Understanding Blur and Model Learning in Projector Compensation

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Abstract

Radiometric compensation enables data projectors to use textured surfaces such as automobiles, building and theater stages as projection screens, accomplished by modelling the reflectance characteristic of the surface and inverting it to find the compensation function. In this paper, we explore the effects of point spread function / blur of the projector on the performance of existing radiometric compensation algorithms. Two changes to the existing model are proposed which help to consider projector blur in model learning. Proposed changes can be combined with any radiometric compensation strategy to improve its perceptual performance without increasing the computational complexity.

Fig. 1: Projector-camera system for radiometric compensation.

1 Introduction

Projection onto three dimensional textured surface requires geometric and radiometric compensation to correct for the distortions due to the projection surface. The compensation requires a projector – camera setup as shown in Fig. 1. The camera provides feedback of the projection which can be used to learn the surface reflectance properties. The compensation models developed with the learned properties can be used to modify the incoming target image such that the modified image, when combined with the background's shape and texture, gives the appearance of an undistorted target image.

Structured light patterns [1] are used to find the geometric mapping between the projector and camera. The pixel correspondence from the mapping is necessary to correlate the camera pixels to its corresponding projector pixels. After geometric mapping, radiometric compensation is required to correct for the target image's texture distortion due to the projection surface. To understand the surface's texture characteristics, a calibration set is formed by projecting a series of colored images and capturing its response. The radiometric functions f_r developed from the calibration set, models the transformation of the projector image P by the projection surface to produce the captured camera image C:

$$C = f_r(P) \qquad (1)$$

This function is developed for each projector – camera pixel pair, as the background texture and colour can vary, essentially arbitrarily, from pixel to pixel. The compensation function f_c is found by inverting the radiometric function f_r. The compensation function can take any target image T as input and produce the compensated projector image P_c:

$$P_c = f_r^{-1}(T) \qquad (2)$$

$$C_c = S(P_c) \qquad (3)$$

where S represents the transformation by the background surface. C_c is the camera captured compensated image, ideally equivalent to the target image T. Since the radiometric function is developed for each projector pixel, it is necessary for the model to be simple and efficient. In this paper, we explore the two widely used radiometric compensation models. Bimber *et. al.* [2] proposed to model the radiometric function as follows,

$$C_L = EM + P_L FM \qquad (4)$$

F is the form factor, M is the surface color and E accounts for environmental light. C_L is the color reflected from the surface and P_L is the color from the projector for channel L. The model is developed for each pixel in every channel of the projector. Grossberg *et. al.* [3] proposed a framework to find the radiometric function and projector response function assuming the camera response function is known. The radiometric function was modelled using matrices as follows,
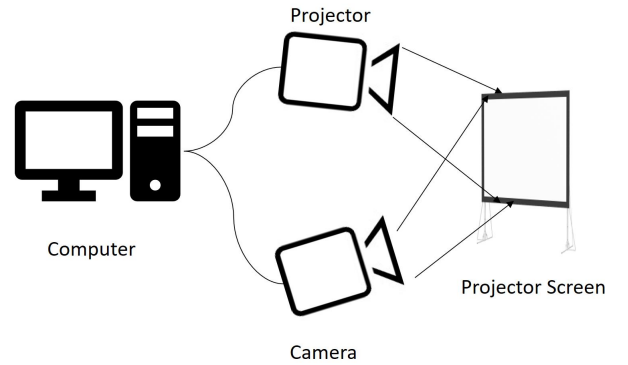
$$C = VP + K, \qquad (5)$$

where

$$C = \begin{bmatrix} c_R \\ c_G \\ c_B \end{bmatrix}, V = \begin{bmatrix} v_{RR} & v_{RG} & v_{RB} \\ v_{GR} & v_{GG} & v_{GB} \\ v_{BR} & v_{BG} & v_{BB} \end{bmatrix}, P = \begin{bmatrix} p_R \\ p_G \\ p_B \end{bmatrix}, K = \begin{bmatrix} k_R \\ k_G \\ k_B \end{bmatrix} \qquad (6)$$

Here, unlike Bimber's model (4), each channel of the camera depends on all three channels of the projector. This is required as the projector and the camera can have overlapping spectral responses. Similar to Bimber's model (4), Grossberg's radiometric model (5) is developed for each projector-camera pixel pair. The different variations of the model were proposed in literature [4, 5, 6, 7]. The existing radiometric compensation models assume that the luminance of one projector pixel affects the reading of only one camera pixel and does not consider inter-pixel coupling [8].

In this paper, we propose a novel radiometric compensation framework that can be combined with the existing models to increase its performance. The following section discusses the effect of inter-pixel coupling on radiometric compensation model's performance. Section [3] explains the proposed framework. Section [4] describes the experiments setup and results followed by conclusions.

