Automatic Aesthetics-based Lighting Design with Global Illumination

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Abstract
In computer graphics, lighting plays an important role in the appearance of a scene. A change in the configuration of light sources can lead to different aesthetics in the final rendered image. Lighting design becomes increasingly complex when using sophisticated global illumination techniques. In this paper, we present a new approach to automatically design the lighting configuration according to the aesthetic goal specified by the user as a set of target parameters. Target parameters are used to set up an objective function which is minimized using an optimization method. The results show that our method can be used to automatically design a lighting configuration that will give to the final image a classic photographic look.

Categories and Subject Descriptors (according to ACM CCS): I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Color, shading, shadowing, and texture

1. Introduction

In computer graphics, global illumination rendering methods take into account multiple phenomena such as reflection, refraction and scattering. However, because of these numerous phenomena, it is difficult to know beforehand what the resulting image will look like. Achieving a desired image style can be a time-consuming and tedious effort if performed through a trial-and-error process.

To obtain a satisfying result automatically, the user has to express his intent by providing a set of target values as properties of the final image. The goal is to change iteratively the parameters of the 3D scene to fit the specification. A lot of parameters of the scene can be taken into account. Among which are: 1) position, size, flux of the light sources 2) reflectance of the materials 3) distribution of the objects in the scene.

Methods used to compute lighting parameters to fit a given set of constraints are called inverse lighting methods. We present in this paper an inverse lighting method which takes as input the aesthetic intent of the user. This aesthetic intent is specified by a set of parameters. Our method minimize an objective function which expresses the distance between the current image aesthetic and the desired result. This function is minimized to find the optimal parameters of the lighting.

In this article, we will mainly address two target aesthetics used in films and photography: high-key and low-key pictures. High-key and low-key aesthetics focus on one object of the scene, called henceforth *main object*. High-key images are bright, do not have too much contrast, nor feature dark shadows cast by the main object. Low-key images have a darker tone, their contour lines are highlighted and the background is usually black. They also feature high values of contrast.

2. Related Works

Inverse lighting methods, introduced by Kawai et al. [KPC93], are used to find a light configuration that produces an image with the desired characteristics. This is an ill-posed problem. These methods allow us to compute an ideal lighting configuration for the 3D scene, given a lighting specification. This lighting specification is considered as a target that represents the desired result.

Inverse-lighting methods differ by the type of target they use, the optimization process, but also by the parameters they modify. In the rest of this section, we will distinguish two categories of inverse-lighting methods: image-based and global methods. For more details, the reader can refer to the survey on inverse-lighting problems by Patow and Pueyo [PP03].

Image-based Methods Inverse-lighting in the context of radiosity had been discussed by Schoeneman et al. [SDS*93]. The user provides a target radiosity vector, which elements are the desired radiosity of each patch of the scene, by painting on an image of the scene with a brush. The goal of this method is to find the emittance of each light source in the scene. Light source positions and orientations are fixed, and only their emittance is automatically computed. Moreover, the user has to provide the target image using the painting interface, which can be a time-consuming task.

The SAIL model presented by Zupko and El-Nasr [ZEN09] does not use an image of the scene as a target. Instead, the provided target is an image of an illuminated sphere. The target image is thus independent of the scene. However, generating and understanding such an image can be a difficult task for the user.

Global Methods do not use an image as a target. Instead, they use a set of target values for descriptors that describe an image's aesthetics. These methods proceed by minimizing an objective function, often a linear combination of several terms.

Kawai et al. [KPC93] use a linear combination of three terms that measure the mean brightness, non-uniformity and peripheral characteristics of the lighting of the scene. The weight assigned to each of these terms is specified by the user so that he can construct his own constraint. The objective function is minimized iteratively using the Broyden-Fletcher-Goldfarb-Shanno non-linear optimization method (BFGS) [ZBLN97].

Fernandez et al. [FB14] introduce an efficient way to solve a radiosity-based inverse lighting problem. Desired values for the mean and variance of the radiosity values are provided, and an optimization operation is performed. Many other existing works use radiosity-based rendering methods to optimize the placement of light sources in architectural settings [CSFN11, CdAS12].

The method introduced by Shacked and Lichinski [SL01] computes the lighting configuration that is optimized for understanding the shape and fine details on the scene's objects. In this technique, the authors optimize by gradient descent the direction of the point light sources (θ_i, ϕ_i) and their associated intensity. To achieve this optimisation, it uses an objective function f_q that is a linear combination of terms defined as follows:

$$\begin{aligned} f_q &= \sum_{s \in S} w_s f_s, \\ S &= [mean, var, hist, grad, edge, dir], \end{aligned} \tag{1}$$

where the terms f_s measure different distances between the targeted parameter values and the associated luminance mean f_{mean}, the luminance variance f_{var}, the luminance histogram f_{hist}, the magnitude of gradients f_{grad}, the appearance of edges f_{edge} and the elevation of light sources f_{dir} (this term is optional).

