Final project report of CMPT828: Illumination in Images and Video

Intrinsic Images by Entropy Minimization

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Abstract

We recover invariant image, which is 2D chromaticity, from a single unsourced 3-band color image. Our method bases on the observation that the invariant direction is that along which the projection minimizes entropy in the resulting invariant image. Results, demonstrated on images with unknown camera, show that the proposed method successfully removes shadows from unsoursed imagery. Further more, we try to recover full-color images with shadow removed using edge detection and re-integration.

1. Introduction

Recovering illumination-invariant and intrinsic image from a color image has drawn lots of attention in the field of computer vision [1] [2] [3] [4]. One of the crucial reasons is that shadows in an image can fail many computer vision algorithms, such as segmentation, tracking, and recognition.

The task of this project is to work out the invariant chromaticity image, with shadows removed, from images that arise from un-calibrated cameras. Our method is based on the observation that, projecting in the correct direction minimizes the entropy in the resulting greyscale image. For a set of color patches under changing lighting, pixels corresponding to each color patch with different lighting falls on an approximately straight line in a 2D log-chromaticity space. If we project all these pixels onto a line perpendicular to the set of straight lines, we end up with a greyscale image, which results in low entropy, as in Fig. 1(a). Otherwise, if we instead project in some other directions, the projected a greyscale images result in higher entropy, as in Fig. 1(b).

Hence the idea of this project is evident, the correct invariant direction is that along which the projection minimizes the entropy. For the real images, change in lighting is automatically provided by the shadows in the images themselves.

Finally, we recover a full-color shadow-free image using edge detection and re-integration.

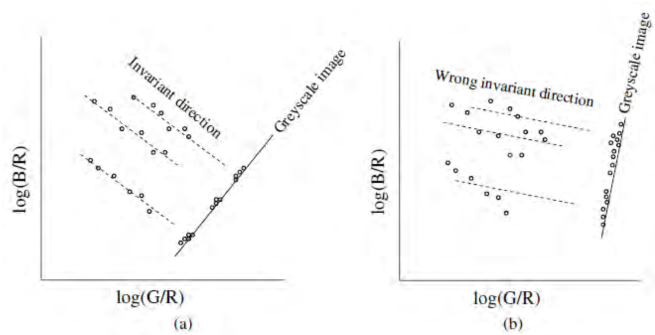

Figure 1: Intuitive observation for entropy minimization.

2. Algorithm

Now our goal is to find the minimum-variance direction for lines in Fig 1. In fact, for the given image, we have no idea which points fall on which lines, so entropy minimization is the key to finding the correct invariant direction.

2.1 Algorithm steps

1) Form a 2D log-chromaticity representation χ of the input image.

2) For $\theta_i = 1°...180°$

   a) Form greyscale imgae I

   b) Calculate entropy η

   Min-entropy direction θ_i is correct projection for shadow removal.

3) Form L_1 chromaticity image of 2D invariant log-chromaticity.

// To get full-color shadow-free image

4) Shadow edge detection.

5) Form a gradient for each color channel, fix up the gradient on shadow edges and re-integrate.

