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A reality check for radiometric camera response recovery algorithms

Ahmet Oğuz Akyüz *, Aslı Gençtav

Department of Computer Engineering, Middle East Technical University, Universiteler Mahallesi, Dumlupinar Bulvari No: 1, 06800 Cankaya Ankara, Turkey

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ABSTRACT

The radiometric response of a camera governs the relationship between the incident light on the camera sensor and the output pixel values that are produced. This relationship, which is typically unknown and nonlinear, needs to be estimated for applications that require accurate measurement of scene radiance. Until now, various camera response recovery algorithms have been proposed each with different merits and drawbacks. However, an evaluation study that compares these algorithms has not been presented. In this work, we aim to fill this gap by conducting a rigorous experiment that evaluates the selected algorithms with respect to three metrics: consistency, accuracy, and robustness. In particular, we seek the answer of the following four questions: (1) Which camera response recovery algorithm gives the most accurate results? (2) Which algorithm produces the camera response most consistently for different scenes? (3) Which algorithm performs better under varying degrees of noise? (4) Does the sRGB assumption hold in practice? Our findings indicate that Grossberg and Nayar's (GN) algorithm (2004 [1]) is the most accurate; Mitsunaga and Nayar's (MN) algorithm (1999 [2]) is the most consistent; and Debevec and Malik's (DM) algorithm (1997 [3]) is the most resistant to noise together with MN. We also find that the studied algorithms are not statistically better than each other in terms of accuracy although all of them statistically outperform the sRGB assumption. By answering these questions, we aim to help the researchers and practitioners in the high dynamic range (HDR) imaging community to make better choices when choosing an algorithm for camera response recovery.

1. Introduction

Photographic images captured by most cameras are typically stored in a nonlinear color space. In film cameras, this nonlinearity is a result of the nonlinear response of the chemicals used in the film to light. In digital cameras, on the other hand, the nonlinearity is intentionally introduced by the electronics and the firmware during the analog-to-digital conversion and remapping, as optical elements and sensors are inherently linear (see Fig. 1).

Using a nonlinear color space not only serves the purpose of gamma-correction, but also mimics the light response of the human visual system. The human visual system is highly nonlinear, and it is theorized that this nonlinearity allows better utilization of the limited bandwidth of the retinal pathways [4]. Similar to the human eye, digital cameras can encode a large range of incoming light values to a limited number of bits by using a nonlinear color space. Nonlinear encoding also serves to reduce the quantization artifacts and noise as it uses more bits in darker regions for which the human eye is more sensitive to intensity transitions [5]. Finally, nonlinearity is utilized for aesthetic purposes which can be a distinguishing factor between the images produced by different camera manufacturers.

Ideally, digital cameras are expected to adhere to the sRGB standard which has well-defined color primaries and nonlinearity [6]. However, in practice, most digital and film cameras have response curves that are widely different from the sRGB standard [7] (see Fig. 2). Therefore, in applications that require high radiometric precision, such as creating radiance maps from multiple exposures [8,3,2,9], shape from shading algorithms [10,11], and computational photography [12], it is vital to recover the response curve of the camera used rather than relying on the sRGB assumption.

Until now, several methods have been proposed that attempt to recover the unknown response of a digital camera from a set of bracketed exposures [1–3,13–15]. Each method approaches the problem from a different standpoint and makes assumptions about the shape of response curves. However, a formal evaluation of these algorithms in terms of how accurately they estimate an unknown camera response is not available. Our goal in this study is to fill this gap by comparing the performance of the algorithms with respect to three important metrics. Our contributions can be summarized as:

- Developing three metrics that can be used to compare the performance of radiometric response recovery algorithms.

* Corresponding author. Tel.: +90 312 210 5565.
E-mail address: akyuz@ceng.metu.edu.tr (A.O. Akyüz).

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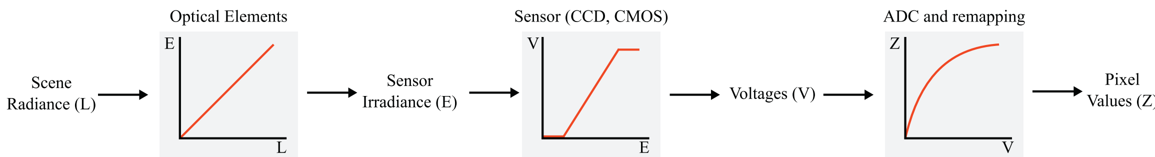

Fig. 1. An abstraction of the photographic pipeline. Typically, the optical and sensor elements are linear, but nonlinearity is introduced during analog to digital conversion and remapping.

