HDR Image Compression based on Local Adaptation for Scene and Display Using Retinal Model

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Abstract

Retinal adaptation process helps the human visual system to see a high dynamic range scene in the real world. This paper presents a simple static local adaptation method for high dynamic range image compression based on a retinal model. The proposed simple model aims at recreating the same sensations between the real scene and the compressed image on the display device when viewed after reaching steady state local adaptation respectively. Our new model takes the display adaptation into account in relation to the scene adaptation based on the retinal model. In computing local adaptation, the use of nonlinear edge preserving bilateral filter presents a better tonal rendition in compressing local contrast and preserving details while avoiding banding artifacts suffering from normally in local methods.

Introduction

From sunlight to starlight, the *HVS* (Human Visual System) can see about fourteen orders of dynamic range scene in the real world. “What’s the human vision seeing?” and “How to recreate a realistic scene” have been eternally pursued by scientists. In the recent years, the multiple exposure technology of digital camera makes it possible to get the *HDR* (High Dynamic Range) images of six orders of magnitude. However most of the conventional display devices are still low dynamic range (*LDR*) of around two or three orders of magnitude. To recreate the same viewer’s sensations on the display devices as real scenes, *HDR* to *LDR* compression is indispensable.

Recreating the *HDR* images to *LDR* devices is known as tone mapping. The *HVS* is actually an ideal tone mapping system. As known, although *HVS* can see so huge dynamic range scene luminance, the range it can perceive simultaneously is relatively narrow compared over the entire range. The *HVS* deals with the high dynamic range of scene luminance by a process called adaptation, which charged by the cells in the retina.

Adaptation process plays an important role in visual appearance of any viewed scene. Basing on eye adaptation, the existing visual tone mapping methods can be simply classified into global model[1-3] and local model[4-15]. Global model mimics the steady state of *HVS*, which is simple and efficient due to dealing the whole image with a single spatially- invariant Curve, but also for this reason it is weak in preserving local contrast. The local model works well in preserving local visual contrast due to dealing the image with spatially variant operation, such as multiple-resolution Gaussian decomposition, while often suffering from artifacts around high contrast edges.

Since eye adaptation is highly localized to allow us to see both dark and bright regions in the scene, in this paper, we follow the local method and propose a simple local model for *HDR* image compression based on a retinal model which predicts the response of eyes at any given adaptation level. Aiming at recreating the same sensations between the real scene and its range compressed image on the display devices when viewed after reaching steady state local adaptation respectively, the model computes both adaptations not only for the scene but also for the image on display devices. Therefore, the proposed model is a completely local model. In dealing with local adaptation we use the nonlinear bilateral filter to suppress the banding artifacts across the high-gradient edge regions suffering from in conventional local models. The proposed model works well in improving the visibility in light and shadow areas while preserving pleasing contrast.

After reviewing previous works in *HDR* image compression, the successive Sections introduce the retinal model and detailed derivations of our entire operator. After that, we show some experimental results. Finally we make a conclusion.

Related Work

During the last decade, there are a lot of published models in *HDR* image compression. Tumblin and Rushmeier[1] suggested that the images produced by tone reproduction when displayed on the *LDR* devices should cause the same sensations as the real scenes do. Their operator used the results of Stevens and Stevens[16]. However, because they used a single spatially invariant adaptation level for the scene and another adaptation level for display, though their tone reproduction operator preserves the apparent brightness of scene features, the very bright or dim areas are obscure.

The *HVS* takes time to adapt to large changes in scene luminance, which has a profound effect on visual appearance. Pattanaik et al.[2] proposed a time dependent operator, which takes the time adaptation of *HVS* with the psychophysical data into account and successfully simulated the process based on a simplified Hunt Model[17]. Alessandro Artusi et al.[4] developed the work of Pattanaik et al.[2] by including a chromatic adaptation. However, due to global processing in adaptation, both models have the weakness in preserving local contrast.

