

A Suitable LDR Image from HDR by CIELAB Based Tone-Mapping Algorithm

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Abstract— This paper presents an analysis of the CIELAB color feature based tone mapping technique. After analysis of these techniques we had concluded that saliency based tone mapping algorithm is not computationally efficient as good as the proposed methodology. There is different Saliency-based Tone mapping methods for High dynamic range images that have the halo artifacts significantly reduced. The visual quality of tone-mapped image, especially based on salient regions, is enhanced by the saliency-aware weighting. Experimental results show that the proposed method produce good results on a variety of high dynamic range images as saliency-aware technique. The proposed method is more computational efficient and the visual quality of the proposed method is also improved as of saliency based tone mapping.

Keywords—CIELAB Colour Space; Tone Mapping; HDR Image; Weighted Least Square Filter

I. INTRODUCTION

We experience in our daily life that the real world scenes often have a very wide range of luminance values. The saliency-aware weighting based perceptually guided filter is applied to design a local tone-mapping algorithm for HDR images such that both extreme light and shadow regions can be reproduced on conventional low dynamic range displays. In particular, the perceptually guided filter is applied to decompose the luminance of the input HDR image into a base layer and a detail layer. The saliency-aware weighting is then adopted to design a saliency-aware global tone mapping for the compression of the base layer [1]. Further it is used as the background of the proposed method. The quality of the image can be improved with the concept of lots of images of same object at the same position can be taken as the raw images. Although it would be possible to capture high dynamic range (HDR) photos with the future digital cameras. In any one single shot only a part of the real world high dynamic scene is visible with the current technology. Such a scenario is illustrated in Figure (1). It is an indoor scene with the sunlight coming through the window and the camera was placed at the dark end.

To make the features visible near the window, less exposure was used. However, this made the scene further away from the light source too dark [14]. We increased the exposure interval to make the features visible in the dark end. To human observers, however, all features in the darkest as well as the brightest areas are equally clearly visible simultaneously. In fact, recent technologies have made it relatively easy to create numerical luminance maps that capture the full dynamic range of real world scene [14], [15]. For a sequence of low dynamic range images of the same scene taken under different exposure levels, a HDR radiance map of the scene can be generated. Several works

try to select the most appropriate LDR images to generate the HDR image where many LDR images with various exposures are already captured and stored; it implies that larger storage, as well as higher energy consumption is needed for such scenarios.



Fig 1: Digital HDR images of the same scene taken with different exposure intervals.

In this paper, we promote an alternative edge-preserving operator, on the basis of Weighted Least Squares framework. This framework was initially used to reduce ringing while deblurring images in the existence of noise [17] and it is closely related to biased anisotropic diffusion [18]. Recently, the framework was employed for even propagation of sparse constraints [19] [20]. We show that the WLS-based operator is robust and adaptable, and may be used in many applications that have been based on the Bilateral Filter (BLF), at the cost of large computation times. We found this operator to be mainly well-suited for progressive coarsening of the images, and for the extraction of details at various spatial scales. Thus, we use it to create a new kind of an edge-preserving multi-scale image decomposition, which provides an excellent foundation for multi-scale high dynamic range and low dynamic range tone mapping, detailed enhancement, and contrast manipulation. The remainder of this paper is organized as follows. In the II section the base-detail decompositions as background of the proposed method. Next, in the Section III we show HDR tone mapping process. Section IV presents a detailed

comparison of result proposed method decompositions with previous schemes based on saliency based tone mapping, while Section V concludes the paper.

