Pixel-Wise Radiometric Line Scanner Calibration

Francois Johannes Louw†, Masaaki Iiyama†, Takuya Funatomi‡, and Michihiko Minoh†
†Kyoto University,‡Nara Institute of Science and Technology
louw@mm.media.kyoto-u.ac.jp

Abstract

Calibrating the response function of a line scanner is very important in many fields of computer vision. We propose a method to reduce nonequivalence present in response functions of pixels. Contrary to current state-of-the-art methods our method uses a linear light source which is usually attached to line scanners for pixel-wise calibration. We define a radiant intensity function for a linear light source and fit it to captured images to calibrate the response function. We applied our method to a line sensing camera to remove streaking noise when scanning and experimental results showed a significant reduction of noise in the system.

1 Introduction

Line scanners, which consists of a 1D line camera and a linear light source, are widely used in many computer vision applications that are sensitive toward pixel values, such as in factory automation systems. Many advanced methods for such applications rely on the assumption that the response function of a camera is relatively equivalent among pixels, but this assumption is not true: there are some nonequivalence present among pixels. This nonequivalence can interfere with some processes and thus needs to be fixed. In this paper we propose a method to reduce nonequivalence present in a 1D line camera by calibrating a response function for each individual pixel. Although current state-of-the-art methods can calibrate the response functions of cameras, they do not use a linear light source but only use point light sources or uniform light sources for radiometric calibration, so they are not suitable for use with line scanners. We define a Radiant Intensity Function (RID) for a linear light source and use it for calibration. Another contribution of our method is that our method calibrates a response function for each individual pixel. Most of the existing methods calibrate the camera on an image-average or patch-average level but can not calibrate on a pixel-wise level. Our pixel-wise calibration has an advantage that it provides better noise removal with calibration of the camera.

This paper discusses related research in section 2. We describe our method in section 3. A description of our equipment and its configuration is in section 4. Section 5 describes the calibration of the line sensor. We show experimental results in section 6 and provide a discussion in section 7.

2 Related Work

There are many methods that calibrate an image sensor in order to reduce noise[1][2][3][4][5][6][7][8]. Many of these methods rely on calibrating the sensor using one correction function for the entire sensor[1]. These methods yield valid image-average calibrations. Properties of Charge Coupled Device (CCD) image sensors are well defined from the perspective of machine vision by analysing the statistical properties of the noise that is produced by each step of the digitization process[1]. More recently advances with the statistical modelling and simplification of the response function defined in [1] produced a model that takes into consideration non linear effects[2].

A majority of current state-of-the-art methods rely on calibrating a CCD sensor by using image patches and calibrating according to each patch by using filters[3][4][7][8]. These methods produce accurate image-average or patch-average calibrations but lacks the ability to produce accurate pixel-wise calibration. Our method produces camera calibration functions for each pixel seperately. Existing methods use point light sources or uniform light sources for radiometric calibration. However, line scanners are usually equipped with linear light sources, so existing methods are not applicable for calibrating line scanners.

There are some research into determining calibration for each pixel in space applications which rely on a statistical model of each step in the acquisition phase[5]. Our method does not require extensive knowledge of the camera hardware by not analysing the camera response function statistiaclly. This results in easier computation of the camera response function and can be applied to many situations where enough information to analyse the camera is not available.

3 Camera Response Function

The typical response model used by state-of-the-art methods as defined in[1] is given in equation 1.

$$D = (I + N_{DC} + N_S + N_R) \times A + N_Q \tag{1}$$

This defines the digital value of the pixel (D), which is equal to the number of collected photons (I), the number of dark electrons due to dark current (N_{DC}), the zero mean Poisson shot noise with variance depending on I and N_{DC}, the amplifier generated zero mean read noise (N_R) and the overall system gain (A). This voltage signal is then quantified and as a result quantification noise, (N_Q), affects the final digitized form. Our method replaces the gain A with a non-linear function and seperates equation 1 into an equation that has the components that are dependent on the amount of light received, F_D, and another that has zero mean stochastic components, F_S.

