

Refracting Reality: Generating Images with Realistic Transparent Objects

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Figure 1. Image generation with optically-accurate refractions and consistent reflections. (Top) Images generated by FLUX [22] with masked transparent sphere inpainting, exhibiting physically impossible refractions. (Bottom) Images generated by our method, Snellcaster, with refractions and reflections that follow physical laws. (Inset) Close-up of the refractive object as synthesized (left) and rendered (right) with an occlusion mask by Blender from a lifted 3D model. The latter provides approximate ground truth, albeit with incorrect lighting.

Abstract

Generative image models can produce convincingly real images, with plausible shapes, textures, layouts and lighting. However, one domain in which they perform notably poorly is in the synthesis of transparent objects, which exhibit refraction, reflection, absorption and scattering. Refraction is a particular challenge, because refracted pixel rays often intersect with surfaces observed in other parts of the image, providing a constraint on the color. It is clear from inspection that generative models have not distilled the laws of optics sufficiently well to accurately render refractive objects. In this work, we consider the problem of generating images with accurate refraction, given a text prompt. We synchronize the pixels within the object’s boundary with those outside by warping and merging the pixels using Snell’s Law of Refraction, at each step of the generation trajectory. For those surfaces that are not directly observed in the image, but are visible via refraction or reflection, we recover their appearance by synchronizing the image with a second generated image—a panorama centered at the object—using the same warping and merging procedure. We demonstrate that our approach generates much more optically-plausible images that respect the physical constraints.

1. Introduction

First, there’s the room you can see through the glass—that’s just the same as our drawing room, only the things go the other way.

Lewis Carroll

Text-to-image generation has become increasingly proficient at synthesizing images that faithfully model many aspects of the real world, while conforming to the text prompt. In many cases, the illusion that the image was taken by a real camera under a physical imaging process is very convincing, with apparently correct shading, shadows, specularities, and perspective distortion, as well as detailed textures, shapes and plausible configurations. However, transparent objects, and refraction in particular, are not well modeled, as shown in Figure 1. Unlike reflection, where the indirectly observed surfaces are usually out-of-frame and so can be hallucinated, refraction allows surfaces to be viewed both directly *and* indirectly. For example, in Figure 1, the cushions on the sofa are imaged directly, but they are also visible (with some warping) on the sphere. This provides a constraint on the color of the sphere pixels, which cannot just be hallucinated. Nonetheless, generative models typically do just hallucinate this, or merely apply an arbitrary

small-scale warping to (inaccurately) mimic refraction; the underlying optical principles have not been learned.

We remedy this by directly enforcing the optical principles of refraction at every step of the image generation process. We do so by synchronizing [19] corresponding pixels on an imaged refractive object with those outside the object boundary, where correspondences are found using Snell’s Law [1], the object’s geometry and material properties, and the scene’s geometry. In our setup, we assume that we have a text prompt describing a scene containing a refractive object, access to a 3D model of the object (such as from a text-to-3D generator), its material properties (including the refractive indices and absorption properties), and its pose (we use a heuristic to place the object on a horizontal surface near the optical axis). We further assume that there is only a single refractive object that does not scatter light and has a uniform index of refraction.

However, this synchronization process is not able to handle refracted or reflected pixel rays that intersect with surfaces that are occluded or outside the camera’s field-of-view. These unconstrained generated pixels may then not conform to a realistic completion of the scene observed in the image. To ensure plausibility, we propose synchronizing the image with another generated image: a panorama centered at the refractive object. The panorama is warped and merged with the perspective view, including the transparent region, so that the refractions and reflections capture a consistent scene.

Concretely, our proposed method generates an image from a text prompt, estimates its depth map, and then generates a new image, synchronized at each timestep to the refraction-warped original and a concurrently generated panorama centered at the transparent object. Our contributions are:

1. a method for generating images involving a single transparent, refractive object;
2. a synchronization approach that facilitates constrained generation of corresponding pixels within an image, here used for refracted pixel rays; and
3. a synchronization approach that facilitates consistent generation of unconstrained, unseen pixels, here used to infer plausible occluded or out-of-frame refracted and reflected pixel rays.

2. Related Work

While the generation of images with correct refraction has not been widely considered in the literature, other aspects of light transport have been addressed.

