Light Shapes: Perception-Based Visualizations of the Global Light Transport

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In computer graphics, illuminating a scene is a complex task, typically consisting of cycles of adjusting and rendering the scene to see the effects. We propose a technique for visualization of light as a tensor field via extracting its properties (i.e., intensity, direction, diffuseness) from (virtual) radiance measurements and showing these properties as a grid of shapes over a volume of a scene. Presented in the viewport, our visualizations give an understanding of the illumination conditions in the measured volume for both the local values and the global variations of light properties. Additionally, they allow quick inferences of the resulting visual appearance of (objects in) scenes without the need to render them. In our evaluation, observers performed at least as well using visualizations as using renderings when they were comparing illumination between parts of a scene and inferring the final appearance of objects in the measured volume. Therefore, the proposed visualizations are expected to help lighting artists by providing perceptually relevant information about the structure of the light field and flow in a scene.

CCS Concepts: • **Human-centered computing** → **Visualization**;

Additional Key Words and Phrases: Light transport, visualization, lighting design, perception

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1 INTRODUCTION

Complex sceneries are ever-present in computer graphics either as a context of primary action (e.g., cinematography and game design) or as the main focus (e.g., architecture and interior design). Lighting plays a crucial role in modeling virtual scenes because of its strong influence on the appearance of objects, materials, and spaces. In turn, objects, materials, and spaces influence the resulting light in a scene. For example, both the appearance of objects and the physically measured properties of the light differ in a room with white walls from that in a room with black walls (Xia et al. 2017a). Therefore, in order to consciously manage the looks of a scene, one should keep in mind the intricate model of all light interactions, a sheer impossible task. Common practice in

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computer graphics is the use of preview renderings to see the results of scene manipulations. A disadvantage of this approach is that inferring the illumination from a resulting image suffers from ambiguities of interactions between light, material, and shape perception (Belhumeur et al. 1999; Marlow et al. 2012; Pont and te Pas 2006; Zhang et al. 2015) and consequently might be insufficient to understand how a certain light effect was achieved. Besides, a repetitive rendering wastes a significant portion of working time. Thus, an explicit visualization of light in a scene can be a powerful tool to help in the design of its appearance.

Conventional light visualizations for lighting designers, i.e., false-color plots of the luminance, show luminance distribution over the scene surfaces or planar cross-sections (e.g., Dialux, Lighting Analysis Assistant of Autodesk 3ds Max, LiteVis (Sorger et al. 2016)). This approach provides little more information than a simple rendering and is not enough to explain how light affects appearance including shading, shadowing, 3D texture, highlight contrast, and so forth. In a recent review of artistic appearance, lighting, and material editing approaches, Schmidt et al. (2016) recognized the necessity of methods conveying more information about lighting than preview renderings, while they also acknowledge the difficulty of light visualization because of its high dimensionality.

The visualization of light transport, which shows the propagation of light through a known 3D environment, is gaining attention in the computer graphics field. Many researchers (Reiner et al. 2012; Schmidt et al. 2013, 2016; Zirr et al. 2015) acknowledge the difficulty of light transport analysis and visualization because light travels in every possible direction through any point in an empty space and interacts in a complicated manner with the environment. There are a number of studies on volumetric light visualization (see Section 2.1), yet many of those provide analyses that are too complex for many users in the lighting design realm. Moreover, a lighting designer might not need to see all the light interactions in order to manipulate illumination in a scene. Most important is to judge the variations of light that have a strong influence on the human visual perception of objects/scenes. Our visualizations show perceptually relevant light properties, accessible to a user after a brief instruction.

We address light visualization from lighting design and perception perspectives, with a focus specifically on showing intensity (in our tool—mean spherical illuminance), direction, and diffuseness of light. These three are the basic properties that underlie our visual experience of light and are perceptually meaningful and make sense to anyone—in contradistinction to, for instance, the sixth-order spherical harmonic component or number of photons in a specific direction. Moreover, these components are used as the basic building blocks to compose a light “atmosphere” in architectural perception-based lighting design (see Section 2.2). Consideration of only these three light parameters turns our light transport visualization problem into one of tensor field visualization, along with the concept of “light flow” that is well known and used in architectural lighting design (Ashdown 1998; Cuttle 2003; Cuttle 1973). A tensor field can be visualized via a wide range of primitives that allow simultaneous representation of the three parameters. We chose three types of shapes: arrows, ellipsoids, or tubes as presented in Figure 1.

Our main contribution is thus a new approach to light visualization inspired by insights from architectural lighting design and perception. The principal feature of our approach is visualizing perceptually relevant properties of light as a tensor field—in a manner that can be easily understood also by lighting artists without a computational background.

