On the Influence of Dynamic Illumination in the Perception of Translucency

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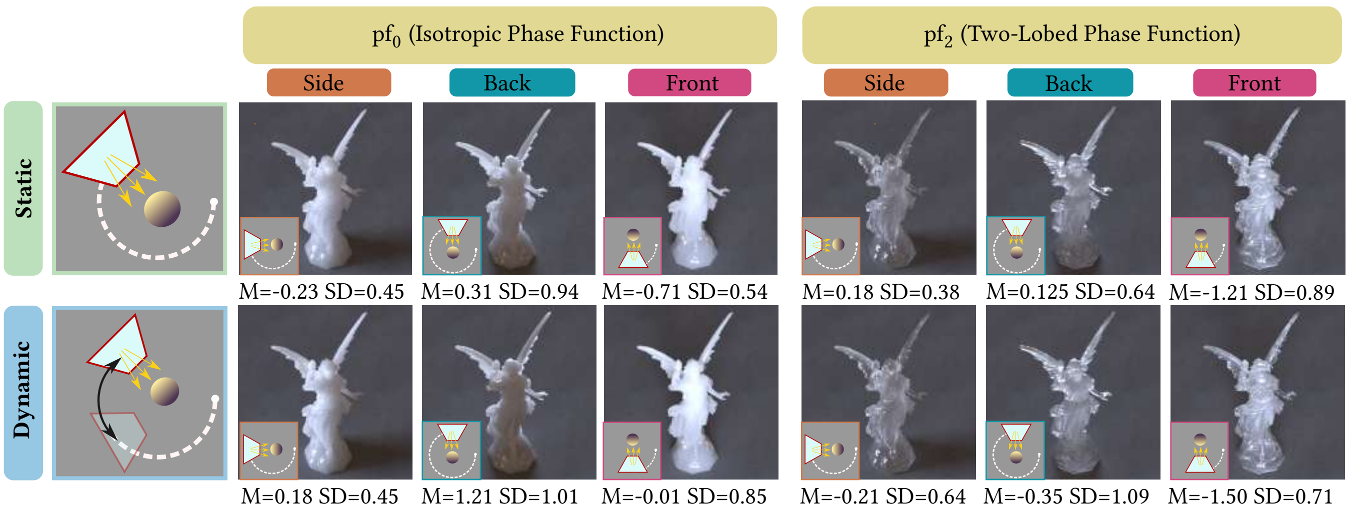

Figure 1: We analyze the effect of dynamic natural illumination on the perception of translucent materials. We design a matching experiment where participants estimate the optical density (the extinction coefficient σ_t) of a reference object with *static* (top row) or *dynamic* (bottom row) illumination. We do this under three different light directions in the match stimulus (*side, back* and *front*, depicted in the inset of each image), for different optical properties of the translucent medium. The images depict our test object, rendered with the average density estimated by participants for each condition, for a fixed reference density $\sigma_t = 4.0$ (M and SD represent the mean and standard deviation of the estimation error). Surprisingly, there are no significant differences between static and dynamic illumination when estimating the reference (ground-truth) density.

ABSTRACT

Translucent materials are ubiquitous in our daily lives, from organic materials such as food, liquids or human skin, to synthetic materials like plastic or rubber. In these materials, light penetrates inside the surface and scatters in the medium before leaving it. While the physical phenomena responsible for translucent appearance are well known, understanding how human observers perceive this type of materials is still an open problem: The appearance of translucent objects is affected by many dimensions beyond the optical properties of the material, including shape and illumination. In this work, we focus on the effect of illumination on the appearance of translucent materials. In particular, we analyze how static and dynamic illumination impact the perception of translucency. Previous studies have shown that changing the illumination conditions results in a constancy failure, specially in media with anisotropic phase functions. We extend this line of work, and analyze whether motion can alleviate such constancy failure. To do that, we run a psychophysical experiment where users need to match the optical density of a reference translucent object under both dynamic and static illumination. Surprisingly, our results suggest that in most cases light motion does not impact the perceived density of the translucent material. Our findings can have implications for material design in predictive rendering and authoring applications.

CCS CONCEPTS

• **Computing methodologies** → **Perception**.

KEYWORDS

human perception, translucency, subsurface scattering, rendering

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1 INTRODUCTION

Material recognition is a task that human observers perform on a daily basis, under a variety of environmental conditions. Distinguishing what an object is made of, and even estimating its high-level properties—whether it is fragile or soft, whether the surface is rough, etc.—, is crucial for the interaction with our surroundings. However, despite decades of research on how humans perceive the real world, the complete psychophysical processes taking place when perceiving materials are far from being fully understood [Anderson 2011; Fleming 2014].

In this work, we focus on the perception of translucent materials. These are ubiquitous in nature, from marble, glass or water, to organic materials such as skin or milk. Translucent materials are a complex class of materials, in which light penetrates below the surface and scatters inside the material. This creates a non-local illumination effect, where light paths incoming at a certain point on the surface might emerge somewhere else in the object, creating a diffuse, blurred appearance.

The physical processes of light-matter interactions in translucent objects are well understood and are generally approximated using Radiative Transfer Theory (RTT) [Chandrasekhar 1960]. However, the physical model does not explain the final perceived appearance of translucent objects, which is strongly related to the perceptual response to the proximal stimuli. Small variations in the optical properties governing the RTT can lead to large variations on the final perceived appearance, which might depend on external *confounding* factors, including geometry, illumination or context.