II. BACKGROUND OF PROPOSED METHOD

In computational photography, images are often decomposed into a piecewise smooth base layer and one or more detail layers. The base layer represents the larger scale variations in the intensity, and is usually computed by applying an edge-preserving smoothing operator to the image (sometimes applied to the logarithm of luminance or to the lightness channel of the CIELAB color space). The detail layer is defined as the difference (or the quotient) between the original image and the base layer. Each of the resultant layers may be manipulated separately in various ways, depending on the application, and probably recombined to yield the final result. Computation of the base layer is the process of image coarsening. The process of coarsening must be done with awareness in order to avoid artifacts that might occur once the base and the detail layers are manipulated independently and recombined. The ideal edge-preserving filter should neither haze nor sharpen the edges that separate coarse scale image features, while smoothing the regions between such edges. Unfortunately, such an operator does not exist, because generally it is impossible to unambiguously determine which edges should be preserved. Furthermore, in order to produce multi-scale base layer and detail layer decomposition, the operator must allow increasingly larger image features to migrate from the base layer to the detail layer. In other words, it must allow increasingly larger regions to become increasingly smoother.

III. PROPOSED TONE MAPPING METHOD

The background of the proposed method incorporates the image formation model. Here we explain the basic steps of proposed method. Firstly image is acquired and decomposed it in the base and detail layer to manipulate the low and high frequency components according to requirement for the HDR to LDR conversion for displaying on LDR display device. Our decompositions are easily harnessed to perform detail preserving compression for the HDR images. It is described in detail as below:

A. Decompositions

Using the edge-preserving operator described above, it is simple to construct a multi-scale edge-preserving decomposition, fashioned after the well-known Laplacian pyramid [21]. The decomposition of the image component into different layers consists of a coarse, piecewise smooth, version of the image, along with a sequence of difference in images, capturing detail at progressively finer scales. Let g denotes the input image, we would like to construct a $(k+1)$ -level decomposition. Let u^1, \dots, u^k denotes progressively coarser versions of g . The coarsest version of these versions, u^k will serve as the base layer b and the k number

of detail layers defined as $d^i = u^{i-1} - u^i$, where $i = 1, \dots, k$ and $u^0 = g$. The original image g is easily recovered from the decomposition by simply summing up the base and the detail layers:

$$g = b + \sum_{i=1}^k d^i \quad (1)$$

Note that we do not perform any down sampling on the smoothed image u_i , as smoothed images are obtained via edge-preserving smoothing and are not band-limited in the normal sense. Thus, the multi-scaled decomposition is a complete description of the given input image.

B. RGB to CIELAB Transformation

We have implemented a simple interactive tool for the manipulation of the tone and contrast of details at various scales. An image is given, we firstly construct a three-level decomposition (b as coarse base level and $d1:d2$ as two detail levels) of the CIELAB lightness channel. This is done by using the first (non-iterative) construction given by eq. (1). After that the user is then presented with a set of sliders for controlling the base layer exposure h , also the boosting factors $d0$ for the base, and $d1;d2$ for the medium and fine detail layers. At each pixel p , the result of the manipulation \hat{g} is then given by

$$\hat{g}_p = \tau \mu + S(\delta_0 \eta b_p - \mu) + S(\delta_1 d_p^1) + S(\delta_2 d_p^2) \quad (2)$$

Where μ is the mean of the lightness range, and S is a sigmoid curve, $S(ax) = \frac{1}{1 + \exp(-ax)}$ (appropriately shifted and normalized). The goal of the sigmoid is to avoid the hard clipping that would otherwise take place when the detail layers are boosted significantly. The term $S(\delta_0 \eta b_p - \mu)$ controls the exposure level and contrast level of the base layer, while the boosting of the medium and fine scale details are controlled by remaining terms. Note that once the decomposition has been computed, in real time, the eq. (2) is evaluated.