Image Generation with Light Transport. Image relighting aims to change the illumination conditions of a scene or object while preserving material appearance and geometry. Learning-based methods [18, 28, 34, 38, 42, 51] are

widely used in image relighting, where a network is trained to predict a harmonized image from the input composite. Recently, some works [3, 6, 15, 20, 31, 47, 48] exploit generative models [22, 33] to improve relighting by manipulating the illumination of the image foreground using information from the background. For shadow generation, existing methods can be divided into rendering based and non-rendering based approaches. Rendering-based methods [16, 17, 35–37] require explicit knowledge of lighting, reflectance, and scene geometry to generate shadows for inserted virtual objects using rendering techniques. Non-rendering methods add realistic shadows to composite images without inferring 3D information, and are mostly GAN-based [12, 14, 26, 49] and diffusion-based [27, 39, 50]. For our task, we do not employ the aforementioned relighting or shadow generation models; instead, we use a finetuned FLUX Kontext image editing model to jointly perform relighting and shadow synthesis as a post-processing step, enhancing the realism of the generated transparent object within our scene.

Image Generation with Reflections. Looking more specifically at the case of generative modeling with reflections, Dhiman et al. [7] introduce SynMirror, a large-scale dataset of mirror scenes, together with MirrorFusion, a depth-conditioned diffusion inpainting method that generates geometrically consistent and photorealistic mirror reflections. Their results show that diffusion models can be adapted to faithfully render reflections when augmented with geometry cues. Similarly, Phongthawee et al. [29] propose DiffusionLight, which leverages diffusion models to insert chrome balls into images for single-image lighting estimation. By fine-tuning Stable Diffusion XL [30] with LoRA [13], they enable HDR light probe estimation from standard LDR images, achieving convincing illumination across diverse in-the-wild scenes. Both approaches illustrate how targeted conditioning can significantly improve realism for reflective effects.

Synchronized Generation. Numerous studies have explored synchronized generation by sampling synchronously from multiple diffusion paths while maintaining consistency across them. SyncDiffusion [24] introduces a joint diffusion synchronization module using a perceptual similarity loss to generate coherent montages. Visual Anagrams [9] synchronises diffusion paths from different viewpoints by averaging the predicted noise at each step. SyncTweedies [19] averages the predicted clean images using Tweedie estimates [32]. SyncSDE [23] proposes a probabilistic framework that explicitly models correlations between diffusion trajectories. SaFa [5] applies latent swapping as a high-performance alternative to averaging, which supports the generation of seamless audio and panoramas. Closer to the problem of refractive and reflective image generation,

Chang et al. [2] explore generative frameworks for creating anamorphic images with latent rectified flow models. Their goal is to produce an image that reveals a second image when a specific mirrored object is placed on a physical copy of the image and is viewed from the correct viewpoint. Our work builds on this underlying idea of synchronizing warped views of the same image to, in our case, model accurate refraction and reflection.

3. Preliminaries

In this section, we outline the technical background used in our approach, relating to flow matching and light transport.

3.1. Flow Matching

In flow matching [25], a clean latent $z_0 \sim p_{\text{data}}$ can be transformed into pure noise $z_1 \sim \mathcal{N}(0, I)$ by evolving the latent under an ordinary differential equation (ODE):

$$dz_t = v_\theta(z_t, t, p) dt, \quad t \in [0, 1], \quad (1)$$

where z_t denotes the latent at time t , and the velocity v_θ is typically parameterized by a neural network that can be optionally conditioned on a text prompt p . At inference, samples can be generated by reversing this process, integrating the ODE from z_1 back to z_0 . The ODE can be discretized and solved using classical numerical integration schemes such as forward Euler:

$$z_{t-\Delta t} = z_t + \Delta \sigma v_\theta(z_t, t, p), \quad (2)$$

where $\Delta \sigma = \sigma_{t-\Delta t} - \sigma_t$ and σ_t denotes the noise schedule at time t , with $\sigma_0 = 0$ (clean) and $\sigma_1 = 1$ (pure noise). Optionally, stochasticity can be added by turning the backward process into a stochastic differential equation (SDE):

$$z_{t-\Delta t} = z_t + \Delta \sigma v_\theta(z_t, t, p) + |\sigma_t - \sigma_{t-\Delta t}| \epsilon, \quad (3)$$

where $\epsilon \sim \mathcal{N}(0, I)$ is Gaussian noise.