$$\begin{aligned} D &= F_D(I) + F_S \\ F_D(I) &= A(I + E[N_{DC}]) + N_Q \\ F_S &= A(S[N_{DC}] + N_S + N_R) \end{aligned} \tag{2}$$

The light dependent equation F_D consists of the amount of photons received, the expected value of the dark current noise and the quantification noise. The zero mean stochastic equation F_S consists of the stochastic component of the dark current, the shot noise and the read noise. We do not analyse the stochastic component of the response function. Our method regards the intensity dependent function, F_D as one unknown equation that can be solved numerically. To solve an unknown function the Taylor series expansion is considered. The Taylor series expansion of the function F_D is defined in equation 3.

$$F_D(I) = \sum_{n=0}^{\infty} \frac{F_D^{(n)}(a)}{n!}(I-a)^n \tag{3}$$

Each pixel is considered to be the origin of its own response function that is dependent on the received intensity, I. Because of real world limitations an infinite sum of an unknown function cannot be calculated. Thus we approximate the original function as a Maclaurin series polynomial with order m that is expanded in equation 5.

$$F_D(I) \approx \sum_{n=0}^{m} \frac{F_D^{(n)}(0)}{n!}(I)^n \tag{4}$$

$$F_D(I) \approx C_0 + C_1 I + C_2 I^2 + C_3 I^3 + ... + C_m I^m \tag{5}$$

Coefficients $C_0, \ldots, C_m$ are real valued and unique for each pixel, thus the function F_D is dependent on I and the pixel x,$F_D(I,x) \approx \sum_{n=0}^{m} C_n(x) I^n$.

I is the light intensity that is received at each pixel. All intensities are normalized to a value from 0 to 1. Note that our calibration reduces the nonequivalence of the response function, but does not calibrate the absolute strength of the response function.

To configure the Maclaurin polynomial coefficients we capture several images with different intensities. Using a known light source and a known reflection surface, the expected light entering the image sensor is calculable and can be used as a known intensity value. The response function's coefficients are fitted to the captured image to produce the expected signal. This yields the response function present at each pixel.

4 System Configuration

The system configuration of our method is shown in figure 1. A 1D line sensing camera is connected to a telecentric lens and a light source with a known RID is rigidly attached. The camera assembly is mounted perpendicular to a flat recording surface and can be adjusted, closer and further away. To capture a sample the camera assembly scans the recording surface. During scanning the camera assembly always remains perpendicular to, and at a constant distance from, the recording surface. For our calibration method we scan a card which has Lambertian reflective properties. An example of a scanned image is shown in figure 2.

The sample shows the camera resolution on the horizontal axis. The vertical axis is the direction that the camera assembly scanned the recording surface. Figure 2 shows one scan at one intensity level. Our method relies on having more than one scan at different intensity levels. Multiple scans are performed with the camera assembly adjusted to different heights to produce different intensities. To remove the zero mean stochastic

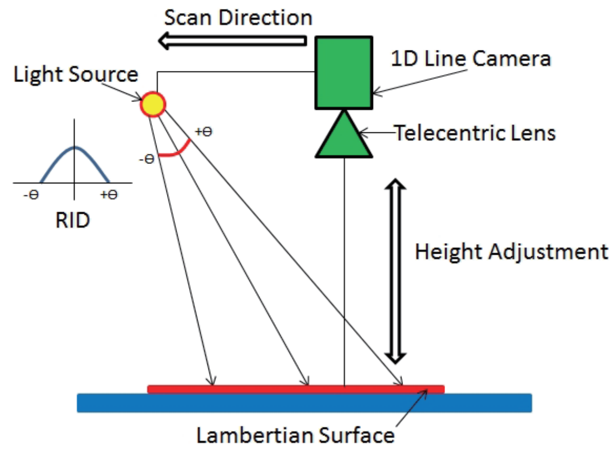

Figure 1. Diagram of system configuration.