2 RELATED WORK

2.1 Light Transport Visualization

In recent years, the visualization of light transport was addressed for several goals. Some researchers use light visualization to demonstrate the working of their computation methods or to study the optical mechanisms behind the light transport. Such representations often require a high level of technical expertise to understand them and are less suitable for practical purposes of light artists. For example, Durand et al. (2005) presented a signal processing framework for analysis and visualization of space-angle frequency spectra of the radiance

Fig. 1. Fragment of a scene and three types of light visualizations. Left to right: scene rendering, arrow visualization, ellipsoid visualization, and tube visualization. Note that the visualizations were presented in a viewport, in which the default shading is incongruent with the actual light field and thus the visualizations provide the only cue to the light field. For the formal evaluations of our proposed methods we placed five bunnies' silhouettes (four shown) for comparison of light properties in each image.

function. This framework was extended by Ramamoorthi et al. (2007) to gradient analysis of the basic shading steps, showing the relationship between spatial and angular effects on appearance. The technique of Zirr et al. (2015) provides information about the amount of light scattering in the neighborhood of a given point. Although they produce visualizations of light throughout the whole scene, their approach seems to be hard to grasp without understanding vector field topology and also quite time consuming, since the stated computation time ranges from 1 to 5 hours. In contrast to the studies listed above, our goal is to visualize light in an intuitive way even for novice users.

One of the most straightforward methods of light transport visualization is showing it as rays or in the form of ray trees, light paths, or light beams (Gribble et al. 2012; Nowrouzezahrai et al. 2011; Simons et al. 2016). In the field of optics, relevant studies have been done on capturing and visualizing physical light as traces of light through fluorescent liquids or frame-wise propagation of light (Hullin et al. 2008; Velten et al. 2013). However, such representations might be cluttered due to the presence of too many rays/paths and provide only directional information. Moreover, one should mentally integrate all rays to infer the final effect on the appearance of the scene. Schmidt et al. (2013) in their light paths clustered the paths and contracted them toward the paths' medial axis within a user-specified region of interest. This approach reduces clutter but still only tells about light paths' directions. Impressively, the authors also provided a possibility to manipulate the visualized light paths in physics-based rendering contexts and, for example, to move shadows and caustics.

Another approach is to visualize certain properties of light transport in a volume of a scene. Reiner et al. (2012) proposed a set of light transport visualization tools for interactive exploration of scenes. Two of these tools translated a single probe measurement to a spherical plot or a particle flow. To explore the whole scene, a user needed to manually move the probe over the volume, seeing the results in each point separately, and then integrate them mentally. Their "light path inspection" tool recursively clustered measurements from other probes to show from which direction a point is illuminated. Their "volumetric control" tool showed rasterized light paths in a volume. Chajdas et al. (2011), in their paper about environment map probe placement, selected probes' positions in sinks of an irradiance gradient field, which was visualized as a grid of arrows. Their illustrations give a clear impression of the irradiance gradient field (directional component) in a space. Jacobs (2014) proposed a similar technique in the Radiance lighting simulation software (Ward 1989). For multiple points in a grid, Jacobs showed the direction of light via an arrow direction and intensity (illuminance) as both arrow length and color. Mury et al. (2009) visualized the physical light (radiant flux transfer) using tubes. The light tubes are tangential to the light vector (net flux transfer) and their thickness is inversely proportional to the strength of the light vector (see Section 3.1). Xia et al. (2017a) extended the tube visualization by adding color saturation and brightness to represent the diffuseness and the light density, respectively.

Table 1. Examples of Naming Light Properties in Different Fields

Field	Intensity	Direction	Diffuseness	Other
lighting design (Kelly 1952)	intensity and brightness	direction	diffusion	spectral color
photography (Hunter et al. 2007)	brightness	direction	contrast	color
perception (Koenderink et al. 2007)	intensity	direction	diffuseness	
computer graphics (Birn 2013)	brightness	angle	softness	color temperature, throw pattern

In this article, we bring together the advantages of volumetric light visualizations listed above with knowledge of human perception (see Section 2.2) and apply that in visualizations that represent the variation of three perceptually meaningful light properties throughout a scene, underlying our visual experience of the light and basic components in lighting design. As representation shapes we chose arrows and tubes, because their suitability for light visualization was already demonstrated by Murry et al. (2009) and Jacobs (2014), and ellipsoids, as an alternative tensor visualization.

2.2 Perceptually Relevant Light Properties

A professional involved in scene or image creation must know how to use light as a tool to change the appearance of that scene or image. Typically, lighting artists are guided by their own knowledge combined with trial-and-error procedures (Gershbein and Hanrahan 2000; Kim and Noh 2009). By repetitively adjusting, rendering, and viewing a resulting scene, they experiment until they are satisfied, judged via their visual perception of the result. Would there be a more efficient, scientifically informed manner to find what combination of light properties reveals their scene best?