C. Edge-Preserving Smoothing via WLS

In this section, we first explain an alternative edge-preserving smoothing approach on the basis of WLS optimization framework, and after that show how to construct multi-scale edge-preserving decompositions that capture detailed variations at various scales. Edge-preserving smoothing may be viewed as a compromise between two contradictory goals. Given an input image g , we seek for a new image u , which, on the one hand, is as close as to g , and at the same time, u is as smooth as possible everywhere, excepting across significant gradients in g . Formally, this may be expressed as seeking the minimum of

$$\sum_p (u_p - g_p)^2 + \lambda \left(a_{x,p}(g) \left(\frac{\partial u}{\partial x} \right)^2 + a_{y,p}(g) \left(\frac{\partial u}{\partial y} \right)^2 \right) \quad (3)$$

where the subscript p denotes the spatial location of a pixel. The goal of the data term $(u_p - g_p)^2$ is to reduce the distance between image u and image g , while the second term (regularization) strives to achieve smoothness by reducing the partial derivatives of u . The smoothness

requirement is enforced in a spatially varying manner via the smoothness weights α_x and α_y , in eq. (4) which depends on g . Finally, λ is responsible for the balance between the two terms; increasing the value of λ results in progressively smoother images u .

$$\alpha_{x,p}(g) = \left(\left| \frac{d}{dx}(g) \right|^\alpha + \varepsilon \right)^{-1} \quad \alpha_{y,p}(g) = \left(\left| \frac{d}{dy}(g) \right|^\alpha + \varepsilon \right)^{-1} \quad (4)$$

where α is the log-luminance channel of the input image g , the exponent (typically between 1.2 and 2.0) determines the sensitivity to the gradients of g , while ε is a small constant (typically 0.0001) that prevents division by zero in areas where g is constant. It should be noted that the smoothness coefficients in the above equation, separate between gradient in the x and y directions, the resultant operator is not rotationally invariant, with a small tendency to preserve axis aligned edges more than diagonal ones.

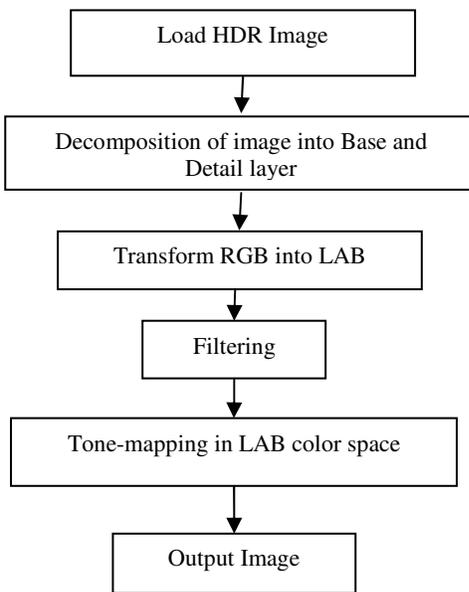


Fig.2 Block Diagram of the Proposed Algorithm

We find that this simple tool is very effective for controlling the amount of the local contrast at the various scales. The effective manipulation range is extremely wide; it usually takes a slightly extreme manipulation to cause artifacts to appear in image.

D. Recovery of the Tone mapped result Image

The WLS-based operator is used as an edge-preserving filter. A coarsening sequence generated in this manner and the corresponding detail layers. Using the base and detail layer decomposition produces the results. Here the detail layers are attenuated, rather than boosted, to achieve a stylized abstract look. Using progressively coarser decomposition levels increases the degree of abstraction in the resulting image. These abstractions can also be combined together in a spatially varying manner to provide

more detail in areas of interest. We do this with an interactive painting interface; a more automated mechanism is described in [25]. The images are overlaid with edges extracted from the appropriate detail layers.

E. Performance Parameters

It is straightforward to estimate the variance by the maximum likelihood (ML) criterion. It is given by

$$\sigma^2 = \operatorname{argmax} P(Y|H, X, \sigma^2) \quad (5)$$

Universal Image Quality Index (UIQI): An universal image quality index, is easy to calculate and applicable to various image processing applications. Instead of using traditional error summation methods, this index is designed by modeling any image distortion as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion. Although this index is mathematically defined and no human visual system model is explicitly employed, experiments on various image distortion types show that it exhibits surprising consistency with subjective quality measurement. It performs significantly better the UIQI. It shows the image quality of the image in terms of number. As formulated as follows: from the comparison of images

$$Q = \frac{4\sigma_A\sigma_B\mu_A\mu_B}{(\sigma_A^2 + \sigma_B^2)(\mu_A^2 + \mu_B^2)} \quad (6)$$

IV. RESULTS

We have implemented a number of simple tools that use our multiscale edge-preserving decompositions for photographic tone manipulation, HDR tone mapping, detail enhancement, and image abstraction. Below, we briefly describe these tools and show some results. Note the purpose of these tools is to demonstrate in the simplest possible way the robustness and versatility of our decompositions.