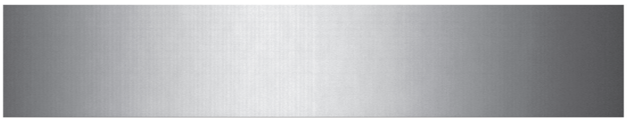

Figure 2. Sample of captured data.

components from the scans, we take the average of each scan in the vertical direction of the image. Different intensities' averages are plotted in figure 3.

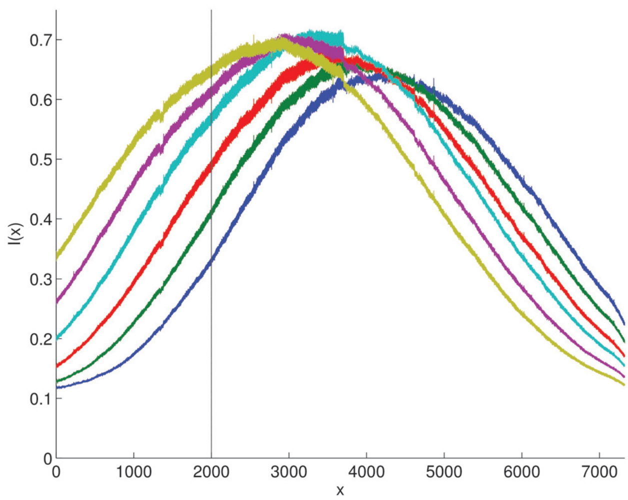

Figure 3. Average plots of multiple scans.

In figure 3 the horizontal axis is the camera resolution and the vertical axis is the normalized value of each pixel. Visual inspection clearly shows the nonequivalence present in the original image. This nonequivalence in the response of the camera must be removed or reduced. Visual inspection of figure 2 also reveals streaking in the image in the direction of the scan. Generally this is neglectable, but in intensity sensitive applications it causes problems.

5 Calibration of Line Sensor

To calibrate a line sensor we need to determine the function $F_D(I,x)$ from equation 2. The stochastic component F_S has a zero mean that reduces to zero when we take the average of a scan. To calculate the

Maclaurin expansion coefficients of $F_D(I,x)$ the light intensity $I(x)$ must first be determined.

5.1 $I(x)$ estimation

The light intensity function, $I(x)$, at pixel x is calculated from the RID function of the light source and the angle of the incident light, ϕ. Our method uses a linear light source whose RID function is given by $\mathrm{RID}(\theta)$, where θ is the angular displacement from the front of the light. A linear light source is the most practical and most commonly used in scanning applications. For calibration purposes it is reasonable to assume that other features of light sources such as strobing or stripe sources are disabled. This light source is not parallel to the line image sensor, as is shown in figure 4, thus the intensity of the incident light on the recording surface varies along the recording line.

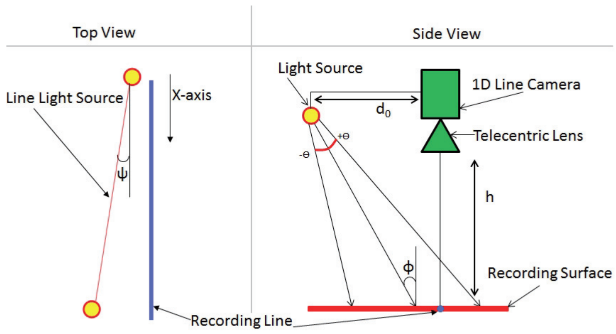

Figure 4. Linear light source and recording surface illustration.

Additionally the angle of the incident light, $\phi(x)$, varies according to:

$$\phi(x) = \tan^{-1}\frac{d_0 + x\sin\psi}{h} \tag{6}$$

The height between the recording surface and the light source is h, the horizontal distance between the recording point and the light source is d_0 and the angle between the recording line and the linear light source is ψ. Our method uses a Lambertian surface as the recording surface, thus the light intensity observed at pixel x is given by equation 7.