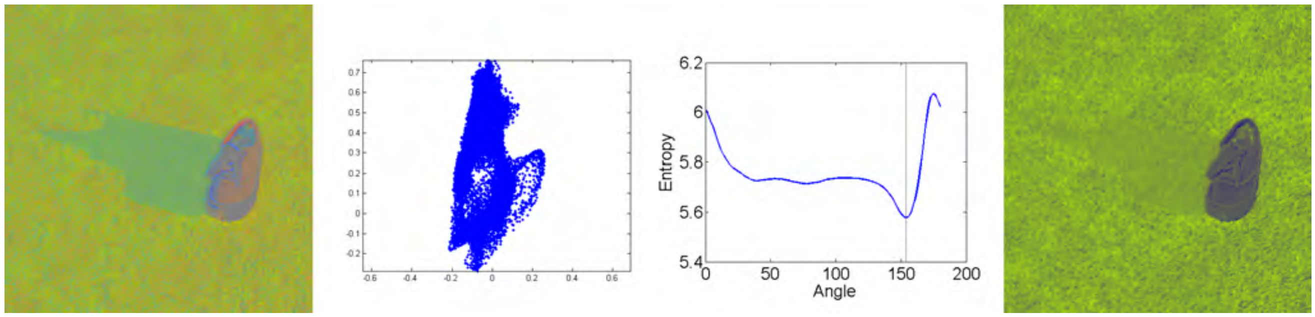

Figure 2: (left): L_1 chromaticity of the input image. (middle left): geometric mean 2D chromaticity. (middle right):entropy of projected image, versus projection angle. (right): invariant L_1 chromaticity.

2.2 2D log-chromaticity presentation

Following the assumptions and notations in [5], we have 2-vector chromaticity $\boldsymbol{c} = \{c_1, c_2, c_3\}$,

$$c_k = R_k / \sqrt[3]{\prod_{i=1}^{3} R_i} \equiv R_k / R_M. \tag{1}$$

Then we form log of Eq. (1),

$$\begin{aligned} \rho_k &= \log(c_k) \\ &= \log(s_k/s_M) + (e_k - e_M)/T, k = 1..3, \end{aligned} \tag{2}$$

with

$$\begin{aligned} s_k &= k_1 \lambda_k^{-5} S(\lambda_k) q_k, s_M = \sqrt[3]{\prod_{j=1}^{3} s_j}, \\ e_k &= -k_2/\lambda_k, e_M = -k_2/3 \prod_{j=1}^{p} \lambda_j, \end{aligned}$$

Eq. (2) is a straight line parameterized by T. And we have

$$\rho_1 + \rho_2 + \rho_3 = \log(R_1 R_2 R_3) - \log(R_M^3) = 0,$$

which means point $\boldsymbol{\rho} = (\rho_1, \rho_2, \rho_3)^T$ falls onto the plane

$$\boldsymbol{\rho} \cdot \boldsymbol{u} = 0, \boldsymbol{u} = (1, 1, 1)^T. \tag{3}$$

To characterize the 2D space, we consider the projector $\boldsymbol{P}_u^{\perp}$, which has two non-zero eigenvalues, so its decomposition reads

$$\boldsymbol{P}_u^{\perp} = \boldsymbol{I} - \boldsymbol{u}\boldsymbol{u}^T = \boldsymbol{U}^T \boldsymbol{U},$$

where $\boldsymbol{U}$ is a 2×3 orthogonal matrix. $\boldsymbol{U}$ rotates 3-vector $\boldsymbol{\rho}$ into a coordinate system in the plane 3,

$$\boldsymbol{\chi} \equiv \boldsymbol{U}\boldsymbol{\rho},$$

where $\boldsymbol{\chi}$ is 2-vector. We call $\boldsymbol{\chi}$ the geometric mean 2D log-chromaticity space, as the second figure in Fig. 2.

2.3 Entropy minimization

In the 2D log-chromaticity space, given the projection angle θ, we project $\boldsymbol{\chi}$ to the line indicated by θ

$$I = \boldsymbol{\chi} \cdot (\cos\theta, \sin\theta)^T = \chi_1 \cos\theta + \chi_2 \sin\theta.$$

Then we build a histogram of the projected greyscale image I, with the bin width according to Scott's Rule [6]

$$bin\_width = 3.5 std(I) N(I)^{1/3}.$$

Due to the noise, we use the middle 90% of the data in I. We define entropy η as follows

$$\eta = -\sum_i p_i \log(p_i), \tag{4}$$

where p_i is the height of each bin. The third figure in Fig. 2 shows the entropy versus projection angle $\theta = 1°...180°$.