The importance of intensity, direction, and diffuseness of light for designing illumination is pointed out in multiple fields: architectural lighting design (Cuttle 2003; Descottes and Ramos 2013; Innes 2012; Kelly 1952; Russell 2008), photography and drawing (Hunter et al. 2007; Yot 2001), and, of course, computer graphics (Birn 2013; Brooker 2006). There is no universal terminology adopted by all fields, and authors describe the same (or very similar) properties in different terms; see the examples in Table 1. These light properties determine scene appearance for a large part (Ramamoorthi and Hanrahan 2001a), for instance, the modeling (how well 3D shape is brought out), material attributes (for instance, 3D texture roughness or softness (Zhang et al. 2015)), and spatial perception (for instance, how wide or high a space looks). Here it should be noted that most natural materials show a major diffuse mode in their reflectance, and that the appearance of this mode is determined by these mathematically lower-order light properties (the higher-order ones are “diffused out” (Ramamoorthi and Hanrahan 2001b)). Since we perceive light by its effects on objects and people in scenes, and not by looking directly at the sources, these properties also form the major part of our experience of light itself (Koenderink et al. 2007; Pont 2013; Schirillo 2013). In addition, the higher-order angular frequencies of the spherical harmonic approach are important in a statistical sense, for instance, for glossiness and atmosphere/gist perception.

Psychophysics provides a rich background for understanding how the human visual system processes interactions between light, shape, and material (Fleming et al. 2003, 2004; Koenderink and van Doorn 2003; Koenderink et al. 2003; Maloney and Brainard 2010; Marlow et al. 2012; O’Shea et al. 2010; Pont and te Pas 2006; Pont et al. 2015; Zhang et al. 2015). Perception of light properties was researched less extensively, yet there are multiple results that could be useful for computer graphics lighting artists.

Some studies focus on a single light property or a combination of two. For example, Lopez-Moreno et al. (2010) measured the accuracy of human vision in detecting lighting inconsistencies in images. Gerhard and Maloney

(2010) investigated sensitivity to a change in light direction. Toscani et al. (2017) studied how changing the illumination intensity on a moving object influences the perception of the object's lightness. Morgenstern et al. (2014) found that performance on judging light direction is worse in diffuse light, largely because of the intrinsic difficulty of lighting direction discrimination.

Koenderink et al. (2007) tested the sensitivity of human observers to all three light properties in empty space. They created a binocularly viewed scene under three light conditions and placed a virtual white spherical probe on top of the scene images. Observers could control the lighting of the sphere. The task was to set the lighting of the sphere as if it was in the scene. They demonstrated that observers have robust expectations about a matte object's appearance in accordance with the illumination of a surrounding scene. Xia et al. (2014, 2017) confirmed these results for real scenes using a setup with two independently controlled scenes that were optically mixed via a semitransparent mirror.

It is rather difficult to judge multiple light properties simultaneously and entirely in the observer's mind, because this task is complex due to their interactions and because light is an ungraspable and quite abstract "matter" to most people. If one needs to add spatial dimensions to the task, i.e., estimate the three light properties throughout a scene space, it becomes even harder. In an earlier study, we (Kartashova et al. 2016) compared physical measurements of light fields in a scene under three illuminations and visual inferences on photographs of those conditions. We found that, although human observers have a robust impression of the light field, this impression is simplified with respect to the physical truth and agrees with homogeneous, converging, and diverging superpatterns (van Doorn et al. 2012).

In the current study, we intended to visualize the light properties (intensity, direction, and diffuseness) of which the influence on human perception of objects and space was confirmed by multiple studies and additionally to determine the global superpatterns in the perception of light itself.

2.3 Measuring and Visualizing the Physical Light

Gershun (1936) was the first to introduce the concept of *light vector*, defined as the net transport of radiant power, and *light field*, defined as a five-dimensional function describing the radiance arriving at a point x, y, z from direction θ, ϕ (usually called a "plenoptic function" in graphics). Ramamoorthi and Hanrahan (2001a) demonstrated that lighting for matte convex objects can be successfully approximated by the first three components of a spherical harmonics (SH) decomposition, losing only about 1% of information. The SH components can be related to lighting design terms. The zeroth-order component, a monopole, corresponds to ambient light, uniform light coming from all directions. The first-order component is a dipole, the orientation of which matches the orientation of the light vector. The second-order component is a quadrupole varying from a "clamp" (i.e., illumination from opposite light poles (combined with a dark ring)) to a "ring" (i.e., illumination from a ring surrounding an object (combined with two dark poles)). Consequently, the primary direction of light in a point can be derived from the orientation of the first-order component. Diffuseness can be acquired from the ratio between the first- and zeroth-order SH components (Xia et al. 2017a), and intensity (mean spherical illuminance) can be acquired from the magnitude of the zeroth-order component. Recently, Mury et al. (2007, 2009) demonstrated that the lower-order SH components of physical light fields can be reconstructed for points in between relatively few measurements using interpolation. This finding allows us to sample the light field using a limited amount of points in our measurement grids.

Mury et al. (2007, 2009) used a custom-made device called a "plenopter" with 12 sensors evenly distributed over a sphere to sample the second-order SH approach to the light field. Note that the second-order SH description has nine coefficients, and therefore such a 12-sensor apparatus suffices to capture it. Xia et al. (2017b) showed how a cubic apparatus with only six sensors suffices to robustly measure the first-order SH approach to the light field (having four coefficients) and that the ratio of the first- and zeroth-order determines the diffuseness. Moreover, they showed that the approach by Cuttle (2003, 2013), a researcher in the architectural light design

field, comes down to the same measurements. Cuttle's formulas for the cubic meter are simpler to calculate than an SH approach (Xia et al. 2017b) and therefore we will use them.

