Estimation of the Radiometric Response Functions of a Color Camera from Differently Illuminated Images

Khurram Shafique and Mubarak Shah
School of Electrical Engineering and Computer Science
University of Central Florida, Orlando, FL-32816
khurram,shah@cs.ucf.edu

Abstract

The mapping that relates the image irradiance to the image brightness (intensity) is known as the Radiometric Response Function *or* Camera Response Function*. This usually unknown mapping is nonlinear and varies from one color channel to another. In this paper, we present a method to estimate the radiometric response functions (of R, G and B channels) of a color camera directly from the images of an arbitrary scene taken under different illumination conditions (The illumination conditions are not assumed to be known). The response function of a channel is modeled as a gamma curve and is recovered by using a constrained nonlinear minimization approach by exploiting the fact that the material properties of the scene remain constant in all the images. The performance of the proposed method is demonstrated experimentally.*

1 Introduction and Related Work

The output of an imaging system is a brightness (or intensity) image. The brightness in this image is related to the image irradiance by a mapping called the *Radiometric Response Function* of the imaging system. The knowledge of this response function is important for the applications that require scene radiance or image irradiance measurements as input, for example, shape from shading [14], photometric stereo [13], color constancy [6] and image based rendering [11]. Even common computer vision tasks such as appearance matching, background modeling, tracking in multiple cameras, edge detection and blurring can benefit by using the image irradiance values instead of the brightness values. Although assumed otherwise in most of the above methods, the response function of an imaging system is usually nonlinear. This nonlinearity arises from several aspects of the photometric processes, such as, the film response in the case of film photography, digitization process, scanning, and the built-in nonlinear responses in digital cameras to mimic the film response or to compensate for the nonlinear responses in the display device. In addition, in the case of color cameras, each channel may have a different response function.

One approach of estimating the radiometric response function involves imaging a calibration image with a full range of known radiance values (e.g., Macbeth chart) under uniform illumination conditions [1]. Due to the difficulty in using this method in general situations, other methods have been presented which estimate the parametric or nonparametric form of the response function directly from the images. Farid [3] used higher order statistics of image irradiance to recover the response function in the form of a Gamma curve. Most of the other techniques make use of differently exposed spatially registered images of the same scene taken with varying, known exposure settings [2, 4, 9, 8, 7, 12]. These techniques differ from each other by their assumptions on the behavior of the response function (for example smoothness or monotonicity) and choice of the model. Mann and Picard [8] used Gamma function as a parametric model. In [9], Mitsunaga and Nayar approximated the function by a low degree polynomial. Nonparametric estimation of the function is performed in [2, 12], where the estimation process is constrained by assuming the smoothness of the response function. Grossberg and Nayar [4] estimated the parameters by projecting the response function to a low dimensional space of response functions obtained from a database of real world response functions.

In this paper, we present a technique to recover the radiometric response functions of a color camera by using differently illuminated images of an arbitrary scene. Images under different illumination conditions have widely been used to determine the scene structure [13] and the orientations of surface normals with respect to the illumination [14]. However, to the best of our knowledge, no research has been reported in the literature that use multiple illumination images for the recovery of the radiometric response function. One advantage of the proposed algorithm is that we do not assume any knowledge about the illumination in the images (except that they are different), neither do we impose any restrictions on the exposure settings, such as constant or known exposure. We exploit the fact that the material properties of the scene do not change, and recover a parametric form of response functions by nonlinear minimization of an error function based on this fact.

The organization of the paper is as follows. In the next section, we review the model of image formation that is used to derive the proposed estimation approach, which is presented in Section 3. In Section 4, we demonstrate the results of the proposed approach on a variety of response functions. Section 5 concludes the paper.

2 Model of Image Formation

The appearance or brightness of a scene point in the image depends on various parameters, such as, illumination at the point, camera geometry, scene structure, material properties and camera parameters. Let L denote the radiance from a scene point. We assume that L can be written as the sum of products of (a) material related terms K_i and (b) lighting/viewing geometry and object shape related terms G_i [10] as:

$$L = \sum_{a=1}^{r} K_a G_a \tag{1}$$

This assumption is true for various illumination models [10], for e.g., Lambertian, Oren-Nayar and Torrence-Sparrow.