$$I(x) = \mathrm{RID}(\phi(x) - \theta_0)\cos(\phi(x))\rho \tag{7}$$

The reflectance coefficient of the recording surface is ρ and the angle between the front of the light and the recording line is θ_0. If the angle of $|\psi|$ is small and a light with a peaky RID function, such as an LED, is used, the variation of $\cos(\phi(x))$ will be significantly smaller than that of the RID. Thus $I(x)$ can be approximated as:

$$I(x) \propto \mathrm{RID}(\phi(x) - \theta_0) \tag{8}$$

To calculate $I(x)$ an RID function is fitted to each set of averaged images. The linear light source that we use has an RID function that is described by an exponential curve $\exp(-\theta^2/w^2)$. The parameters that need to be estimated are θ_0 and the width of the curve w. To fit the RID function, we use a 1st order Maclaurin expansion of $F_D(I,x)$ and reformulate it as:

$$\begin{aligned} F_D(I,x) &\approx C_0(x) + C_1(x)I(x) \\ &= \overline{C_0} + \overline{C_1}I(x) + \epsilon(x) \\ D(x) &= \overline{C_0} + \overline{C_1}I(x) + \epsilon(x) + N_Q \end{aligned} \tag{9}$$

Where ϵ is a zero mean residual. From an averaged image $D(x)$, we acquire $I(x), \overline{C_0}, \overline{C_1}$ by minimizing:

$$\min_{I(x),\overline{C_0},\overline{C_1}} \sum_x \left|D(x) - \overline{C_0} - \overline{C_1}I(x)\right|^2 \tag{10}$$

5.2 $F_D(I)$ estimation

From the discussion in section 3, the pixel intensities of the averaged images $D(x)$ are modelled for an m^{th} order Maclaurin expansion by:

$$D(x) = \sum_{n=0}^{m} C_n(x)I_a(x)^n \tag{11}$$

Knowing the value of an observed pixel x, $D(x)$, after removing the zero mean stochastic components, and with an estimated light intensity, $I(x)$, the Maclaurin polynomial coefficients of the camera response function can be calculated. To illustrate our method, in figure 3 we intersect the averages of different intensities at an arbitrary point, in this case at $x = 2000$. We plot the input image points $D(x)$ along with the fitted RID intensity values $I(x)$ in figure 5. Our method uses polynomial regression to establish an optimal fitting of the Maclaurin expansion that relates $D(x)$ to $I(x)$. In figure 5 we use a second order Maclaurin expansion for fitting.

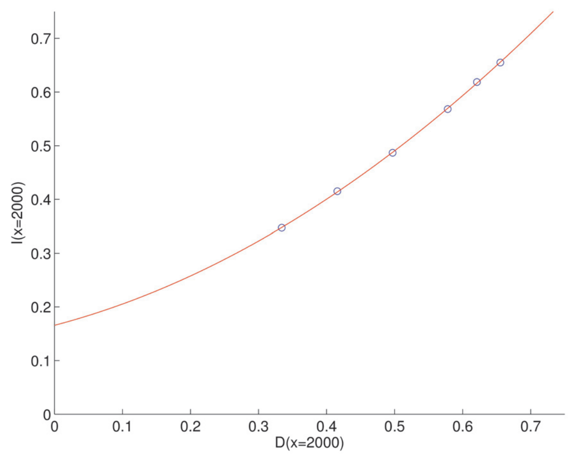

Figure 5. One pixel calibration function example.

In order to calculate the true intensity $I(x)$ from a given image $D(x)$, equation 11 needs to be inverted. To simplify this inversion we use polynomial regression to calculate the inverted equation's Maclaurin expansion coefficients, $Q(x)$. For s samples with different intensity levels, the polynomial regression equation for the m^{th} order Maclaurin approximation of the inverted response function is given in equation 12. Each pixel has a Maclaurin polynomial expansion with order m that represents the inverted non-stochastic camera response function.

$$\min_{Q(x)} \sum_{a=1}^{s} \left| I_a(x) - \sum_{n=0}^{m} Q_n(x)D_a(x)^n \right|^2 \tag{12}$$

6 Experimental Results

To evaluate our method we applied it to real world data. Six samples were scanned at different distances from the recording surface to use for calibration. We calculated the average of each sample and applied our method to calculate the second order Maclaurin expansion of the camera response function. Samples that were not used for calibration, at arbitrary distances from the recording surface, were then calibrated by the calculated coefficients. Figure 6 shows a calibrated output image at the top and the uncalibrated input image at the bottom.

