Ecological optics of natural materials and light fields

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ABSTRACT

The appearance of objects in scenes is determined by their shape, material properties and by the light field, and, in contradistinction, the appearance of those objects provides us with cues about the shape, material properties and light field. The latter so-called inverse problem is underdetermined and therefore suffers from interesting ambiguities. Therefore, interactions in the perception of shape, material, and luminous environment are bound to occur.

Textures of illuminated rough materials depend strongly on the illumination and viewing directions. Luminance histogram-based measures such as the average luminance, its variance, shadow and highlight modes, and the contrast provide robust estimates with regard to the surface structure and the light field. Human observers performance agrees well with predictions on the basis of such measures. If we also take into account the spatial structure of the texture it is possible to estimate the illumination orientation locally. Image analysis on the basis of second order statistics and human observers estimates correspond well and are both subject to the bas-relief and the convex-concave ambiguities. The systematic robust illuminance flow patterns of local illumination orientation estimates on rough 3D objects are an important entity for shape from shading and for light field estimates. Human observers are able to match and discriminate simple light field properties (e.g. average illumination direction and diffuseness) of objects and scenes, but they make systematic errors, which depend on material properties, object shapes and position in the scene. Moreover, our results show that perception of material and illumination are basically confounded. Detailed analysis of these confounds suggests that observers primarily attend to the low-pass structure of the light field. We measured and visualized this structure, which was found to vary smoothly in natural scenes in- and outdoors.

Keywords: material, texture, shape, light field, ambiguities, illuminance flow, inverse problem, vision

1. INTRODUCTION

The visual appearance of objects is subject to appearance metamery: the perceptual similarity of the appearance of objects with physically different structures (materials, shapes, surface structures). Images of scenes (pictures or retinal images) are 2-dimensional while the scenes' layouts are 3-dimensional, light fields\(^1\) in scenes are described by 5-dimensional functions, material reflectance is described by 4-dimensional functions and material texture by 6-dimensional functions. (I neglect color for clarity, though this dimension could be added in a straightforward way.) Thus it is clear that the so-called inverse problem, namely estimating scene properties from an image, which is addressed in machine and human vision, is heavily underdetermined. We need to retrieve more dimensions than there are in the image. Many combinations of scene layouts, light fields and material properties may result in the same image. Although the images suffer from shape-light field ambiguities, shape-material ambiguities, and material-light field ambiguities, we do not perceive the world to be ambiguous. However, many experiments on shape-, light field- and material perception have resulted in subject-dependent differences and interactions between the perceived shape, material and light field.\(^2-4\) Can the ambiguities, which are basically present in images, explain these perceptual differences and can they be described by appearance metamer sets? How do natural scene statistics (e.g. of light fields\(^5,6\)) constrain these sets? The only formal description of how such combinations result in the same image concerns the bas-relief ambiguity:\(^7\) if the elevation of a light source with respect to a perfectly matte object will be lowered, the same image structure will result if the relief of the geometry will be decreased.

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The so-called forward problem, rendering an image based on known scene properties, is addressed in computer graphics. Here we lose dimensions, which might seem a fundamentally simple problem. However, as all designers, graphics artists and vision scientists know from experience, it is very hard to produce convincing and realistic artificial images. Graphics and design software are hard to handle, especially with regard to the mutual tuning of illumination, material reflectance and 3-D modeling. Understanding this fundamental scientific issue will lead to important insights for graphics and visualization.

These basic ideas underlie our studies into ecological optics; the optical properties and visual perception of natural scenes. We focus on natural materials and natural light fields. In this paper we present an overview of our studies. In each section we will first present our studies into optical properties and machine vision and second those into human vision.

