21st International Conference on Pattern Recognition (ICPR 2012)
November 11-15, 2012. Tsukuba, Japan

Predicting Environment Illumination Effects on Material Appearance

Jiří Filip Michal Haindl Jaroslav Stančík
Institute of Information Theory and Automation of the AS CR *Varos s.r.o.*
jiri.filip@utia.cz

Abstract

Environment illumination is a key to achieving a realistic visualization of material appearance. One way to achieve such an illumination is an approximation by rendering of the material surface lit by a finite set of point light sources. In this paper we employed visual psychophysics to identify a minimal number of point light sources approximating realistic illumination. Furthermore, we analyzed stimuli images and correlation of their statistics with obtained psychophysical data. Finally, image statistics were identified which can predict such a minimal environment representation for three tested materials, depending on the visual properties of the illumination environment.

1 Introduction

Achieving a realistic appearance of real-world materials in virtual scenes is impossible without environment illumination. Such an environment can be approximated by its model to any required precision. In an idealized model we could assume that parameters of the environment are known. Unfortunately, the exact environment parameters are seldom known, therefore an application of the model mostly introduces unknown approximation errors. One way to achieve the desired illumination is to use a global illumination approach, generating an image by tracing the path of light through pixels in an image plane and simulating the effects of its encounters with virtual objects. This approach theoretically provides excellent quality at the cost of high computational requirements, so achieving real-time rendering in this way requires specialized graphics hardware. Several image-based approaches emerged to remedy these drawbacks. These approaches typically represent captured illumination environment by a finite set of directional lights. Although methods exist nowadays allowing real-time rendering from such environment representations, they rarely take into account the visual properties of environment illumination (further denoted as EI) and/or the material being illuminated.

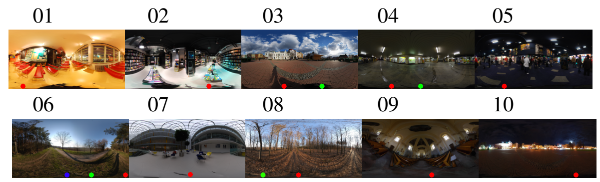


Figure 1. Tested illumination environments.

Prior work: The idea of illumination by means of environment maps was first introduced in [2] and further applied in [3]. As global illumination algorithms based on ray-tracing were computationally demanding, importance sampling methods were developed [1], [4] representing the environment map by means of a finite set of directional lights. The importance of context environment information and specular reflection for perception of surface reflectance was studied by [7] with the conclusion that observers can match correct environment based only on the surface reflectance. [10, 11, 8] studied effect of shape, EI and reflectance on human perception. Subjects' perception of realistically textured scenes was analyzed [9, 6] and used for [5] material appearance data compression. We are not aware of any work that has applied psychophysical methods to assess both bidirectional textured material appearance and EI-dependent perceptual effects.

Paper contribution: In this paper, we use a psychophysical study (Section 3) to determine the simplest representation of EI which preserves visual fidelity of the original environment. Furthermore, we use this information to derive a statistical feature (Section 4) predicting such representations automatically for novel EIs (Section 5).

2 Data Preparation

Environment Acquisition and Representation

For purposes of our work we acquired ten different illumination environments (see Fig. 1). Each environment was obtained by merging eight overlapping photos taken with a fish-eye lens. Each such environment (2048×1024 pixels) was represented by a finite set of directional lights using the median-cut algorithm [4] as follows. Every environment image is first gammacorrection compensated ($\gamma = 2.2$) to obtain the original linear response of the camera sensor. The algorithm then iteratively splits the input environment map image into even sets of regions by cutting the regions at the point where the medians of the cut regions' luminance are mutually equal. For rendering, the environment map is wrapped over a sphere surrounding the illuminated object. To compensate over-representation of regions near the poles, the luminance pixels of the environment map are weighted by cosine of the inclination angle. Fig. 2-top shows the compensated environment 02 represented by 128 light by means of the median-cut algorithm. An example of the sphere illu-

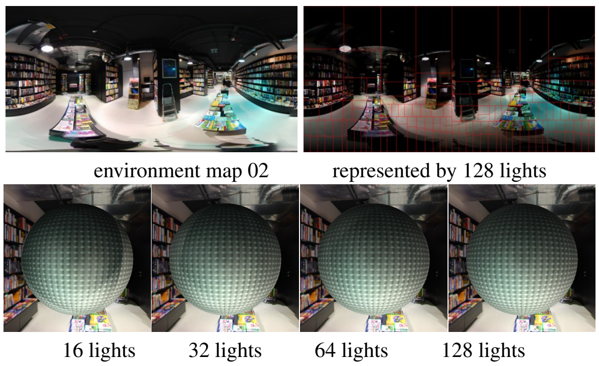


Figure 2. Example of environment illumination. The spheres are illuminated by different numbers of lights.

minated by a different number of lights approximating the environment by median-cut algorithm is shown in Fig. 2-bottom. The quality of shading and presence of disturbing seams on the object's surface are clearly dependent on a number of lights. Our goal is to identify the lowest number of lights that preserve the naturalness of EI and suppress these visible artifacts.