The image irradiance E is proportional to the scene radiance L and is given as [5]:

$$E = L\frac{\pi}{4}\left(\frac{l}{h}\right)^2 \cos^4\alpha \tag{2}$$

where, h and l are the focal length and diameter (aperture) of lens respectively and α is the angle that the principal ray makes with the optical axis. If t is the time of exposure, and f is the radiometric response function of the camera, then the image brightness B is related to image irradiance as $B = f(Et) = f(X)$.

We model the response function f of each color channel as a gamma function, i.e., $f(X) = \beta X^\gamma + \alpha$. However, the parameter α can be removed by estimating the mean of the thermal noise of the camera (which can be done by taking an image with the lens cap on) and subtracting it off from the brightness values, i.e., by forcing the condition $f(0) = 0$. The model can be further simplified by assuming that the brightness and the irradiance values are both normalized from 0 to 1, i.e., $f(1) = 1$. Thus, the resulting response function f is given by:

$$B = f(Et) = (Et)^\gamma \tag{3}$$

where, γ is the sole model parameter. The inverse response function g can now be written as:

$$E = g(B) = \frac{1}{t}f^{-1}(B) = \frac{1}{t}B^{\frac{1}{\gamma}} \tag{4}$$

The problem is to estimate the parameter γ for each color channel of a given camera. In the next section, we present a method to estimate these parameters simultaneously from the images.

3 Estimation Scheme

Let $I_1, I_2, \ldots, I_n$ be the n images of the same scene under different illuminations and $p(x, y)$ be a point on a 2D image lattice. From equations 1 and 2, the image irradiance E_{ic} at the point p in the color channel $c \in \{r, g, b\}$ of the image I_i, $1 \le i \le n$, is given by:

$$\begin{aligned} E_{ic} &= \left(\sum_{a=1}^{r} K_a^{(c)} G_a^{(i)}\right) \frac{\pi}{4}\left(\frac{l_i}{h_i}\right)^2 \cos^4\alpha_i \\ &= F_i\left(\sum_{a=1}^{r} K_a^{(c)} G_a^{(i)}\right) \end{aligned} \tag{5}$$

where the quantities $F_i = \frac{\pi}{4}\left(\frac{l_i}{h_i}\right)^2 \cos^4\alpha_i$ and $G_a^{(i)}$ vary from image to image but are constant for every color channel in an image. On the other hand, the terms $K_a^{(c)}$ vary with color channels but are constant for the same color channel over all images. That is, the material properties at each point p remain constant.

For $r = 1$, for example, the Lambertian model of illumination, these material properties can be separated out in each image I_i by taking the ratios of irradiance values of different color channels, i.e., E_{ir}, E_{ig} and E_{ib}. Whereas, for $r = 2$, cross-ratios of irradiance values of different color channels in two distinct images are independent to the quantities F_i and $G_a^{(i)}$ [10]. That is, for all $i \ne j$ and every point $p(x, y)$, the following term is independent to the above quantities:

$$\frac{E_{ir}E_{jg} - E_{jr}E_{ig}}{E_{ir}E_{jb} - E_{jr}E_{ib}} = \frac{K_1^{(r)}K_2^{(g)} - K_1^{(g)}K_2^{(r)}}{K_1^{(r)}K_2^{(b)} - K_1^{(b)}K_2^{(r)}} \tag{6}$$