Local operators, traditionally basing on multi resolution decomposition algorithm, such as Gaussian decomposition, work well in measuring and preserving local image contrast. Retinex model[5-11] is a typical local operator which has been widely used in image processing, such as color image appearance improvement, and also *HDR* image compression. Though local operators can preserve local contrast and details well, they also cause some unpleasing banding artifacts around high contrast edges. The *MSR* (Multi-Scale Retinex)[12,13] integrates multiple *SSR* (Single-Scale Retinex)[9-11] with different kernel size to avoid the banding artifacts as well as preserving good color appearance. To suppress artifacts normally 3-7 SSR images are needed which increases time computation and the selection for weights is ambiguous[18].

Ledda et al.[14] developed a local time dependent adaptation model based on the work of Pattanaik et al.[2], they computed local adaptation for scene images with an edge preserving filter, called bilateral filter proposed by Tomasi and Manduchi[19], and used by [14,20] to suppress banding artifacts. This idea is very interesting, but they used a single spatially invariant adaptation level for display images, which neglecting the adaptation process when eye sees anything, hence leads to the dark and light details loss in display images.

Retinal Model

Though the *HVS* is capable of seeing a high dynamic range scenes, it can simultaneously perceive dynamic range around five orders of magnitude which is very narrower compared with the entire range of *HVS* known as over fourteen orders of magnitude. The *HVS* changes its sensitivity depending on the luminance in the visual filed, which is known as adaptation. Adaptation dynamically adjusts these narrow response functions to conform better to the available light, finally sees dynamic range scenes over fourteen orders of magnitude. Most of research work on the *HVS* adaptations has been done during past years. The model used by Pattanaik et al.[2] is first proposed by Naka and Rushton[21] in 1966 to describe fish *S*-potentials, after that most researchers also proved the *S*-shaped response of retinal cells[22,23], which is used by other authors to psychophysical model of brightness perception[24]. The response of retinal cells can be expressed as follows:

$$R(I) = \frac{I^n}{I^n + \sigma^n} \tag{1}$$

where I is the light intensity, R is the response of retinal cells, σ is the I value that causes the half-maximum response, and n is a sensitivity control parameter, selected from 0.7 to 2.0[24], for example n=0.73 in the Hunt Model[17]. The σ is considered to be determined by adaptation to the overall scene intensity. Therefore it plays an important role in visual system adaptation process, which can be explained well by Eq.(1). The dark adapted eye suddenly thrown into a high light environment will cause glare in the eye so that we cannot see well. This is because the small dark adapted σ while high intensity I makes the response of eye reaches saturation, but with the time passed, σ gradually restores high adaptation level, the response of visual system $R(I)$ comes down, the eye can see normally again. On the contrary the light adapted eye suddenly thrown into dark environments, the eye cannot see the objects at the beginning. This is because the high adaptation level σ while low intensity I makes the response of visual system $R(I)$ almost to zero, but with the time passed, σ becomes small and the sensitivity of eye gradually restored, the visual system restores the ability of seeing objects in the dark environments.

Figure 1 shows the response of retina over the luminance and how the response is affected by different adaptation levels, which helps us to understand the adaptation process well. From left to right, Figure 1 shows the responses of retina at adaptation level 0.001, 0.01, 0.1, 1, 10, 100 and 1000 respectively. From Figure 1 we can also see that the retinal response is a *S*-shape curve when drawn in logarithmic domain. This confirms that the eye compresses the very high and very dark shadow dramatically while keeping the middle range invariant to preserve well contrast.

Proposed Local Adaptation Model

In this section, we will describe our model in detail. For clarity, we will divide several subsections to introduce it. First, we give the tone reproduction framework of our proposed model. After that, the display adaptation and scene adaptation will be introduced respectively.