Numerous works have been devoted to understanding how such factors affect our perception of translucent objects [Chowdhury et al. 2017; Xiao et al. 2014, 2020]. However, existing literature analyzing their influence on the perception of translucency has focused on static viewing and illumination conditions. This is a rather strong limitation, since it limits the viewing condition to a single snapshot, and reduces the potential information encoded in the temporal domain, which human observers are known to leverage for gathering additional data. For example, it has been shown that non-static conditions favour accurate glossiness perception [Doerschner et al. 2011; Sakano and Ando 2010; Wendt et al. 2010].

In this work, inspired by this line of papers, we analyze the perception of translucent objects under *dynamic illumination conditions*. In particular, we aim to understand whether dynamic illumination can or not reduce the problem of constancy failure, which has potential applications in authoring or previsualization, where the common setup assumes static illumination. Such static setup has been largely explored, including illumination configurations targeting better shape [Rusinkiewicz et al. 2006; Vergne et al. 2009] or material [Bousseau et al. 2011] understanding. However, even a carefully fine-tuned appearance might break when the illumination changes, due to the aforementioned problem of constancy failure. Our goal is to complement previous behavioral studies that noted how users tend to use viewpoint motion [Gigilashvili et al. 2018], exploring how the temporal evolution of shading can improve over this problem.

To do that, we compare the performance of observers when determining the density of translucent objects under both static and dynamic lighting conditions (an example is shown in Fig. 2). We perform a series of guided tasks, where participants estimate material properties under a variety of lighting conditions and optical parameters (see Fig. 1). The results of our experiments confirm, as discussed in previous works, that both the direction of the illumination and the scattering directionality are key factors determining the perception of translucency. However, quite surprisingly, we observe that humans perform equally well when assessing optical properties of translucent materials in both static and dynamic scenarios, suggesting that we do not leverage the extra information encoded in the temporal dimension in this particular scenario. In addition to furthering our understanding on how we perceive translucent objects, the fact that static stimuli can suffice for certain applications can have implications for computational design of materials, authoring tools, or predictive rendering applications.

Figure 2: Left: Selected frames of a dynamic reference stimulus (video) used in our experiment, illustrating the changes in appearance as the illumination moves. Right: Example of a static reference stimulus used. From left to right, the light rotation used to render the stimuli is 135°, 180°, and 225° for the frames of the dynamic Reference, and 210° for the static Reference.

2 BACKGROUND AND PREVIOUS WORK

Here we briefly revise the literature in the context of perception of translucent materials. For an exhaustive survey on the perception of materials we refer the reader to the broader work of Fleming [2014], while for a survey focused on the perception of translucency we suggest the exhaustive work done by Gigilashvili and colleagues [2021b].

2.1 Physical Background

Translucent materials are a special kind of materials where light penetrates inside the surface, and scatters around until it emerges back, potentially from a position different from the incident position. In their simplest form, they are a dielectric with real index of refraction η, and a rough interface, generally modeled statistically using a microfacet model [Walter et al. 2007], with roughness parameter ρ (see Figure 3). Under certain assumptions, light transport in the medium is characterized by the Radiative Transfer Equation (RTE) [Chandrasekhar 1960], which in its integro-differential form models the differential change in radiance L at point $\mathbf{x} \in \mathbb{R}^3$ and direction $\omega \in \mathcal{S}^2$ as

$$\omega \cdot \nabla L(\mathbf{x}, \omega) = -\sigma_t L(\mathbf{x}, \omega) + \sigma_s \int_{\mathcal{S}^2} \mathrm{pf}(\mu) L(\mathbf{x}, \omega') d\omega', \quad (1)$$

where the medium is defined by its bulk scattering parameters: the extinction σ_t $[\mathrm{m}^{-1}]$ (related with the density of the material),

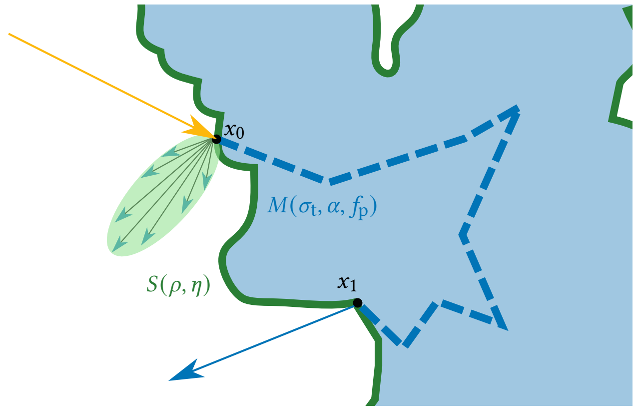


Figure 3: An incoming beam of light (orange arrow) hits a translucent object at point x_0. Part of the light is reflected at the dielectric boundary (in green), modeled by the interface roughness ρ and the index of refraction of the medium η. The remaining light is refracted inside the medium, characterized by its extinction coefficient σ_t, single scattering albedo α, and phase function pf. Light is scattered and absorbed inside the medium, until it eventually re-emerges at point x_1, potentially different from x_0.

the scattering coefficients $\sigma_s = \alpha\sigma_t$ [m^{-1}], the single scattering albedo $\alpha \in [0, 1]$ [unitless], and the phase function describing the directional behaviour of scattering $pf(\mu)$ [sr^{-1}], with $\mu = \omega \cdot \omega'$ and $. \cdot .$ the dot product. Note that the RTE (1) assumes independent, uncorrelated scatterers. In our work, we focus in homogeneous uncorrelated media.