Since, none of the terms on the right hand side of the above equation depends on the image pair i, j, the expression is invariant to illumination conditions, shapes and other camera parameters. Similarly, two other invariants can be obtained by changing the terms r, g and b in the subscripts in cyclic order [10]. From equation 4, the above invariant can be written in terms of the model parameters $\mathbf{z} = [\gamma_r, \gamma_g, \gamma_b]^T$ and the brightness of images as follows:

$$V_{i,j}(\mathbf{z}) = \frac{E_{ir}E_{jg} - E_{jr}E_{ig}}{E_{ir}E_{jb} - E_{jr}E_{ib}} = \frac{B_{ir}^{1/\gamma_r}B_{jg}^{1/\gamma_g} - B_{jr}^{1/\gamma_r}B_{ig}^{1/\gamma_g}}{B_{ir}^{1/\gamma_r}B_{jb}^{1/\gamma_b} - B_{jr}^{1/\gamma_r}B_{ib}^{1/\gamma_b}} \tag{7}$$

where, B_{ic} is the brightness of pixel p in the channel c of the image I_i. We want to find a set of parameters $\mathbf{z}$, such that, at each point (x, y) in the 2D image lattice, the invariant $V_{i,j}(\mathbf{z})$ yields the same value for each pair of images I_i and I_j. Because of the different sources of noise in images, instead of matching the invariant at each point on the lattice, we find the parameters for which the distribution of invariant is the same for each pair of images. We do this by minimizing the sum of the distances between the normalized histograms $H_{i,j}(\mathbf{z})$ of $V_{i,j}(\mathbf{z})$ for each image pair I_i and I_j, i.e, the error function $e(\mathbf{z})$ is given by:

$$e(\mathbf{z}) = \sum d\left(H_{i,j}(\mathbf{z}), H_{k,l}(\mathbf{z})\right) \tag{8}$$

where, the summation is over all the invariants computed from the distinct pairs of images of the same scene. The distance d between two m bin histograms, S and T is the modified Bhattacharyya coefficient and is computed as:

$$d(S, T) = \sqrt{1 - \sum_{i=1}^{m} \sqrt{S_i T_i}} \tag{9}$$

The error function is minimized by using a trust region method for the nonlinear minimization. The approximate Jacobian matrix is calculated by using the finite difference derivatives of the error function. The response functions of the different channels of the same camera are usually correlated and are not very different from each other. To reduce the search space and to avoid false local minima of the error function, we constrain the search process so that the difference between the parameters of different channels between them is not very large.

4 Results

In this section, we show the effectiveness of the proposed method by experimental evaluation. We use two sets of images, where each set contains four images of the same scene under different illumination. The images are radiometrically calibrated and the images of each set are spatially aligned. The images are shown in Figure 1. The error term in equation 8 is minimized by using the images of both sets, where the distance is measured only for the histograms of images that belong to the same set. To avoid noisy measurements, pixels with large gradients were not included in the estimation process.

In the first experiment, we kept the gamma parameter fixed for all color channels and subjected each image to the nonlinear responses with a variety of gamma values in the range [0.3 3.0]. The error function $e(\mathbf{z})$ for some of the parameter values is shown in Figure 2. It can be seen that the error function reaches a unique global minimum at the correct value of the parameter. Figure 3 shows the plot of the estimated parameters against actual parameters. On average, the parameters were estimated within 2.97 percentage of the true values.

Figure 1: Two sets of images that are used for evaluation

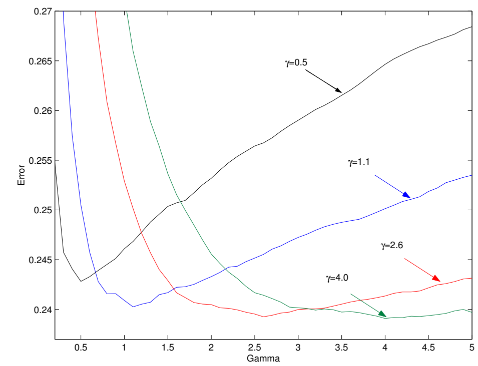

Figure 2: Error function computed after applying gamma correction with gamma=0.5, 1.1, 2.6 and 4.0 respectively. The minima of the error also occur at the same values in the respective curves

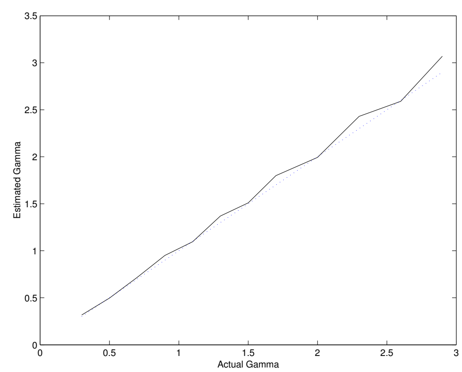

Figure 3: Plot of estimated gamma values vs actual values: Dotted line shows the ideal response.