3 LIGHT VISUALIZATION FRAMEWORK

In this section, we describe the principles and the prototype of our light visualization tool. The objective of this article was to visualize the light properties in such a way that observers are able to infer the light properties in a viewport preview as well as from a full rendering. Extracting just three perceptually relevant light properties from (virtual) measurements allows us to visualize light as a tensor field via a grid of ellipsoids, arrows, or tubes.

The workflow of our tool was as follows: the user specifies a volume in which the light should be visualized; our script creates a grid of sensors; the user makes and exports the measurements via the Lighting Analysis Assistant (LAA) tool of the Autodesk 3ds Max system; the resulting data is processed, imported back to the modeling environment (3ds Max in our case), and represented in the form of shapes (arrows, ellipsoids, or tubes), which visualize the calculated light properties. The user can view the visualizations from an arbitrary viewing direction and manage the visualization shapes in a similar way as other objects in a scene (move, edit visibility, delete, etc.). Note that the objects in the viewport are typically "shaded" in a default manner that bears no relation to the actual scene illumination. So, in the viewport, the shapes of the visualizations are the only source of information about light.

It is important to note that our prototype is intended to merely demonstrate the potential of the proposed light visualization method. It consists of a script for placing the measurement grid; code for translating the measurements to light properties, calculating tubes, and creating visualization matrices; and a script for importing visualization matrices back into 3ds Max and creating the shapes in the volume of the scene in the viewport (see Figure 2). Each type of visualization represents the (variations of the) light properties via (variations of) shapes' size, proportions, and orientation.

Our prototype created a visualization about 2 to 10 times faster than it took to make a full rendering of the same scene. However, we will not focus on the performance times. The reason is that every component of the prototype might be brought to real-time performance using existing computer graphics algorithms. We did not explore the efficiency of the used algorithms because the focus of the article was the perceptual rather than the computational efficiency. We provide an overview of the possibilities of prototype improvement in the discussion.

3.1 Measurements

In our prototype of the visualizing tool, the (virtual) measurements are performed using the LAA, which allows creating planes with grids of sensors in arbitrary positions of modeled scenes (requires the use of the 3ds Max mental ray renderer). Our measurement script first needs the user-specified bounds of a volume for visualization and the number of measurements on each axis. Then it creates and places sensor planes evenly over that volume (see Figure 3). The grid of sensor planes is aligned such that in each measurement point there are six sensors, which face the positive and negative directions of each axis, as if they are on the six faces of a microscopic cube. Next, the user runs the measurements and batch-exports the results (a file for each plane) using LAA. The resulting data files contain the following (relevant for processing) information: the position of each sensor, its orientation, and the amount of direct, indirect, and total illumination arriving at the sensor. Then, our algorithm regroups the data from planes to points (sets of six measurements in each measurement point, forming a cubic illuminance measurement) and calculates the light properties according to Cuttle's (2003, 2013) formulas:

$$E_{(x)} = E_{x+} - E_{x-} \quad (1)$$

$$|E| = \sqrt{E_{(x)}^2 + E_{(y)}^2 + E_{(z)}^2} \quad (2)$$

$$\sim E_X = \frac{E_{x+} + E_{x-} - |E_{(x)}|}{2} \quad (3)$$

Fig. 2. Workflow scheme of our prototype for visualization creation. Light measurements are performed via the Lighting Analysis Assistant (LAA) tool of 3ds Max.

Fig. 3. Measurement grid in one of the scenes. Measurement planes are shown as green lines. The lowest horizontal up-facing plane is colored according to its sensor measurements (for demonstration purposes) varying from red (high illuminance) to blue (low illuminance).

$$\sim E = \frac{\sim E_X + \sim E_Y + \sim E_Z}{3} \quad (4)$$

$$E_{scalar} = \frac{|\mathbf{E}|}{4} + \sim E \quad (5)$$

$$D = 1 - \frac{|\mathbf{E}|}{4E_{scalar}}. \quad (6)$$

$\mathbf{E}_{x+}$, $\mathbf{E}_{x-}$ are the measurements in the positive and negative directions along the x-axis (analogous for y and z). $\mathbf{E}_{(x)}$ is the light vector component (analogous for $\mathbf{E}_{(y)}$ and $\mathbf{E}_{(z)}$). $\mathbf{E}_{(x)}$, $\mathbf{E}_{(y)}$, and $\mathbf{E}_{(z)}$ constitute the light direction. $|\mathbf{E}|$ is the light vector magnitude.

$\sim E$ is the symmetric illuminance. E_{scalar} is the scalar illuminance or the mean illuminance in a point, which we took as a measure of light intensity. The diffuseness D ranges from 0 (fully collimated light) to 1 (fully diffuse light).

Table 2. Demonstration of the Visualizations' Shapes' Variations Respective to Variations of Light Conditions

Parameter	Renderings	Arrows	Ellipsoids	Tubes
Intensity
Direction
Diffuseness

The column "Renderings" contains images for varying light properties; the visualizations' columns contain shapes resulting from measurements in corresponding light conditions. In this table, the variations of the properties were achieved by changing lighting intensity, lighting direction, and ground plane color in order to vary intensity (mean illuminance), direction, and diffuseness, respectively.