2.2 Perception of Translucent Appearance

Several works on material perception has focused on opaque surfaces, studying the relationship between optical properties and appearance [Pellacini et al. 2000; Wills et al. 2009], the effect of geometry on visual equivalence [Ramanarayanan et al. 2007], understanding the interplay between geometry and illumination [Lagunas et al. 2021; Vangorp et al. 2007], or motion [Mao et al. 2019; Vangorp et al. 2009], or distance [Filip et al. 2008; Jarabo et al. 2014] on appearance, or building intuitive spaces for describing appearances [Lagunas et al. 2019; Serrano et al. 2016].

In the context of translucent materials, understanding how humans perceive them is still an open research field. While early studies [Metelli 1974] accepted that the human visual system (HVS) categorized materials based on inverse optics, the seminal work by Fleming and colleagues [2005] suggested that the HVS extracts some low-level statistics from the proximal stimulus, and then learns the association between the low-level statics and the material's property. Following the intuition of Fleming and colleagues, other authors proposed the local contrast of the non-specular zone as a possible low-level cue used by the HVS to infer properties of translucent materials [Motoyoshi 2010]. More recently the work of Marlow et al. [2017] suggested that the covariance between surface orientation and light intensity is used as a clue in translucency perception. The fact that the HVS extracts image statistics allows to explain some constancy failure cases. *Geometry*, for example, can alter the perception of translucent materials, making smooth edges perceived as more translucent than sharp edges, as shown by Xiao et al. [2020]. The reverse has been also found true: Bumpy surfaces might look smoother depending on how much light is scattered inside the object [Chowdhury et al. 2017]. These two findings relate with the fact that we probably use the illumination gradient to estimate surface curvature: If we have a smooth gradient between a bright and a dark area, we usually assume that the geometry is smooth. While this in general is true for smooth opaque objects, for translucent materials such association between gradient and geometry does not hold particularly well. The internal surface scattering causes a non-linear redistribution of the energy inside the object [**?**]. Another important clue for translucency are thin edges: Chowdhury and colleagues [2017] observed that removing silhouette edges from the stimulus altered the perception of the observer. This can be explained on that users tend to pay more attention to thin areas when assessing the level of translucency of objects, as reported by Gigilashvili et al. [2019]. In our work we want to measure whether the motion of the shading gradient impacts the perception of translucent materials.

Lighting conditions have also been proven to be another confounding factor when observing translucency [Xiao et al. 2014]: Objects that were lit from behind appear optically-thinner, while the same object frontally lit is perceived to be more optically-thicker. These results, however, were dependent on the phase functions of the scattering material: As expected, light direction was more relevant in forward scattering media where light penetrates deeper in the material, while had little effect in isotropic media. However, all these works analyzed static illumination: It has been argued that motion might improve this translucency failure [Gigilashvili et al. 2021b; Xiao et al. 2014], given that users tend to observe translucent objects dynamically [Gigilashvili et al. 2021c]. In this context, our work tries to fill this gap, by focusing on understanding the impact of dynamic lighting when observing translucent objects.

3 EXPERIMENT DESIGN

The goal of our study is assessing the effect of having dynamic illumination on the perception of translucent materials. More specifically, evaluating whether dynamic lighting leads to a more accurate perception of translucent appearance as compared to a static counterpart. We do this through a matching task, which has been used successfully in similar contexts [Xiao et al. 2014]. In it, the participants need to adjust the density of the scattering medium of a Match image to resemble that of the Reference stimulus, in an asymmetric matching task (see Figure 4). In our work, this is done in two different conditions: with a *static* and with a *dynamic* illumination in the Reference stimulus (in the latter case the Reference stimulus is thus a video). Each condition is evaluated for a variety of illumination directions, and material properties, in particular the phase function and the density (the medium extinction coefficient μ_t).

3.1 Stimuli

Sample stimuli used in the experiment can be seen in Figure 4. The stimuli are rendered images featuring the *Lucy* statue from the

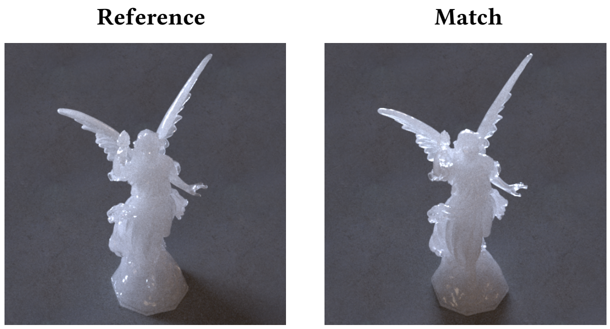
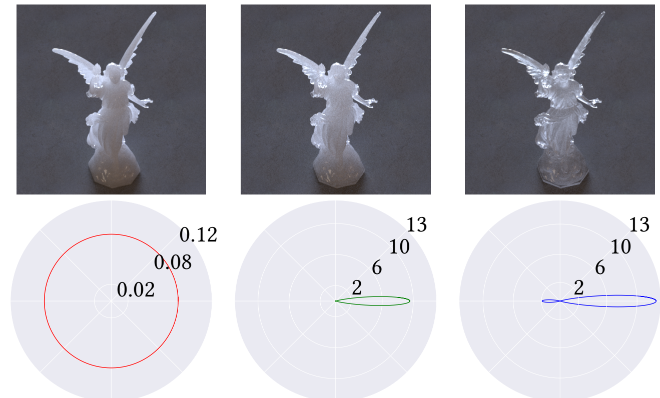


Figure 4: Experiment design. We show the user two images, or a video and an image, side-by-side. The user is asked to edit the Match image density (right) until it visually matches the Reference (left).