2.4 3-vector presentation

After finding the invariant angle $\boldsymbol{e}^{\perp}$, we firstly form the 2-vector presentation of $I_{e^{\perp}}$, via a 2×2 projector $\boldsymbol{P}_{e^{\perp}}$

$$\begin{aligned} \boldsymbol{\chi}_{e^{\perp}} &= \boldsymbol{P}_{e^{\perp}} \boldsymbol{\chi}, \\ \boldsymbol{P}_{e^{\perp}} &= \boldsymbol{e}^{\perp} (\boldsymbol{e}^{\perp})^T / \|\boldsymbol{e}^{\perp}\|. \end{aligned}$$

Then we add back enough $\boldsymbol{\chi}_{extralight}$ so that the median of the top 1% brightest pixels has the same 2D chromaticity of the original image, as that in [4],

$$\boldsymbol{\chi}_{e^{\perp}} \longleftarrow \boldsymbol{\chi}_{e^{\perp}} + \boldsymbol{\chi}_{extralight}.$$

Now we go back to 3-vector representation of $\boldsymbol{\chi}_{e^{\perp}}$, that is the estimate of $\boldsymbol{\rho}$ and $\boldsymbol{c}$,

$$\tilde{\boldsymbol{\rho}} = \boldsymbol{U}^T \boldsymbol{\chi}_{e^{\perp}}, \tilde{\boldsymbol{c}} = \exp(\tilde{\boldsymbol{\rho}}). \tag{5}$$

Once we have an estimate $\tilde{\boldsymbol{c}}$ of the geometric mean chromaticity in Eq. (1), we can go over to the more familiar L_1-based chromaticity $\boldsymbol{r} = \{r, g, b\}, r + g + b = 0$, via

$$\tilde{\boldsymbol{r}} = \tilde{\boldsymbol{c}} / \sum_{j=1}^{3} \tilde{c_k}. \tag{6}$$

The forth figure in Fig. 2 and the third column in Fig. 3 illustrate invariant 2d chromaticity images with shadow removed.

2.5 Full-color image

Using a re-integration method similar to that in [3], we can go on to recover a full-color shadow-free image, as in Fig 5. There are two steps to regain the full-color image: finding a shadow-edge, and then re-integrating.

The first step is carried out by comparing edges in original image with that in its recovered invariant chromaticity image. For the second stage, for each color channel, we zero the gradient across shadow-edge regions. Go to Fourier space, project onto integrable version by inverting the effect of derivatives in Fourier space and projecting onto integrable basis. Inverse Fast Fourier Transform (IFFT) gives back original image, up to an additive constant.

3. Results

All the images used in this project obtained by a Nikon D70s camera. Fig. 2 shows the pipeline of this project. Given an image (far left shows its L_1-chromaticity), we compute its geometric mean 2D chromaticity (middle left), then we examine the entropy of the projected grescale images over $0°$ to $180°$ (middle right), and the angle resulting in the minimum entropy is used to generate the invariant L_1-chromaticity image (far right).

A given camera, e.g. Nikon D70s , has the unique correct characteristic direction to attenuate illumination effects. Our entropy minimization in Fig. 2 provides a close approximation of this angle: $154°$. When applying this angle to other images shot by the same camera, results in Fig. 3 illustrate this angle is correct.

Fig. 4 is our edge detection method. The left column is the original image (top) and its L_1-chromaticity image (bottom), while the right column shows their individual edge detection results. We use the Canny method from Matlab with parameters $\delta = 5, threshold = 0.2$. By comparing these two sets of edges, and removing short ones, we obtain the edge mask of shadow regions. Due to the edges being quite fuzzy, we widen our edge mask to a width of 4 pixels. By zeroing the gradient across the shadow edges, going to fourier space, projecting to integrable basis, and applying IFFT, we recover a full-color image with shadows removed.

Fig 5 illustrates our attempt of recovering full-color shadow-free image. From what we can see, our attempt is not very successful, but we do make the shadows much lighter, and closer to the surrounding region. The reason of our failure lies in our trivial method of simply zeroing the gradient across shadow edges. In fact, in the real images, shadow edges are always quite fuzzy, that is why we make

Figure 3: Additional invariant images, columns show original image, L_1 chromaticity image, and L_1 chromaticity image.