3.2 Visualizations

After converting the light measurements to light properties, the algorithm acts differently depending on the visualization type (arrow, ellipsoid, tube) as shown in Figure 2. For each visualization we describe the concepts behind it and then explain how the light properties were processed and mapped to the geometrical properties of the shapes used.

3.2.1 Arrows. The arrow visualization is an extended version of Jacobs's (2014) representation of the set of light vectors pointing at the directions where, locally, on average, the light comes from. In his visualization, Jacobs showed light intensity through both the size and color of an arrow, whereas in our approach, we visualize the mean illuminance through the arrow length and the diffuseness through the width of the arrow shaft: the thicker the shaft, the more diffuse (less directed) the light is (see Table 2). An arrow is a perfect visualization for the light direction, since it is the most reasonable representation of a vector. The arrowhead-shaft ratio is a suitable visualization for the diffuseness, because the arrowhead is always of the same size, whereas the ratio with the shaft thickness differs, so the shaft thickness judgments do not suffer from perspective distortion.

Having the light properties calculated for each measurement point, the algorithm saves them as a matrix consisting of measurement coordinates and corresponding light properties. Then the user can run the script for the arrows, which imports this matrix back into 3ds Max and draws arrows at the measurement points. The script aligns the directions of the arrows with the directions of the light vectors using rotations. The lengths and widths of the arrows are initialized as a constant, which can be adjusted in the script to fit the arrows to the size of a scene, and then automatically scaled with respect to the light properties in each point.

3.2.2 Ellipsoids. The concept behind the ellipsoid visualization is similar to that for the arrows and is inspired by tensor visualization (Westin et al. 1999). Like arrows, ellipsoids were chosen for their ability to represent multiple properties through variation of proportions. The orientation of the long axis of the ellipsoid is aligned with the light vector. The length of the long axis of each ellipsoid corresponds to the mean illuminance. The proportion of the short and long axes corresponds to the diffuseness. Thus, the more spherical the ellipsoid is, the less pronounced the direction appears, and the higher the diffuseness is. Fully diffuse light does not have a dominant direction and is thus represented by a sphere.

The ellipsoids show intensity variations via size differences. This visualization suffers from a 180-degree direction ambiguity because of the ellipsoid's symmetry. Additionally, the perspective affects the apparent size

of the ellipsoids. The ellipsoids are generated in a very similar manner as the arrows. First, they are initialized as spheres in every measured point, then the long axes are stretched linearly with respect to their values of $1/\text{diffuseness}$, and finally they are rotated to match the light vectors' directions.

3.2.3 Tubes. The light tube visualization was first introduced by Gershun (1936) and first sampled and visualized throughout a real scene by Mury et al. (2009). A tube is always tangential to the light vector, and in our visualizations its width is inversely proportional to the mean illuminance (in the approaches of Gershun and Mury et al., width was inversely proportional to the strength of the light vector). The intuition behind this choice is derived from fluid flow representations: the smaller the tube is, the stronger the flow.

In empirical studies, it was found that usually a tube starts at a light source and finishes at a light-absorbing surface while getting thicker—and that the set of tubes representing the “light flow” (Cuttle 1973) shows a structure diverging out from the source (Kartashova et al. 2016; Mury et al. 2009). An advantage of the tubes is that they show in one glance the “flow of light” through the scene. Thus, a user can see the global light flow structure without the need to “mentally interpolate” discrete measurements. The diffuseness could be represented on the tubes via color, brightness, or pattern of texture (Xia et al. 2017b). However, in the current study, we chose to restrict our visualizations to variations of shape to allow fair comparisons in the user study.

The generation process of the tubes differs from that of the arrows and ellipsoids, because a tube represents (interpolated) values over several points. After calculating the light vectors and mean illuminances for all measurements, the linear interpolation function is calculated for both properties independently. In order to calculate the tubes, our algorithm iteratively calculates points constituting tube paths through the volume plus mean illuminances at those points for the widths of the tubes. Before running the algorithm, a user defines how many tubes should be visualized for each axis, plus the initial thickness of the tubes and the number of iterations of the algorithm. These settings need to be manually adjusted to the size of the scene and the complexity of light properties' variations over the volume. For example, for more complex luminous environments, it might be better to use many thin tubes instead of a few thicker ones in order to show subtle and fine-grained variations of the light flow structure. The algorithm calculates the first values for the matrix by setting the starting points for the tubes' paths, such that the tubes' origins are evenly distributed over the visualization volume. The mean illuminances and light vectors' directions for the starting points are calculated using the linear interpolation functions. On the next and following iterations, the algorithm makes a step of user-defined step size in the light vector direction, saves the new coordinates, then calculates the light vector direction and mean illuminance of the new point. The ending condition for each tube is either reaching a predefined maximum number of steps leaving the measured volume, or fluctuating in a small area (which usually means that the tube reached a light source in the visualized volume). Finally, a separate script imports the resulting matrix into 3ds Max and visualizes the tubes using splines. At this point, the tubes' initial widths can be manually scaled with respect to the size of the scene. The paths of the tubes correspond to the points recorded in the matrix.