Discussion Providing a target image [SDS*93, ZEN09] is a time-consuming process and although the result may feature the right highlighted areas, it may not communicate the aesthetics expected by the user.

The work presented by Shacked and Lichinski [SL01] uses an objective function to better understand the 3D shape of the main object. Moreover, this is done in a simple setting (object is isolated, uniform background) and without using physically based rendering (direct only, OpenGL rendering with differents intensities for specular and diffuse material)

In contrary, the goal of our work is to cover a broader range of aesthetics. The user should be able to control the lighting design process through target values used by the objective function. We want to take into account multiples light reflections. The solution should also provide flexibility in terms of nature of light sources, whereas only point lights are considered by Shacked and Lichinski [SL01]. In particular, we are interested in studying the influence of the size of the light sources on the final result.

As Shacked and Lichinski [SL01], we specify a main object for the scene to evaluate the aesthetics properly. This is analogous to photography where an isolated subject is considered. The rest of the image is considered as a background. Contrary to Shacked et al., we do not consider objects on a uniform background, but we consider them as part of a complete scene, and the appearance of the background contributes to the overall aesthetics.

Using our method, the user can express his aesthetic intent by defining target parameters. Thus, our objective function is completely configurable: it is made of several terms, each one taking into account one target value. In this approach we are mainly interested in light-based aesthetics, we do not consider composition or color-appearance, and we focus on luminance values. In the next section, we will introduce our approach to define the objective function and to design the optimization process. Our contributions to inverse-lighting consist in:

- describing different lighting aesthetics
- considering both object and background appearances
- taking indirect lighting into account
- handling area light sources parameters

3. Overview of the approach

In this section we will detail the different steps of our method (Fig. 1). Then, in the section 4.1, we will give further details on the free variables, the evaluation of the objective function and the optimization process.

Our goal is to allow the user to modify the aesthetics of a scene by changing the appearance of the main object and the

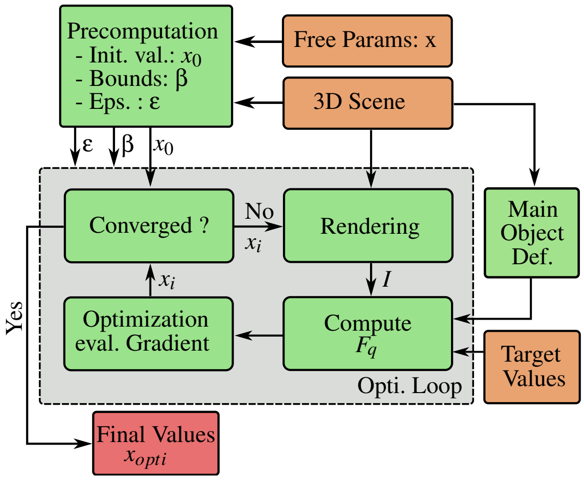

Figure 1: Our framework picture. Green boxes represent the different process of our algorithm. Orange boxes represent the value provided by the user. Red box is the result of our algorithm.

background. In order to make it feasible, our method takes as input (orange boxes in Fig. 1): the 3D scene description, free parameters x whose values have to be determined automatically and the target values which describe the desired aesthetics.

Before running the optimization process, we automatically find some values during a pre-processing step: the initial value x_0 of the free variables, the bounding values β of these variables and the gradient evaluation step ε for each variable.

The optimization loop (gray box in Fig. 1) is used to find a set of parameters that minimize the objective function. At each iteration, the scene is rendered using a global illumination technique. Then new values of the parameters to be optimized are computed. The objective function f_q is computed as a linear combination of terms and the different terms that will be described in the next subsection. Then, the optimization algorithm performs a gradient descent. At the end, the algorithm will return final values x_{opti} of the free variables.

4. Approaching an aesthetics with function minimization

The goal of our method is to automatically design a lighting configuration that brings a target aesthetics to the scene in the context of global illumination. In our context, we want the user to have control on the aesthetics of the scene. Furthermore, in the context of global illumination, the range of attainable aesthetic is wider than when only considering direct illumination. With this aim in view, as we want our approach to be as generic as possible, any rendering method can be used, and any kind of light source can be considered.

