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Postfiltering for color appearance in synthetic image visualization

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Abstract. *In the photorealistic image synthesis process, an accurate approximation of the spectral light radiance field of a synthetic scene is carefully reproduced, with the goal of generating a synthetic image that is indistinguishable from the actual one. The paradigm of photorealism requires a comparison of the real scene and its synthetic reproduction, and the two visual representations should be studied under the same conditions to make a correct comparison and evaluate the degree of accuracy. To reproduce the same observing conditions, we need to define a sort of synthetic observer (given the impossibility to enter into a synthetic world) to compensate the deep differences in the viewing conditions, between the real and synthetic images. Various solutions have been proposed to this end; most of them are based more on perceptive measures of the human visual system (HVS) under controlled conditions, rather than on the HVS behavior under real conditions, e.g., observing a natural image and not a controlled black and white or colored pattern. Besides the comparison problem, difficulties can arise from the visualization phase, whose purpose is to display the final results of the simulation model on a monitor screen or printed paper. This is known as the tone reproduction problem, and in most cases, one has to find the best solution to compress an extended dynamic range of the computed light field into the limited range of displayable colors. Several solutions have been proposed to solve this problem. On the contrary, no mapping is usually made in case of low luminance and extremely limited dynamic range images, and consequently photorealism and visual appearance are lost. We propose a working hypothesis to solve the appearance and the tone reproduction problems in the synthetic image generation, integrating the Retinex model into the photorealistic image synthesis context, including in this way a model of the HVS in the image synthesis process.*
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1 Introduction

Most of the scientific problems that arise for generation of accurate images have been solved by new methods that compute the optical field produced by the interaction of light and materials. The reproduction of the optical field (luminance) on different supports (monitor or print) opens up problems of accurate reproduction of the luminance dynamics and of the color distribution. The computational complexity of the numerical methods needs solutions suggested by a deep understanding of how we perceive. In the field of image coding and compression, important results have been obtained to find efficient methods to lossy encode images while preserving the relevant information. The notion of visual redundancy makes it possible to reduce the spatial resolution of chromatic components, thus improving the efficiency of compression methods, leaving the loss of information almost unnoticeable.

We are mainly interested in the reproduction of a computed luminance field of a synthetic scene—displayable on a monitor—that does not have a real counterpart. In such cases we have no comparison metric, because no reference image exists, and the quality of the synthetic image can be evaluated only on the basis of the observer's experience and taste. We find two critical aspects. First suppose we want to simulate a scene whose luminance dynamics are so small or so large that only psychophysical adaptation should allow an observer to perceive its contrast. Second, the spectral characteristics of the light sources or the scene color composition give rise to a color recovery process (color constancy). These cases are intrinsically visual appearance simulation problems, whose solution need a human visual system (HVS) reference model. Our working hypothesis is to adopt Retinex as the HVS reference model, and to use the Retinex algorithm as a filter applied to a

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computer-generated luminance field without using any mapping operator, like the XYZ to RGB transform.

First, we recall the major synthetic image generation methods. Then we analyze the appearance problem in photorealistic synthetic imaging. After this, we discuss the aspects of the HVS that are more relevant to our purposes, and the major problems arising in its application. Furthermore, we present possible approaches to the tone reproduction problem, focusing on the case of low-luminance scenes. As examples, we present some critical images that try to simulate the lighting of museums or art galleries for interior design purposes, discussing the relevant results.

2 Lighting Computation for Image Synthesis

The goal of photorealistic image synthesis is the generation of digital images that are indistinguishable from real scenes, given a geometric representation of the scene and a photometric description of light sources and material properties. The first step to this goal is the computation of the light interaction with the geometric model of the scene, incoming to the image plane that simulates a virtual camera. Considering light as an electromagnetic wave, in the interval 380 to 780 nm, the problem of light-media interaction (surfaces of the objects as well as the participating medium) might be approached by trying to solve Maxwell's equations of electromagnetic field. Unfortunately, the solution of such equations for any nontrivial real-world problem is not feasible. An approximate solution derives from a radiometric approach, based on the radiant energy analysis over the electromagnetic spectrum. Therefore, photometric functions, such as spectral luminance $L_v(\lambda)$, may be obtained by simply weighting the equivalent spectral radiometric functions, such as the spectral radiance $L_e(\lambda)$, by the human spectral efficacy function $K(\lambda)$ with the known relation $L_v(\lambda)=L_e(\lambda)K(\lambda)$.