4 USER STUDY

We evaluate the performance of our visualizations through a user study, in which 14 participants perform two types of tasks, one related to comparison of light conditions between parts of the scenes and the other to inferring the appearance of objects.

4.1 Goal

In renderings, inferences of light properties are made based on cues resulting from interactions of the light with the environment (shadows, shading, highlights, etc.), while the arrow/ellipsoid/tube visualizations (AET visualizations) directly represent the light properties. So, the perceptual processes underlying these inferences are

Fig. 4. Examples of the renderings and light visualizations for two scenes (first row: Room 1, Illumination 1; second row: Room 2, Illumination 2). Left to right: scene rendering, arrow visualization, ellipsoid visualization, and tube visualization.

different. We performed a psychophysical user study in order to evaluate how informative the AET visualizations are for estimating the light properties in comparison with rendered images.

We set up an experiment investigating two typical actions in a 3D light designer workflow (Gershbein and Hanrahan 2000; Pellacini et al. 2007): (1) comparing light conditions between parts of a scene and (2) inferring what the appearance of an object would be if that object were placed in a specific location in the scene based on the light conditions in that location. The stimuli consisted of renderings of the scenes or one of the AET visualizations in the scenes. In the first part of the study, participants were asked to rank-order three positions in the scene with respect to a specific light property. In the second part of the experiment, we showed several objects that were rendered in the scene and then presented them in isolation, without a background, and asked observers to match those objects to locations in the scene.

4.2 Scenes

We illuminated three models of rooms, each in two ways, so that observers could not match one-to-one scene geometry and illumination. For each of the resulting six scenes we created renderings and visualizations (see examples in Figures 1, 4, 5, and 6 and full set of scenes and visualizations in the supplementary materials). The AET visualizations were placed in most of the scenes' empty volume, in grids of $6 \times 10 \times 5$ shapes for the arrows and ellipsoids and a corresponding starting positions' grid for the tubes. The renderings were done for output images sized 800×600 pixels and the following renderer setup: mental ray, minimum one sample per pixel, maximum 128 samples per pixel, maximum 500 photons per sample. The majority of the objects in the scenes were matte. We used area light sources (flat or spherical).

In order to refer to specific positions, we added five (Stanford) bunnies in the measured volumes of every scene. Each bunny was attached to a pole standing on the floor or another horizontal surface to depict the position of the bunny in the scene. We placed the bunnies such that the light properties in their locations differed widely between bunnies. As the processing speed of our prototype is not real time, we captured the viewport and renderings of the scenes in advance and then demonstrated the resulting images in the experiment interface.

4.3 Interface and Tasks

The user interface of both parts of the experiment consisted of a scene block, question-and-answer (Q&A) block, view control block, and help button. In each trial, a scene rendering or visualization was presented in the scene

Fig. 5. Experiment interface, part 1. The stimulus is at top left (Room 3, Illumination 1); the view control block is below the stimulus; the help button is at the top right; the Q&A block asking to compare a property value between the bunnies is at the bottom right.

block. Each scene contained bunnies presented as silhouettes. All bunnies were rotated such that they had the same silhouettes, independent of their position in the scene. The view control block had radio buttons for selecting the frontal or the side-viewing direction, and a slider for stepping through the visualizations in depth (four layers, not active for the renderings). Moving the slider made closer shapes invisible, in order to see the further ones without occlusions. The help button opened a window with a short explanation of the visualizations and examples of them for a scene not used in the experiment.

In part 1 of the experiment (see Figure 5), participants rank-ordered three bunnies according to one light property. Specifically, in each trial we asked two questions, one to pick the bunny with the highest and one to pick the bunny with the lowest value of the property:

- On which bunny is the light most intense? / On which bunny is the light least intense?
- On which bunny is the light direction closest to straight from above? / On which bunny is the light direction furthest from straight from above?
- On which bunny is the light most diffuse? / On which bunny is the light least diffuse?

In part 2 (see Figure 6), we asked observers to match five white, Lambertian shaded bunnies in the Q&A block to five bunnies' silhouettes in the scene according to the expected appearance of the bunnies at the positions of the silhouettes. The order of the images of the bunnies in the Q&A block was randomized. When the observer changed the viewing direction of the scene, the images of the shaded bunnies also changed accordingly. The interfaces did not allow picking the same answers for both questions in part 1 or picking the same number for two shaded bunnies in part 2.

Before the start of the experiment, all observers did a training session, in which we checked whether they understood the interface, tasks, and visualizations (e.g., how a shape variation reflects a light property). It was not possible to pass a trial of the training session without picking the correct answers. After this, a participant first went through part 1 of the experiment, then through part 2. Part 1 consisted of tests for six scenes for three properties (two for the tubes where diffuseness was excluded) and four conditions (renderings, arrows, ellipsoids, and tubes), making $6 \times 3 \times 3 + 6 \times 2 \times 1 = 66$ trials. Part 2 consisted of six scenes and four conditions (renderings, arrows, ellipsoids, and tubes), so 24 trials in total. The order of trials in both parts was randomized.