Materials Representation

Contrary to using reflectance only (BRDF) [10, 11, 8] we represented material appearance using view- and illumination-dependent textures (BTF) [5] samples *alu* (Fig. 2), *corduroy*, and *leather* (Fig. 3) from the BTF Database Bonn[1].

Rendering of BTF using a finite set of n_i directional lights can be described as their convolution with each pixel

$$L_r(x, y, v) = \sum_{i=1}^{n_i} BTF(x, y, \omega_i, \omega_v) L_i(x, y, \omega_i), \quad (1)$$

where ω_i, ω_v are illumination and viewing directions, $L_i(x, y, \omega_i)$ is radiance of individual lights and $L_r(x, y, v)$ is final radiance reflected by the sample.

3 Psychophysical Experiment

The goal of the experiment was to analyze the material-dependent sensitivity of human subjects to a simplified representation of different real-world illumination environments.

Pairs of static images of size 640×640 pixels were used as experimental stimuli, representing a material BTF rendered on a sphere. Each pair consisted of a reference rendering using the 256 lights and another rendering using a set of 16, 32, 64, 128, or 256 lights. Pairs of images were displayed simultaneously, side-by-side as shown in Fig. 3. We used the shape of a sphere because its geometry provides a wide range of illumination and viewing combinations without introducing unwanted higher curvatures, which could mask sought artifacts. All three test materials were rendered in ten test environments. As some environments were used in multiple views, the total number of different tested illuminations was fifteen. Azimuthal positions of views are shown in Fig 1 as red (the first view), green (the second view), and blue (the third view) dots at the bottom of environment maps. Given three materials, fifteen environments, and five quality levels of illumination representation, the total number of stimuli was 225.

Figure 3. Experimental stimuli showing a sphere in illumination environment (256 vs. 32 lights).

Twenty volunteers (8 females, 12 males) participated in the experiment. All participants had normal or corrected to normal vision and were naive with respect to the purpose and design of the experiment. The participants were shown the stimuli in a random order and asked a yes-no question: *'Can you spot any differences in the material covering the two objects?'*. Participants were asked to answer in 3 seconds to avoid decision based on a minor local difference. It turned out that 94 % of the responses were made in 2 seconds. All stimuli were presented on a calibrated monitor during night under dim room ceiling light.

By averaging the responses of all participants, we obtained psychometric data relating the average response to different numbers of lights, environments, and materials. The numbers of lights required for each EI and material were obtained from a psychometric function using 25% threshold [5] and are shown in Fig. 4.

4 Relation to Illumination Maps Statistics

We analyzed the relation between obtained human visual attention and feasibly computable statistics of stimuli and environment maps. We were inspired by the image salience methods, therefore we took a cir-

[1] http://btf.cs.uni-bonn.de/

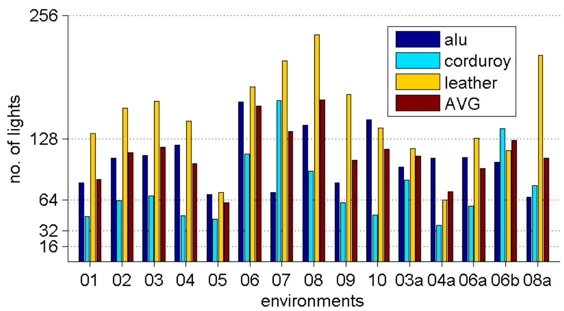
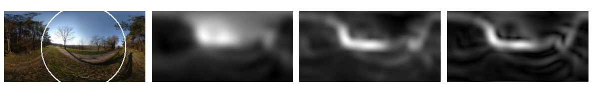


Figure 4. Estimated minimal number of lights for EIs and materials.

cular Gaussian-weighted window (with shape specified by a parameter σ) to obtain the local mean value μ_L, standard deviation σ_L, and energy e_L ($e_L(x,y) = \sqrt{(\partial I/\partial x)^2 + (\partial I/\partial y)^2}$). These features were applied on environment maps (I) down-sampled to resolution 256×128 pixels. Results for the Gaussian window $\sigma = 5$ are illustrated on the environment map in Fig. 5. As these features describe local properties of individual pixels, their mean $\mu(\mu_L)$, $\mu(\sigma_L)$, $\mu(e_L)$ and standard deviation values $\sigma(\mu_L)$, $\sigma(\sigma_L)$, $\sigma(e_L)$ were computed for EI map description.