Classifier-free guidance (CFG). To enhance the quality of generated samples, classifier-free guidance is usually used. The guided velocity is obtained by linearly combining the conditional and unconditional predictions:

$$\hat{v}_t = (1 + \omega) v_\theta(z_t, t, p) - \omega v_\theta(z_t, t, \emptyset), \quad (4)$$

where ω denotes the guidance scale. Increasing ω amplifies the influence of the conditioning prompt, typically improving visual consistency while reducing diversity and occasionally causing over-saturated outputs.

Euler estimates. At any intermediate timestep t with noise level σ_t , an estimate of the clean latent z_0 can be obtained by taking a single Euler step using the current velocity prediction $v_\theta(z_t, t, p)$:

$$z_{0|t} = z_t - \sigma_t v_\theta(z_t, t, p). \quad (5)$$

This equation can be seen as the flow matching equivalent of Tweedie’s formula [32] in diffusion models.

3.2. Light Transport: Refraction and Reflection

In this section, we outline the equations governing refraction and reflection, as well as our ray casting procedure used to compute the pixel–pixel mappings. Since we are considering materials with piecewise constant refractive indices, we represent light paths as piecewise linear functions. They are parameterized by N points $\{\mathbf{x}_i\}_{i=0}^{N-1}$ and unit direction vectors $\{\mathbf{d}_i\}_{i=0}^{N-1}$,

$$\mathbf{r}(t) = \sum_{i=0}^{N-1} \mathbf{1}_{[\tau_i, \tau_{i+1})}(t) (\mathbf{x}_i + (t - \tau_i) \mathbf{d}_i), \quad (6)$$

where $\mathbf{1}_A(t)$ is an indicator function testing $t \in A$, the initial pair $(\mathbf{x}_0, \mathbf{d}_0)$ is given by the camera origin and pixel direction vector, and the cumulative distance is given by $\tau_i = \sum_{j=1}^i \|\mathbf{x}_j - \mathbf{x}_{j-1}\|$, excepting for $\tau_0 = 0$ and $\tau_N = \infty$.

We compute a refraction path $\mathbf{r}^R$, which may include multiple refractions and total internal reflections, and a reflection path $\mathbf{r}^A$, which only considers the dominant first reflection, since secondary reflections usually have negligible impact. For the refraction path $\mathbf{r}^R$, we cast a ray from position $\mathbf{x}_i$ in direction $\mathbf{d}_i$ until it hits a surface of the refractive object at point $\mathbf{x}_{i+1}$. Then the next direction $\mathbf{d}_{i+1}$ is computed using Snell’s Law [1],

$$\mathbf{d}_{i+1} = \alpha_i \mathbf{d}_i + (\alpha_i \beta_i - \sqrt{\gamma_i}) \mathbf{n}(\mathbf{x}_{i+1}), \quad (7)$$

where $\alpha_i = \nu_i / \nu_{i+1}$, $\beta_i = -\mathbf{d}_i^\top \mathbf{n}(\mathbf{x}_{i+1})$, $\gamma_i = 1 - \alpha_i^2 (1 - \beta_i^2)$, ν_i is the refractive index of the i^{th} material, and $\mathbf{n}(\mathbf{x})$ is the unit surface normal at point $\mathbf{x}$. If $\gamma_i < 0$, total internal reflection occurs instead and the direction is given by the Law of Reflection,

$$\mathbf{d}_{i+1} = \mathbf{d}_i - 2(\mathbf{d}_i^\top \mathbf{n}(\mathbf{x}_{i+1})) \mathbf{n}(\mathbf{x}_{i+1}). \quad (8)$$

For the reflection path $\mathbf{r}^A$, the first reflected direction $\mathbf{d}_1^A$ is given by Eq. 8.

4. Transparent Object Image Generation

Our training-free image generation method, which we name Snellcaster since it casts rays that are curved according to Snell’s Law [1], is visualized in Figure 2. First, an image I_0^- is generated given a text prompt p^- , which has any reference to the transparent object removed, and its depth map D^- is estimated using MoGe-2 [41]. We then generate two images concurrently: a perspective image guided by prompt p , which includes the transparent object, and a panoramic image guided by augmented prompt p^{360} , centered at the transparent object’s location. At each denoising timestep t , we compute Euler estimates $I_{0|t}$ and $I_{0|t}^{360}$ using Eq. 5 for both views, warp them using precomputed geometric correspondences from ray tracing, and blend them together to