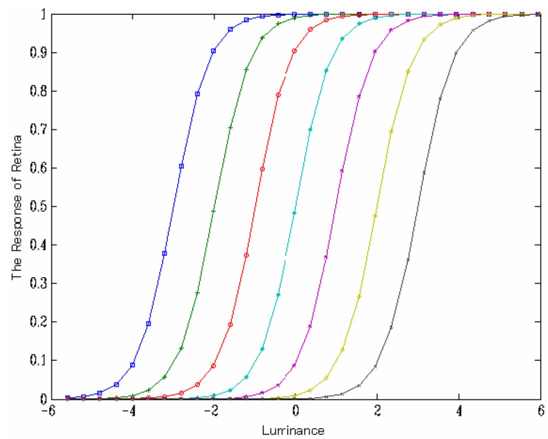


Figure1. *The response of retina at adaptation level: 10^{-3}, 10^{-2}, 10^{-1}, 1, 10, 10^{2}, 10^{3} over the luminance intensities*

Tone reproduction framework

Our model is based on the tone reproduction framework of Pattanaik et al.[2], which first proposed by Tumblin and Rushmeier[1]. Here, we rebuilt the framework of Pattanaik et al. in Figure 2, in which the upper pair of the model computes viewed scene appearance, and the lower pair of inverse models computes the display luminance to match the scene appearance. The adaptation model transforms the scene luminance to the retinal response R_{scene}, and the appearance model converts R_{scene} to the appearance vector Q, which is computed by subtracting the reference black response R_{blk} from $R(I)$, then by inverse transforms to convert scene appearance into display luminance. The adaptation model of Pattanaik et al. is an abbreviated version of sophisticated model of static color vision by Hunt[17]. The model of Pattanaik et al.[2] assumes that *HVS* can assign equivalent appearance to dim displays and very bright or very dark scenes by a simple linear mapping of visual responses.

Our model starts from the Pattanaik's adaptation model in Ref.[2], but is basically different from that on the points of

[1] Display appearance is considered to be equivalent to scene appearance as shown in Figure 3.

[2] Both scene and display adaptations are local.

[3] Display adaptation is formulated in relation to scene adaptation by retinal model.

[4] Bilateral filter is applied to mimic the edge preserving of *HVS* to reduce the banding artifacts.

Rewriting the Eq.(1) to express the response of *HVS* to a spatially variant scene function, Eq.(2) is obtained. As well, Eq.(3) expresses the response of *HVS* to a display. For simplicity, denoting the world scene and the display as the symbols w and d respectively, R_{scene} and $R_{display}$ in Figure 2 are represented as $R_w(x,y)$ and $R_d(x,y)$ respectively. The $\sigma_w(x,y)$ and $\sigma_d(x,y)$ present the half saturation level parameters for the world scene and the display respectively. As well, $I_w(x,y)$ and $I_d(x,y)$ represent the world scene and the display luminance respectively.

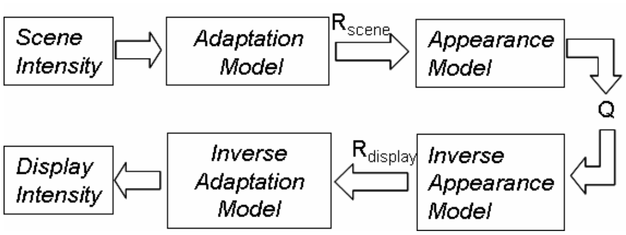


Figure.2 Tone reproduction framework of Pattanaik et al.[2]

