REMOVING SHADOWS FROM A SINGLE REAL-WORLD COLOR IMAGE

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ABSTRACT
In this paper, we propose a new algorithm to remove shadow from a single color image. We first project log-log chromaticity coordinates onto an angle of illumination-invariant direction to obtain an illumination independent grayscale image. Then color information is added back by comparing intensities in the original and illumination-invariant grayscale images, and taking both global tonality and pixel-wise color into account. Finally, the result color image without shadow is recovered. The proposed method simplifies the color restoration procedure and therefore requires much less computation. Experimental results show that the new method can produce shadow-free images with same quality as those shown in previous work.

Index Terms—Shadow removal, illumination invariance, color restoration

1. INTRODUCTION
In many image processing tasks, it is very important to distinguish between intensity change caused by different reflectance and that due to scene illumination effects. In particular, many tasks require the separation of shadow which is essentially the variation of intensity and color caused by scene illumination. However, conventional algorithms for shadow removal based on the assumption of intensity or color constancy may lead to unfavorable outcomes.

In order to derive an intrinsic image, Weiss [1] used the median filter to process a sequence of images captured in the same scene which have constant reflectance and time-varying illumination condition. Although the method guarantees the problem is well-posed, it simultaneously restricts its application scope. In [2], diverse clues, such as intensity, color, and 3D composition of objective surface, were employed by Tappen et al. to train a classifier which was used to detect shadow edges. They then corrected ambiguous regions by belief propagation to remove shadow from a single image. The biggest disadvantage of this method is that training the classifier requires more effort.

The retinex algorithm is also widely used for dynamic compression. Since it is considered to be able to simulate human vision perception of lightness and colors, Land [3, 4] evolved retinex from the random path computation [5] form to spatially center/surround opponent operation [6]. However, this method cannot remove shadow while retaining color.

Finlayson et al. [7, 8] designed a mechanism to automatically detect and remove shadow based on chromaticity projection. The color information can also be restored. However, the limitation of this method is that it requires the pre-knowledge on the light source and camera intrinsic parameters. Meanwhile, the computation complexity is high due to the iteration scheme required during the color restoration phase. In this paper, we introduce a new method to improve Finlayson et al.‘s work. Our method takes both global and local color information into account so that the color restoration can be performed in a more efficient way after shadow removal. Experimental results show that the proposed method can produce shadow-free images with quality as good as those produced by Finlayson et al. in [7].

2. SHADOW REMOVAL
2.1. Generation of an illumination-invariant grayscale image
According to [7, 8] by Finlayson et al., we are able to produce an illumination-invariant grayscale image if the following three assumptions are satisfied. First, the original shadowed image can be modeled by the Lambertian model. Second, scene illumination has to be restricted as Planckian. Finally, the camera sensitivities can be described by Dirac delta functions.

We define chromaticities in band-ratio three-element vectors as:
\[
\begin{align*}
    x_i &= \frac{x_i}{\rho}, k \in \{R, G, B\} \\
    \rho &= \sqrt{\text{RGB}}
\end{align*}
\]

where \(\rho = \sqrt{\text{RGB}}\). By restricting illumination to be modeled by Wien’s approximation to Planck’s law, we can form the logarithm of \(x_i\) and summarize it in the vector form:

\[
x = s + \frac{1}{T} e
\]

where \(x\), \(s\) and \(e\) are all three-element vectors (for more details please refer to [7]). \(s\) depends on surface reflectance and camera sensitivity functions but not on illumination, and \(e\) only depends on the camera but not on surface reflectance and illuminant condition. For each surface exposed in different illumination circumstances, \(s\) and \(e\) are constant and only the color temperature \(T\) varies.

![The original image](image1.jpg)

(a) The original image

(b) \(x'\) moves along a line

(c) Projection entropy

(d) 1D Shadow-free image

Fig. 1. Generation of illumination-invariant grayscale image.

In order to transform three-dimensional vectors to two-dimensional vectors, we define a transformation matrix as follows:

\[
U = \begin{bmatrix}
    \frac{1}{\sqrt{3}} & \frac{1}{2\sqrt{3}} & \frac{1}{2\sqrt{3}} \\
    \frac{1}{2\sqrt{3}} & \frac{1+\sqrt{3}}{2\sqrt{3}} & \frac{1-\sqrt{3}}{2\sqrt{3}} \\
    \frac{1}{2\sqrt{3}} & \frac{1-\sqrt{3}}{2\sqrt{3}} & \frac{1+\sqrt{3}}{2\sqrt{3}}
\end{bmatrix}
\]

and let

\[
x' = Ux, e' = Ue
\]

In such case, the log-chromaticity vector \(x'\) for a given surface moves along a straight line as \(T\) changes. Its direction is dependent on \(e'\), i.e. the camera properties. We can project the log-chromaticity vector \(x'\) onto the orthogonal vector to \(e'\) that we denote as \(e''\) in order to determine an illumination invariant image, which is the 1D shadow-free image, as illustrated in Fig. 1. After processing all pixels in the original image, our illumination-invariant representation is given by a grayscale image \(P\):

\[
P' = x'e''', \ P = \exp(P')
\]

where \(e''' = (\cos \theta, \sin \theta)\), and \(\theta\) is called the angle of invariant direction.