Lighting models are an approximate representation of light-media interaction, and are devised in such a way that the light distribution can be computed in a short time. Apart from a radiometric approach to the formulation of lighting models, in the history of computer graphics some empirical models (Lambertian,[1] Phong,[2] and Blinn[3]) were proposed. All these models try to describe the light-surface interaction only at the surface level in a simple and computationally efficient way. For example, no participating medium and very simple surface properties can be modeled. These are called local lighting models, since they are based on local point sampling on the surfaces, without considering the different possible origins of the incoming light. A second limit in such models is the extremely simple description of the reflectance properties of materials.

In radiometry, the reflectance properties of surfaces are described through the bidirectional reflectance distribution function (BRDF), while the transmission properties are described by the bidirectional transmission distribution function (BTDF). The two functions taken together describe the bidirectional scattering distribution function (BSDF). Given the incident radiance L_i through a solid angle $d\omega_i$ at an angle $\phi_i,\ \theta_i$ with respect to the surface normal, the reflected radiance L_r is given by Eq. (1) (see Fig. 1):

$$L_r(\lambda)=\mathrm{BRDF}(\lambda,\phi_i,\theta_i,\phi_r,\theta_r)L_i(\lambda)\cos\theta_i d\omega_i. \tag{1}$$

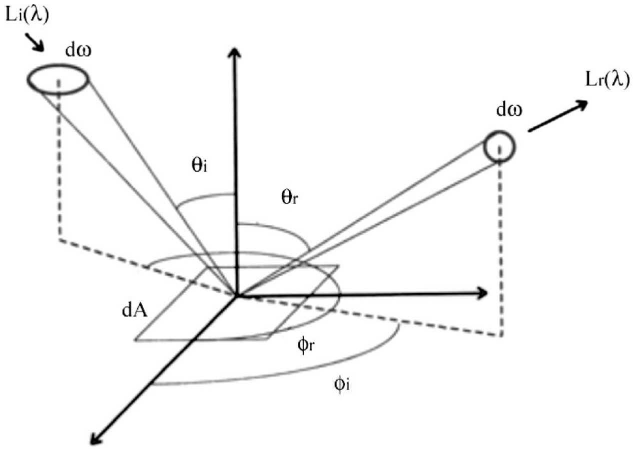

Fig. 1 BRDF function.

Unfortunately, this function is not analytically known. It can be sampled with lengthy and difficult measures, since it depends on the two directions of incidence $\phi_i,\ \theta_i$ and reflection $\phi_r,\ \theta_r$, and on the wavelength of the light radiation (and even on the position on the surface of the material if this is not homogeneous). The research on local lighting models tries to describe the BRDF in a simplified way, like Ramamoorthi in Ref. 4, who proposes a signal-processing-based solution to recover BRDF from images (inverse rendering). Other solutions use functions interpolated from sampled values.

More accurate local lighting models, based on radiometry, have been proposed by Cook and Torrance,[5] and He *et al.*,[6] while Kajiya,[7] and Poulin and Fournier[8] proposed models for anisotropic surfaces of conductors. To simulate dielectric materials, enhanced local lighting models consider the subsurface light scattering effect, which is described by a superset of the BRDF, known as the general bidirectional surface scattering distribution function (BSSRDF). This effect accounts for the surface texture appearance of marble, plastic, milk, and even human skin, depending on the scale and subsurface structure (molecular, multiple layers, etc.).[9–12] Subsurface scattering can also be solved by diffusion theory, and has been introduced first by Stam[13] and followed by Jensen *et al.*,[14] who enhanced this approach also for anisotropic materials and optimized it for the ray-tracing global lighting model. Using these models, it is possible to accurately simulate complex phenomena such as color bleeding inside materials and light diffusion across shadow boundaries.

