

# Reasoning about Photo Collections using Outdoor Illumination Models

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## 1. Introduction

Natural illumination plays a critical role in the appearance of outdoor scenes, and in the variation of scene appearance over time. For example, in Figure 1, the images from a photo collection of the Statue of Liberty show a variety of illuminations possible. Many vision tasks, such as photometric stereo and intrinsic image decomposition, require reasoning about this illumination and how it interacts with the scene. This outdoor illumination is far from arbitrary—it is dominated by a few elements including the sun, sky, and weather, which in turn depend in a fundamental way on factors such as where on Earth a scene is located, and the time at which a photo was taken. The computer graphics community has developed increasingly sophisticated models of outdoor illumination that take parameters such as place and time, and compute a predicted outdoor environment map for those conditions. Surprisingly, these illumination models are not yet widely used in computer vision, despite the importance of outdoor illumination in the appearance of scenes.

Our work explores the connection between community photo collections of an outdoor scene at a given location on Earth, and the distribution of lighting conditions for that scene predicted by these illumination models. Despite the power of these predictive models, using them to reason about scenes from unstructured photos is still a major challenge, in part because these photos are often taken from unknown or inaccurately labeled times—the images represent a “soup” of different observations of the scene under varying but unknown illumination.

Our insight is to couple *statistics* of outdoor illumination with statistics of the photo collection. That is, despite the unstructured nature of the photos, we expect the statistics of the collection as a whole to mirror statistics across all possible outdoor illuminations for that particular scene. We build on the photometric ambient occlusion work of Hauagge *et al.* [1], which explored the connection between pixel statistics over a photo collection and simpler distributions of illumination (such as point sources distributed uniformly over the hemisphere), and related this to the local visibility (or ambient occlusion) of each scene point. However, we significantly extend that work to handle the more realistic scenario of varying illumination in outdoor scenes.

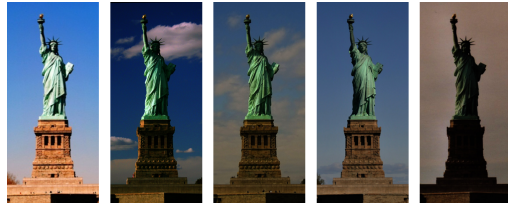


Figure 1: Images of the Statue of Liberty under a variety of natural illumination conditions.

## 2. Modeling the illumination of a point

The illumination arriving at a point in an outdoor scene depends on several key factors. The **geographic location** and the **time and date** of an observation together determine the position of the sun in the sky: location and date constrain the sun position to a well-defined path, and time of day determines where the sun lies on this path. For a given point in the scene, its **surface orientation** affects how much and which portion of the sky’s illumination reaches it. Finally, the point’s **local visibility** can be affected by surrounding geometry that occludes some portion of the sky dome.

To handle local visibility, we adopt the model of ambient occlusion proposed by Hauagge *et al.* [1] which models local geometry around a point as a simple cylindrical hole with angle  $\alpha$  from the normal to the opening. We generalize this method for determining  $\alpha$ , albedo, and illumination to work under much more complicated outdoor illumination by leveraging existing outdoor illumination models. In short, our model considers the irradiance incident at an outdoor scene point on a clear day as a function  $L(\phi, \lambda, t, \alpha, \vec{n})$  where  $(\phi, \lambda)$  are the geographic latitude and longitude,  $t$  is the time and date,  $\vec{n}$  is the normal vector, and  $\alpha$  is the local visibility angle given by our crevice model. Figure 2 shows examples of  $L$ —in the form of spheres rendered under predicted outdoor illumination, for varying times and local visibility conditions, at a given location on Earth.

## 3. Method

We take as input a georegistered 3D point cloud generated from structure from motion and multi-view stereo, which provides geographic location  $(\phi, \lambda)$ , estimated surface nor-

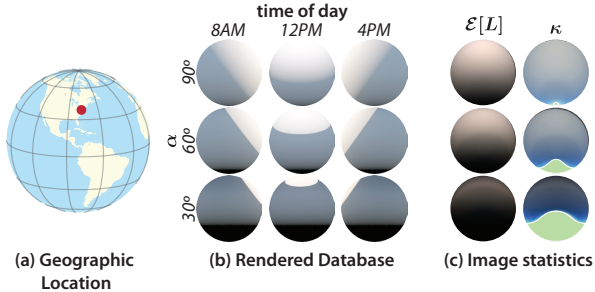


Figure 2: For a given geographic location (a), we render a database of spheres (b) covering all possible times of a full year and visibility angles. (c) We compute  $\mathcal{E}[L]$  and  $\kappa$  for each  $\alpha$ . Green regions correspond to combinations of normal direction and crevice for which we cannot reliably recover albedo.

mals ( $\vec{n}$ ), and a set of observed pixel values for each point  $x$  ( $I_x$ ). We first estimate the albedo of each reconstructed point  $x$ , then use the albedo to estimate lighting and time of day for each photo of the scene.

