Towards Quantitative Measurement of Light Transport in Unconventional Optics

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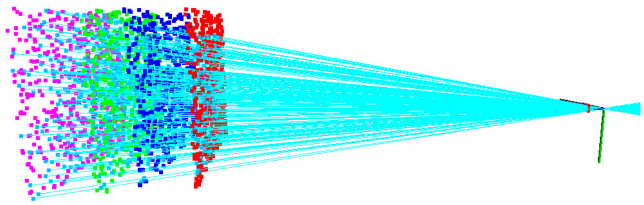

Figure 1: Light ray (cyan) geometry of the device under test (DUT) reconstructed after observing their intersections with an LCD at different positions, as estimated by screen pixels identified by sinusoidal patterns. The rays approach the optical center of the DUT, as determined by independent calibration, within a radius of 1mm.

Abstract

We present preliminary results of our ongoing research towards determining light ray geometry in optical systems. The ray geometry is estimated independently using a moving LCD screen as calibration target.

Keywords: Pattern Recognition, Structured Light, Light Path Triangulation

1 Introduction

With the long term goal of researching methods to calibrate catadioptric imagers with flexible mirror designs, we are currently developing a system capable of calibrating light ray geometry independently per ray for a camera with arbitrary mapping of rays to sensor pixels (*device under test, DUT*). In order to avoid the usage of expensive measurement equipment like optical benches and high precision positioning accessory, we have developed a system using a LCD monitor as calibration target. The monitor is positioned by hand and tracked in space with an existing image-based calibration technique using a calibrated camera (*reference device (RD)*). Displaying phase-shifted sinusoidal patterns on the LCD, we identify a map between each ray observed in a general digital camera and screen pixel positions on each recorded position. The ray geometry can then be computed as least-squares fit to the intersection points. In this extended abstract, we present the technique and report an early result.

2 Related Work

Catadioptric systems – imagers which combine lenses and reflective elements – can be calibrated without reconstructing the light path. Lanman et al. [6] used few recordings of calibration patterns, e.g. a checkerboard, for mirrors of known shape. As we want to be flexible regarding the actual mirror shape and the number of mirror views, a different approach is needed. Kutulakos et al. [5] have developed a method to triangulate the light path with patterns displayed on LCDs implementing environment matting techniques. However the position of the pattern displaying screen has to be known and controlled precisely. Furthermore, they present a theory which describes the requirements for traceable light paths in relation to camera views and participating reflective or refractive objects. Calibrating a screen-camera system has been presented by Francken et al. [2] using Gray codes. More recently Weinmann et al. [9] presented a complex system consisting of several screens and cameras. Displaying Gray code patterns on the different displays, they are able to estimate the reflective surface of complex shapes through normal estimation. Instead of reflecting surface geometry, we aim for a direct estimation of observable rays.

Our approach implementing sinusoidal patterns is inspired by the work of Scharstein and Szeliski [8], where these patterns have been successfully used to calculate depth maps. Kammel et al. [4] have applied such patterns with a fixed camera-screen installation in order to measure reflective surfaces via normal estimation. We want to exploit the robust recognition of sinousidal patterns in the scope of single display pixels so that a cost effective setup can be realized without the necessity of a high-precision optical bench system as used by Kutulakos et al. [5].

3 System Overview

3.1 Imaging Model

The principle behind the identification of individual LCD screen pixels via sinusoidal patterns is based on coding the pixel position in phase shifted sine functions. By taking several pictures with the DUT for different patterns, we can recover the pixel position with seperate measurement sequences for rows and columns. We discuss now the process for determining x coordinate (an analogous process recovers the y coordinate). Following the mathematical exposition given in [8], one screen row can be described as a sine function of frequency $f_l = n_l/w$ with w being the screen width in pixels and n_l the number of visible sine periods, resulting in a displayed brightness

$$L(x) = A_{\min} + (A_{\max} - A_{\min}) \cdot \tfrac{1}{2}\left(\sin\left(2\pi f_l x + \phi_k\right) + 1\right). \quad (1)$$

Here, the pixel position x along the screen row is coded in the phase of the sine, which is shifted over several observations k by ϕ_k. We employ the approach by Scharstein and Szeliski to recover x in a least-squares solution hierarchically for several frequencies l.