(a) $\mathbf{pf}_0$ (b) $\mathbf{pf}_1$ (c) $\mathbf{pf}_2$

Figure 5: Polar plots illustrating the shape of our three phase functions (bottom), together with their effect on the appearance of a translucent object (top) (all other parameters are kept fixed). Note the large magnitude difference in the primary lobes of $\mathbf{pf}_1$ and $\mathbf{pf}_2$, and with the isotropic $\mathbf{pf}_0$.

Stanford 3D Repository [Levoy et al. 2005], which is often used to evaluate the perception of translucency due to its combination of thick and thin features [Gkioulekas et al. 2013; Xiao et al. 2014]. All stimuli were generated using the Mitsuba 0.6 physically-based renderer [Jakob 2010].

As explained in Sec. 2.1, translucent objects are often modeled by a scattering medium inside their volume, and a dielectric interface at the surface of the object. We model the interface as a smooth dielectric ($\rho = 0$), so that it presents highlights that are associated with translucent materials [Fleming and Bülthoff 2005; Gkioulekas et al. 2013; Motoyoshi 2010]. For the scattering medium, we fix the index of refraction to $\eta = 1.5$, which is a common value in translucent objects such as wax and glass [Gigilashvili et al. 2021a], and the single scattering albedo to $\alpha = 0.99$, following previous work [Gkioulekas et al. 2013], so scattering dominates over appearance. These parameters are fixed for all the stimuli shown in the study, while we analyze the role of the remaining two parameters that model the behavior of the scattering medium: the density (or extinction coefficient) σ_t and the phase function pf.

Density. The Reference stimuli are thus rendered using four different density levels, ranging from 3 to 6 in logarithmic scale, such that $\sigma_t = \exp(d)\ \mathrm{m}^{-1}$, with $d = [3..6]$. In the Match stimuli, the density is the parameter that the participants in the study will need to adjust so that the material looks like that of the Reference; participants will be able to adjust it within the range $d = [0..10]$, with a step size of 0.25. For reference, the height of the *Lucy* is set to 5.23 m.

Phase function. We render the stimuli with three different phase functions that yield perceptually distant appearances according to Gkioulekas et al. [2013] (see Figure 5). The first phase function, pf_0, is a purely isotropic one (i.e., $\mathrm{pf}_0(\mu) = 1/4\pi$). The other two phase functions, pf_1 and pf_2, are two-lobed (backward and forward) phase functions defined using two von Mises–Fisher distributions as

$$\mathrm{pf}_{1,2}(\mu) = w\, f_{\mathrm{vMF}}(\mu; k_1) + (1-w)\, f_{\mathrm{vMF}}(\mu; k_2)\,, \tag{2}$$

where the exact definition of $f_{\mathrm{vMF}}(\mu; k)$ can be found in Appendix A. Phase function pf_2 is aggressively forward scattering, while pf_1 presents a less prominent forward lobe than pf_2 (see Table 1).

Illumination. Each trial in the matching task is composed by a Reference and a Match stimulus; the illumination in both is never the same, to create an asymmetry in the matching task and avoid pixel-by-pixel comparisons. We illuminate the scene using a captured environment map, in contrast with most previous works, which employ different forms of synthetic lighting [Fleming and Bülthoff 2005; Xiao et al. 2014]. This has the advantage that natural environment maps are more realistic, as well as usually preferred over synthetic illuminations when comparing surface reflectance of materials [Fleming et al. 2001, 2003; Lagunas et al. 2021]. When selecting the environment map, we seek a tradeoff between naturalness and controllability, to be able to assess the influence of lighting direction. We use the *Ennis* environment map, shown in Figure 6. In it, most of the irradiance comes from one main region and two other smaller areas, making the illumination highly directional while retaining a natural setup. Having such directional lighting has the additional benefit of creating more dramatic changes in the appearance when rotating the environment map. We use the large area light (marked in red in Figure 6) as a reference for the direction of the illumination. We further slightly blur areas outside it to reduce high frequency reflections, following initial pilot studies that showed that the movement of the highlights across the surface when rotating the environment map could be distracting for participants, whereas our focus lies on the properties of the medium. Blurring out the details alters the original, captured environment map; a similar result could have been obtained by making the surface rougher, but this would have increased the rendering time to generate the stimuli. Slightly blurring the environment map thus offered a good compromise between realism, efficiency, and placing the focus on the scattering medium.