The other challenge of lighting model research concerns the answer to the question: where is the incident radiance of Eq. (1) coming from? The simplest answer is: directly from the light sources. Many computer graphics rendering software and 3-D hardware processors rely on this simple assumption. But in the real world, light also comes (indirect lighting) from diffuse and specular reflections and transmissions from other objects in the scene. The solution to this problem leads to the definition of a global lighting model. The first attempt to compute indirect lighting was proposed by Whitted[15] with backward ray tracing, sampling light radiance with straight rays that start from the observer, through the image plane, searching for surfaces in the scene and using a recursive computation for the specular reflection and transmission of light rays backward to the light sources. This approach gives an accurate simulation of specular reflection and transparency, but does not account for diffuse interreflections, an important effect in indirect lighting that has been usually approximated with an empirical constant parameter called ambient light. The main disadvantage of ray tracing is its computational cost that quickly increases as the scene model complexity grows.

A different approach to ray tracing, called radiosity, is based on an approximate solution to the radiant energy (irradiance) balance in a closed environment. The first radiosity method implemented by Goral *et al.*[16] computes the radiant energy interchange between perfectly diffusive (Lambertian) surfaces. The solution is based on a finite element approximation, which requires surface subdivision into a mesh of patches. Different from ray tracing, the results are view independent, under the hypothesis that the observer does not affect the scene lighting, and the scene does not change. This allows fast image rendering for real-time walkthroughs of the geometric model. While radiosity computes a good approximation of light diffuse interreflection, it does not account for specular reflections and transmissions.

Kajiya[17] formalized the global lighting problem with the rendering equation, which describes the light transport in a generic scene. He also uses Monte Carlo approximation to solve the integral equation applied through a variance reduction scheme, called hierarchical sampling, aimed at reducing the number of samples. Another solution to the rendering equation is due to Wallace, Cohen, and Greenberg,[18] who presented a two-pass method for computing global illumination: the first pass, view independent, is based on the radiosity computation, while the second, view dependent, is based on ray tracing for reflecting and transmitting surfaces. Chattopadhyay and Fujimoto[19] presented a bidirectional ray tracing, where sampled rays are traced forward from the light source and backward from the viewpoint. Another important extension to the ray tracing method, which accounts for diffuse interreflections, was presented by Ward, Rubinstein, and Clear.[20] This approach was the starting work for the development of Radiance,[21] public domain rendering software, which uses a Monte Carlo technique for the indirect lighting contribution due to diffuse interreflections computed at a point selected by the rendering process. Finally, one of the first complete multipass global illumination models was presented by Chen *et al.*[22] They use radiosity for indirect lighting, illumination maps for caustic light effects, and path tracing for the final image rendering.

A more general description of the global lighting computation is due to Glassner,[1] who proposes the full radiance equation, which describes complex phenomena too, like phosphorescence and fluorescence, light polarization, and the scattering and absorption by participating media. This formulation is an integral equation of light radiance that cannot be solved analytically. Under simplified restrictions, a numerical Monte Carlo integration can be applied. When the restrictions are no participating medium, no phosphorescence, no fluorescence, and no light polarization, the radiance in the generic point r due to the radiation coming from point s on a surface, along the direction ω, can be expressed as the sum of the radiance L^e, possibly emitted by the point s in the direction ω, with the integral of all the incoming light contribution reflected from s to r, as shown by the simplified rendering equation:

$$L(\lambda,r,\omega)=L^e(\lambda,s,\omega) + \int_\theta \mathrm{BRDF}(\lambda,s,\omega,\omega')L(\lambda,s,\omega')\cos\theta' d\omega', \tag{2}$$

where the integration is extended to all the surfaces of the scene, and ω' and θ' are all the hemispherical directions of the incoming radiance from the surrounding environment to the points. Equation (2) is simply an extension of Eq. (1), considering all possible directions of the incoming light radiance and the light possibly self-emitted by the reflecting surface.