In the next subsections, we will introduce the different terms of the objective function used by the minimization process (Section 4.1). Then, we will list the different free variables that the algorithm can tune automatically (Section 4.2) . Finally, we will describe the optimization process and the automatic pre-computation step (Section 4.3).

4.1. Objective function

Similary to Shacked and Lichinski's method [SL01],The objective function is a linear combination of several terms (Eq. 1) but with a different term set S. In this set, each term define a distance in $[0,1]$ between a value computed on a rendered luminance image I and a target value provided by the user. In the next subsections, we will detail how to compute the different terms of the objective function.

4.1.1. $\mathbf{f_{meanObj}}$,$\mathbf{f_{meanBack}}$, $\mathbf{f_{varObj}}$ and $\mathbf{f_{varBack}}$

These terms control the mean and the variance pixel luminance value on the object and on the background respectively. In terms of aesthetics, the terms $\mathbf{f_{mean}}$ control the overall brightness of the object and of the background and $\mathbf{f_{var}}$ control how smooth the background and the object appear. The target values $t_{meanObj}$, $t_{meanBack}$,t_{varObj} and $t_{varBack}$ range in $[0,1]$. The terms are computed as follows:

$$f_{meanObj} = \frac{|\bar{I}(object) - t_{meanObj}|}{max(t_{meanObj}, 1 - t_{meanObj})} \quad (2)$$

$$f_{meanBack} = \frac{|\bar{I}(background) - t_{meanBack}|}{max(t_{meanBack}, 1 - t_{meanBack})} \quad (3)$$

$$f_{varObj} = \frac{|\sigma(object) - t_{varObj}|}{max(t_{varObj}, 1 - t_{varObj})} \quad (4)$$

$$f_{varBack} = \frac{|\sigma(background) - t_{varBack}|}{max(t_{varBack}, 1 - t_{varBack})} \quad (5)$$

where $\bar{I}(x)$ and $\sigma(x)$ are the mean luminance and the luminance standard deviation over object pixels or background pixels.

4.1.2. $\mathbf{f_{grad}}$

The gradient term f_{grad} is used to control the shading gradient on the object's surface. If the target value is high, then the shape of the object will appear as more pronounced. A low value will make the contours more subtle. Using a pair of Sobel filters, we compute two gradient images $G_x = A \star I$ and $G_y = A^T \star I$. We obtain for each pixel $p_{i,j}$ the gradient vector $\nabla l_{i,j} = (G_x(i,j), G_y(i,j))$. The average shading gradient norm is then computed as follows:

$$g(object) = \sqrt{\frac{1}{N_{obj}} \sum_{p_{i,j} \in object} |\nabla l_{i,j}|^2} \quad (6)$$

where $object$ is the set of pixels marked as object's pixels in the image mask, and N_{obj} the number of these pixels. The final term f_{grad} which is the distance to t_{grad} is defined as:

$$f_{grad} = \frac{|g(object) - t_{grad}|}{max(t_{grad}, 1 - t_{grad})} \tag{7}$$

4.1.3. $\mathbf{f_{hist}}$

As explained in the work of Martin et al. [MFSG08], luminance histograms must be used with other descriptors to express an image's aesthetics. However, by using supervised learning on well known aesthetics (such as high key, low key, and medium key images), a signature histogram can be extracted for each class. These signature histograms are then used as target that will be compared with the luminance image's histogram. Signature used in this paper are given in the additional materials.

Minimizing the objective function brings the image's histogram closer to the target histogram. The f_{mean} and f_{var} terms have an influence on the value of the term f_{hist}. However, f_{hist} describes the complete luminance distribution and does not provide any spatial information, whereas f_{mean} and f_{var} evaluate statistics for distinct areas of the image, so these terms are more complementary than they are redundant. This term is evaluated as the Matsusita distance between two discrete distributions [CS02] and normalized to be between $[0,1]$:

$$f_{hist} = \left[\sum_{i=0}^{b-1}(\sqrt{p_i} - \sqrt{q_i})^2\right]^{0.5} \left[\sum_{i=0}^{b-1} max(q_i, 1 - q_i)\right]^{-0.5} \tag{8}$$

where b is the number of bin in the cumulated histogram, p_i and q_i is the $i-th$ cumulated value of the signatures histogram and the image's histogram.

