoroch.

Kľúčové slová: HDR, tone mapping operator, trblietivý efekt, automobilový lak