Two different approaches to solve the rendering equation lead to explicit approximation and implicit sampling. The first tries to construct an explicit representation of the radiance that satisfies the equation; an example of this approach is the radiosity algorithm. The second approach, implicit sampling, aims at computing the radiance only at sampled points of the scene, which may be points on the image plane like the ray-tracing method. The Monte Carlo ray-tracing approach to solve the rendering equation allows us to simulate almost all complex light distribution phenomena, avoiding the mesh subdivision of the surfaces required by the radiosity algorithm, a procedure that for complex scenes may require a huge memory amount. To overcome computational complexity and high-frequency noise, Jensen and Christensen[23–25] introduced the use of photon maps, a global illumination model based on a two-pass method that allows us to simulate complex phenomena such as caustics, diffuse interreflections, and participating mediums in complex scenes. One key point on the computation of the lighting model, evident from Eqs. (1) and (2), is that the radiance and the BRDF are functions of the wavelength. Often, rendering software, for computation efficiency, only samples the spectrum on the three wavelengths corresponding to the colorimetric RGB peaks, which do not correspond directly to sampled wavelengths in the visible interval 380 to 780 nm; they are colorimetric abstraction constructed on the tristimuls theory.

3 Photorealism and Visual Appearance

In the previous discussion, what is missing is the observer. The accurate physical models that have been developed to simulate light material interaction limit their effect on the computation of the light field as a product of some material properties, some light source properties, and some participating medium properties. (We recall that most of the previously mentioned models do not consider phase properties of the light, which are the basis of other relevant effects, like holography and interference patterns, or light polarization.) But synthetic images are created for an observer, who is the final judge of the result. In the particular case of photorealistic image synthesis, the realism is evaluated with respect to an abstract idea of what a real image of a scene should be, or by a direct comparison to a photo or a video display of the corresponding real scene. In general, this

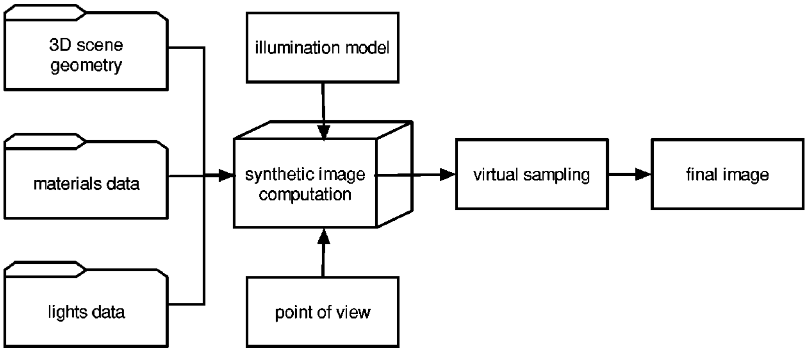

Fig. 2 Synthetic image generation process.

second situation is used for testing purposes, i.e., to validate a computational method to generate realistic images.

Studies about HVS mechanisms and visual appearance are not recent,[26–28] however, in the field of computer graphics, where efficiency plays an important role, only recently some researchers have addressed the problem of including the observer into the synthetic generation process. Research on tone mapping of synthetic images dates back to 1993, with the work of Tumblin and Rushmeier.[29] Pattanaik *et al.*[30] consider the visual appearance of a photorealistic synthetic image as an evaluation criterion and a desirable requirement. The idea underlying their work is that it is not necessary to compute data relative to details that are invisible to a normal observer, therefore speeding up the computation. To find out what is or is not perceived, HVS contrast sensitivity function analysis (chromatic and nonchromatic) is one of the basic techniques. Unfortunately, most HVS models considered by the computer graphics community give much importance to the ability of discriminating spatial frequency, but do not consider nonlinearity of color perception.

An important appearance-related problem that also has to be considered to improve the observer's final judgment is the tone reproduction problem. Synthesized (or acquired) image dynamic range can be much smaller or much greater than the device range. Tone reproduction aims at mapping the image dynamic range into the given device, keeping or improving the naturalness of the image. Following a classification proposed by Di Carlo and Wandell,[31] two major methods have been designed, and are still being improved: those based on a tone reproduction curve (TRC) and those based on some tone reproduction operator (TRO).

Besides the tone reproduction basic goal, we are also interested in solving other problems that arise when synthetic images are produced for a generic human observer. Light source characteristics play a relevant role, inducing color shifts and luminance irregularities that can be eliminated only by simulating color constancy processes. Moreover, the scene composition can generate color illusions, or induced color casts, that in normal viewing conditions are often discounted by the HVS.

