DIP PROJECT PROPOSAL

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Project ID: 14

Project Name: Intrinsic Images in the Wild

Team Members:

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Github link:

https://github.com/bruce-wayne99/Intrinsic-Images-in-the-Wild

Goals of the project:

1. The goal of intrinsic images is to separate an image into two layers, a reflectance (albedo) image and a shading (irradiance) image, which multiply to form the original image.
2. Reliable algorithms for separating illumination from reflectance in scenes would enable a range of applications, such as image-based resurfacing, texture transfer between images, relighting, material recognition, and other interior design tasks.

Problem Definition

What is the problem?

Intrinsic image decomposition is a long-standing inverse problem with many applications in graphics and vision. There has been significant recent progress on the problem of intrinsic image decomposition, aided by the release of the MIT Intrinsic Images dataset , which contains carefully constructed ground truth for images of objects. However, intrinsic image decomposition is still very challenging, especially on images of real-world scenes. There is currently no standard dataset for evaluating intrinsic images on images of such scenes, due in part to the challenge of capturing real-world photos with known ground truth reflectance and illumination. To span the rich range of real-world scenes we need a large set of images. For this scenario, both careful measurement and using rendered images of synthetic scenes are not practical or satisfactory.

How things will be done?

A large-scale database of Intrinsic Images in the Wild has been collected with real-world photos of indoor scenes, with crowdsourced annotations of reflectance comparisons between points in a scene. This dataset is the first of its kind for intrinsic images, both in its scale and in its use of human annotation: the dataset contains over 5,000 images featuring a wide variety of scenes, and has been annotated with millions of individual reflectance comparisons.

Motivated by this new dataset, we will be creating a new intrinsic image decomposition algorithm designed for images of real-world scenes. This algorithm makes use of the fact that many surfaces in indoor scenes share the same material and reflectance, resulting in longrange sharing of reflectances across a scene (for example, a painted wall spanning an entire image). We build this algorithm on recent work in **fully connected conditional random field (CRF)** which was used for image detection and segmentation to enable such long-range connections in our algorithm. We train our algorithm on this Intrinsic Image dataset to find most optimal values for all the hyperparameters involved in the algorithm.

Intrinsic Image Algorithm

Our algorithm works as follows:

1. First, we hypothesize a set of reflectances **R** that are likely to exist in the image—one can think of this set as a “**palette**” of reflectances that we can draw on for that image.

2. The set R is unique for each image and, for a typical run of our algorithm, will contain **20 entries** once our algorithm converges. After first choosing an initial set of reflectance colors R using clustering, we iterate between two stages:

- We label each pixel with a reflectance chosen from R such that **p(R, S | i)** is maximized. Where **R is the reflectance layer**, **S is the shading layer** and **I is the given image**.
- We adjust the reflectances in R by minimizing discontinuities in the **shading layer S**.

3. The first stage improves the reflectance layer, and is optimized using discrete labeling; the second stage improves the shading layer, and is optimized using **continuous L1 minimization**.

Expected Results

This algorithm should perform very well for real-world scenes. While it is particularly good at finding a single reflectance to explain large continuous regions, it can also handle intricate textures such as wallpapers and bricks. Even when there are many surfaces that do not fit the diffuse reflectance model (such as glossy metals or tinted windows), the model often would be returning a reasonable result.

Team members and tasks assigned

Task Assigned	**Team Member**	**Timeline**
Data preprocessing and initialization	Sushman KVS	18th October
Developing probability model and optimizing reflectance using fully connected Conditional	Subramanyam MNS	25th October

random field(CRF).		
Optimize for shading	Sushman KVS	10th November
Training the algorithm for optimization.	Subramanyam MNS	15th November
Code brushup and other adjustments.	Both	20th November