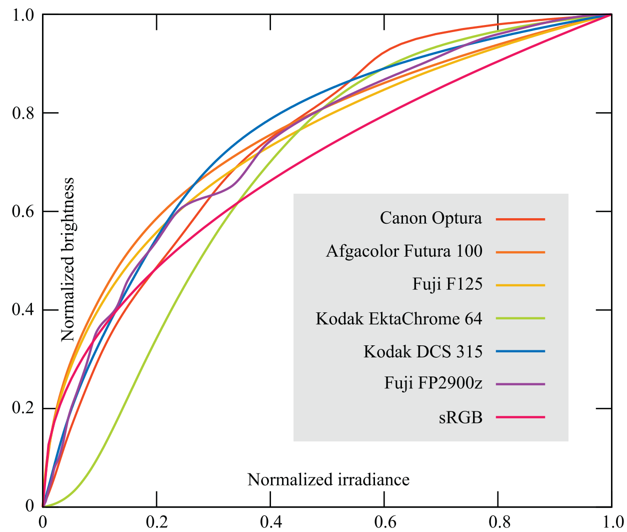

Fig. 2. Response curves of various digital and film cameras. The data source is obtained from the DoRF database (http://www.cs.columbia.edu/CAVE/databases).

- Using these metrics to conduct a rigorous evaluation of four commonly used response recovery algorithms.

2. Background

Many methods exist to recover the unknown radiometric response of a photographic camera. These methods can generally be classified as multi-image or single-image methods. In multi-image methods, multiple exposures of the same scene are used to determine the change in pixel values with respect to a change in exposure enabling one to determine the camera response. These methods rely on the *reciprocity* principle which states that the total exposure X is equal to the product of the image irradiance E and the exposure duration Δt:

$$X = E\Delta t. \quad (1)$$

However, pixel values, Z, are not linearly related to X but rather to a function of it:

$$Z = f(X) = f(E\Delta t) \quad (2)$$

Thus, by varying Δt for a pixel with constant irradiance, one can detect the change in Z, and from there infer the shape of the camera response function, f.

Single-image methods, on the other hand, cannot make use of the reciprocity principle but rely on other cues. Farid observed that nonlinear processing causes specific higher-order distortions in the frequency domain [16]. By detecting and minimizing these distortions one can recover the radiometric response of a camera. Lin et al. [17] argued that edge colors should change linearly between regions of different uniform intensities. Thus, they proposed a function that maps the nonlinear distribution of edge colors to a linear distribution. Later, their method is extended to work on edge histograms for grayscale images [18].

Table 1
Definition of terms used in the equations.

I_p	Irradiance of pixel p
Z_{qp}	Intensity of pixel p in image q
M_{qp}	Normalized intensity in the range [0, 1]
t_q	Exposure time of image q
$R_{q,q'}$	Exposure ratio between images q and q'
$w(x)$	Weighting function
$f(x)$	Camera response function
$g(x)$	Inverse camera response function, $f^{-1}(x)$
Q	Number of exposures to combine
P	Number of pixels in each image

In this work, we focus on multi-image response recovery algorithms that are commonly used to create high dynamic range (HDR) images [9]. The specific algorithms that we evaluated are Debevec and Malik's method [3] (abbreviated as DM), Mitsunaga and Nayar's radiometric self calibration [2] (MN), Robertson et al.'s estimation theoretic approach [15] (RBS), and Grossberg and Nayar's [1] principle component analysis based algorithm (GN). Each algorithm is briefly reviewed in the following subsections. The terms used in the following equations are given in Table 1.

2.1. Debevec and Malik's method (DM)

Debevec and Malik present the response recovery problem as the minimization of the following quadratic objective function [3]:

$$\mathcal{O} = \sum_{q=1}^{Q}\sum_{p=1}^{P}\{w(Z_{qp})[\tilde{g}(Z_{qp}) - \ln I_p t_q]\}^2 + \lambda\sum_{z=1}^{254}[w(z)\tilde{g}''(z)]^2, \quad (3)$$

where $\tilde{g} = \ln f^{-1}$ and w is a tent shaped weighting function defined as

$$w(z) = \begin{cases} z/127.5 & \text{for } z \le 127.5, \quad \text{(a)} \\ (255 - z)/127.5 & \text{for } z > 127.5. \quad \text{(b)} \end{cases} \quad (4)$$

The first term in Eq. (3) is the data fitting term and the second term is used to force smoothness. Increasing the value of λ brings the recovered response closer to a more idealized logarithmic shape at the cost of deviating it from the actual observations. As this formulation yields an overdetermined system of equations, the unknowns $\tilde{g}$ and I_p can be found in the least squared sense using singular value decomposition.

2.2. Mitsunaga and Nayar's method

Mitsunaga and Nayar, on the other hand, argue that (the inverse of) any response function can be modeled using a higher order polynomial:

$$f^{-1}(x) = \sum_{n=0}^{N} c_n x^n. \quad (5)$$

This reduces the problem of response recovery to determining the coefficients, c_n, and the degree, N, of the polynomial that