Instead of using a tone reproduction curve or a tone operator, we propose a postfiltering approach, based on the following paradigm. The synthetic image generation methods compute a radiance field as the interaction of light and materials of the virtual scene. The radiance field is as accurate as the computational method allows. The observation process consists of sampling such an ideal world, giving rise to a picture. In other words, the physical simulation method creates images that are ''there, outside in the world of ideas,'' that, in turn, are transformed into pictures when an observer samples them. In reproducing this phenomenon, the psychophysical adjustment and the relative tone reproduction depend on the kind of virtual sampling process chosen. The sampler can be a virtual camera or a virtual person. When a virtual camera is the sampler, a digital photograph is the final picture, and we assume that the picture formation process is the same process of image formation in a camera. Therefore, the optical transfer function should be computed as well as the spectral response of the CCD or film emulsion, through which the image will be stored. In the other case, if the sampler is a virtual person, the picture is the result of the image formation process of the HVS. The optical transfer function of a typical human

Fig. 3 An example of an HDR image displayed, keeping the details in interior (left) or exterior (right) levels of luminance readable.

Fig. 4 Retinex prefiltering of HDR image of Fig. 3.

eye should be computed as well as the spectral response of the HVS, the contrast sensitivity, and the color constancy processes. In the first case, the final image should preserve the characteristics of the computed radiance field. No psychophysical adjustment happens, and it is perfectly correct to search for a tone reproduction curve, or a tone reproduction operator that simply maximizes the dynamics reproduction. In the second case, in turn, we expect to reproduce some of the mechanisms that are typical of the HVS (e.g., lightness or color constancy) that the mentioned operators are not able to simulate. A scheme of this process is presented in Fig. 2.

4 Modeling the HVS

We must not confuse the internal biological structure of the HVS with its functional modelization that is being considered in this approach, whose aim is to mimic HVS behavior.

HVS models, as proposed in the context of digital imaging, are generally composed by two stages: a visual encoding stage and the display mapping stage.[32] Visual encoding computes the appearance of each pixel in relation to the rest of the image, taking into account contrast sensitivity and modeling lateral inhibition of receptive fields and edge emphasis. In this phase, HVS mechanisms are performed both on local and global aspects of the image, while most HVS-based synthetic imaging approaches consider only global adjustments. Color perception models try to recover, via a spatial comparison, the invariant surface spectral reflectance properties of each point, realizing in this way the color constancy mechanisms of the HVS. An interesting characteristic of the HVS is that this computation is done independently on the three RGB chromatic channels, corresponding approximately to the three retinal cone spectral sensitivities.

The spatial decomposition is performed to differentiate the intensity signal over space, the derivative is thresholded to eliminate smooth changes, and finally the (thresholded) derivative is integrated over space to recover the surface reflectance component.[32] Threshold is one of the nonlinear parameters that affect the final image contrast, and consequently the realism of the final picture. Spatial comparison is the mechanism that transforms a radiance distribution into an appearance-based image.

Retinex[28,33,34] is one of these models. It carries out the image spatial decomposition, with a threshold mechanism and a final average recomposition. Therefore, it is a model that performs color constancy at the same time as lightness adaptation, which is a necessary step to the solution of the problem of synthetic image appearance-based equalization.

According to the Retinex theory, every color sensation derives from three independent stimuli in the three long, medium, and short wavebands (briefly RGB). For each waveband, the relative channel lightness R of each point is computed as the mean value of several relative channel lightnesses r along a number N of random paths across the image, ending at that point. For the three RGB channels, these computations are executed independently.

$$R^{i}_{R,G,B}=\frac{\sum_{k=1}^{N} r^{i,j_k}_{R,G,B}}{N}, \tag{3}$$

with

$$r^{i,j}_{R,G,B}=\prod_{x\in \mathrm{path}} \frac{I^{x+1}}{I^{x}}, \tag{4}$$

where I^{x} and I^{x+1} are the pixel channel values at the location x and $x+1$ along the random path.

Retinex has a reset mechanism. If, during a path computation, a lighter area is found, the ratio chain of the formula in Eq. (4) is forced to 1, making the computation restart from this area. The effect of the reset mechanism is to consider the lightest area of an image as the reference value for the color white.