4.2. Free variables

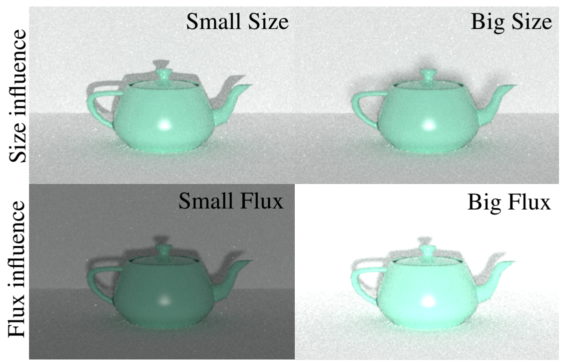

Figure 2: Influence of the light parameter on the rendering. With a constant flux, the size controls the shadows strength. With a constant size, the flux controls the light's contribution.

The output of our algorithm is a set of lighting parameters values that minimizes the objective function. A point light can be defined using a 3D position and a intensity value. An area light source has a size that also influences the lighting of the scene. As shown in Fig. 2, the size of the area light and the flux can change the aesthetics of the rendered image. However, changing its size does not have the same impact as changing the flux on the objective function's value. This could cause a problem in the optimization process as the gradient of the size variable could be low hence provide few information. Instead of using the flux, we use the emitted luminance which introduces correlation between this value and the scale of the light source.

Moreover, the scene setup itself influences the space of achievable aestetics. For example, bright material for background makes it impossible to obtain a low-key image . To overcome this problem, we propose to the user an option to change the material properties for all background objects. This is done by modulating the V channel of the HSV material's color.

4.3. Optimization

The optimization step uses an implementation of the L-BFGS-B algorithm [ZBLN97] used by Kawai et al. [KPC93] that takes into account additional constraints such as bound parameters. During the optimization process, the objective function is minimized by a gradient descent technique. However, our objective function does not have an analytic expression and partial derivatives are approximated numerically.

However, the free parameters have different orders of magnitude and need to be bounded. For example, the size of the light source needs to be strictly positive and bounded so that the light source does not mask the main object. Moreover, for estimating the gradient by finite difference, a proper order of magnitude of ε (variable step) needs to be chosen. A too small value may produce no significant change in the image. A too large value may compromise the minimization. The parameters themselves are scaled to have similar orders of magnitude. Thus, when testing for convergence, the gradient is comparable for each variable. The initial values x_0 of the free variables are important for the optimization: if we start from an initial value set so that only one light source contributes to lighting, the optimization may only modify that light source and falls into a local minimum.

All these values (bounds, initial values, epsilons) are found automatically during the step described as a "precomputation step" in Fig 1. For more implementation details, the reader can refer to the additional material.

5. Results

The method described above as been implemented in Python using the LBFGS-B [ZBLN97] optimization method. The rendering step has been performed with the Mitsuba rendering platform [Jak10]. To speed-up the optimization process, all the intermediate images have a lower resolution than the final one. Our implementation has been applied to different scenes with different target values to obtain an optimal lighting configuration that corresponds to a desired aesthetics. This section highlights some of the results we obtained using this method.

Table 1 presents the two sets of target values and the weights used in the objective function. These two configuration will be used for all our scenes. The High-key configuration "HK" will target a bright background and low variance on the object. We use a High-key histogram signature. The Low-key configuration "LK" will target bright object but dark background to get contrast. Moreover, the variance on the object should be high, to reflect self-shadowing. The signature is a Low-key histogram signature. For the weights of the objective function, we use the same weights for the background and the main object. We use a bigger weighting value for the histogram term f_{hist} as it describes the image globally.

function term	HK	LK	weight
$t_{meanObj}$	0.47	0.47	0.5
$t_{meanBack}$	0.78	0.04	0.5
t_{varObj}	0.24	0.63	0.4
$t_{varBack}$	0.17	0.04	0.4
t_{grad}	0.39	0.39	0.2
t_{hist}	high	low	1.0

Table 1: Configurations and weights used for the target function.

Figure 3: *Girl* (left column) and *Creature* (right column) scenes. First row: optimization for a High-key aesthetic. Second row: optimization for a Low-key aesthetic.

Figure 3 shows the result of our method for two different scenes: on the left, the *Girl* scene, with two planar light sources ; on the right, the *Creature* scene, with a planar light source behind the camera and two spherical light sources in the background. These two scenes have been rendered using path tracing with the Halton sequence.

As we can see in the second and third row of Fig. 3, we can reach two different aesthetics with the same scene. Final values for the *Girl* and the *Creature* scenes are shown in table 2. In the former scene with HK configuration, we obtain a bright background with low variance, and low variance on the object. In the LK configuration, we obtain a dark background with low variance and a high variance on the object to bring contrast. For the *Creature* scene with HK configuration, we still have shadows on the background as the background is large and difficult to fill completely. In the LK configuration, we see high contrast on the main object, and a dark background. Timing information are shown. We used an Intel(R) Core(TM) i7-2630QM CPU @ 2.00GHz to generate the results.