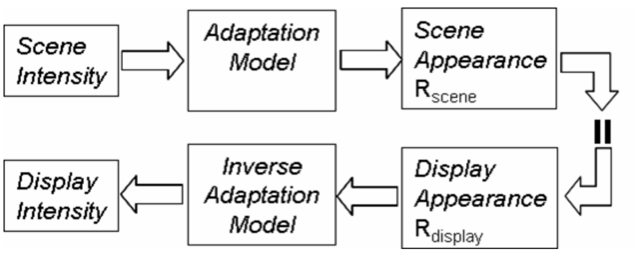


Figure 3. *Tone reproduction framework of proposed model*

$$R_w(x,y) = \frac{I_w(x,y)^n}{I_w(x,y)^n + \sigma_w(x,y)^n} \tag{2}$$

$$R_d(x,y) = \frac{I_d(x,y)^n}{I_d(x,y)^n + \sigma_d(x,y)^n} \tag{3}$$

We aim at recreating the same sensations between the world scene $I_w(x,y)$ and the range compressed image $I_d(x,y)$ on display devices when viewed, which claims the appearance of the world scene $R_w(x,y)$ is equivalent to the appearance of display image $R_d(x,y)$ as follows:

$$R_d(x,y) = R_w(x,y) \tag{4}$$

According to Eq.(2) through Eq.(4), the relationship between the output display intensity $I_d(x,y)$ and the world scene intensity $I_w(x,y)$ can be expressed as follows.

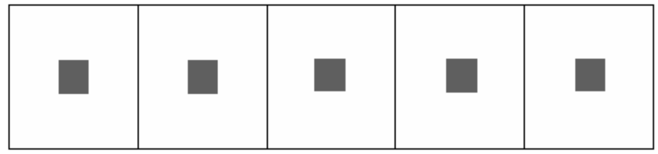
$$\frac{I_d(x,y)}{\sigma_d(x,y)} = \frac{I_w(x,y)}{\sigma_w(x,y)} \tag{5}$$

Eq.(5) shows our model is a contrast preserving model and the parameter n is omitted.

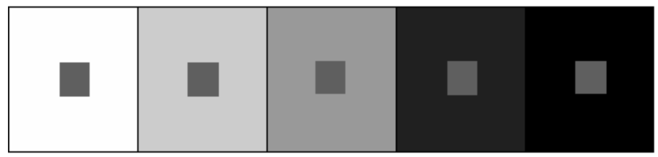
Display Adaptation

As expressed by Eq.(5), the decisions of $\sigma_w(x,y)$ and $\sigma_d(x,y)$ are the key points to compute $I_d(x,y)$. The proposed operator aims at the same considered pixels in the real world scene and its range compressed image on display devices can cause the same sensations of *HVS* after their own local adaptation respectively, therefore it adopts local adaptation models both for scene and display image. Before introducing the computation of scene adaptation, we first describe in detail the computation of display adaptation.

For simplicity, most published methods assumed that display observers have fixed steady state adaptation levels [1, 2, 14] and apply a single spatially invariant adaptation level to the whole image, for example 10-30cd/m^2 is used in [1]. However, the local adaptation processes actually take place at any time, regardless viewing the images on display devices or viewing the scene in the real world. The following phenomena show the local illusion of *HVS* well.



(a) The same center on same surround



(b) The same center on different surround

Figure 4. *The simultaneous contrast*

Figure 4 shows the famous simultaneous contrast phenomena [25]. The luminances of the center small squares are same in both Figure 4 (a) and (b). In Figure 4 (a), the center squares are surrounded by the same white surround, so they showed the same appearance as we observed. But when they are surrounded by different surround, they are observed very different though they have the same luminance. In Figure 4 (b), from left to right, with the surround tends to darker, the center square tends to lighter appearance. Conversely, from right to left, as the surround tends to lighter, the center square tends to darker appearance. These phenomena verified the appearance is closely related to the surround background and shows the local adaptation characteristics of *HVS*. Furthermore, the local adaptation processes take place whenever they observe scene in the real world or images on the display devices. If a single spatially invariant adaptation level is applied to display, the display visual appearance can not be correctly recreated.