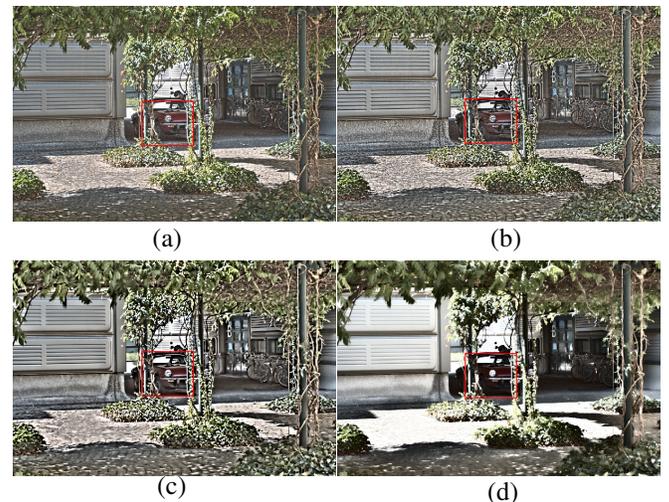


Fig.3 (a) Result image of the Saliency based tone mapping and (b), (c) and (d) Result image of the propose tone mapping algorithm with fine, medium and coarse detail respectively.

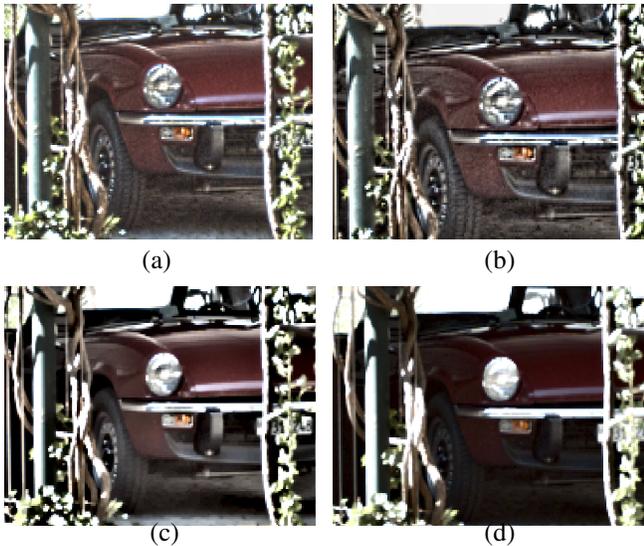


Fig.4 Zoom of Result Image from fig 2 with proper visibility (a) Result image of the Saliency based tone mapping and (b), (c) and (d) Result image of the propose tone mapping algorithm with fine, medium and coarse detail respectively.

TABLE 1 PERFORMANCE PARAMETER FOR CAR IMAGE

Method	mean	Variance	UIQI
SALIENCY TM	0.4413	0.0774	0.7090
PROPOSED1	0.4464	0.0586	0.9968
PROPOSED2	0.4446	0.0776	1.0263
PROPOSED3	0.4613	0.1032	1.3227