	Girl		*Creature*	
final value	HK	LK	HK	LK
$v_{meanObj}$	0.47	0.45	0.45	0.44
$v_{meanBack}$	0.82	0.18	0.78	0.13
v_{varObj}	0.21	0.33	0.23	0.25
$v_{varBack}$	0.13	0.06	0.21	0.11
v_{grad}	0.51	0.46	0.50	0.50
f_{hist}	0.137	0.278	0.187	0.184
f_q	0.284	0.609	0.308	0.529
timing (sec.)	569	810	718	467

Table 2: Final values, f_{hist} and f_q values for the *Girl* and the *Creature* scenes (Fig. 3).

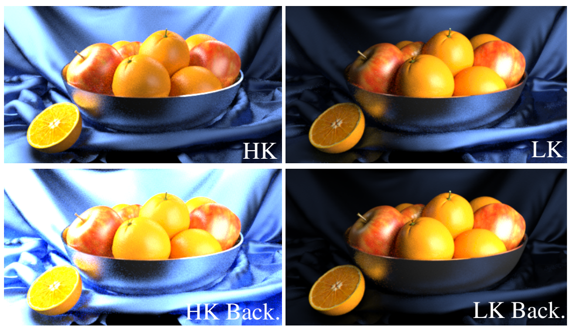

Figure 4: *Fruit basket* scene. First row: The HK and LK results without changing the background. Second row: The HK and LK results without changing the background.

Figure 4 shows the results with a more complex scene and the results are summed-up in table 3. This scene is rendered with a bidirectional path tracing technique. Three different light sources are optimized at once. However, the glossy and uneven background surface makes it difficult to reach Low-key and High-key aesthetics. In both cases, the variance of the background has to be low, which is difficult to reach with glossy reflections. In the case of the Low-key image with background albedo optimization, because the albedo of the background is reduced, reflection from the object's glossy surfaces are reduced, and the background appears less glossy. Final values are presented in table 3. Influence of the

	without back.		*with back.*	
final value	HK	LK	HK	LK
$v_{meanObj}$	0.52	0.46	0.70	0.46
$v_{meanBack}$	0.42	0.16	0.68	0.07
v_{varObj}	0.27	0.25	0.23	0.27
$v_{varBack}$	0.30	0.15	0.30	0.06
v_{grad}	0.58	0.52	0.74	0.54
f_{hist}	0.241	0.197	0.079	0.125
f_q	0.618	0.602	0.456	0.419

Table 3: Final values for the *Fruit Basket* (Fig. 4, second row), f_{hist} and f_q values with and without background albedo optimization.

rendering process on variance has to be taken into account. Indeed, Monte Carlo estimator provide a precise estimation of the $f_{meanObj}$ and $f_{meanBack}$ values. Other cost function are sensitive to the variance of the estimator. In this paper, we set-up manually the rendering technique to have minimal noise. We plan to find an automatic solution as future work.

6. Future improvements

Our method can be further improved to provide even more flexibility for expressing the desired image aesthetics. For instance, in this paper, only the luminance distribution has been considered. In the future, we want to consider color distribution similar to color transfer applications. In general, describing and controlling the desired aesthetics needs further research.

The optimization procedure can be improved. Indeed, gradients are computed by finite differences by recomputing the rendering process from scratch. However, gradient computation can be automatically performed during the rendering process. Moreover, we know that some free variables have a specific impact to the rendering as shown in Fig. 2. A multi objective optimization algorithm may help to be more robust and find the optimal configuration faster.

More complex lighting configurations need to be studied. The position of the lamps are fixed in our method. However, wrong light positions can prevent the technique from reaching a correct minimization. This issue will be addressed in an future work.

7. Conclusion

This article introduced a new method for inverse rendering that accounts for target parameters given by the user to specify a desired image aesthetics. These target parameters are used to parametrize an objective function that is then minimized iteratively. After each iteration, new values for the parameters of the scene (in our case, scale and luminance of the light sources, material in the background) are set up, and we re-evaluate the objective function. We tested our approach with two classic photographic styles (high-key and low-key) and we obtained good results that communicate the desired aesthetics, as specified by the target parameters. In the objective function, we use simple luminance metrics. It could be interesting to investigate the use of higher level metrics such as saliency to take into account the visual perception.

Acknowledgements

The different scenes can be download at blendswap.com. *Girl* is by Sharon. *Creature* is by Kevin Hays. *Fruit basket* is by Andrew Price.

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