In our approach, some differences have to be taken into account in comparison to [8]. While we do not need to estimate surface albedo – the original approach was used for structured light 3D scans –, we separately calibrate for the opto-electronic response functions of display and camera. The parameters $A_{\min}$ and $A_{\max}$ describe the minimum and maximum grayscale values which can be applied while remaining in the zone of maximal camera and display precision.

3.2 Recovering the Display Position

In order to map the observed intersections of *DUT* camera rays to ray geometry in world space, we need to know the position of the display pixels in absolute world coordinates. This is achieved

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by observing the display with the RD, a camera of moderate, calibrated distortion. In our experiments, we calculate the distortion with the camera calibration algorithms provided by the OpenCV framework [1]. The initial calibration has been performed by taking various pictures of a printed checkerboard pattern. Although the calibration could be done using the same sinusoidal patterns that are used to estimate ray geometry, many different orientations of the calibration pattern have to be observed in order to estimate the intrinsic camera parameters, especially the focal length. The sinusoidal patterns can, however, be used to refine the calibration. In contrast to checkerboard patterns, the sine pattern images are not required to be fully visible which makes it easier to cover the whole image space.

The quality of the per pixel reconstruction of the recorded and normalized pattern images can be assessed by fitting a plane to the data. If the distortion coefficients of the camera are estimated precisely and the pattern images have been corrected accordingly, the reconstructed display pixel positions in width or height lie on a plane in 3D space. Using a RANSAC algorithm to determine the plane parameters, the number of inliers inside a certain threshold can be calculated. As it turns out, reconstructed values near the screen borders are unreliable compared to center pixels as the effect of backlight bleeding is most prominent in these regions, which directly influences the displayed sine patterns.

3.3 Reconstructing Ray Geometry

The corrected and combined display pixel position data corresponding to the RD camera image pixels can be used to calculate the relative 3D positions of the screen and the RD using the OpenCV framework, and thus establish the positions of the rays recorded by the DUT in a global coordinate system. Reprojecting the estimated display position and, correspondingly, each 3D position of the reconstructed display pixel position onto the RD camera image plane and comparing this result to the actual image pixel provides a measure for the quality of the found rotation and translation vectors.

In principle, it is possible to calculate the light ray geometry for any camera pixel, if display pixel coordinates belonging to only two different display locations and their estimated 3D positions are available. As even small deviations in the pose estimate of the display locations can lead to severe errors in the estimated light ray direction, however, more observations, and, accordingly, more display locations, are desirable. With multiple data points available, we fit a straight line to the data points.

The operating volume is only limited by the depth of field of the DUT and RD. As the ray geometry is estimated independently, partial views of the display are sufficient, provided each DUT pixel has seen several positions.

4 Preliminary Results

So far, we have performed experiments with a Canon 5D Mark II camera and a Canon zoom lens objective 24-70 mm both in the roles of DUT and RD camera to test the feasibility of the approach. The first experiments using a LCD with a resolution of 1600x1200 pixel and a diagonal of 20" show promising results. Positioning the display at four positions located between 650 and 890 mm away from the camera, the light rays reconstructed only by the estimated 3D position of display pixels, which have been identified by the same camera pixel, converge in a circle with a radius of 1.0 mm around the optical center of the camera, as calibrated by the separate distortion estimation, see Figure 1 for a plot.

5 Conclusion

The proposed method based on phase shifted sinusoidal patterns on LCDs presents a cost effective method for the independent calibration of ray geometries in general cameras. Over time, this can be expected to lead to more precise models of optical distortions, the knowledge of which may facilitate improvements in software improving image quality such as the approach by Heide et al. [3].

As the presented setup can be easily modified to use more recent, high-resolution display technology, the achievable precision can be expected to improve further. While the system so far supports pinhole DUTs with arbitrary geometry, future work will involve measuring and modeling DUTs with more general aperture shapes.

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