In the *static* condition, the Reference stimulus is rendered with a back-side illumination, in which the main light is at an azimuthal angle of 210° (back and side illuminations have been shown to be more informative than front ones [Xiao et al. 2014]). In the *dynamic*

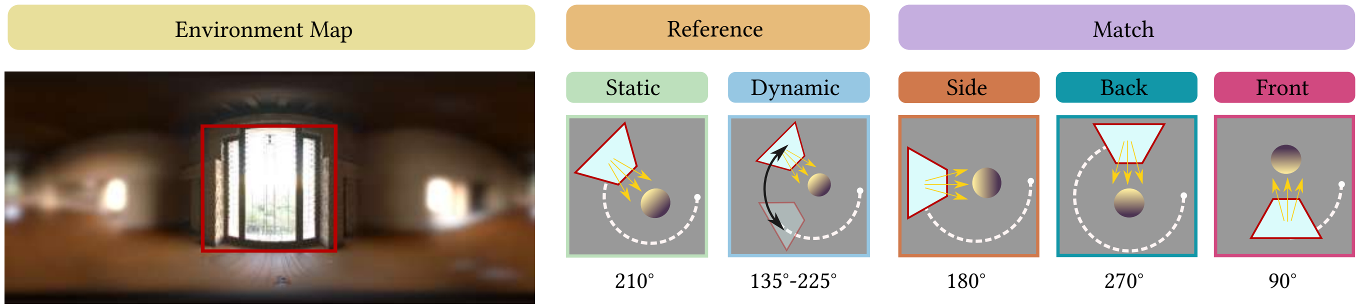


Figure 6: Left: *Ennis* environment map used to render our stimuli. We highlight in a red box the window used as a reference for the rotation. Middle: Schematic representation of the two different illumination conditions for the Reference, where in the dynamic case the illumination rotates around the object. Right: Schematic representation of the three illumination setups for the Match images. Below each, we report the rotation angle along the azimuthal direction.

condition, we render 45 frames, spanning from azimuthal=135° to azimuthal=225°, and the frames are then played in a bounce-loop. We set the video's frame rate at 30 frames per second (fps), and a rotation speed of 2° per frame. From preliminary tests , this speed seemed a good fit between showing the stimuli with enough speed to avoid an almost static Reference, and slow enough to show the evolution of the light patterns as the illumination moved. To account for the influence of the illumination direction, the Match stimulus is rendered under three different lighting directions: *side* (main light at 180°), *front* (main light at 90°) and *back* (main light at 270°). Figure 6 illustrates the lighting scheme for both the Reference and Match stimuli, in the static and dynamic conditions.

3.2 Procedure

The experiment is carried out in two separate sessions, one for the *static* condition, and another one for the *dynamic* condition. The two sessions are separated by at least 24 hours, to avoid fatigue and learning effects. The order of the two conditions is randomized, and its potential effect checked in the subsequent analysis. Each session consists of 36 randomized matching trials (4 densities × 3 phase functions × 3 light directions).

Before starting the experiment, the participant is asked to fill in an anonymous questionnaire including basic demographics and questions about previous knowledge in computer graphics and art. During the experiment, we record the responses of the participant to the matching tasks.

3.3 Participants and Apparatus

The experiment protocol is in accordance with the Declaration of Helsinki, and was approved by the institution's Research Ethics Committee. Twelve participants (4 female, 8 male), with an average age of 30.3 years (±8.42) and normal or corrected-to-normal vision, took part in the experiment. All participants completed the experiment (they could withdraw at any point).

The experiments took place in a room with a controlled, constant illumination using an office light. The stimuli were shown on an ASUS Vz239he 24" LCD display that had been previously color calibrated and the viewer was asked to sit at a distance of 60cm. We tonemapped the HDR renderings to sRGB using a simple exposure-gamma tonemapper with $\gamma = 2.2$ and fixed exposure.

4 DATA ANALYSIS

Our experiment has three within-subjects factors, described in detail in Sec. 3: light motion (2 levels, *static* or *dynamic*), light direction (3 levels, *front*, *side* and *back*), and phase function (3 levels, pf_0, pf_1 and pf_2). Since it is a matching task, our dependent variable is the error in the estimated density adjusted by the participants, $\sigma_{t,est} - \sigma_{t,real}$, where $\sigma_{t,est}$ is the density estimated by the user and $\sigma_{t,real}$ is the actual density present in the Reference. We analyze our data using a repeated measures ANOVA, with post-hoc pairwise comparisons with Bonferroni correction when applicable. We set the threshold ϵ to consider a factor statistically significant at $\epsilon = 0.05$. No data was discarded due to outlier rejection. We also measured and analyzed the time to completion of each trial, but we found only a first-order interaction between time spent and the light direction. However, the successive Post-Hoc analysis did not highlighted any common pattern. While we discuss here the main significant effects and interactions; the full results of the analysis can be found in Appendix B.

4.1 Does a dynamic lighting setup improve density estimation?

The first question we sought to answer was whether having a dynamic lighting setup led to improved density estimation with respect to the static counterpart. Our analysis revealed no significant effect of the light motion factor on the error incurred by participants ($p = 0.1016$). Fig. 7 plots the estimated density against the real density for each condition, and illustrates how the trends are similar for both the static (top row) and dynamic (bottom row) cases.

