Modelling the Opto-Electronic Conversion Function (OECF) for application in the stitching of panoramic images

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1 Abstract

We address the question of mapping colour in a panoramic image built by stitching several uncalibrated digital photographs. To map the colours, we need to identify the Opto-Electronic Conversion Function (OECF) of the camera. In modelling this function, there is a trade-off between the complexity of the curve, i.e. the number of its parameters, and the flexibility of the curve shape. Having too many parameters will lead to an ill-posed estimation problem that will fail under noisy conditions. The common practice minimizes the squared error between the linear data computed from the initial pictures. We will show that for this case, a degenerate OECF can deliver an optimal result in a least-squared error sense. The existence of this degenerate solution impairs the robustness of the estimation. We define a monotonic curve which has few parameters, behaves approximately linearly with respect to these parameters, and has a tunable complexity (i.e. the number of parameters is adjustable during the estimation). The mapping problem is expressed as a minimization of a dedicated error metric between the set of images, and does not result in degenerate OECFs.

2 Introduction

By stitching together several pictures taken with a digital camera, one notices that the colours in the images do not match. This is due to differences in exposure, and differences in the white balancing between two pictures. To equalize the colours, and to compensate for these operations, one has to know the OECF of the camera. Several methods have been proposed in the literature to estimate the camera OECF [1, 2, 3, 4], but most of them require to have aligned pictures as input. If we want to perform a simultaneous pose estimation (to align the pictures [5]) and OECF estimation (to correct the colours), we need a parametric OECF model that has few parameters and that has a quasi linear behaviour with respect to them. These conditions ensure that the estimation will eventually converge to the right solution.

In the following section, we present a model that fulfils these requirement, and introduce an optimisation criterion that does not have any degenerate solutions as is the case for the mean squared error metric.

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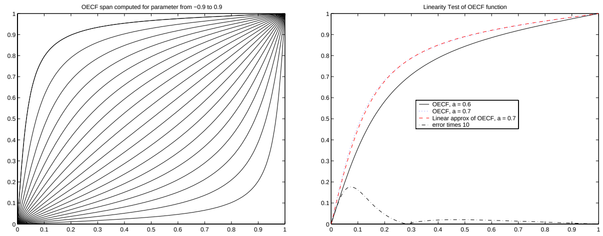

(a) (b)

Figure 1: Plot of the OECF. (a) Illustrates the span of the OECF defined in (1) for $a = \{-0.9, -0.8, ..., 0.9\}$. (b) Tests the linearity of the function with respect to parameter a ($a = 0.6$). The upper-dotted curves are the linear approximation of the curve superimposed to the exact curve ($a = 0.7$). The bottom curve is the error between the approximation and the exact curve, amplified by a factor 10.

3 The OECF Model

Our basic function used to model the OECF is given by

$$S_a(x) = x + \frac{2}{\pi}\arctan\left(\frac{a\sin(\pi x)}{1 - a\cos(\pi x)}\right), \quad (1)$$

where a is the unknown parameter; $a \subset\ ]-1;1[$. The function is monotonic and its inverse is found by changing the sign of a. It has also an almost linear behaviour in a, i.e.

$$S_{a+\Delta a}(x) \simeq S_a(x) + \frac{\partial S_a(x)}{\partial a}\cdot \Delta a.$$

Figure 1 illustrates this argument. In order to give more flexibility to the function, we can use two parameters a and b:

$$S_{a,b}(x) = x + \frac{2}{\pi}\arctan\left(\frac{a\sin(\pi x)}{1 - b\cos(\pi x)}\right), \quad (2)$$

which is the same function as (1) when $a = b$. A sufficient condition for the function being monotonic is given by

$$|2a - b| < 1.$$

4 The Error Metric

The usual error metric used to estimate OECF is the squared error measure:

$$e = \|S(x_1) - \tau S(x_2)\|^2,$$

where x_1 and x_2 are the pixel values of a single point in the scene, $S(\cdot)$ is the OECF and τ a parameter that accounts for the difference in exposure of the two pictures. If τ and the OECF are both unknown, then the minimum of e has a trivial and degenerate solution, namely

$$\tau = 1, \quad S(x) = \text{const.}$$

By imposing that S ranges from 0 to 1, one may think to avoid this degenerateness, but in fact, the solution $S(x) \simeq$ const, and $\tau = 1$ in the region of the histogram that contain most of the data still delivers a very small error. To avoid this problem, we use an error metric expressed in the equalized images space, namely

$$e = \left\| x_1 - S^{-1}\left(\tau S(x_2)\right) \right\|^2 .$$

Since it uses one of the original pixel values, instead of two transformed values, it avoids the degenerate solution. For implementation reasons, it is convenient to approximate it by

$$e = \left\| \frac{S(x_1) - \tau S(x_2)}{\partial S(x)/\partial x|_{x=x_1}} \right\|^2 . \tag{3}$$

5 The Complete Model

To perform the colour match, we will consider a system with a single OECF, assuming it is the same for the three colour channels and that is does not change from picture to picture. We will correct for white balancing and exposure combined by estimating three exposure parameters τ: one per colour channel. This assumes that the camera performs the white balancing by using a gain factor in each colour channel in raw camera space. Finally, the OECF and exposure parameters are found by minimizing the error in (3):

$$\{S(\cdot), \tau_R, \tau_G, \tau_B\} = \arg\min \left\| \frac{S(x_{1R}) - \tau_R S(x_{2R})}{\partial S(x)/\partial x|_{x=x_{1R}}} \right\|^2 + \left\| \frac{S(x_{1G}) - \tau_G S(x_{2G})}{\partial S(x)/\partial x|_{x=x_{1G}}} \right\|^2 + \left\| \frac{S(x_{1B}) - \tau_B S(x_{2B})}{\partial S(x)/\partial x|_{x=x_B}} \right\|^2 ,$$

computed over all pixels of the image pair.

The most straightforward way of equalising the colours[1] consists in applying the OECF inverse to one of the pictures, apply the gains to adjust the white point and reapply the OECF:

$$I_c = S^{-1}\left([\tau_R, \tau_G, \tau_B]^T \cdot S(I) \right) , \tag{4}$$

where I is the original image, and I_c is the colour corrected one.

6 Results

The model is tested on an image pair taken with a hand held camera on automatic settings for white point and exposure. The system computes the difference in exposure and white point as well as the camera displacement between the two pictures [5]. The result is shown in Figure 2 blended using a checkerboard technique to emphasize the colour mismatch. Figure 2(a) shows the uncorrected mosaic. In Figure 2(b), the lower image has been colour corrected according to Equation 4. The correction works well, since the squares of the checkerboard blending are almost invisible—except in the area where the original pixel values are clipped (saturation). In general, our OECF model is much stabler than the existing ones, but does not offer as much flexibility. Additionally, in the examples we tested, the use of equation (2) instead of equation (1), i.e. adding one more parameter, produces an improvement that is most of the times very small, if any.

[1] This is not the best way to do colour correction, but it allows to see if the OECF is correctly estimated.

(a) (b)

Figure 2: Illustration of the colour correction. (a) Original mosaic without any change in the pixel values. The images are blended like a checkerboard. (b) Corrected Mosaic: the lower image has been colour corrected.

References

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