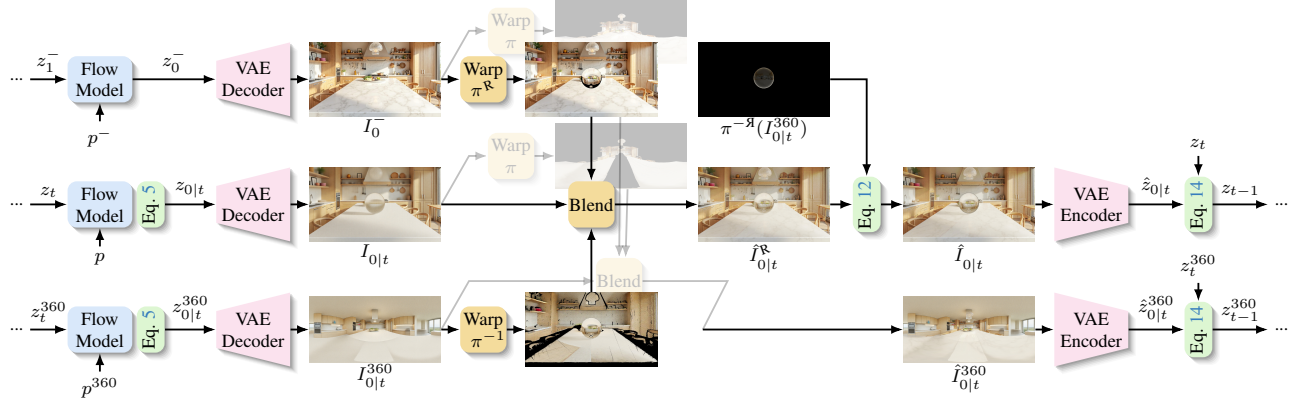


Figure 2. Snellcaster flowchart. (Top) An initial image I_0^- is generated using Flux [22]. Its depth map D^- is estimated (not shown) and is used to place the transparent object on a horizontal surface near the optical axis. Rays cast through this object are refracted according to Snell’s Law [1] and intersect with the estimated geometry, defining the warping functions. These are used to synthesize an image with correct refraction for the surfaces visible in the original image. (Middle) In the main branch, we generate the perspective image from prompt p , including the transparent object. (Bottom) In the auxiliary branch, we concurrently generate a panoramic image from augmented prompt p^{360} , centered at the transparent object’s location, to consistently fill in occluded or out-of-frame surfaces. (All) At each denoising step t , we compute Euler estimates of the clean images for both branches $I_{0|t}$ and warp them using the precomputed geometric correspondences. These are blended with the warped original image to obtain a complete perspective and panoramic image. Finally, we combine refractive and reflective contributions using Fresnel’s equations, before encoding back into latent space for the next denoising step.

enforce physical consistency. Finally, we combine refracted and reflected contributions using the Fresnel equations to produce the final image, which is encoded back into latent space for the next denoising step.

4.1. Computing the Warping Functions

Before generation begins, we pre-compute pixel-to-pixel warping functions by ray tracing through the 3D scene geometry, as outlined in Sec. 3.2. We first convert the depth map D^- into a 3D mesh and place the transparent object mesh onto a horizontal surface near the optical axis.

Self-warping. To model refraction through the transparent object, we cast rays from the perspective camera through each pixel, tracing their paths through the foreground mesh according to Snell’s Law [1] and intersecting with the background mesh. Projecting these intersections back to the image plane yields π^R , which maps pixels inside the transparent object to their corresponding background locations in I_0^- , as caused by refraction.

Cross-view Warping. The perspective camera does not observe occluded or out-of-view surfaces. We therefore generate a panoramic view centered at the transparent object, which approximates the surrounding scene as viewed from each point on its surface. To get the panorama-to-perspective warping, rays are cast from the perspective camera to refract through the foreground mesh and intersect with the background mesh, including its bounding box. The intersection directions are then projected onto the panorama to yield π^{-1} , the refraction component for panorama-to-

perspective warping, with the refracted color c^R at each pixel sampled from the corresponding intersection direction. Similarly, tracing reflected ray paths from the perspective camera and projecting them onto the panorama yields π^{-R} , the reflection component for panorama-to-perspective warping, with the reflected color c^R sampled along the reflected direction d_1^R on the equirectangular panorama. Conversely, casting straight rays from the panoramic camera and projecting their directions onto the perspective image plane yields π , which warps the perspective view to the panoramic view. These warping functions are computed once and reused throughout the generation process.