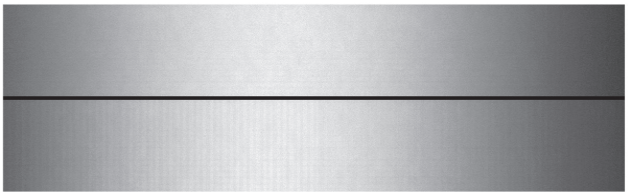

Figure 6. Calibrated output and original input.

Visual inspection shows the calibrated image only has stochastic noise remaining with the streaking noise removed. The average of the uncalibrated sample and the average of the calibrated sample in figure 7 shows that the noise was succesfully removed. The zoomed insert shows the improvement of the smoothness of the output.

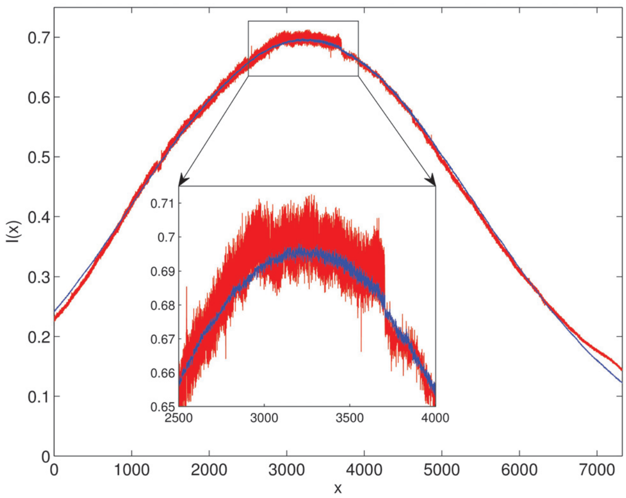

Figure 7. Averages of output and input.

To analyse the performance of our method we evaluate the smoothness of the original and calibrated output. For evaluation we use a sample that was not used for calibration and apply our response function to obtain an output image. We fit the linear light source RID function to the input sample, as described in section 5, and use the fitted RID as the ground truth. The equations for evaluationg the smoothness of the average of the original image S_i, the average of the output image S_o and the fitted RID function S_e is given as:

$$S_e = \sum_x \left| \frac{\partial RID(x)}{\partial x} \right|$$

$$S_i = \sum_x \left| \frac{\partial D(x)}{\partial x} \right|, D_i = \sum_x |D(x) - RID(x)|$$

$$S_o = \sum_x \left| \frac{\partial I(x)}{\partial x} \right|, D_o = \sum_x |I(x) - RID(x)|$$

The ground truth is smooth along x, so an ideal output image will also be smooth. We also evaluate the difference between: the RID function and the averaged original input D_i, and of the output image D_o. For different orders of the Maclaurin expansion we obtain different results for our evaluation, given in table 1. Comparing S_i and S_o, D_i and D_o, our method significantly reduces the nonequivalence of the response function.

Table 1. Smoothness Evaluation

	$m=1$	$m=2$	$m=3$	$m=4$	$m=5$
S_o	7.28	7.97	8.09	8.46	8.09
D_o	14.54	10.49	7.18	7.54	6.99
$S_e = 1.02$		$S_i = 66.11$		$D_i = 53.68$	

The smoothness does not change significantly when a Maclaurin expansion with $m > 3$ is selected, but processing time increases exponentially. Thus for our experiments we use a value of $m = 3$ or for cases that require faster results a value of $m = 2$.

7 Conclusion

In this paper we have proposed a novel method to calibrate the camera response function of line scanners. Our method produced a camera response function that sucessfully removed nonequivalence present in the system. Our method can be applied to 1D sensors and also to 2D sensors. A 2D sensor will require significantly more processing power because of the increased amount of pixels present in the system.

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