2. NATURAL MATERIALS

2.1 Reflectance

The Bidirectional Reflectance Distribution Function (BRDF) describes the reflectance of opaque materials at the mega scale (in the far field, where 3D texture is not resolved). The reflectance function describes how the reflectance is distributed over the hemisphere of viewing directions, for all illumination directions. BRDFs of real materials cover a far wider range of modes than matte-shiny variations. Examples are asperity scattering causing velvety appearance, split-specular reflections on gauze-like structures and backscattering by pitted surfaces. Usually, the BRDFs of natural materials are quite complicated, but fortunately rather smooth functions. Simplified models of material reflectance functions, which may be used to produce graphics, often do not obey basic physical laws. These facts should be reckoned with in experiments on material perception, which we will do in the sequel of this paper. In this paper we will not go into details about reflectance properties, and proceed with the intriguing properties of natural materials on the meso scale instead.

2.2 3D textures – the radiance distribution

Most natural surfaces are rough on the micro scale, which becomes visible due to shading, shadowing, interreflections and occlusion effects on the micro scale, causing 3D texture: image texture due to the illumination of rough surfaces. Such 3D textures depend strongly on the viewing direction and on the illumination conditions, see figure 1. Note that due to qualitative differences the textures cannot be “texture mapped”, in contradistinction to 2D “wallpaper” type of textures. Typically, the interreflections and shadowing effects will not be local, rendering the problem impossible to solve analytically. Therefore, we need a statistical approach for typical surfaces.

Figure 1. An example of 3D texture due to the illumination of a rough surface: corrugated cardboard of which the middle circular part has been rotated 90 degrees with regard to its surroundings. The shading, shadowing, interreflections and occlusion effects on the micro scale cause strong effects on the appearance on the meso and macro scales, which are dependent on the viewing and illumination directions. Note the total contrast reversal between the leftmost and rightmost images and the differences in the salience of the textures of the middle image.
The simplest measures of texture are based on the distributions of radiance, which can be studied via the histograms of pixel values in image textures (because generally the radiance values correspond monotonically with the pixel values). We ignore color. From pixel gray value histograms one may derive simple measures such as the average gray value, the variance of gray values, percentiles (for instance the 5% and 95% percentiles, as robust measures of minimum and maximum values for natural textures), and the texture contrast. Such measures vary systematically as a function of illumination and viewing angles. The most simple micro facet model which explains variations of mean and extremum radiance values of 3D textures and of the texture contrast is the Bidirectional Texture Contrast Function (BTCF\textsuperscript{16}), which can be used to do semi-quantitative estimates with regard to surface roughness.

The appearance of rough locally matte material, for instance plasterwork or wrinkled paper, is almost uniquely defined by the illumination direction. Such materials locally scatter light in a diffuse manner, that is, almost Lambertian, such that the viewing angle becomes (almost) irrelevant. Lambert’s surface attitude effect\textsuperscript{17} states that, if \( \mathbf{n} \) denotes the outward surface normal, and \( \mathbf{i} \) the direction towards the light source (both assumed to be unit vectors), then the surface irradiance caused by the incident beam is proportional to the inner product \( \mathbf{n} \cdot \mathbf{i} \). Thus the image intensity at any point is proportional with the cosine of the obliquity of the incident beam at the corresponding surface location. More specifically, for a surface albedo \( \varrho(u, v) \) (where \( \{u, v\} \) denote parameters on the surface), and radiance of the incident beam \( N \) one has

\[
I(u, v) = \frac{\varrho(u, v)N}{\pi} (\mathbf{n}(u, v) \cdot \mathbf{i}),
\]

where \( I(u, v) \) denotes the image intensity at the location in the image corresponding to the surface location \( \{u, v\} \). Conventionally one assumes \( \varrho(u, v) = \varrho_0 \), a constant (often even \( \varrho_0 = 1 \)).