A critical problem in the algorithm is the choice of the random path. The results depend on the randomness and on

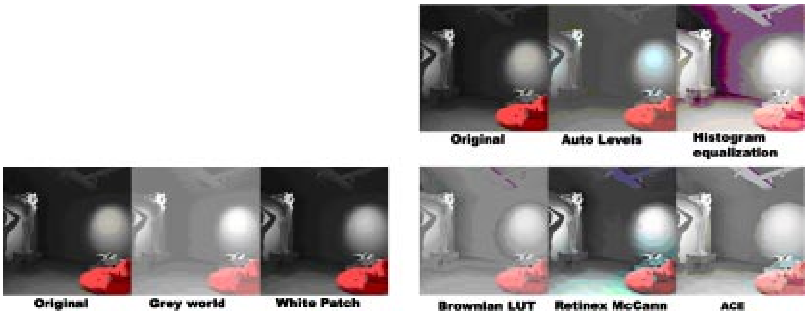

Fig. 5 Comparison of different postfilterings indoors: the high figure-to-background contrast is obtained by minimizing ambient diffuse light; direct illuminance <500 lux.

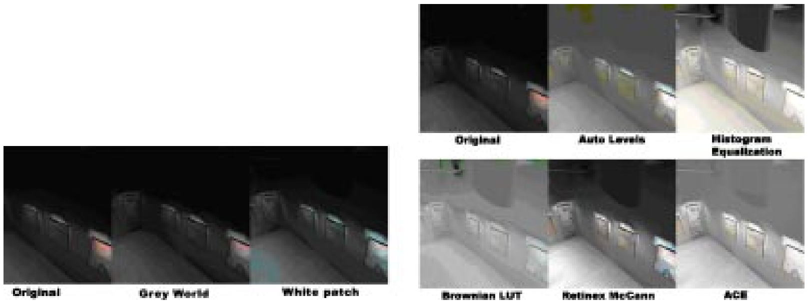

Fig. 6 Comparison of different postfilterings indoors: the simulation uses a very low level of illuminance on the paintings (<100 lux), obtaining also a reduced contrast, not visible in the original.

the number of the paths that are chosen for the computation. Moreover, the results depend on the threshold value making low-reflectance ratios (which correspond to a smooth shading) less relevant.

Changing these and other details, several implementations of Retinex have been realized so far. Most of them give comparable results.[35,36] We use McCann's[37] and Brownian LUT Retinex versions[36] together with an alternative HVS model, automatic color equalization (ACE).[38]

5 Applying the HVS Model

To solve the tone mapping problem, several approaches have been developed so far,[39–42] from tone reproduction operators to more detailed models of the HVS.

The basic parameters involved in the tone reproduction problem are lightness and contrast. The name ''tone reproduction'' can suggest that lightness plays the main role, but the perception mechanisms of our HVS link together lightness and contrast in its inner mechanisms. In fact, the major part of the vision models for image-based rendering use the contrast sensitivity function (CSF) to determine a lightness threshold in relation to the image local frequency content.

A widely accepted contrast measure for common digital images does not exist. Two different classic contrast measures with their relative physiological tests can be considered (the Weber contrast used in experiments with a-periodic signals like spot on background tests, and the Michelson contrast used with periodic signals as sinusoidal gratings), but both are defined and tested in simplified conditions, not in a complex context like, e.g., a photographic image. Moreover, these contrast measures are global, while contrast, for instance in usual photography, is a concept related also to local properties of a picture. A video photometer can be used to capture and measure the luminance of a view and to infer information about the contrast. Nevertheless, these instruments do not measure the spectral luminance but only the total luminance, and the estimate depends on the light source color temperature. Histograms can say something about contrast on a set of equal or very similar images, but the same criteria can fail when applied to another set of different images. A qualitative notion of contrast can be taken from the photographic context, where high-contrast pictures have high lights and dark shades, while keeping the visibility of all the details, giving the image a property often expressed as depth in contrast to flatness. However, contrast plays a fundamental role in modeling vision performances. Our HVS not only performs mechanisms like lightness constancy or color constancy, but also does a sort of contrast constancy. Moreover, some visual effects, e.g., the White's effect, cannot be explained simply with low-level vision mechanisms, but a higher cortical process has to be involved to understand these effects.