However, as expressed in Eq.(5), the computation of $\sigma_w(x,y)$ is comparable easily because the $I_w(x,y)$ is known, such as using Gaussian filter. However, since the display luminance $I_d(x,y)$ to be recreated display image, it is still unknown, the decision of $\sigma_d(x,y)$ is difficult. Using the retinal response model to get the display adaptation and considering the scene adaptation as input, and the display adaptation as output, the display adaptation can be expressed as follows:

$$\sigma_d(x,y) = \frac{\sigma_w(x,y)}{\sigma_w(x,y) + \alpha} \tag{6}$$

Just as same as Figure 1, Equation (6) has also a *S*-shape curve. Due to the narrow range of display devices, it is unable to show the very dark and very light intensities in the real scenes. Corresponding to this, the display adaptation levels should match the similar narrow range of display luminance due to the local adaptation characteristics described above. Equation (6) can ensure this well. For example, the darker and lighter scene adaptation level than display are dramatically compressed to ensure the display adaptation levels in the range of display devices. Furthermore because the curve is monotonic it can also ensure that the scene light adaptation corresponds to the light display adaptation and the dark scene adaptation corresponds to the dark display adaptation. The parameter α is different for each image.

By Eqs.(5) and (6), the display luminance $I_d(x,y)$ is expressed as follows:

$$I_d(x,y) = \frac{I_w(x,y)}{\sigma_w(x,y)+\alpha} \tag{7}$$

Equation (7) shows that $I_d(x,y)$ is only related to the scene adaptation half point level $\sigma_w(x,y)$ and the parameter α, which make our model very simple.

Scene Adaptation

Equation (7) shows the decisions of $\sigma_w(x,y)$ and α are the key points to compute the display intensity $I_d(x,y)$. We adopt a similar local method for computing the scene adaptation $\sigma_w(x,y)$ to that for computing the surround image in Retinex which is a classic visual model for eliminating the influence of non-uniform illumination proposed by Land et al. first. The output of Retinex is determined by taking the *Center/Surround* (*C/S*) ratio of the pixel at any given point in the scene. Retinex model has been improved during past forty years. Kotera et al.[15] proposed a linear adaptive scale-gain *MSR* model based on *C/S*. In computing the surround image, to keep the color balance, they used only luminance image $Y(x,y)$, which expressed by Eqs.(8) and (9).

$$S_m(x,y,\sigma_m) = G_m(x,y) \otimes Y(x,y) \tag{8}$$

$$G_m(x,y) = Kexp\left\{-(x^2+y^2)/\sigma_m{}^2\right\},\ \iint G_m(x,y)dxdy = 1 \tag{9}$$

We follow the same method to compute scene adaptation $\sigma_w(x,y)$ by only luminance channel. In addition, $I_d(x,y)$ and $I_w(x,y)$ are applied to luminance channel too. By testing a single Gaussian filter with different kernel size, we found it is difficult to suppress the banding artifacts across high gradient edges. To avoid the banding artifacts, we substitute the Gaussian filter by bilateral filter, an edge preserving filter proposed first by Tomasi and Manduchi as an alternative to anisotropic diffusion[19] and used by Durand et al.[20] and Ledda et al.[14]. Equations (10) through (12) express the bilateral filter.

$$\sigma_w(s) = \frac{1}{k(s)} \sum_{p \in neigh(s)} f(p-s)g(I_p - I_s)I_p \tag{10}$$

$$k(s) = \sum_{p \in neigh(s)} f(p-s)g(I_p - I_s) \tag{11}$$

$$g(I_p - I_s) = e^{-\frac{(I_p - I_s)}{2\sigma_g^2}} \tag{12}$$

As expressed by Eq.(10), the bilateral filter is composed of two Gaussian filters, one is standard Gaussian filter $f(p\text{-}s)$ in the spatial domain, which can be expressed by Eq.(9). The other is an influence function in the intensity domain which decreases the weight of pixels with large luminance differences over center pixel I_s as expressed by Eq.(12).

The parameter σ_g specifies what gradient luminance should stop diffusion, so the output of the pixel s is determined mainly by the pixels in the periphery that are spatially close to and have a similar intensity, therefore avoiding banding or haloing artifacts.