In this setting it is evidently only the normal component \( \mathbf{i}_\perp = (\mathbf{n} \cdot \mathbf{i}) \mathbf{n} \) of the direction of the incident beam with respect to the local surface that is (at least partially) observable through the “shading”. Fluctuations of the surface normal on finer than some fiducial scale are considered due to “roughness” and not to “shape”, that is surface relief. Such roughness can be observed to lead to image “texture” which depends mainly on the tangential component \( \mathbf{i}_\parallel = \mathbf{i}_\perp - \mathbf{i} \) of the direction of incidence. The contrast “explodes” near the terminator of the attached shadow, or, in other words, the texture becomes very salient for almost grazing illumination, see figure 2. This effect can frequently be observed in natural scenes and is well known to visual artists.\textsuperscript{18,19}

Figure 2. An example of 3D texture on a rough object: the sphere was illuminated with a collimated beam coming from the right at 60 degrees from the line of sight. The texture contrast is at a minimum where the beam hits the sphere at right angles and ‘explodes’ near the shadow terminator, where the illumination grazes the surface.
The 3D texture contrast function can be described using a simple micro facet model. We assume a range of slants of micro facets at any point of the sphere centered on the fiducial slant (the local attitude on the global object) and extending to an amount $\Delta \theta$ (the maximum local attitude due to 3D surface corrugations) on either side. A more realistic model (e.g.), using a statistical model of the surface, allows calculation of the full histogram of radiance at the eye or camera and yields essentially the same results as the most simple model presented later. The main effects are due to the fact that the local facet normals differ in slant from the fiducial slant. The major features of the 3D texture contrast can be understood from a classical “bump mapping” approach, which only recognizes the statistics of the orientations of surface micro facets, disregarding the height distribution completely.

A contrast measure is essentially a measure that captures the relative width of the histogram. There are some distinct notions of contrast in common use, and each has its uses. We used the following contrast definition: the difference of the maximum and minimum irradiance divided by twice the fiducial irradiance. For real textures we deal with the 5% (“minimum”), 95% (“maximum”) and 50% (median radiance) levels, which are robust measures required for natural images. The median radiance may often be used as an estimate of the fiducial radiance, but it may well be biased, especially near the terminator.

From observation of the contrast functions we are able to estimate some overall measures of the slope distribution (for details and empirical data see). Such comparatively crude, but very robust measures suffice to obtain quite reasonable estimates of the main features of 3D texture (the spread of surface normals about the average). The resulting functions can be finetuned on the basis of more detailed estimates such as the exact shape of the histograms, and other types of measures based on the spatial structure of 3D texture.

Analysis of the exact shapes of the histograms of BTFs shows that the histograms generally consist of one or more modes which vary (or even (dis-)appear) as a function of the viewing and illumination geometry. In figure 3 a “rough plastic” (sample 4) BTF subset from the Curet database (http://www.cs.columbia.edu/CAVE/curet) is shown, together with its –smoothed– histograms and an analysis of the histogram modes. The black bars are shown in the centres of the modes, with a height equal to half the maximum value of the mode and a width equal to an eighth of the width of the mode. We chose this sample, because the modal structure contains the three most common modes observed for materials in the Curet database. These modes are easy to trace to image texture properties, and, moreover, easy to name, with reference to the optical effects which cause them: the shadow mode (the small peak at the very left), the highlight mode (the small peak at the very right) and the broad middle mode which might be called a “diffuse mode”. For different materials, these modes were observed in different combinations and for different angles.

However, this categorization does not apply to all common materials. For example, sometimes more than three modes are observed and sometimes a single narrow mode which cannot be attributed to one of the former optical effects. In order to handle such cases one needs to take the specific physical effects into account. Examples of such an analysis include the backscattering mode, the split specular mode and the surface scattering mode.