4.2. Cross-view Synchronization

At each denoising timestep t , we synchronize the perspective and panoramic views to ensure appearance and geometry consistency. We obtain Euler estimates for both views using Eq. 5, and decode the latent states to $I_{0|t}$ and $I_{0|t}^{360}$ in pixel space for the warping and blending, due to the fact that warping in latent space does not correspond to the same geometric transformation in pixel space [2].

Synthesizing Physics-Based Refractions. To incorporate the known background geometry, we apply the self-warping function π^R to the clean object-free image I_0^- to obtain $\pi^R(I_0^-)$, which shows the background as it would appear through the transparent object. Similarly, we warp the panoramic estimate to the perspective view and get $\pi^{-1}(I_{0|t}^{360})$, incorporating scene content invisible from the perspective camera. We then blend the three components in

the perspective view together,

$$\hat{I}_{0|t}^{\mathbf{R}} = \phi((I_{0|t}, I_{0|t}^{360}, I_0^-), (\pi^{\mathbb{I}}, \pi^{-1}, \pi^{\mathbf{R}}), \lambda), \quad (9)$$

where $\pi^{\mathbb{I}}$ is the identity warp and ϕ denotes an occlusion-masked blending operation with value-weighted averaging that preserves fine details of the images [2], given by

$$\phi(\mathcal{X}, \mathcal{Y}, \lambda) = (1 - \lambda) \frac{\sum_i M(\mathcal{Y}_i) \odot \mathcal{Y}_i(\mathcal{X}_i)}{\sum_i M(\mathcal{Y}_i)} + \lambda \frac{\sum_i M(\mathcal{Y}_i) \odot |\mathcal{Y}_i(\mathcal{X}_i)| \odot \mathcal{Y}_i(\mathcal{X}_i)}{\sum_i M(\mathcal{Y}_i) \odot |\mathcal{Y}_i(\mathcal{X}_i)|}, \quad (10)$$

where $M(\mathcal{Y}_i)$ is the occlusion mask associated with the i th element of the sequence of warping functions $\mathcal{Y}$, and the divisions are element-wise. For the panoramic view, we perform an analogous synchronization procedure:

$$\hat{I}_{0|t}^{360} = \phi((I_{0|t}^{360}, I_{0|t}, I_0^-), (\pi^{\mathbb{I}}, \pi, \pi), \lambda). \quad (11)$$

Synthesizing Plausible Reflections. Transparent objects exhibit both refraction and reflection, with their relative contributions determined by the viewing angle. Using the reflection warping $\pi^{-\mathbf{R}}$ we warp the panoramic estimate to obtain the reflected appearance $I_{0|t}^{\mathbf{R}} = \pi^{-\mathbf{R}}(I_{0|t}^{360})$. The refractive and reflective color contributions are then combined using the Fresnel equations [10],

$$\mathbf{c}' = \frac{1}{2}(R_p + R_s)(\mathbf{c}^{\mathbf{R}} - \mathbf{c}^{\mathbf{R}}) + \mathbf{c}^{\mathbf{R}}, \quad (12)$$

$$R_p = \left(\frac{\nu_1 \beta_0 - \nu_0 \sqrt{\gamma_0}}{\nu_1 \beta_0 + \nu_0 \sqrt{\gamma_0}} \right)^2, R_s = \left(\frac{\nu_0 \beta_0 - \nu_1 \sqrt{\gamma_0}}{\nu_0 \beta_0 + \nu_1 \sqrt{\gamma_0}} \right)^2, \quad (13)$$

where R_p and R_s are the reflection coefficients for parallel and perpendicular polarized light. The blending is performed in linear color space, with the result $\mathbf{c}'$ converted to sRGB to obtain the final pixel color $\mathbf{c}$ [40].

Updated Denoising Step. These final synchronized Euler estimates $\hat{I}_{0|t}$ and $\hat{I}_{0|t}^{360}$ are then encoded back to latent space. The resulting latents $\hat{z}_{0|t}$ and $\hat{z}_{0|t}^{360}$ are used to guide the subsequent denoising step:

$$z_{t-1} = z_t + \frac{\sigma_{t-1} - \sigma_t}{\sigma_t} (z_t - \hat{z}_{0|t}), \quad (14)$$

ensuring that both views remain consistent.