2 Limitations

The existing radiometric models assume that each camera pixel's intensity depends only on its corresponding projector pixel intensity and environmental light. In practical scenarios, capturing the projector image, leads to the luminance of one projector pixel, affecting the intensity reading of multiple adjacent camera pixels. The presence of the inter-pixel coupling [8] can lead to incorrect learning of the radiometric model and lead to artifacts in the compensated camera image.

A part of the background shown in Fig. 2a was illuminated by the projector. Fig. 2b shows the histogram equalized camera image, displaying the effect of inter-pixel coupling. The brightness leakage from the illuminated regions to the non-illuminated regions is captured by the camera. The existing radiometric compensation does not consider inter-pixel coupling, so the additional intensity in the non-illuminated regions is associated with the background texture, resulting in incorrect learning of the surface properties. A major source of inter-pixel coupling is at the projector. The point spread function of the projector can blur the input image creating spatial dependencies. Since the blur of the projector depends on the contents of the input image, different projector images in the calibration set can lead to different performance by the compensation model. For a spatially uniform projector image P_u as shown in Fig. 3, the projector's blur function will not alter the intensities of the image.

$$B * P_u = P_u \qquad (7)$$

As P_u does not contain any contrast, it will not be affected by the blur B. If the calibration set is developed with similar projector-

camera images, the radiometric function $\hat{f}$ calculated from this set will not be aware of the blur function of the projector.

$$\hat{f} = \arg\min_{f} \|f(P_u) - S(B * P_u)\|$$
$$= \arg\min_{f} \|f(P_u) - S(P_u)\| \tag{8}$$

Where S represents the distortions by the background surface. The compensated projector image P_c for a given target image T is calculated as follows,

$$P_c = \hat{f}^{-1}(T) \tag{9}$$

The calculated P_c, unlike the uniform projector images in calibration set P_u, will not be spatially uniform in intensity. Since the radiometric compensation model did not consider the effect of B, distortion of the non-uniform P_c by the blur function B, will necessarily lead to artifacts in the compensated camera image:

$$B * P_c \neq P_c \tag{10}$$

$$S(B * P_c) \neq S(P_c) = T \tag{11}$$

Using spatially uniform projector images in the calibration set can cause artifacts in the compensated camera image. So we need a framework which can optimize the performance of the compensation model by using the most suitable calibration set.

3   Proposed Method

In the previous section, we discussed existing radiometric compensation algorithms and their limitations. Since the models do not consider inter-pixel coupling, which are prominent at the surface edges [8], compensation may fail to fully hide the background texture.

We propose two changes to the existing radiometric compensation framework. The radiometric model is developed for each pixel in the projector image, so the changes are proposed in such a way that it does not increase the model's complexity. First, the compensation function is deduced directly from the calibration set. Second, the calibration set is modified to contain spatial uniform camera images and their corresponding projector images.

The human visual system is sensitive to abrupt changes in intensity [9]. So the emphasis of the proposed model is to obtain smooth images on the projection surface which can completely hide the background texture. Sankar *et. al.* [10] studied the impact of calibration images on the performance of radiometric compensation. Due to the presence of inter-pixel coupling, existing radiometric compensation models produce artifacts with patterns similar to the pattern of camera images in the calibration set. So the proposed approach modified the calibration set to contain spatially uniform camera images. The smooth camera images reduce the patterning of the artifacts leading to perceptually pleasing compensated images.

After obtaining the calibration set, the compensation function is defined as

$$P = f_i(C), \tag{12}$$

where P and C are projector and camera images from the calibration set. The existing radiometric function models the background's surface reflectance and inverts the model to find the compensation function. Due to the presence of inter-pixel coupling, the compensation function may not be equivalent to the inverse of the radiometric function. Hence, directly developing the compensation function from the calibration set gives the best estimate of the required function. The proposed model also avoids the noise amplification of the forward approach and makes the radiometric compensation algorithm more robust.