There is, however, a significant first-order interaction between light motion and phase function ($p < 0.001$). The type of phase function (see Fig. 5) has a significant effect on the ability of participants to estimate density in the case of the dynamic setup ($p < 0.001$), but not in the case of the static setup ($p = 0.3889$): The error remains roughly constant across phase functions for the static case (marginal means $M_{pf_0} = -0.16$, $M_{pf_1} = -0.23$, $M_{pf_2} = -0.33$), while in

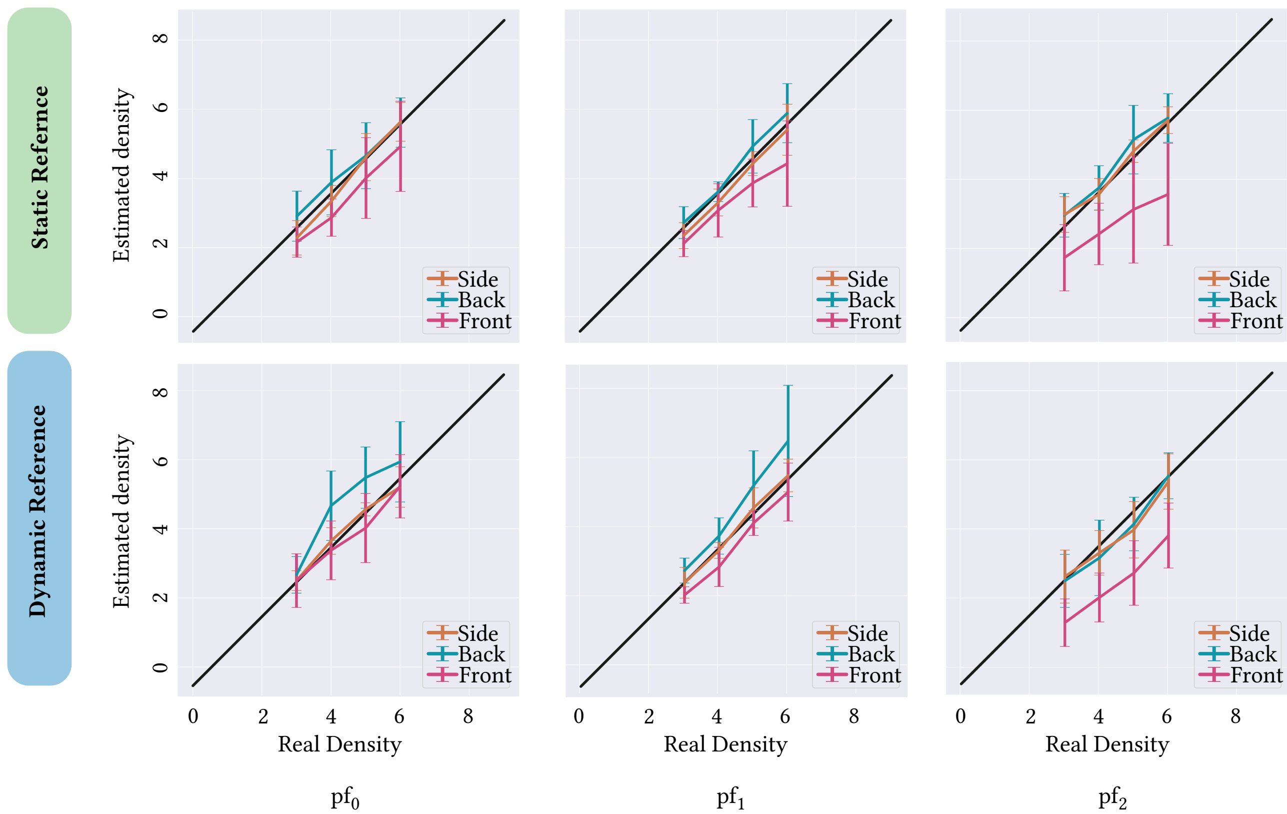


Figure 7: Results, averaged across participants, showing the estimated density with respect to the real density, for the static (top row) and dynamic (bottom row) cases. We report also one standard deviation of the estimated density as error bar. Columns correspond to the three phase functions tested, and line colors to the three different light directions used (*side, back* and *front*). The black line marks the ideal (ground truth) response.

the dynamic case a large increase in error is observed for the most forward scattering phase function, pf$_2$(marginal means $M_{pf_0} = 0.19$, $M_{pf_1} = 0.10$, $M_{pf_2} = -0.65$).

4.2 Is there a more favorable light direction for density estimation?

Light direction has a significant effect on the accuracy of the estimation, both in the static and dynamic cases ($p < 0.001$). Further, there is an interaction between the phase function and the light direction ($p < 0.01$). Post-hoc analyses reveal the nature of this effect, which is shown in Fig. 8 (bottom). The *front* light direction is consistently harder to estimate than the *side* and *back* conditions (marginal means $M_{side} = -0.05$,$M_{back} = 0.22$, $M_{front} = -0.90$), and the effect is aggravated in the case of phase function pf$_2$, the most forward scattering one (see Fig. 8). The higher error when viewing the Match front lit might also be caused by the experimental setup, since the *front* (90°) light condition is the farthest from the static Reference (210°), while the *side* (180°) and *back* (270°) conditions are visually closer to the static Reference. We further discuss this topic in section 5.

Interestingly, in the dynamic lighting setup, there is no significant effect of the light direction for pf$_0$, whereas in the static case the *front* condition is performing worse than the *side* one, and worse than its dynamic counterpart. Although a weak effect, this suggests that the dynamic lighting may be aiding in the estimation of the density for the challenging *front* case. This only occurs, however, for the isotropic pf$_0$, and not for the more complex pf$_1$and pf$_2$, where the error remains similar between the static and dynamic conditions.