The actual and the estimated curves are shown in Figure 4.

Next, we applied different responses to the different color channels. Figure 5 shows three different cross sections of three dimensional error function $e(\mathbf{z})$ for one such case, where the applied parameters were $\gamma_r = 1.5$, $\gamma_g = 0.5$ and $\gamma_b = 1.0$. The red, blue and green curves show the error e obtained by varying the parameters of the respective color channel while keeping the other two parameters constant. Once again, the minima correspond to the true values of the parameters.

Figure 6 shows the actual and obtained response curves

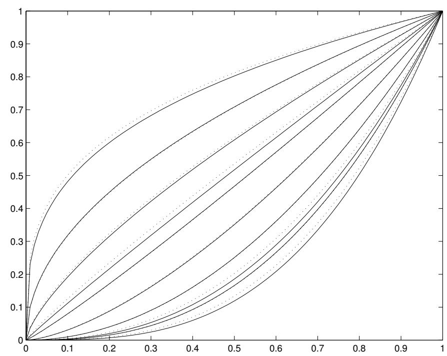

Figure 4: Performance of the algorithm was tested by applying different gamma responses to the radiometrically calibrated images. Here we show some of the actual gamma responses (dotted curves) along with the recovered responses (solid curves) .

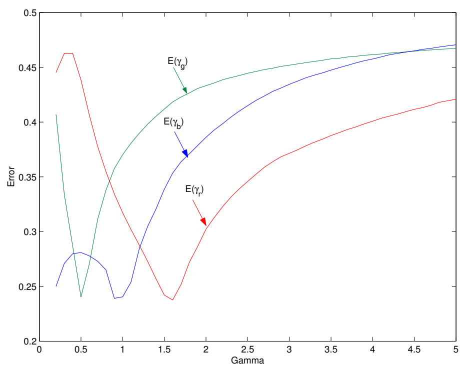

Figure 5: Three cross sections of a three dimensional error function. The applied response function has the parameters, $\gamma_r = 1.5$, $\gamma_g = 0.5$ and $\gamma_b = 1.0$. The red, green and blue curves show the error $e(\mathbf{z})$ obtained by varying the parameter of the response of respective channels while keeping the other two parameters constant

for three different experiments. The response curves of red, blue and green channels are shown using their respective colors. The actual functions are shown by dotted curves, whereas the estimated functions are shown by solid curves.

5 Conclusion

We have presented a framework for estimating the radiometric response function of color cameras directly from the images of the same scene taken under different illuminations. The proposed framework uses illumination and geometric invariants to compute a nonlinear error function, which is minimized to obtain the parameters of the response functions. The proposed method is experimentally evaluated and is shown to produce reasonable results. Future work includes the use of flexible models for response functions and analyzing the affect of system parameters on the quality of estimation.

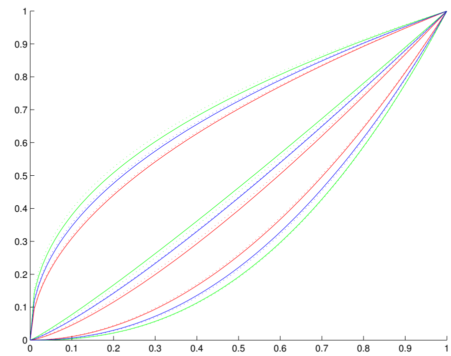

Figure 6: Estimated (solid curves) and actual (dotted curves) response functions for different color channels.

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