2.2. Automatically determining the angle of invariant direction

In order to derive the illumination-invariant image, we need to determine the angle of the invariant direction \(\theta\), namely the direction of \(e''\). Although we can achieve this through repetitive experiments, it is obviously inconvenient. In this paper, we employ the method proposed in [8] to automatically determine the angle of invariant direction by analyzing a real image.

Vector \(x'\) of a shadow image presents a series of parallel lines in 2D log chromaticity space. If we project these \(x'\) to the direction of \(\theta\), the scalar quantity would be more concentrative than projecting to other directions. Here we employ the concept of “entropy” to describe intensity distribution. Entropy is an important index measuring average amount of information in informatics and defined as follows:

\[
\eta = -\sum_i p_i \log p_i
\]

where \(p_i\) is the probability of signal \(i\) and \(\eta\) is entropy. As a result, the projection onto the angle of invariant direction produces the minimum entropy.

For acquiring the angle of invariant direction, we should take two steps. First we perform projection throughout 0 to 180 degrees to access a series of grayscale images. Then we calculate the entropy of every grayscale image and determine degrees of the angle of invariant directions by finding out the minimum entropy. An example is shown in Fig. 1c.

3. COLOR RESTORATION

While we remove shadow using the method described above, the original color information is also lost. In this section we introduce a new algorithm for adding appropriate color back into the illumination-invariant grayscale image.

In order to assure that the results produced by the new algorithm do not miss each pixel’s luminance, we transform the original image into the grayscale form by (7):

\[
I_{\text{gray-scale}} = \frac{1}{3}(I_R + I_G + I_B)
\]
Where: $I_{\text{grayscale}}$ is grayscale image; $I_s$, $I_o$ and $I_s$ are three color channels values of original color image. Then we compare their brightness by applying (8).

$$G' = \frac{P - I_{\text{grayscale}} + P - I_{\text{grayscale}}}{2} + I_{\text{grayscale}} \quad (8)$$

In this way, we can always obtain the larger luminance value between the original and illumination-invariant images. In another word, we can always keep brightness of the bright region in the image, as illustrated in Fig. 2a.

![Fig. 2. Color restoration. (a) Adjusted illumination invariant grayscale image. (b) Shadow-free color image.](image)

In order to obtain an acceptable shadow-free color image, we take into account both the global image tonality and local color at each pixel. In our approach, the tonality of the original image is employed to recover color information. Each color channel’s contribution is computed as:

$$c_{nj} = \frac{\text{sum}(I_j)}{\text{sum}(I)}, \quad j \in \{R,G,B\} \quad (9)$$

where $\text{sum}(I_j)$ is the sum of pixel values in $j^{th}$ color channel, and $\text{sum}(I)$ is the pixel values’ sum of the whole image. Finally, we obtain the shadow-free color image by:

$$O_j = G'(c_{nj} \cdot \alpha + (1 - \alpha) \cdot I_{\text{grayscale}}) \quad (10)$$

where $\alpha$ is a coefficient. The bigger $\alpha$ is, the more the result image will change towards monochromaticity. The final result is shown in Fig. 2b.

4. EXPERIMENTAL RESULTS

Our algorithm is tested on a set of images used by Finlayson et al. and also on some images captured by a Caplio R4 digital camera. Our results are shown in Fig. 3. We found that our methods can produce shadow-free images as good as those produced by Finlayson et al. in [7], while the whole process is simplified by the proposed method. Readers may further refer to [7] for a close comparison.

5. CONCLUSIONS

We propose a new mechanism to remove shadow using only a single color image without any calibration of camera. We project band-ratio chromaticities onto the illumination-invariant direction to derive an illumination-invariant grayscale image, and introduce “entropy” to automatically determine the projection angle. Then we compare the illumination-invariant grayscale image with the grayscale image transformed from the original color image, and retain the brightness of the brighter regions between the two images. Finally, the original image tonality is used to balance each pixel’s color. The experimental results have similar quality as those shown in previous work, while the performance is boosted.

It should be noted that there still exist some restrictions when applying our algorithm, e.g. the assumption of the Lambertian reflectance model, the Planckian light source and cameras with Dirac delta sensitivity response. Our approach also requires a variety of colors presented in the original image. If color information is not abundant, the projection may lead to nearly the same value on every pixel.

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6. REFERENCES

Fig. 3. Several examples of our algorithm. (a) The original images, (b) Grayscale form of original images, (c) Illumination invariant grayscale images, (d) Adjusted grayscale images, (e) Shadow-free color images.