Further Details and Post-processing. All warping operations are performed using Laplacian pyramid warping, as in [2]. This reduces boundary artifacts and aliasing, since pixel data is sourced from the image with the appropriate resolution for the level of expansion or contraction caused by the warp. Like FreeDoM [46] and LookingGlass [2], we use time travel [43] to improve multi-view consistency. All details are in the supplement. After the entire generation process is complete, we apply a foreground object relighting (harmonization) model [22] as a post-processing step to add shadows and specularities conforming to the light sources in the rest of the image.

5. Experiments

In this section, we outline the experimental setup, especially how we measure success in this physics-based generation task, present the qualitative and quantitative results of the method, and report some key analyses.

5.1. Experimental Setup

Dataset. Our dataset consists of 10 text prompts describing indoor and outdoor scenes that contain a transparent object. Each prompt has 5 variations, resulting in 50 distinct scenes. For each scene, we consider 6 different transparent objects (sphere, cylinder, pyramid, fox, dog, and sculpture), yielding a total of 300 unique scene-object combinations. Indoor scenes, where other objects are closer to the transparent object, are significantly more challenging for modeling refractions, compared to outdoor scenes where the simplifying assumption that surfaces are infinite-distant is more reasonable. In the main paper, we primarily consider the illustrative case of a glass sphere, which humans are relatively good at grokking: the background should appear flipped about the horizontal and vertical axes of the sphere, with distortion increasing towards the boundary. Despite the simplicity of the geometry, image generators are unable to plausibly synthesize images containing this object. In the supplement, we show more examples of other objects, where the complexity of the refraction paths is challenging even for humans to intuit.

Compared methods. We compare our approach against one inpainting model and four state-of-the-art text-to-image models. The inpainting baseline is a FLUX-based inpainting model [22], which takes as input the clean reference image I_0^- (corresponding to prompt p^-) together with a foreground mask indicating the location of the glass object, and generates the object within the specified region. The text-to-image models include FLUX-dev [22], FLUX.2-dev [21], Qwen-Image [44], and Stable Diffusion 3.5 (large) [8], conditioned on the full prompt p that explicitly includes the glass object. For fair comparison, we use the same random seed as that used to generate the clean reference image.

Metrics. Evaluation of image generation quality is challenging, especially when assessing the physical correctness of the result. To assess image quality and how well it conforms to the input text, we report the CLIP score [11] and ImageReward score [45]. Note that these models are not trained to prefer realistic refractions, so can only be used to evaluate whether our refraction synchronization procedure caused the image quality to deteriorate. To assess refraction fidelity, we compare the refracted pixel rays to those rendered by computer graphics software (Blender [4]) from the same RGBD image, masking out those pixels that intersect with unobserved surfaces. We report the masked peak signal-to-noise ratio (PSNR) on grayscale images with



Figure 3. Qualitative comparison across six scenes. The first column is rendered in Blender with the estimated geometry and appearance from I_0^- , which provides a reference for the true refractions and reflections, under the caveats that the light sources and colors are incorrect and that there is missing data where refracted surfaces are not directly observed in the image I_0^- . The last three columns are generated using Snellcaster (ours), a FLUX inpainting model, and the standard FLUX-dev generative model using the same random seeds. Our approach conforms significantly better to the true refractions, with the expected left-right and up-down flips and radial warping in sphere scenes.

histogram matching, and the masked LPIPS distance. The color adjustment is necessary, because the Blender image is not harmonized with respect to lighting, so the refracted region will have some expected differences in color and structure. Nonetheless, our synthesized image should still conform well with the main structure in the ground-truth.

Implementation details. We use the FLUX-dev [22] flow-matching architecture, with $T = 20$ denoising steps, the default guidance scale of 3.5, and generate images of resolution 720×1280 (perspective) and 1024×2048 (equirectangular panoramic). The algorithm hyperparameters are set as follows: detail-preserving averaging coefficient λ is

Table 1. Quantitative comparison of our method against FLUX-dev [22], FLUX.2-dev [21], Qwen-Image [44], Stable Diffusion 3.5 (Large) [8], and FLUX-based inpainting model [22], averaged across all 300 scene-object combinations (10 prompts $\times$ 5 variations $\times$ 6 objects). Metrics include the CLIP score, ImageReward score, masked PSNR, and masked LPIPS. Our method consistently outperforms the baselines in terms of refraction modeling (measured by PSNR and LPIPS), without sacrificing text alignment and image aesthetics (CLIP and ImageReward).

