Project 14

Intrinsic Images in the Wild

Team Members:

1) MNS Subramanyam(20161190)
2) Sushman KVS(20161143)

GITHUB LINK:

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

PROBLEM STATEMENT AND MOTIVATION:

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.

GOALS:

- 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.
- 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.

APPROACH AND WORK DONE SO FAR:

1. DATA PREPROCESSING AND INITIALIZATION
    a. In this stage we will be storing our input image in a class model and declare necessary methods to be applied in that model.
    b. We will be declaring methods to map our input RGB image to various other spaces such as IRG(Intensity, Red chromaticity, Green chromaticity).
    c. We would compute a palette of reflectance colors, for this we do **kmeans clustering** in IRG space. We do clustering in IRG space because it is observed that chromaticity and intensity describe the pixels more properly than the RGB pixel colors.
    d. By applying kmeans algorithm we get the label centres. We use the intensities and chromaticities of these major k centres for the rest of the process.
    e. We would also writing methods to handle binary masks (neglecting some pixels of the input image).

2. <u>OPTIMIZING REFLECTANCE LAYER</u>
    a. In this stage we try to assign each pixel a label from the set of reflectances computer before using kmeans clustering.
    b. We use a **fully connected conditional random field** which takes the unary costs, pairwise costs and features associated with the pixels as input and returns the set of labels for each pixel which would minimize the total cost and increase the probability of reflectance layer defining the image.
    c. Unary costs and pairwise costs are computed by using the formulas as mentioned in the paper. We use intensity, chromaticity and pixel locations for computing these costs.
    d. We run the conditional random field over 10-15 iterations and get the optimized reflectance and the corresponding shading layer.

<u>MILESTONES LEFT:</u>

1. <u>OPTIMIZING SHADING LAYER AND SMOOTHNESS</u>
    a. Still we have to optimize our shading layer and smoothing is also important since we want the shading channel to very smoothly across smooth surfaces.
    b. We would want to shading layer in a number of iterations by adjusting the number of iterations as mentioned in the paper.
    c. Also for smoothing we have to add one more term for unary cost calculation which would compute the cost for smoothing the shading layer.
2. <u>NOVELTY FOR IMPROVEMENT IN PERFORMANCE</u>
    a. Later once the previous mentioned stages are done, we would like to work on optimizing any part of the code.
    b. We would work on optimizing the code and make a plot of times taken by the actual algorithm and the one implemented by us.

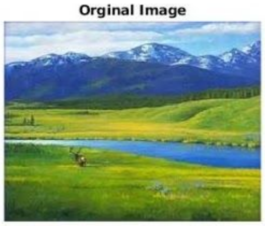
3. FIGURING OUT FAILURE CASES
    a. Hyperparameters are estimated by using image datasets and judgement data as of now using WHDR error.
    b. We would focus on weaknesses of WHDR, synthetic images, colored lighting and hard shadows.
    c. Also presently the algorithm is working well only for indoor photographs as the dataset it is trained mostly comprises of indoor photographs and some natural and outdoor photos.
    d. We would like to train our algorithm on outdoor scenes but that would again require judgement data for those set of images which is another issue.

RESULTS:

INDOOR SCENES:

OUTDOOR SCENES:

Orginal Image

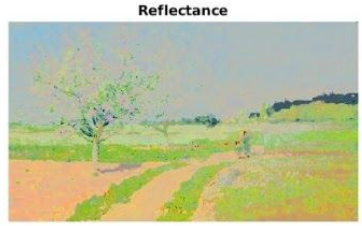


Reflectance

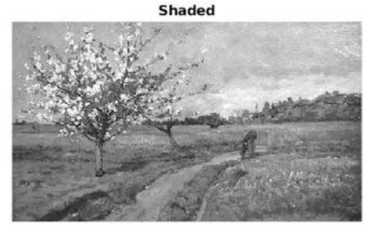
Shaded

Orginal Image

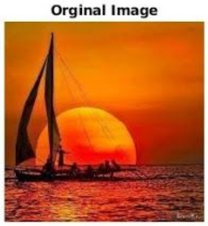
Reflectance



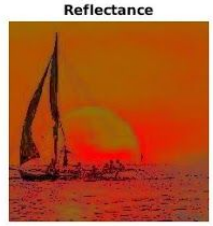
Shaded



Orginal Image



Reflectance



Shaded