**Estimating Albedo in Sunlit Outdoor Scenes.** We adopt a simple Lambertian image formation model  $I_x = \rho L_x$  where  $I_x$  is a pixel observation (i.e., observed color) of a point,  $\rho_x$  is the (assumed constant) albedo at that point, and  $L_x$  is the irradiance as defined above. Suppose we have many observations of a point  $I_x$ , and want to derive the albedo  $\rho_x$ . How can we do this? We could compute the average observed color  $\mathcal{E}[I_x]$ , which would give us the point color as if the point were illuminated by the average illumination for that scene. If we knew the average illumination  $\mathcal{E}[L_x]$ , we could simply divide  $\mathcal{E}[I_x]/\mathcal{E}[L_x]$  to derive  $\rho_x$ .

The key insight here is that we can use a sun/sky model to predict illumination for a given condition, or indeed the *average* illumination for a given scene. In particular, for a given location, time and visibility angle, we can compute a physically-based environment map (we use the model of Hosek and Wilkie [2]) and integrate the irradiance at each normal over the visible portion of the environment map to produce a database of spheres giving values for  $L$  at each normal direction, as illustrated in Figure 2(a-b). We then estimate expected illumination  $\bar{L}(\vec{n}, \alpha)$  as a function of normal and visibility angle by taking the average over a set of times sampled throughout the year.

For each point  $x$ , we have a surface normal estimate  $\vec{n}_x$  from the 3D reconstruction; however we also need the visibility angle  $\alpha_x$  to look up the appropriate expected illumination  $\bar{L}(\vec{n}_x, \alpha_x)$ . Under a simpler lighting model, Hauagge *et al.* [1] showed that  $\alpha$  can be determined analytically as a function of an albedo-invariant image statistic  $\kappa_x = \mathcal{E}[I_x]^2/\mathcal{E}[I_x^2]$ . In our setting, where illumination is more complex, we relate  $\kappa$  to  $\alpha$  by computing  $\kappa(\vec{n}, \alpha)$  over the predicted illumination values provided by the sun/sky model, as shown in Figure 2(c). We let  $\alpha_x$  be the alpha for which  $\kappa(\vec{n}_x, \alpha)$  most closely matches the observed  $\kappa_x$ .

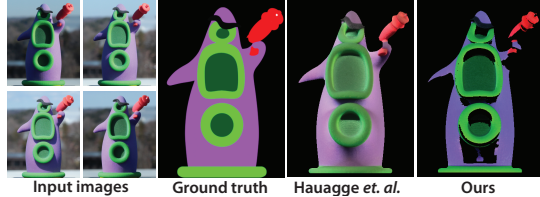


Figure 3: Results of our proposed algorithm  $\rho$ -sunsky compared to  $\rho$ -unif.

**Estimating Time of Day.** With albedos in hand, we can estimate illumination for an image by dividing each visible point's observed color value by the estimated albedo  $L_x = \frac{I_x}{\rho_x}$ . To estimate the time for that image, we can compare this estimated per-point illumination to the illumination predicted by the sun/sky model at a set of times candidate times  $t$  (potentially sampled over the entire year). The predicted time  $t^*$  is then the time for which the observed and predicted illumination are most similar.

**Results.** Figure 3 shows an example of our computed albedo ( $\rho$ -sunsky) on an outdoor photo collection of a 3D printed object captured over the course of a day, compared to the technique of Hauagge *et al.* ( $\rho$ -unif). Our technique recovers a significantly flatter albedo and successfully identifies and discards points whose albedo cannot be recovered accurately. Once computed, this albedo can be factored out to compute a per-image illumination map, which can in turn be used to estimate the time when each image was captured.

## 4. Summary

We believe that coupling physical models of illumination with pixel statistics computed over outdoor photo collections can yield a new class of statistical algorithms for analyzing outdoor photo collections, taming these unstructured collections to provide useful information about materials and illumination. Our work is a first step in this direction, but this remains a ripe area for future study. More broadly, our goal is to extend our approach to use other types of knowledge about the world to improve algorithms for reconstructing and understanding scenes. For instance, the model above currently assumes clear skies; fortunately, weather information is continually recorded at stations around the world. By adding this rich information into our model, we could predict more accurate illumination distributions (and potentially tell weather from a photo). Ultimately, we hope to use these ideas to create algorithms that robustly and automatically compute the time-varying appearance of scenes from the world's photos.

## References

- [1] D. Hauagge, S. Wehrwein, K. Bala, and N. Snavely. Photometric ambient occlusion. *CVPR*, 2013.
- [2] L. Hosek and A. Wilkie. An analytic model for full spectral sky-dome radiance. *ACM Transactions on Graphics*, 2012.