Psychophysical research into 3D texture is still in its childhood, in contradistinction to the literature about “wallpaper” type of textures (see for instance the review by Landy and Graham). Most results for wallpaper textures cannot simply be applied to 3D texture perception, because 3D texture is dependent on both the viewing...
and illumination geometries (wallpaper textures can be mapped using the foreshortening transformation, but 3D textures cannot, see figure 1). The perception of 3D texture is closely related to the interpretation of scenes in general. The interpretation of scenes involves situational awareness, represented by (chrono-)geometrical and light-field frameworks.\textsuperscript{23, 24} Cues which globally specify the light-field framework in natural scenes are 3D texture gradients,\textsuperscript{23} shading, shadowing, atmospheric perspective, etcetera. The few studies into 3D texture perception which we are aware of present a rather fragmentary picture. With regard to perception and 3D histogram-based cues one should keep in mind that the human visual system effectively signals relative luminance differences (for instance image contrast), not absolute luminance values.

Ho et al.\textsuperscript{25} investigated “roughness” perception for computer generated locally Lambertian faceted textures, which looked similar to wrinkled paper and which were illuminated by a point light source plus an ambient component. The scenes were rendered from two different viewpoints and viewed binocularly. They varied the relief of the surface and the angle of the (point) light source with regard to the virtual surface between 50° and 70° from the tangent plane. The textures were presented in pairs, for which observers had to judge which of the two textures appeared to be “rougher”. All observers judged surfaces to be rougher for more shallow illumination. The addition of objects whose shading, cast shadows, and specular highlights provided cues about the light field did not improve performance. They found that histogram-based properties of the textures, namely the texture contrast, the standard deviation of the luminance, the mean luminance, and the proportion of the texture in shadow accounted for a substantial amount of the observers systematic deviations from roughness constancy with changes in lighting condition. A similar result was found in subsequent studies,\textsuperscript{26} in which they investigated the effects of viewing direction for fixed illumination direction. Thus, histogram-based 3D texture properties affect relief perception, which consequently is dependent on viewing and illumination directions (even though veridical disparity cues were available). In future research we will test whether the perceived roughness (here: the relief height) is inversely related to the perceived elevation of the light source (the bas-relief ambiguity). In a third study they measured “gloss” and “bumpiness” perception for bumpy surfaces which varied in specularity and relief. In the latter study they found an interaction between these two material attributes.

Several authors\textsuperscript{27, 28} noticed that histograms of white and black rough surfaces look qualitatively different (e.g. have different shapes) and that humans seem to be able to discriminate images of white and black rough surfaces (even if the average image gray level is equalized). Motoyoshi\textsuperscript{27, 28} et al. tested lightness and glossiness perception for opaque rough textures of uniform albedo and glossiness (stucco, black cotton fabric and crumpled white paper). They found that, for these specific textures, ratings of lightness were negatively and ratings of glossiness were positively related to the histogram skewness or a similar measure of histogram asymmetry. These results clearly suggest that human observers are sensitive to other modal properties of the histogram besides the width of the diffuse mode and the shadow mode. In fact, manipulation of such properties may be used for image-based material editing\textsuperscript{29} if one reckons with those aspects to which the human visual system is sensitive and those to which human vision is tolerant.

2.3 3D textures – the spatial structure and illuminance flow

The spatial structure of 3D textures provides us with cues additional to their radiance distributions (it is easy to construct two textures with the same histogram but different spatial structures). The simplest inferences concern the width of the autocorrelation function of heights or the width of a typical surface modulation. The distribution of the heights themselves can only indirectly be inferred from the width of the autocorrelation function and the spread of normals. The spatial structure of 3D image textures, as well as their histograms, varies systematically as a function of viewing and illumination of the rough surface, and is of course dependent on the surface geometry and surface reflectance. 3D textures of isotropic random rough surfaces can be anisotropic owing to oblique illumination. It is possible to model this for Lambertian Gaussian random surfaces.\textsuperscript{30, 31} In the case of a frontoparallel plane it can be shown that the direction of the largest eigenvalue of either of the “structure tensors” \( g \cdot g \) or \( \mathbf{H} \cdot \mathbf{H} \) lies in the plane of incidence, where \( g(x, y) \) denotes the depth gradient \( \nabla z(x, y) \), \( \mathbf{H} \) the depth Hessian \( \nabla^2 z(x, y) \) and the operator \( \langle \cdot, \cdot \rangle \) denotes a local spatial average at a scale coarser than the “micro–scale”.\textsuperscript{30} So, on the basis of the second order statistics it is possible to estimate the orientation of the irradiance, which estimates are subject to the convex-concave and bas-relief ambiguities.