Experiment

In this section, we present some examples of our *HDR* image compression technique. As described above, $\sigma_w(x,y)$ is computed by luminance channel, and in Eq.(7), $I_w(x,y)$ represents scene luminance intensity, $I_d(x,y)$ is the display luminance. To build RGB color display image $RGB_d(x,y)$, we use the following equation used by Fattal et al.[26].

$$RGB_d(x,y) = \left(\frac{RGB_w(x,y)}{I_w(x,y)}\right)^{\gamma} \cdot I_d(x,y) \tag{13}$$

Where γ is a gamma parameter, which controls the display image saturation, for our test images it is set to the range of [0.5, 1].

To demonstrate the effect of γ, Figure 5 shows the results with different γ for Memorial Church. The optimum γ can make more natural recreated image as shown in Figure 5(a).

(a) γ=0.5 (b) γ=0.8 (c) γ=1

Figure 5. *The results of Memorial Church for γ=0.5, 0.8, 1.*

The parameter α plays an important role in our model. The α is computed automatically in our model. Our goal is to recreate the scene image into the range of between 0 and 1 on the display devices, so we first compute the mean value of the scene image. Here, if the mean value is larger than 0.5, α is set to 1, while if the mean value is less than 0.5, α is set to 0.1.

We get good results for most of tested images by our model, as shown in Figure 6 (a) and Figure 7 (a), both are 32bit/channel *HDR* images. However, for some high dynamic range images the details in dark shadows can not be preserved well as shown in Figure 8(a). For improvement we multiply I_d(x,y) by an adjustment parameter $c(x,y)$ expressed by Eq.(14) and Eq.(15). The $c(x,y)$ can be considered as a gain parameter, but it only improves the details in shadow areas while preserving the light regions unaffected because $c(x,y)$ tends to be 1 when $\sigma_w(x,y)$ is larger than b gradually.

$$c(x,y) = 1 + a \cdot \exp\left(-\left(\frac{\sigma_w(x,y)}{b}\right)^2\right) \tag{14}$$

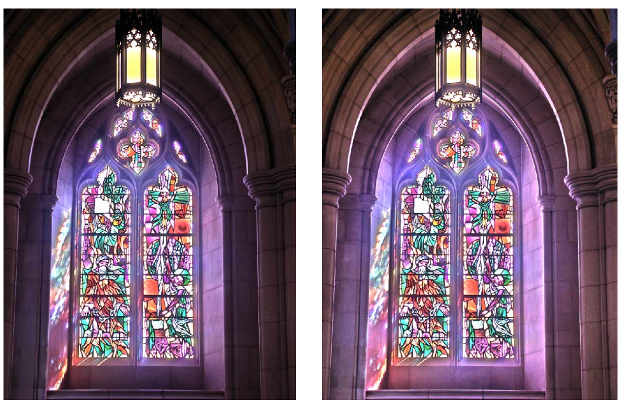
$$I_d(x,y) = \frac{I_w(x,y)}{\sigma_w(x,y)+\alpha} \cdot c(x,y) \tag{15}$$

Where b is an interactive constant parameter determined by user in the range of (0, 0.1) and a is automatically determined by the dynamic range of scene image in our model. For *HDR* image a is set to 1, otherwise to 0.

Figure 8(b) shows the result of rosette after improvement, where a = 1, b = 0.1, γ = 0.5. More dark shadows details are reproduced as shown in Figure 8 (b) than Figure 8 (a). In addition, the improvement is also applied to the images groveC and cathedral respectively. Figure 7 (b) shows obvious improvements and Figure 6 (b) shows some improvements too in dark shadows surrounded by yellow circle.