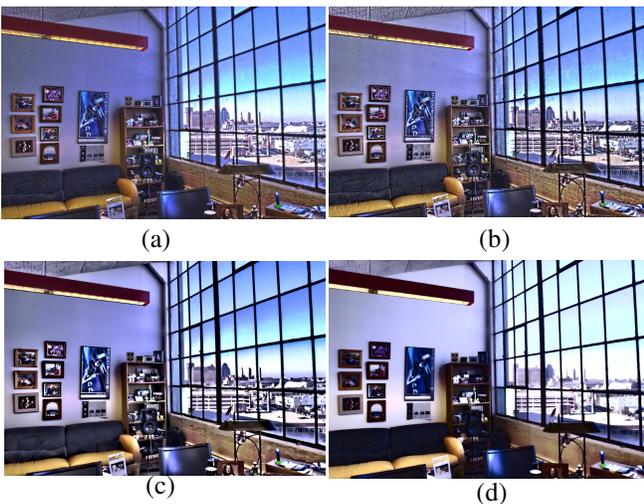


Fig.5 (a) Result image of the Saliency based tone mapping and (b), (c) and (d) Result image of the propose tone mapping algorithm with fine, medium and coarse detail respectively.

The proposed 1 method defines the fine detail tone mapping, the second result of proposed-2 method corresponding to the medium detail tone mapping and the final proposed 3 for the coarse detail tone mapping method.

All the image results and tabular parameter results are shown in fig. 3 and fig.5 and table 1 and table 2 respectively. The zoomed result Images of the fig.3 and fig. 5 are shown in fig. 4 and fig. 6 with more detail of the scene. The performance parameters are also shown in table 1 and table 2.

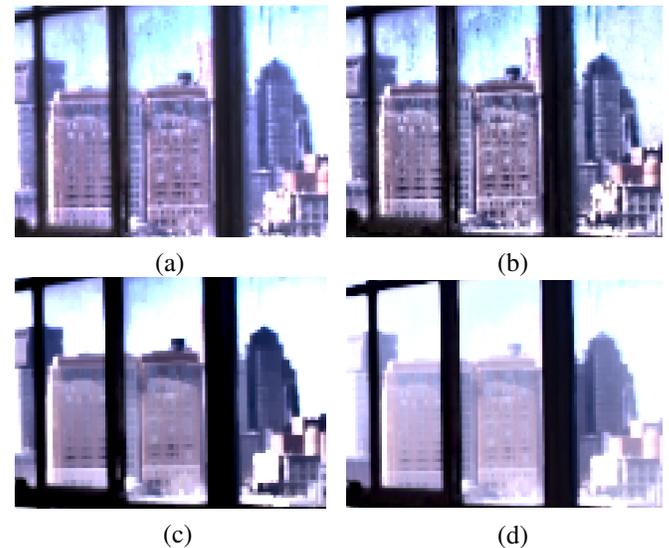


Fig.6 Zoom of Result Image from fig 2 with proper visibility (a) Result image of the Saliency based tone mapping and (b), (c) and (d) Result image of the propose tone mapping algorithm with fine, medium and coarse detail respectively.

TABLE 2 PERFORMANCE PARAMETER FOR OFFICE IMAGE

Method	Mean	Variance	UIQI
SALIENCY TM	0.5241	0.1708	0.5651
PROPOSED1	0.4890	0.0807	0.8554
PROPOSED2	0.4973	0.255	0.8826
PROPOSED3	0.5476	0.1393	0.9955

Any of these tools could have been made much more sophisticated, but this is outside the scope of this paper. In this application, the detail layers are attenuated, rather than boosted, to achieve a stylized abstract look. Using progressively coarser decomposition levels increases the degree of abstraction in the resulting image. These abstractions can also be combined together in a spatially varying manner to provide more detail in areas of interest.

V. CONCLUSION

The manipulation in image is a valuable digital dark room technique. Our results on a HDR to LDR image show that the approach is robust and versatile. The UIQI parameter for the proposed method is approx. 20 percent improved as compared to previous method. In future work we would like to investigate more sophisticated schemes for determining the smoothness coefficients for the WLS formulation in order to further improve the ability to preserve edges and extract details. Another important issue that must be tackled is better handling of color.

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