Empirical data shows that this “illuminance flow”\textsuperscript{32} can be detected reliably for virtually any isotropic random roughness. For textures of the Curet database (http://www.cs.columbia.edu/CAVE/curet) that did
not obey the rather restrictive assumptions of our model at all, we recovered the irradiance orientation with an accuracy of a few degrees. These data were compared with human performance in an experiment in which human subjects judged the source direction.\textsuperscript{33} They judged the azimuth within approximately 15°, except for the fact that they made random 180° flips (expected because of the convex-concave ambiguity) and showed a slight preference for “light from above” settings. The source elevation settings were almost at chance level (the bas-relief ambiguity). So, these results were in good agreement with the data of the model, which based the estimates of the irradiance orientation on the second order statistics of local luminance gradients. This agreement suggests that the underlying mechanism may be located very early in the visual stream.

We also conducted the psychophysical experiment with rendered Gaussian surfaces.\textsuperscript{34} The results were similar in the shading regime (no shadows), but in the shadow-dominated regime the convex-concave ambiguity was resolved (no random 180° flips). Possible candidates for the cue which observers used here might be the difference between cast and body shadow edges and the asymmetric shapes of shadows.

However, in natural scenes one hardly ever views surfaces from the exact normal direction. In the case of oblique viewing the inferences of the irradiance orientation will deviate from the veridical value in a systematic way. If only perspective foreshortening is taken into account we predict that the irradiance orientation can be recovered up to viewing angles of 55°, but for larger angles there are no unique solutions on the basis of this model.\textsuperscript{35} Systematic psychophysics on illumination direction detection as a function of the roughness anisotropy showed that the observers committed the predicted systematic errors.\textsuperscript{36} These results were precise enough to allow the inference that illumination direction detection is based on edge detector (rather than line detector) activity.

\subsection*{2.4 3D textures – the global structure of the illuminance flow}

The local directions of incidence of the illumination on a 3D object can be decomposed into the tangential components and the normal components of the incident beam direction, see figure 4. The shading of the object at the macro scale is primarily determined by the normal components, while the 3D texture of the object at the micro scale is primarily determined by the tangential components. This field of the tangential components of the direction of the incident beam we call the “surface illuminance flow”\textsuperscript{32} and its projection in the image will be called the “image illuminance flow”.

In images of natural scenes the local direction of the illumination is revealed by patches of roughly uniform texture. In this way we are able to map the global structure of the illuminance flow through simple image processing techniques. The illuminance flow is a robust indicator of the light field and thus reveals global structure in a scene. It is an important entity for many subsequent inferences from the image such as shape from shading. For instance, it is possible to obtain low relief on a fiducial frontoparallel plane via the method of ribbons along the flow of light.\textsuperscript{37} The depth is obtained by simple integration of the image intensity contrast along the flow lines, starting at a transverse curve which is assumed to be known. This will yield the relief modulo a depth scaling (the bas-relief ambiguity) and the “additive planes” ambiguity. More general approaches to shape from shading using the illuminance flow are subject of ongoing research.

Human perception of “shading” has been studied for over a century.\textsuperscript{38–40} Human observers are keenly sensitive to image illuminance flow, see the former section. They are less sensitive to obliqueness, but in non-planar objects they are immediately aware of the obliqueness variations due to local surface attitude variations which cause modulations of texture contrast (not just shading). Human observers can use pure shading in the absence of texture as a shape cue, but they are dependent on complementary cues (e.g., contour) to deploy the shading cue effectively,\textsuperscript{41} because of the large group of ambiguity transformations in the case the flow direction is not specified.