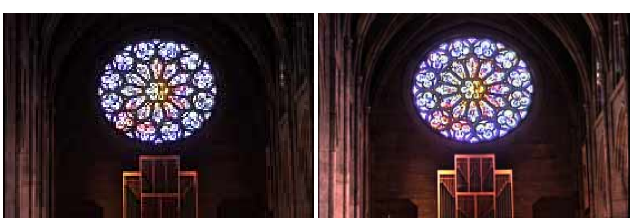
(a) a=0, α=1, σ_g=5I_s,γ=0.5 *(b) a=1, α=1, b=0.1, σ_g=5I_s, γ=0.5*

Figure 6. *The result of groveC by proposed method*



(a) a=0, α=1,σ_g=5I_s,γ=0.5 *(b) a=1, α=1, b=0.1,σ_g=5I_s, γ=0.5*

Figure 7. *The results of cathedral by proposed method*



(a) a=0, α=0.1, σ_g=5I_s,γ=0.5 *(b) a=1, α=0.1, b=0.1, σ_g=5I_s, γ=0.5*

Figure 8. *The results of rosette by proposed method*

All of methods of *HDR* images compression meet a problem preserving details and good contrast at the same time. However, as Larson et al. described [3], most of methods have generally met one of these criteria at the expense of the other. In our model, due to the use of bilateral filter, we adopt 2^o visual field in computing the kernel size, which brings good results in preserving details and pleasing contrast. Figures 9 (a) and (b) shows the results of 32bit/channel *HDR* image Memorial Church with the size of 512*768 by our proposed model with Gaussian filter and bilateral filter used σ_g=5I_s, α=0.1, a=1, b=0.05. Figure 9(a) shows profound banding artifacts around light windows, while Figure 9 (b) suppresses the banding artifacts very well due to stopping the high light luminance in the periphery by σ_g. For comparison, we also show the results of Larson et al. [3] and Durand et al. [20] in Figures 9 (c) and (d). Larson et al.'s result shows better contrast while lost details in light regions compared with our result. Compared with Durand et al.'s result, though our model does not show good details in dark shadow as Durand et al. [20] did, our result shows better contrast preserving for the overall image. In Figure 10 (a) and (b), we show the results of our model and Durand et al. [20] for 32bit/channel *HDR* image Office with the size of 656*1000. As clearly shown, though Figure 10(b) shows better details for outdoors, our result in Figure 10 (a) shows better result in contrast preservation and details for the inside of the room than Durand et al.'s.

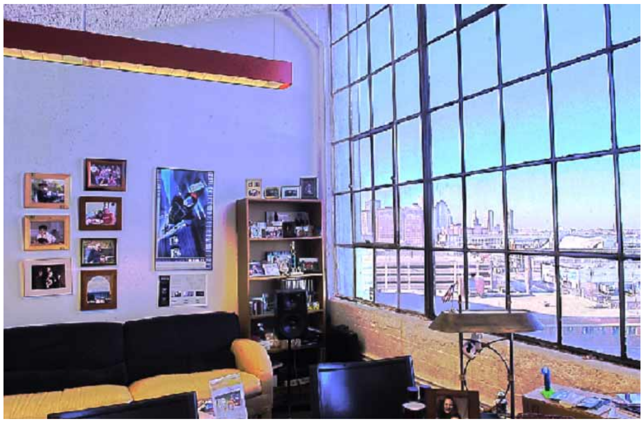
(a)Proposed method by Gaussian filter *(b)Proposed method by Bilateral filter*

(c) Larson et al.[3] *(d) Durand et al.[20]*

Figure.9 *Memorial Church*

Conclusion

In this paper, we proposed a simple static local adaptation method for *HDR* image compression based on retinal model to recreate the same visual sensations between the real scene and the image on display. We adopted a local model both for scene adaptation and display adaptation. To compute the local adaptation, we applied the nonlinear edge preserving bilateral filter, which preserves details and contrast with the suppression of banding artifacts often observed in local models by usual Gaussian filter.



(a)Proposed model

(b)Durand et al. [20]

Figure 10. *Small Office*

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