Method	CLIP $\uparrow$	ImReward $\uparrow$	PSNR $\uparrow$	LPIPS $\downarrow$
FLUX (dev)	32.36	-0.20	12.68	0.48
FLUX.2 (dev)	33.37	0.18	12.15	0.48
Qwen-Image	32.67	0.01	12.55	0.48
Stable Diffusion 3.5 (L)	34.56	0.08	12.25	0.53
FLUX Inpaint	33.44	-0.47	12.66	0.47
Snellcaster (ours)	32.85	-0.32	16.51	0.24

set to 0.5, the number of Laplacian pyramid levels is set to 5, and time travel is repeated 3 times for timesteps in $[0.2, 0.8]T$, following the settings from LookingGlass [2]. Full text prompts (p, p^-, p^{360}) , along with the prompts for foreground object relighting are provided in the supplement. All experiments were run on a NVIDIA A100 80GB GPU.

5.2. Results

Qualitative results, together with the generating image prompts, are shown in Figure 3, along with samples from the underlying text-to-image generator to illustrate the implausibility of the synthesized transparent object when generated without physical guidance. Furthermore, in regions where geometry is missing (masked areas in the Blender reference images), our method produces plausible content by leveraging the synchronized panorama to fill in unseen regions. By contrast, FLUX inpainting and the standard FLUX-dev model generate physically implausible results. For instance, in the living room scene, FLUX inpainting fails to render the sofa behind the sphere, showing unrelated content instead. In the karaoke scene, although both the FLUX inpainting model and FLUX-dev generate glass spheres with tones consistent with the room, background details such as the TV and speakers are completely absent within the sphere. In the landscape scene, the standard FLUX-dev output appears reasonable at first glance, but closer inspection reveals that the mountains in the background are not refracted in the sphere at all. Overall, standard FLUX-dev and FLUX inpainting both fail to synthesize correct physical refractions, either omitting the background objects or rendering something that does not conform to the rest of the image evidence.

Quantitative results are presented in Tab. 1. Across both per-pixel metrics, our method outperforms all other methods. These results confirm that our approach not only



Figure 4. Kitchen scene example of the synchronized object-free image I_0^- (top left), the generated perspective image I_0 (top right), and the auxiliary generated panorama I_0^{360} (bottom). The panorama extends the scene in a plausible way that is consistent with the perspective view.

produces visually more accurate images but also better aligns with the text prompts and scene geometry, demonstrating the effectiveness of cross-view synchronization and physics-based refraction modeling.

In Figure 4, we give an example of the object-free image I_0^- and the auxiliary generated panorama I_0^{360} , as well as the generated perspective image I_0 , for one representative scene. This shows that the panoramic completion of the scene is plausible and is consistent with the perspective view, with sufficient detail for the sphere reflections.

Moreover, to evaluate our method on real-world data, we collect several image pairs, each consisting of one image without a transparent sphere and one with a transparent sphere, captured with a fixed camera. The image without the transparent sphere is used as I_0^- . Starting from random noise, we then apply our generation pipeline to synthesize the final image. Two examples are shown in Figure 5.

5.3. Ablation Study

Quantitative ablation results are shown in Tab. 2, where we evaluate the effect of two key components: the reflection modeling and the panorama synchronization. To ensure a fair comparison, all ablations are performed before relighting, since relighting introduces additional appearance changes that are not directly comparable across variants. We observe that removing either component leads to worse performance, especially for the per-pixel metrics. Among the two components, removing the panorama synchronization leads to a more significant performance drop than removing the reflection component. This is because, while reflections are important, their contribution is relatively subtle compared to refraction, which dominates the appearance of

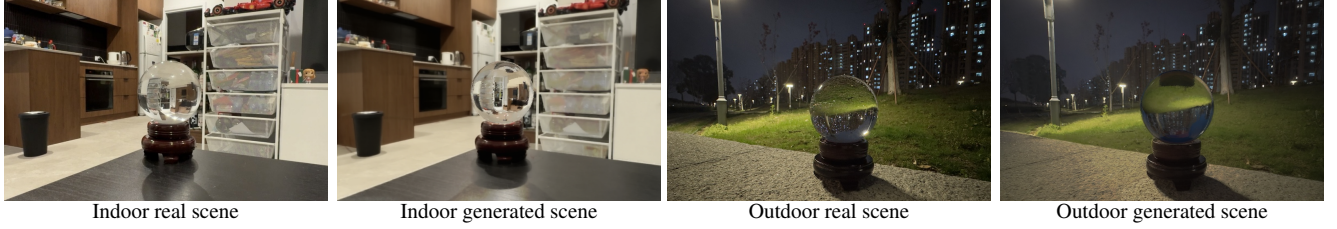


Figure 5. Real-world evaluation on captured scenes. We show two pairs of results from real image pairs collected by a phone camera. Each pair consists of a real photograph containing a transparent sphere (left) and a corresponding image synthesized by our method (right). The first pair shows an indoor kitchen scene, and the second pair shows an outdoor night park scene. Our method takes the image without the transparent sphere as I_0^- and generates the final image with a physically plausible glass sphere inserted into the scene.