Fig. 6. Experiment interface, part 2. The stimulus is at top left (Room 3, Illumination 1); the view control block is below the stimulus; the help button is at the top right; the Q&A block asking to match the bunnies to their positions in the scene is at the bottom right.

4.4 Participants

Two groups of seven participants took part in this experiment. The first group consisted of observers who took part in many visual perception experiments but did not have experience in computer graphics; the second group consisted of participants who had expertise in computer graphics but did not have experience with visual perception experiments. All participants had normal or corrected-to-normal vision. They all gave written, informed consent. All experiments were done in agreement with the Declaration of Helsinki, Dutch Law, local ethical guidelines, and were approved by the TUDelft Human Research Ethics Committee.

4.5 Results

As a metric of performance, we took the percentage of correct answers over all participants and scenes. We compared the results between the two groups of participants (p-value and 95% confidence interval), the experienced observers and the computer graphics professionals, and did not find a significant difference in their results. There was some variation of results between tasks (scenes), but the reason was in the difficulty of the task. For example, in the scene in Figures 5 and 6, bunny number 4 was in the cast shadow of the lamp, which was not noted by most observers in the renderings, and was hardly, but more, noted in the visualization conditions. For both part 1 and part 2 of the experiment, results over all scenes and all observers were above chance levels. The chance levels for part 1 were 0.5 and 0.167 (expressed as fraction correct) for at least one correct and all correct answers, respectively. The chance levels for part 2 were 0.633, 0.258, 0.0917, and 0.008 for at least one, two, three, and five (i.e., all) correct answers, respectively. We present the results as bar charts, which show the fractions of correct answers for each condition over all scenes and all observers (see Figure 7).

For part 1, we found the largest fraction of correct answers for the ellipsoids for intensity (mean illuminance), for the arrows and tubes for direction, and for the arrows for diffuseness (see Figure 7). For part 2 (see Figure 7, last graph), the results show different patterns depending on how many bunnies were matched correctly. For example, renderings are the best for matching at least one bunny correctly, but the arrows show the best results for matching all and at least three bunnies correctly.

We evaluated the significance of the differences between renderings and each of the visualizations via z-tests (two-sided p-value < 0.017 after Bonferroni correction) and confidence intervals (CI, 95%). In part 1 (for all correct results), results for ellipsoids were significantly better than for renderings for interpreting intensity, whereas the

Fig. 7. Experiment results, left to right: part 1 fractions correct for intensity (mean illuminance), direction, and diffuseness, and part 2. The boxplot shows the fractions of fully or partially correct answers. The results are stacked bottom-up, so that all correct answer bars are on the bottom. Thus, to know the fraction of at least N correct, one should sum up bars from all correct to exactly N correct. For example, in part 2, the fraction of trials, in which observers made at least three correct answers using renderings, is around 0.6.

results for arrows and tubes were not significantly different from those for renderings. For direction, arrows and tubes were significantly better than renderings, and results for ellipsoids were the same as for renderings. For diffuseness, arrows were significantly better than the renderings, and ellipsoids were not different. For part 2, the fractions correct did not differ significantly between renderings and visualizations.

In summary, we found that in both parts, using visualizations led to the same or better performance as using renderings. These results show that the visualizations indeed help to compare light conditions in parts of a scene volume and to infer the resulting appearance of objects placed in a visualized volume. Depending on the specific property of light one wants to judge (intensity, direction, diffuseness), ellipsoids, tubes, or arrows give the most optimal visualization.

5 DISCUSSION AND FUTURE WORK

The user study results demonstrate that for our comparison task (part 1), the visualizations, overall, resulted in more correct answers than the renderings. For the matching task (part 2), the visualizations performed as well as the renderings did. Comparing the visualizations with each other was not the main purpose of this user study. We believe, and an informal survey with our participants confirmed, that the choice of shape type here was probably a matter of personal preference. The main result is that all of them showed better or not significantly different performance compared to renderings. We consider the experiment outcomes promising, taking into account that the visualizations were demonstrated in the viewport, and thus their shapes provided the only information about the light in the scene.

It might appear surprising that using a schematic geometric representation of light properties resulted in equal performance to a fully developed rendering. The reason for such a result might be that, as shown by multiple psychophysical studies, the human visual system cannot veridically extract illumination information from light cues (Kartashova et al. 2016; Koenderink et al. 2007; Lopez-Moreno et al. 2010; Marlow et al. 2012; Ostrovsky et al. 2005; Xia et al. 2014). Therefore, it will be difficult for an observer to estimate light properties throughout the empty space of a complex scene. Our visualizations show the light properties explicitly and veridically, which makes them equipotential to renderings for both inferring the variations of the light properties over the scenes and predicting the appearance of objects under the visualized illumination. One could argue that since our visualizations represent light properties and thus what an object would look like in a certain point in space, an alternative could be rendering a grid of simple probe objects in the empty space of a scene. However, such method would require the rendering of every probe object separately, because otherwise the objects would disturb the

scene and each other's illumination (e.g., casting shadows on each other). Additionally, visual guesstimation of light direction and diffuseness from probe appearances suffers from the direction diffuseness and other ambiguities (Pont and Koenderink 2007; Pont and te Pas 2006).