5 DISCUSSION

We have designed a matching task experiment where participants estimated the density of a translucent object under different lighting conditions and material properties. We discuss here our main findings, and contextualize them with respect to previous work.

The influence of light direction. In contrast to previous works investigating the effect of light direction [Xiao et al. 2014], where the stimuli were illuminated with synthetic lighting (e.g., spherical harmonics), here we employ an environment map captured from a real scene, and therefore more representative of a real-world illumination.

Both our findings and Xiao et al.'s [2014] reveal the influence of light direction and its interaction with the phase function. Like

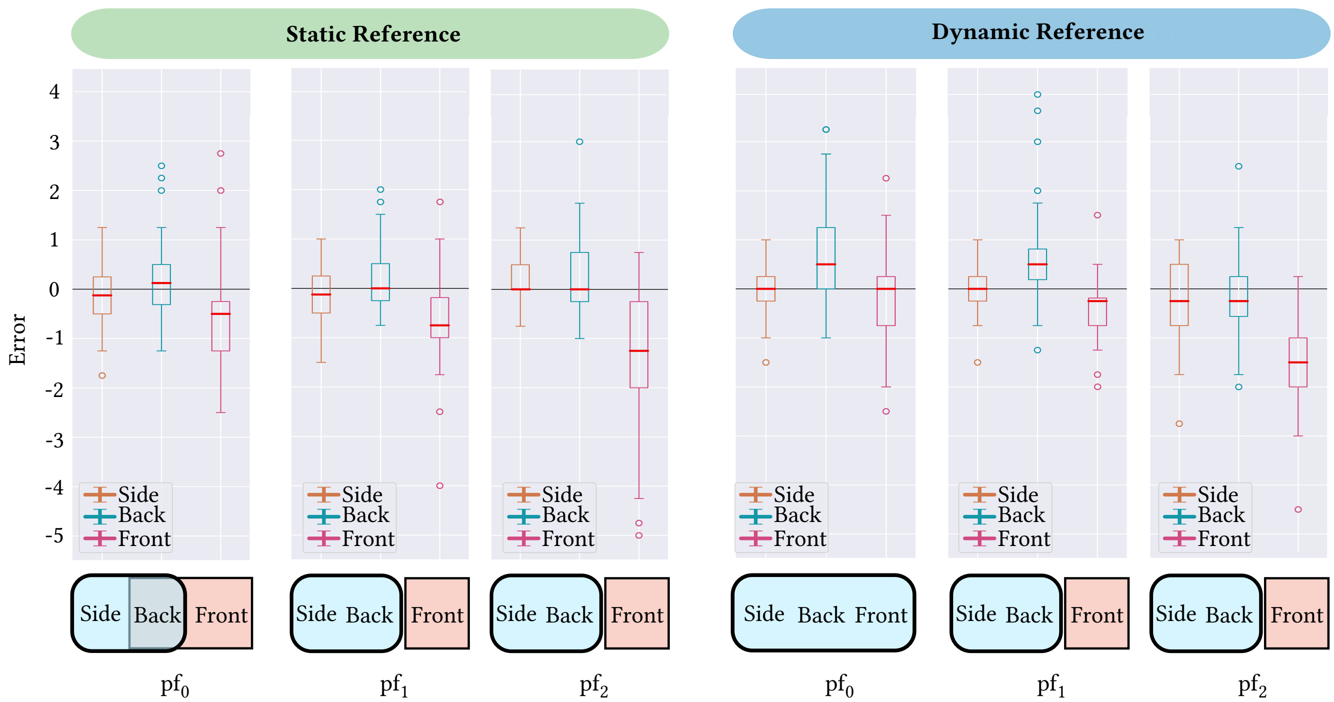


Figure 8: Error in the estimated density for each combination of light condition and phase function, for both the static and dynamic experiments. Below them, we show the results of the post-hoc analysis on the significant differences between light directions for each phase function. Please refer to the text for details.

Xiao et al., we observe that the *front* lighting condition leads to higher inaccuracies in density estimation than side or back lighting, statistically significant in non-isotropic, forward-scattering phase functions. They report an overestimation of the Match density when the *Reference* is frontally lit, and we find an (equivalent) underestimation of the Match density when the *Match* is frontally lit. Frontal lighting has the effect of "flattening" and decreasing local contrast of non-specular surfaces [Chowdhury et al. 2017; Motoyoshi 2010], which can hinder the ability to discriminate between similar appearances. Moreover, we note that pf_2 performs differently than the other two, when frontally lit. We believe that this is caused by the presence of the strong backward and forward scattering peaks, that increases the sharpness of details by forward-scattering light inside the object in all but some contour areas, where backward scattering increases brightness. However, while the trends resulting from light direction are similar for the same phase functions, Xiao et al. find a larger error in the estimated density than in our case. This may be caused by the different types of illumination that we used to render the stimuli: As opposed to Xiao et al.´s low-frequency synthetic illumination, we use a more natural light with a sharp, dominating high-frequency, directional light. As in previous work [Xiao et al. 2020] we hypothesize that the increased directionality of the light emphasizes the translucency specially in thin areas, in which scattering differences are better perceived by our HVS [Gigilashvili et al. 2021c]. This correlates with the perceived effect of illumination on opaque material perception [Lagunas et al. 2021]. Nevertheless, this is just a hypothesis which would require further testing in equivalent conditions.