We are not aware of systematical studies into whether human observers can use shading and illuminance flow as additional cues for shape inferences. Photographers report that the sense of three-dimensionality in pictures may be improved by high texture contrast due to roughness,\textsuperscript{18} which suggests that they indeed may be additional cues. With regard to the use of illuminance flow for light field inferences we are only aware of one paper in which an indication was found that human observers indeed use it as a cue. This study will be addressed in the next section on light fields.
Figure 4. The local incidence direction can be decomposed into a tangential and a normal component (right figure). The image projections of these components are depicted in the left images for canonical, spherical objects, which were illuminated with a collimated beam from four different angles or with a hemispherically diffuse beam (in the columns). The rows depict the color coded directions of the projections of the normal components and their brightness-coded magnitudes, and the directions and magnitudes of the tangential components. Thus, the second row represents the shading and the third row shows the global structure of the illuminance flow for spheres under these illumination conditions.

3. NATURAL LIGHT FIELDS

Illumination types in real scenes cover a much wider range than the point source configurations generally used in computer science. Fleming et al. showed that the performance in gloss perception of computer rendered spheres is higher if the spheres are rendered under “natural illumination” than if they are rendered under a simple point light source. However, it is not yet clear what “natural illumination” means.

Gershun has introduced the very useful and intuitive notion of ‘light field’. The light field is just the radiance as a function of location and direction. In computer graphics it is known as the plenoptic function. At any point in space the light field is a function of direction (spherical function). The radiance can be an almost arbitrary function of location and direction. Light fields of natural scenes are highly complex and vary within a scene from point to point. However, we are primarily interested in the illumination of diffusely scattering surfaces. The implication is that only the low-pass structure of the radiance is of importance, which suggests that the Fourier description might be useful. For a spherical function such as the light field this comes down to spherical harmonics. The first order term is generally known as the ‘light vector’ and has an immediate physical meaning. The quadrupole component which we named ‘squash tensor’ is a useful addition.

We constructed a device called ‘Plenopter’ for measuring this low-pass structure of the light field. The plenopter contains 12 high dynamic range sensors in a regular dodecahedron configuration (the sphere of directions was divided into twelve mutually congruent pentagonal solid angles). Photocells collect radiation from these apertures, which have a diameter of $2 \times 74.75^\circ$. Diaphragms and a diffuser were placed so as to uniformly integrate over the aperture. The photocells were Siemens BPW21 silicon photodiodes (sensitive from 350 nm to 820 nm) connected to logarithmic amplifiers followed by an AD converter. We obtain a dynamic range of about seven decades. A single observation thus yields twelve radiance samples. From this overdetermined sample we find the coefficients of the second order spherical harmonic development by means of a least squares method.

We measured light fields in the outside: in streets, on squares and in forests. We found that the low angular frequencies of natural light fields vary smoothly as a function of position and can be explained and modeled in...
very simple geometrical models. High angular frequencies can be described statistically, and hardly influence the appearance of most matte materials. Furthermore, in different scenes of similar geometries we found structurally similar light fields, which suggests that in some way the light field can be thought of as a property of the geometry.

The smooth variation of the light field’s low order components suggested that instead of specifying the complete light field of the scene it is often sufficient to measure the light field only in a few points and rely on interpolation to recover the light field at arbitrary points of the scene. This is indeed what we found in a subsequent investigation, in which we measured light fields in an empty room under several different types of illumination: the Light Lab (Philips Research). We took plenopter measurements over a regular grid and for any point inside the space enveloped by the measurement points the light field was calculated by means of linear interpolation of the coefficients between the neighbour measurement points. Since the structure of the light field is not obvious from those numbers we developed a method to visualize the global structure of the light field using light tubes. The light tubes are constructed in such a way that they are tangential to the light vectors and that the radius of the tubes is inversely proportional to the magnitude of the light vector. For an example see figure 5a. This visualization gives an intuitive description of the flux propagation throughout 3D scenes and provides information about the quality of light in the scenes.