Using uniform camera images C_u also lead to non-uniform projector images P_{nu}. So the compensation function calculated from the proposed calibration set includes the projector's blur effects during model learning as follows,

$$\hat{f}_i = \arg\min_{f_i} \|f_i(S(B * P_{nu})) - P_{nu}\| \tag{13}$$

The two proposed changes inherently learn the effect of inter-pixel coupling by making minimum changes to the existing radiometric compensation. The smooth camera images needed for the calibration set are acquired through an iterative approach. The iterative
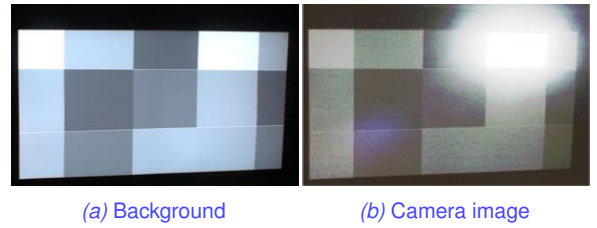

(a) Background   *(b)* Camera image

Fig. 2: One block of (a) the background was illuminated and (b) shows the histogram equalized camera image of the illuminated background. We can observe that the brightness leakage from the illuminated region to the non-illuminated region is captured by the camera.
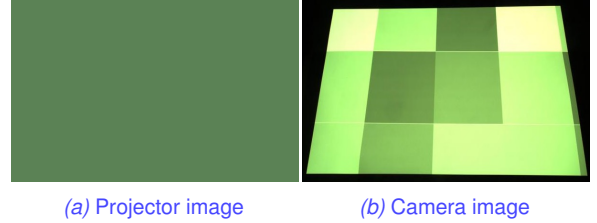

(a) Projector image   *(b)* Camera image

Fig. 3: Conventional calibration set with spatially uniform projector image and its corresponding camera image.

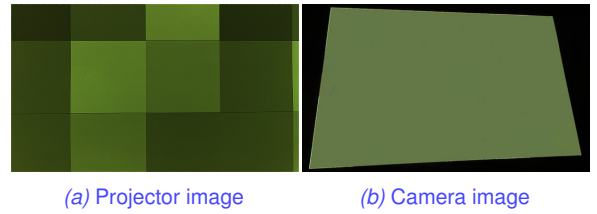*(a)* Projector image   *(b)* Camera image

Fig. 4: Proposed calibration set with spatially uniform camera image and its corresponding projector image.

approach is only used in the offline process to form the calibration set. The compensation function developed from the calibration set is then used with the incoming target images to find the compensated projector image.

4   Experimental Results

A Christie Digital Systems single chip 1920×1200 DLP projector and a 5M-pixel camera were used to form the projector–camera system. The experiment was carried out on a printed background as shown in Fig. 2a. The background was designed to contain sharp edges with varying levels of contrast to help visualize the brightness spread and understand the influence of inter-pixel coupling.

Structured light patterns from gray–scale coding [1] was used to find the geometric mapping between the camera and projector. For unidentified projector pixels, the nearest neighbour method was used to find the corresponding camera pixel. After geometric mapping, the calibration set was formed using an iterative approach. 10 projector – camera image pairs were created, requiring $8-12$ iterations per image, to form the calibration set. The proposed changes were applied to Bimber's [2] radiometric model for each projector-camera pixel pair, compared with the original model as shown in Fig. 5.

The artifacts encountered during evaluation can be divided into radiometric artifacts, due to incorrect learning, and saturation artifacts, where the computed compensated projector image values go beyond the dynamic range of the projector. In this study, we feel that radiometric compensation algorithms should be evaluated on their ability to reduce radiometric artifacts, so only unsaturated pixel locations were considered in error calculation.

A total of 15 target images were tested, projecting onto the background in Fig. 2a, for which the compensated results are summarized in Table 1 and Fig. 5. Interestingly, the RMSE results of the proposed approach, as shown in the table are frequently inferior, and yet visually the results as shown in the figures are far
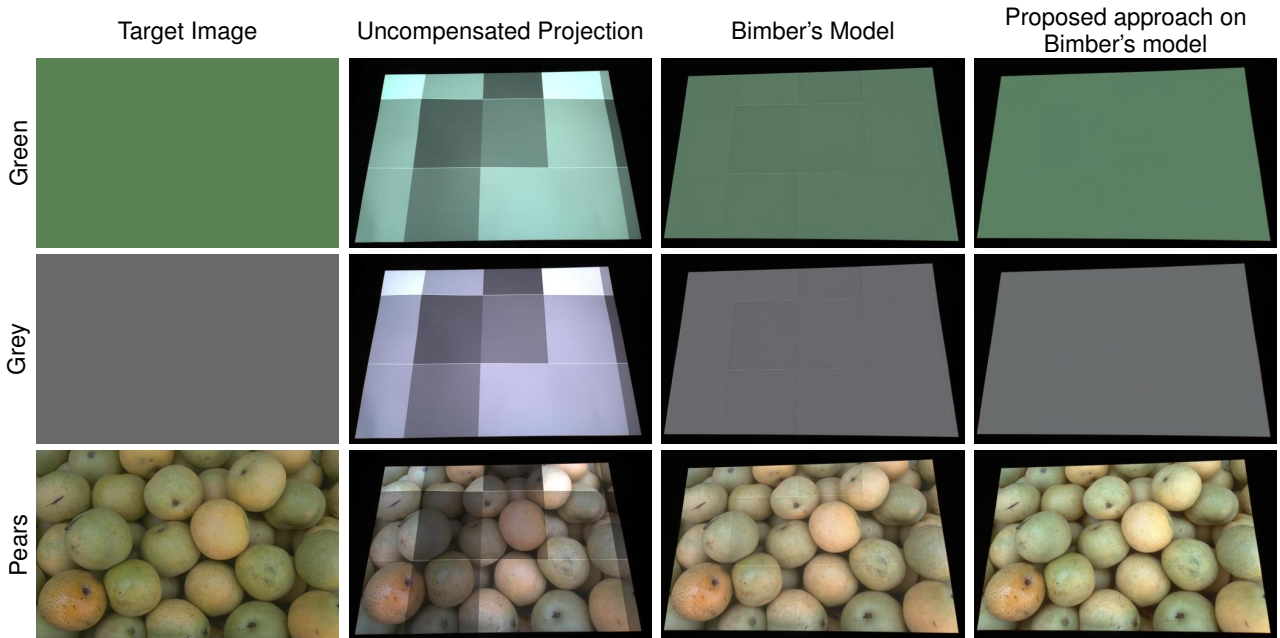
Fig. 5: The results of the proposed approach applied to Bimber's model, given the background of Fig. 2a, one test per row. In every case the proposed approach leads to significant visual improvements in performance