EI map μ_L σ_L e_L

Figure 5. Example of the tested statistics ($\sigma = 5$)

Stimuli Images Analysis

First we used the six proposed features for description of stimuli images used in the experiments. As these images comprise two distinct parts – an environmentally illuminated textured sphere and background – we analyzed these parts separately. Tab. 1 shows correlation of the features with results of the main psychophysical experiment. The correlation was computed as a Pearson correlation coefficient $R_{X,Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$, where X, Y are compared average subject responses with a feature's values, μ and σ are their means and standard deviations. The table shows coefficients for three tested materials and background for a width of Gaussian window $\sigma = 10$. Correlation of the features for textured sphere was relatively low (the highest values $R \approx 0.5$) for $\mu(\sigma_L)$ and $\mu(e_L)$. What is surprising is a higher correlation ($R = 0.63$) of $\sigma(\mu_L)$ computed in a stimuli background. This suggests the hypothesis that variance in stimuli background or contrast between the background and textured sphere significantly influences perception of visual artifacts caused by insufficient representation of environment illumination.

Table 1. Correlation R of the statistics with results of the experiment ($\sigma = 10$).

	$\mu(\mu_L)$	$\mu(\sigma_L)$	$\mu(e_L)$	$\sigma(\mu_L)$	$\sigma(\sigma_L)$	$\sigma(e_L)$
alu	-0.13	0.35	0.28	0.10	-0.11	0.17
corduroy	-0.15	0.35	0.52	0.35	-0.02	0.23
leather	-0.23	0.37	0.48	0.15	0.23	0.17
backgr.	0.37	0.30	0.36	**0.63**	-0.22	0.01
EI	0.39	0.19	0.45	**0.61**	0.25	0.62

Environment Maps Analysis

The results obtained from analysis of the stimuli image opens a question of whether it might be generalized to environment map images. For this reason we identified the region in the maps roughly corresponding to the background visible in the stimuli images (see Fig. 5-left) and computed the proposed features directly on such parts of environment maps. Results of the features' correlation with subjects' responses from the experiment are shown in the last row of Tab. 1. Again there is a high ($R = 0.61$) correlation of $\sigma(\mu_L)$ (variance of the locally averaged part of the environment map) regardless of the size of σ. Such correlation values were also achieved by a local energy feature $\sigma(e_L)$, however only for $\sigma > 9$.

5 Illumination Complexity Prediction

In the applied context of this research we aimed at development of a simple computational method for automatic prediction of a minimal acceptable representation of illumination environment. Such a method would describe dependency of an optimal number of lights on material statistics and environment map statistics. For this purpose, we plotted dependency of the estimated number of lights from the experiment on values of the best feature $\sigma(\mu_L)$ in Fig. 6. While (a) shows such a dependency of $\sigma(\mu_L)$ computed on the tested materials and background from stimuli images, (b) shows dependency of $\sigma(\mu_L)$ on the tested materials and their average, computed directly from environment maps. The plot for each material contains 15 points corresponding to the tested illuminations. In all plots we can see the tendency toward requirement of an increasing number of lights with the increase of a feature's value. To express this dependence analytically we fitted the data points by polynomials of different ranks. Due to a low number of data points and their low consistence, however, this resulted in data overfitting. Therefore, the data points were finally approximated by a linear regression ($y = kd + q$) in a least square sense, resulting in the red outlines shown in the plots. From the slants of the outlines it is apparent that this tendency is clearly material-dependent. Vertical offset of the fitted outlines confirms our previous finding that visual artifacts, introduced by representation of minimal number of lights, were the least apparent for structured *corduroy* and the most apparent for diffuse *leather*.

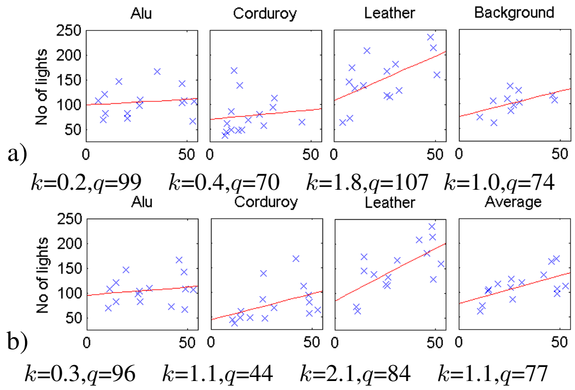


Figure 6. Dependence of number of lights estimated from the experiment on $\sigma(\mu_L)$: feature values (a) computed from stimuli images, (b) computed directly from environment maps. The red outlines - LS linear fit.