Another aspect that has to be taken into account is the ratio between the global and the local adaptation effects in the HVS. The balance between the two components is affected by the image content, in particular by features like spatial frequency distribution and color composition.

For all these mentioned reasons, the parameters tuning and the effect of the image context, e.g., sunsets or underwater pictures, can lead to unwanted or unpredictable results.

6 Tone Mapping Solutions

The tone mapping problem can vary widely, according to the lighting characteristics of the scene. We consider two

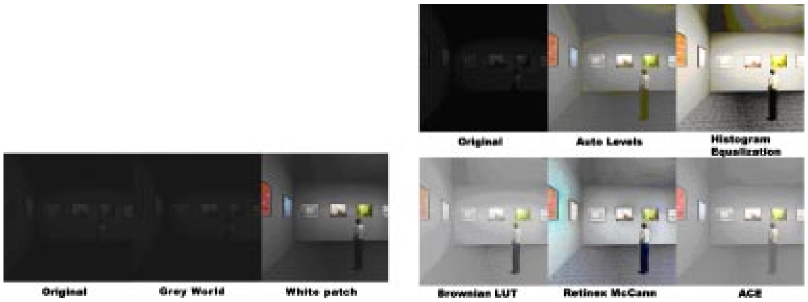

Fig. 7 Comparison of different postfilterings indoors: illuminants (halogen) have been designed to preserve colors; illuminance <100 lux.

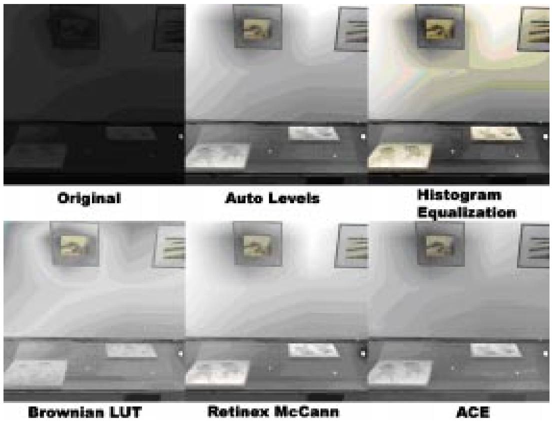

Fig. 8 Comparison of different postfilterings indoors: halogen sources; illuminance <50 lux.

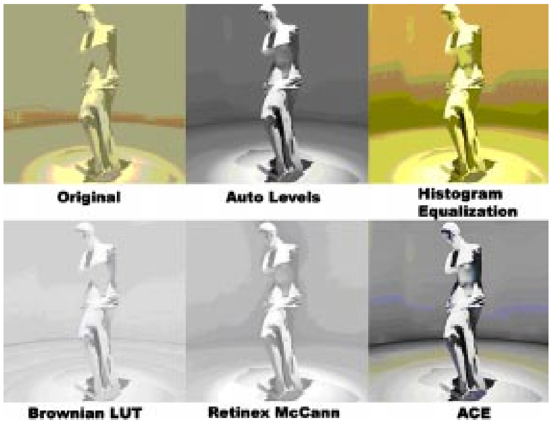

Fig. 9 Comparison of different postfilterings indoors under tungsten lamps.

major cases: first, strong overall contrast and high dynamic range, second, low overall contrast and low tones.

In cases of images with a strong overall contrast (e.g., backlight) and consequently a very high dynamic range in the computed luminance field, the HVS model can be applied before compressing data into the usual 8-bit device channel range.[43,44] In this case, we use the term prefiltering. Prefiltering is a good solution when the original luminance range is known or when images are stored in a high dynamic range (HDR) format. An example is shown in Fig. 3, where an HDR image (from Ref. 41) is displayed with two different linear tone maps: left, the map compresses high tones, emphasizing the details of low tones (interior); right, the map compresses low tones, emphasizing high tones (exterior). In this case, Retinex prefiltering performs an unsupervised local mapping, whose result is shown in Fig. 4. While both high and low tones are emphasized, an effect arises: the shadows around the window. This effect is very interesting and requires further analysis, since it can be varied due to parameter calibration, but it is intrinsic to the Retinex principle. From an appearance viewpoint, this shadow makes the image natural.