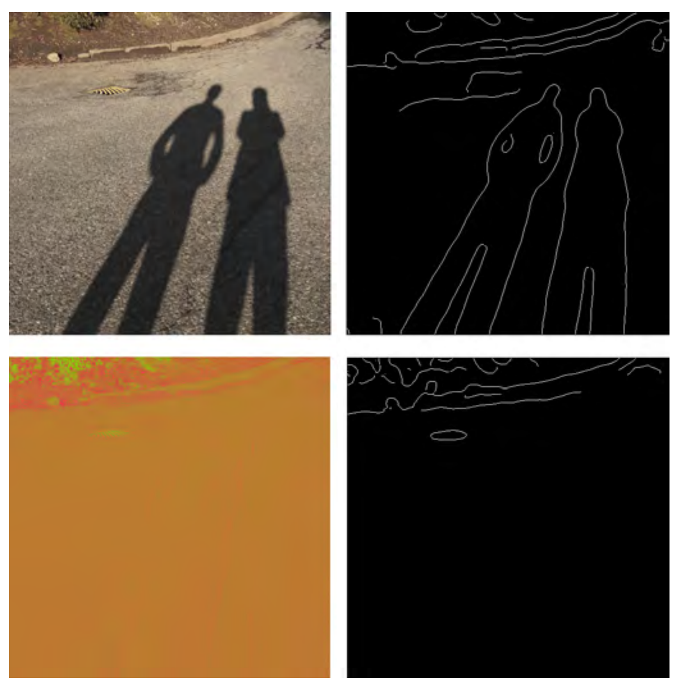

Figure 4: A Edge detection: (left) the original image and its L_1 chromaticity image; (right) edge detection results.

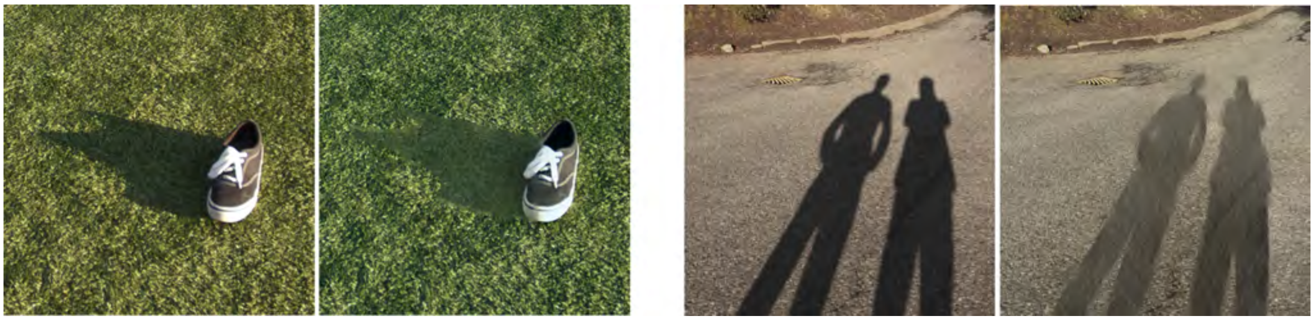

Figure 5: Re-integration results. Even though our naive method doesn't work perfectly, it does make the shadow much lighter.

our edges very wide. If we zero all the gradient in these shadow-edge regions, we lose lots of useful information, as well as very obvious edges would show up in the final recovered image.

Hence, applying more sophisticated edge detection and fixing up method, and re-integration are part of our future work.

4. Conclusions

We implemented a method for finding the invariant direction, and thus a greyscale and hence an L_1-chromaticity intrinsic image that is shadow-free, without any need for a calibration step or special knowledge about an image. The results indicate this proposed processing works well on removing shadows.

For the re-integration stage, we perform re-integration on each color channel to recover the full-color image. The results we obtained show that even our naive method has potential to successed.

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