Image	Uncompen-sated	Bimber	Proposed Bimber
Green	48.98	10.28	8.64
Grey	51.97	4.58	5.17
Pears	48.22	12.22	13.52
15 Test Images	50.35	8.43	8.14

Table 1: RMSE scores for the images in Fig. 5.

stronger, clearly suggesting that alternative metrics to RMSE need to be tested as a next step.

In Fig. 5, three spatially uniform images and one complex coloured image (Pears) were used as targets. Even a casual glance at the figures reveals that the conventional model routinely leaves visually apparent artifacts, even in the textured Pears image, whereas the proposed method, learning the compensation model directly from uniform calibration images, leads to significantly improved compensation in all cases.

5 Conclusions

In this paper, pixelwise radiometric compensation algorithms were explored, specifically considering the influence of inter-pixel coupling for backgrounds having sharp edges. A novel approach was proposed, in which the compensation model is learned directly from smooth calibration images so that the model will reproduce smooth regions well, since the human visual system is far more sensitive to non-uniformities in smooth regions, as opposed to minor imperfections in textured ones.

Ongoing work in this research will test the proposed approach against additional linear and nonlinear radiometric compensation methods, and to develop human–visual–system related metrics, rather than RMSE, for evaluations.

References

[1] S. Inokuchi, "Range-imaging system for 3d object recognition," in *Proc. of 7th International Conference on Pattern Recognition*, 1984.

[2] O. Bimber, A. Emmerling, and T. Klemmer, "Embedded entertainment with smart projectors," in *Computer*, vol. 38.1. IEEE, 2005, pp. 48–55.

[3] M. D. Grossberg, H. Peri, S. K. Nayar, and P. N. Belhumeur, "Making one object look like another: Controlling appearance using a projector-camera system," in *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 1. IEEE, 2004, pp. I–I.

[4] S. Mihara, D. Iwai, and K. Sato, "Artifact reduction in radiometric compensation of projector-camera systems for steep reflectance variations," in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 24.9. IEEE, 2014, pp. 1631–1638.

[5] K. Fujii, M. D. Grossberg, and S. K. Nayar, "A projector-camera system with real-time photometric adaptation for dynamic environments," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 1. IEEE, 2005, pp. 814–821.

[6] C. Feng and L. Yue, "Radiometric compensation techniques based on projector-camera system," in *Journal of Computer-Aided Design and Computer Graphics*, vol. 6, 2015, p. 005.

[7] T.-C. Wang, T.-H. Huang, and H. H. Chen, "Radiometric compensation for procam system based on anchoring theory," in *IEEE International Conference on Image Processing (ICIP)*. IEEE, 2013, pp. 103–107.

[8] J.-S. Liu and H. H. Chen, "Preserving image color appearance on non-white projection surfaces," in *International Conference on Multimedia and Expo Workshops (ICMEW)*. IEEE, 2015, pp. 1–6.

[9] A. Grundhofer and O. Bimber, "Real-time adaptive radiometric compensation," in *IEEE Transactions on Visualization and Computer Graphics*, vol. 14.1, Jan 2008, pp. 97–108.

[10] V. Sankar, A. Gawish, and P. Fieguth, "Impact of training images on radiometric compensation," in *Journal of Computational Vision and Imaging Systems*, vol. 3.1, 2017.