Table 2. Quantitative ablation study on a subset of six scenes (artroom, cafe, dining room, kitchen, living room, office) with the sphere geometry. Ablating either the reflection and panorama components degrades the per-pixel performance (PSNR, LPIPS). Adding in the relighting leads to worse per-pixel metrics, but incorporating shadows is important for visual plausibility.

Model Variant	MAE↓	PSNR↑	LPIPS↓	CLIP↑	ImgR↑
Ours	0.0953	18.21	0.24	34.22	0.51
w/o reflections	0.0964	18.11	0.25	34.20	0.67
w/o pano sync	0.0983	17.98	0.25	33.88	0.64
w/ relighting	0.1137	17.10	0.28	34.61	0.59

the object. In contrast, the panorama branch provides essential information for regions inside the object that are not directly observed, such as areas that are outside the camera’s field of view or occluded by objects. Without this branch, the model must hallucinate these regions, often producing content that is inconsistent with the surrounding scene and does not align smoothly with the background. We further provide a qualitative comparison in Figure 6, where we visualize this effect on a landscape scene. We also show the quantitative effect of relighting in Tab. 2. Although relighting slightly degrades per-pixel metrics, this is expected because it introduces additional lighting and shadow effects that deviate from the ground truth at a pixel level. However, these effects improve the overall visual plausibility of the results, especially the shadow cast by the object, highlighting a trade-off between numerical metrics and perceptual quality. Overall, these results demonstrate that both reflection modeling and panorama synchronization contribute meaningfully to reconstruction accuracy, while relighting primarily improves realism rather than per-pixel metrics.

6. Conclusion

In this work, we have presented a training-free approach for generating images containing a transparent object, where the physical principles of refraction and reflection are respected. It employs cross-view image synchronization to ensure that the generated perspective image I , the object-

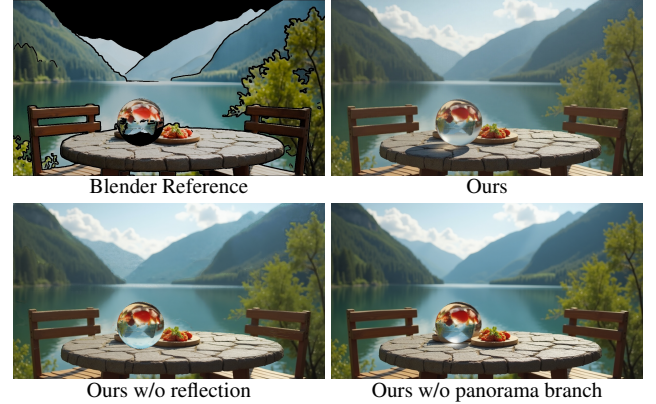


Figure 6. Qualitative ablation on a landscape scene comparing the Blender reference, full method, w/o reflection modeling, and w/o panorama synchronization. Removing panorama synchronization leads to missing or hallucinated content in out-of-view regions, showing its importance for global scene consistency.

free perspective image I^- , and the panoramic image from the perspective of the transparent object I^{360} are compatible, and that the refractive regions receive the correct color. The panorama synchronization further ensures that occluded and out-of-frame regions are plausibly completed, so that the refracted rays that do not hit an observed surface receive a plausible color, and similarly for the reflected rays.

There are many promising directions for future work. Minor extensions include modeling absorption (e.g., tinting) of the transparent object, modeling multiple material types (e.g., a glass of water with a straw), modeling birefringent materials (e.g., Iceland spar), and text-controllable object placement. More significant directions include native lighting and shadow handling via light source estimation and ray tracing, improving the accuracy and consistency of the seen–unseen surface boundary by synchronizing RGBD images and panoramas, and extending the approach to video generation with optically-accurate refractions and reflections. The latter is currently a major failure case of video generation models and acts counter to an immersive suspension of disbelief.

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