The second case occurs when the overall contrast and luminance value of an image are very low. To these images, Retinex (or any other HVS model) can be applied as a post filter, i.e., on the 8 bits per channel linear pixel encoding. We propose to achieve appearance and increase naturalness with a nonlinear remapping, based on a HVS model applied as the last stage in the image generation process. In terms of value tone mapping, dynamic range is not modified, but, as is presented in the following examples, the appearance and the naturalness of the scene can be greatly improved.

To test our working hypothesis, we have applied different algorithms as postfilters to computer-generated images (see Figs. 5–8). The images have been computed using the Lightscape (Autodesk, San Rafael, CA) rendering system, and the purpose of the simulation was to explore the problem of illumination of art galleries and museums. We have compared two versions of the Retinex algorithm, the Brownian LUT version[36] and the multiresolution version implemented by McCann,[37] and ACE,[38] a new algorithm recently developed that has characteristics similar to Retinex. Test cases are particularly critical; the luminance requirements for gallery illumination imply very low luminance levels, so that, in the real scenes, an observer should need an adaptation to the low illumination. To better understand the efficacy of Retinex and ACE based on a nonsupervised global/local approach, we also present some results of simple global tone reproduction methods: Gray World, White Patch, Auto Level (the automatic procedure of Adobe Photoshop, which is a LUT nonlinear mapping transformation), and the Histogram Equalization standard algorithm (Adobe Photoshop implementation).

In all images, global mappings, like Histogram Equalization, Gray World, White Patch, and Auto Levels, present lower performances than HVS-based methods, that, while improving contrast, keep or recover the corresponding colors. Images filtered by HVS-based methods reveal scene details hidden in the linear scaling, and their local adjustment properties result in a natural visual appearance. It is interesting to note in Fig. 9 the warm yellowish color (http://eidomatica.dico.unimi.it/eng/research.html#color) of the scene induced by the tungsten light source that is removed by HVS-based methods. In this figure, the quantization of colors is due to the limited color palette of the original image. A false color picture of Fig. 9 is given in Fig. 10.

7 Discussion and Conclusions

We apply different Retinex and other equalization algorithms to some computer-generated images of virtual

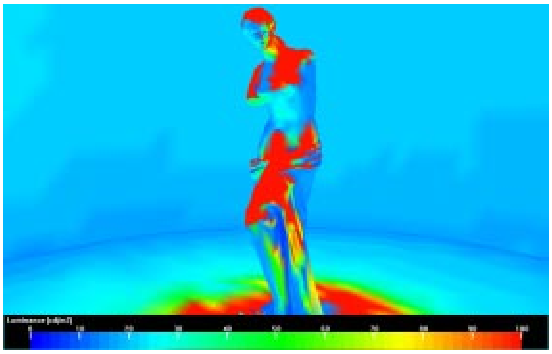

Fig. 10 False color picture of the examples in Fig. 9: background average illuminance 100 lux, max luminance 10.000 lux (log scale).

scenes with very low luminance values. The aim is to test a hypothesis of using Retinex (or alternative HVS models) as a postfiltering stage to solve contrast and color appearance simulation. The test cases explore the problem of illumination of art galleries and museums, and present very low dynamic ranges and local contrasts.

Preliminary results are encouraging. The postfiltering technique is able to map the image values to make their appearance more natural in most cases.

Regarding the comparison between the various HVS models, no absolute winner has been found. According to the authors, this is a good result, since all the Retinex versions and ACE have satisfying comparable performances in every situation.

All HVS models, which have a mixed global/local behavior, perform better than classic global techniques (Gray World, White Patch, Auto Levels, and Histogram Equalization), which, in some cases, introduce unpredictable color shifts. The stronger aspect of the Retinex and ACE algorithms is their ability to perform dynamic range mapping and color recovery at the same time.

Our working hypothesis needs more investigation to better analyze parameter tuning and the different behaviors of Retinex algorithms, and to compare our approach to alternative methods for tone reproduction and color constancy.

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