In comparison with existing light visualization approaches, our tool has a number of advantages. As Reiner et al. (2012) stated, many of the existing methods are very complex and allow only experts to analyze the light transport (Durand et al. 2005; Ramamoorthi et al. 2007; Zirr et al. 2015). Contrarily, we convert measurement results of complex natural light into three perceptually meaningful parameters that are intuitive also to nonexpert users. Unlike light rays or path visualizations (Gribble et al. 2012; Hullin et al. 2008; Nowrouzezahrai et al. 2011; Schmidt et al. 2013; Simons et al. 2016; Velten et al. 2013), we show preprocessed information that allows users “to see the forest through the trees,” i.e. to understand the structure of the light field and its properties' variations in one glance. Finally, different from the most common light visualization tool—the false color plot—our visualizations represent light in a volume, giving much more information about how scene appearance is related to the potential origins of light effects and its interactions with the materials and geometry in the scene.

The inherent characteristics of the proposed tool imply some limitations. First, the concept of reducing visualized information to three light properties eliminates all finer angular features of the light distribution. For example, if a point would be illuminated by two light sources, the visualization would show the average light direction between those sources. A solution for this issue could be adding the so-called squash tensor (Mury et al. 2007), the second order of spherical harmonics that is neglected in our visualizations but that is also important for the appearance of matte objects (Ramamoorthi and Hanrahan 2001a). Mury et al. (2007) showed how this property can be visualized. Moreover, addition of a summary metric of the higher (>2) orders could show the remaining “light texture” or “brilliance” (Pont 2018). Using our visualizations, one would also not be fully able to predict the reflections on a specular object. Perceptually, the specularly reflected higher-order structure of the light field is assumed to be relevant in a statistical sense only, as a “light texture” or what architectural lighting designers call “the play of brilliance” (Kelly 1952; Mury et al. 2007; Pont 2013). In the future, we will study how this light property can be described and visualized.

We see several possible ways to improve and expand the proposed approach. In terms of processing speed, the technique could be significantly improved by implementing a different tool for the light measurements instead of LAA, for example, capturing the full irradiance distribution function (Reiner et al. 2012). We could apply flow visualization techniques for making the visualizations clearer, for example, using streamline seeding techniques for placing the measurement points. Other variables to consider in this regard are the grids' density, shapes' size, and transparency. Moreover, the scaling of the shapes could be adjusted in various ways, depending on the scene environment and goals of the user. One option would be using logarithmic scaling for scenes with large intensity ranges. Adding texture to the shapes might provide more information, for example, to show the light diffuseness. Texturing ellipsoids to imitate shading congruent with the light properties would closely approximate an object's appearance. Furthermore, the color of the shapes can represent the color of the measured light, considering that color is also a common property to describe light. This, however, will require extending the measurement method. Superquadrics (Kindlmann 2004; Schultz and Kindlmann 2010) might be an alternative to the ellipsoid shapes. Splitting the direct and indirect contributions of the light also might produce interesting and useful results. In Figure 8, we show an example of such split arrow visualizations, and it is insightful to see how the directions and diffuseness differ for the two contributions while both contributions show very systematic global structures. Finally, it might be possible, though very challenging, to find a method of editing light transport via editing the visualizations, similarly to what was done in work by Schmidt et al. (2013).

6 CONCLUSION

In this article, we introduced a new approach to visualizing the light in modeled scenes via translating radiance measurements into three light properties that can be visualized as tensor fields. A distinctive feature of our

Fig. 8. Example of visualizations in which we show from left to right: visualizations of the light (as in the rest of this article), only the direct light, and only the indirect light.

approach is visualizing light in the whole volume of a scene. Zirr et al. (2015) commented that many of the recent visualization techniques focus on local regions only; therefore, in order to understand the global picture, a user should manually place a visualization tool around a scene to explore it. The main idea of this article is to extract important properties of light and visualize them as a 3D flow. We proposed three perceptually relevant properties, because they strongly influence the visual appearance of the surrounding world and are widely used in light design in various fields. With our technique, the global changes of light properties can be seen at a glance and from arbitrary viewpoints. Finally, it is rather simple and straightforward to implement. Measurements can be performed by virtual sensors or even a grid of cameras (or in a real scene, allowing architectural applications). The light properties extracting formulas do not require complex calculations. Shape creation is done using basic shapes and splines. Thus, our visualization technique is a promising tool, which, at the same time, is easy to replicate using the presented methods. The work of a digital light artist/designer is often described as a tedious process of hundreds of repeated adjustments and renderings guided mainly by the artist's intuition (Gershbein and Hanrahan 2000; Kim and Noh 2009; Pellacini et al. 2007). Our visualization approach strives to increase their work efficiency by providing quick and quantitative representation of the light conditions. Using such a tool, a light artist can see the changes of light intensity, direction, and diffuseness over a scene and after modifications.

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