The quality of light in a scene influences the appearance and sense of three-dimensionality of objects in that scene. But, the objects in a scene also influence the light field in that scene. A common example of such an optical interaction is fill-in of body-shadows by interreflections (“secondary illumination”) between the body on which the body-shadows exist(ed) and an added object nearby. In figure 5 we show a light tubes representation of the influence of an object on a light field. The light tubes usually run from light sources to light absorbing objects, which is also clearly visible in this example. If a black sphere is added the tubes will be attracted to this sphere due to absorption, while a white sphere “pushes away” the tubes due to reflections from its surface.

Human observers are keenly sensitive to low order properties of the light field in the sense that they have expectations of how a given object would appear if it were introduced in the scene in front of them at some arbitrary location. We measured the visual light field in psychophysical experiments through the introduction of a suitable ‘gauge object’ at several positions in a scene and letting the observer adjust the appearance of that gauge object interactively such that it fits into the scene. We measured perception of the direction (‘direction of the light’), diffuseness (‘quality of the light’ as used by photographers and interior decorators), and intensity of the light field. We used three very different scenes, with very different physical light fields. The images were geometrically and photometrically calibrated, so we were in a position to correlate the observations with the physical ‘ground truth’. We found that human observers are quite sensitive to these parameters of the physical light field and generally arrive at close to veridical settings, although a number of comparatively minor systematic deviations from veridicality can be noted.

We tested illumination and material discrimination using (A) computer generated images of spheres with different reflectance modes and under different canonical illuminations, (B) photographs of real spheres from the Dror Database (with simple reflectance modes but complicated natural illumination, e.g. desk lamp, lab, foodcourt) and (C) photographs of real spherical objects from our “Utrecht Oranges Database” (with simple canonical illumination but complicated material properties in terms of both reflectance and 3D texture, e.g. orange, golf ball, christmas decoration). We found that, even in images of rather complex natural scenes, perception of material and illumination are basically confounded. Overall, illumination and material are confounded most when we present rendered spheres that differ only in reflectance mode under simple canonical illumination conditions. Most helpful was the addition of 3D texture, which suggests that the illuminance flow might indeed be a cue for light field inferences. Interestingly, adding complex natural illumination containing higher order angular frequencies helps to disambiguate this confound in material judgments, but not in illumination judgments. The latter result suggests that human observers primarily attend to the low-pass structure of the light field.

4. DISCUSSION

In conclusion, we have presented an overview of our work on ecological optics of natural materials and light fields. We have identified several possible cues with regard to material, light field and shape perception and described related shape–material–illumination image ambiguities and perceptual interactions between the perceived shape,
Figure 5. An example of a light field representation via light tubes and the influence of an object, which is added in the scene, on the light field. The tubes are tangential to the light vectors and their width is inversely related to the magnitude of the light vectors. They represent the net flux transport due to the combined effects of primary illumination, reflected light and interreflections. The room is represented by the rectangular box and the diffuse light source at the ceiling by the circle (a). In the lower images we show the tubes in the center of the room while it is empty (b), if a black sphere is added (c) and if a white sphere is added (d).
material and light field. In some of the studies it was possible to explicitly attribute effects to very specific image ambiguities. Of course, usually we do not perceive images to be ambiguous. Human observers resolve ambiguities using priors, which are based on statistical regularities in natural scenes. Examples of such priors are the light from above and convexity priors. Also, under natural conditions, human observers usually move their eyes, head and body, which results in many extra cues, such as for instance motion parallax and multiple views. These extra cues will certainly constrain the possible solutions further, but in order to know to what extent formal derivations would be needed. In these formal derivations care should be taken that the optical effects will not be oversimplified. Current models of the optical properties of natural scenes usually ignore or oversimplify the effects of interreflections and of the effects of objects on the light field. One may question whether such effects also constrain the possible solutions to the inverse problem. Thus, in order to study our perception of the real world the ecological validity of stimuli and experimental conditions should still be further developed.

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