The influence of light motion. Previous studies have shown that observers, when offered the possibility, tend to use motion clues when investigating translucent objects, by either moving the head or by directly rotating the object [Gigilashvili et al. 2021c]. Our experiment looks at a slightly different scenario, in which the light source moves around the object. Although similar, these two setups convey different information. By moving the object, or the head, the observer can see the same object from a different perspective, recovering information about the geometry of the object. In our scenario, the participant has extra information about the evolution of light patterns, which could help in the estimation of translucency properties. However, our data do not reveal a more accurate translucency perception in the dynamic with respect to the static case. It seems that participants were not able to leverage the extra information provided by these light patterns. Given the strong influence of light direction on the perception of translucency observed in both our and previous works, this was a surprising result, which requires further investigation. Moreover, analyzing the time that users spent on each trial did not show significant differences between the static and dynamic conditions.

Visual equivalence. While care was taken so that in all cases the Match and Reference were different pixel-wise, to avoid pixel matching, , our lighting setup is such that some Match light directions are closer to the Reference than others. For instance, the *side*

(180°) and *back* (270°) conditions are closer to the static Reference (210°) than the *front* one (90°). This could have led to participants more easily estimating the "correct" optical density when the Match was side- or back-lit than when it was front-lit, since these two conditions might present visual clues that are also present in the static Reference. In this regard, it is interesting to note that in the dynamic Reference condition, in which the illumination spans from 135° to 225° (thus closer to the front-lit match), users did not improve their performance. This seems to further support the idea that people do not use dynamic illumination cues to assess the nature of translucent materials when rotating the illumination. In any case, exploring the visual equivalence in translucent materials, for both static and dynamic scenarios, remains an open problem.

Limitations and future work. As with any study of this kind, our findings are strictly valid only for the conditions here tested. We limited our experiment to one shape (the *Lucy* model) to keep the experiment size tractable, and to focus on the effect of the illumination. Other works have looked into the effect of geometry, and shown differences between simpler (sphere, torus) and more complex geometries [Gigilashvili et al. 2021a], so extrapolation of our findings to a variety of geometries should be done with caution.

An important constraint of our experiment is that participants were not able to control the direction or speed of movement, since they were shown a fixed video, in a loop. We made this choice in order to ensure control of the stimuli and consistency between participants over the stimuli viewed, and because in certain application scenarios free exploration of the object would not be possible. It remains as future work to test whether this would have an effect on our findings.

Another interesting avenue of future work is to further investigate the impact of dynamic lighting with rougher materials. As noted in previous work, there is an interaction between translucency and glossiness perception [Gigilashvili et al. 2021a]. In particular, it seems that the surface halo created by rough materials generates areas with low local contrast, similar to what was noted in previous work [Motoyoshi 2010]. We argue that this constancy failure might be alleviated by a dynamic reference, since the halo created by surface glossiness would likely vary more sharply than translucency. Still, since translucency is a global (not local) effect, understanding the tight interaction between glossiness and translucency under dynamic lighting remains as future work.

Finding that we may be unable to leverage the extra information offered by a dynamic illumination for translucent density estimation can have implications for computational design and editing of materials, both in rendering and fabrication scenarios. We hope this work serves as yet another step towards our understanding of material appearance, and specifically of translucent appearances.

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A VON MISHES-FISHER PHASE FUNCTION

We use the phase function proposed by Gkioulekas and colleagues [2013] to model anisotropic scattering. It is based on the *von Mises-Fisher (vMF)* distribution, defined as

$$f_{\mathrm{vMF}}(\mu; k) = \frac{k}{k\pi \sinh k} e^{k\,\mu}. \tag{3}$$

Each lobe of the phase function is governed by a single parameter $k \in [-100, 100]$, which controls the spread (anisotropy) of the scattering. Table 1 compiles the values used to render our stimuli.

Table 1: Parameters for pf_1 and pf_2, the phase functions defined as a mixture of two von Mishes-Fisher distributions (Eq. (2)).

	k_1	k_2	w
pf_1	100	-0.95	0.6
pf_2	100	-75	0.9

B ADDITIONAL ANALYSIS RESULTS

We report here the full results of the repeated-measures ANOVA. Table 2 reports the results for the case of the error ($\sigma_{t,est} - \sigma_{t,real}$), and Table 3 for time spent per trial. Please refer to the main text for further details.

Table 2: Results of the repeated-measures ANOVA for the error in the estimated density.

Factor	F-Statistic	DF	p-value
light direction	47.3906	(2,22)	0.0000
light motion	3.1918	(1,11)	0.1016
phase function	17.1836	(2,22)	0.0000
direction*motion	0.9743	(2,22)	0.3932
direction*phase function	8.5727	(4,44)	0.0000
motion*phase function	11.1971	(2,22)	0.0004
direction*motion*phase function	1.0834	(4,44)	0.3763

Table 3: Results of the repeated-measures ANOVA for the time spent per trial.

Factor	F-Statistic	DF	p-value
light direction	9.0612	(2,22)	0.0013
light motion	0.0000	(1,11)	0.9976
phase function	2.2318	(2,22)	0.1311
direction*motion	0.3799	(2,22)	0.6883
direction*phase function	1.2806	(4,44)	0.2921
motion*phase function	0.9068	(2,22)	0.4184
direction*motion*phase function	0.7840	(4,44)	0.5418