To show a practical application of our conclusions we acquired an additional five environment maps as is shown in the first row of Fig. 7, and computed the $\sigma(\mu_L)$ feature on backgrounds of selected views (red dots at the bottom of the images). A number of lights was predicted from the regression parameters k, q (Fig. 6) and the feature values. When observing renderings of materials in all test environments there are not any visible artifacts, and the minimal numbers of lights required for rendering vary across both tested environments and materials.

6 Conclusions

In this paper we analyzed human observers' ability to detect visual artifacts caused by under-representation of environmental illumination by a limited set of directional lights. We have found that this ability significantly depends on the type of illuminated material as well as on the type of illumination environment. Generally, an increase of the standard deviation of local mean value in an environment map increases the ability of human observers to detect visual artifacts introduced by means of an insufficient number of lights representing the environment. Therefore, the more visually complex/rich the environment is the more lights are required for its proper representation. We have shown how this number of lights depends on the type of illuminated material, and how it can be predicted from an environment map's statistics.

7 Acknowledgments

We would like to thank the University of Bonn for providing BTF measurements and volunteers for participation in the experiment. This work has been supported by the Grants GAČR 103/11/0335 and 102/08/0593, EC Marie Curie ERG 239294, and CESNET grant 409.

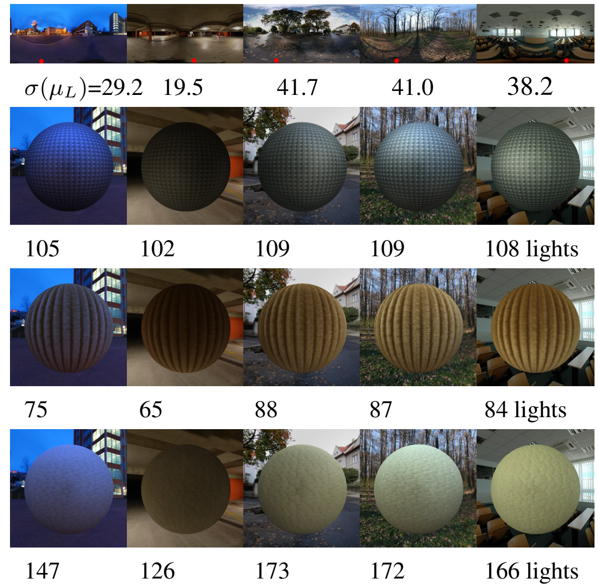


Figure 7. Illumination of the tested materials by the number of lights predicted from the EI statistics.

References

[1] S. Agarwal, R. Ramamoorthi, S. Belongie, and H. Jensen. Structured importance sampling of environment maps. In *SIGGRAPH 2003*, pages 605–612, 2003.

[2] J. Blinn and M. Newell. Texture and reflection in computer generated images. *Communications of the ACM*, 19(10):542–547, 1976.

[3] P. Debevec. Rendering synthetic objects into real scenes: Bridging traditional and image-based graphics with global illumination and high dynamic range photography. In *ACM SIGGRAPH 1998*, pages 1–10, 1998.

[4] P. Debevec. A median cut algorithm for light probe sampling. In *SIGGRAPH 2005 (Posters)*, 2005.

[5] J. Filip, M. Chantler, P. Green, and M. Haindl. A psychophysically validated metric for bidirectional texture data reduction. *ACM TOG*, 27(5):138, 2008.

[6] J. Filip, M. Chantler, and M. Haindl. On uniform resampling and gaze analysis of bidirectional texture functions. *ACM TAP*, 6(3), August 2009.

[7] R. W. Fleming, R. O. Dror, and E. H. Adelson. Real-world illumination and the perception of surface reflectance properties. *Journal of Vision (2003)*, (3):347–368, 2003.

[8] J. Křivánek, J. Ferwerda, and K. Bala. Effects of global illumination approximations on material appearance. *ACM TOG*, 29(4):112, 2010.

[9] J. Meseth, G. Müller, R. Klein, F. Röder, and M. Arnold. Verification of rendering quality from measured BTFs. In *APGV*, 2006.

[10] G. Ramanarayanan, J. Ferwerda, B. Walter, and K. Bala. Visual equivalence: Towards a new standard for image fidelity. *ACM TOG*, 26(3), 2007.

[11] P. Vangorp, J. Laurijssen, and P. Dutre. The influence of shape on the perception of material reflectance. *ACM TOG*, 26(3), 2007.