Calibration of a Laser Stripe Profiler

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Abstract

The calibration of a laser stripe profiler consisting of a laser stripe projector, camera, and linear motion table is considered. A nonlinear system model is used which accommodates radial distortion in the camera lens. The way in which stripe data is extracted from the camera images leads to a natural formulation of the calibration problem as a nonlinear least squares problem. This can then be solved using standard techniques.

1 Introduction

A laser stripe profiler is one of many techniques [1] for generating dense 3D surface information. Such data has uses in computer vision, in computer graphics for generation of realistic object models, and in medical applications.

A laser stripe profiler consists of a laser source, camera, and linear motion platform, in an arrangement such as illustrated in Figure 1. The laser source emits a plane of light which forms an illuminated stripe on the object's surface. This is viewed by a camera displaced from the laser plane. In the indicated arrangement, the stripe runs roughly from top to bottom of the images. The horizontal displacement is related to surface shape. The data extracted from the image is in which column (x-direction) the stripe crosses each row. The position in the x-direction is estimated to subpixel accuracy using a sub-pixel operator such as Gaussian interpolation [2]. Given the camera intrinsic parameters and its relative location with respect to the laser plane, the position of the corresponding point in the laser stripe (i.e., the coordinates in the laser stripe plane) can be estimated by triangulation. Finally, these can be transformed into 3D coordinates by incorporating the known motion of the object relative to the laser plane.

1.1 Previous Work

The classic approach to calibration of a laser striping system [3, 4, 5, 6] is to first use a standard camera calibration technique, such as [7], to estimate the camera parameters. Then the parameters of the laser plane are estimated by projecting observed points into 3D locations and fitting a plane by least squares. This approach has a number of drawbacks. It divides the calibration into two sub-problems which may result in a suboptimal estimate of the parameters. More importantly, it requires an intensity image from the camera. In many systems, this is not feasible because, for example, the camera lens is heavily filtered so that only the laser light is visible, or the images are processed on the fly within the sensor to extract stripe data and thus only stripe position data is available.

As noted above, part of the 3D data generation procedure can be viewed as mapping observed image points to positions in the plane of the laser stripe. The latter is given by the distance from the camera optic centre to the point in the laser stripe plane along the ray through the camera image point. It is commonly referred to as "height" and forms a 1D function of the image coordinates. Estimating this function directly is the basis of several methods.

In [8], the height is assumed to be a cubic function of image coordinates. A set of parallel planar surfaces (at different spacings off the motion table) are scanned. The parameters of the cubic are estimated from the known distance between the surfaces.

In [9], a more sophisticated calibration target is used which has a staircase like face. By scanning this, the height function is densely sampled. This data is used in a look-up table, along with linear interpolation, to approximate the height function on scanned objects. Height measurements are converted to 3D coordinates by assuming that the height is in the Y-Z plane (i.e., this plane contains the laser source) and the motion is in the X-Y plane.

For these polynomial methods to generate accurate results, a complex calibration target is needed so that densely sampled data is generated. Better accuracy is obtained using a physical model of the system [10].

In [11], a linear system model is used. A 3D coordinate, $\mathbf{X}_l$, frame is associated with the laser plane (such that the laser lies in $x = 0$). It is assumed that the transformation from this coordinate frame to a world coordinate frame in which some calibration objects are measured is known. Since the model is linear, the map from image plane coordinates to a 2D coordinate frame for the laser plane is specified by a 3×3 homotopy. By aligning the axes of 2D laser plane coordinates with the y and z axes of $\mathbf{X}_l$, a map can be defined from image plane coordinates to $\mathbf{X}_l$. This is specified by a 4×3 matrix, of which the top row contains 0 and the bottom 3 rows contain the homotopy from image plane to laser plane. The elements of this matrix can be estimated from the image plane locations of image points generated from several known world planes.

In [12], a nonlinear model of the system is used which incorporates standard terms in the camera model to handle radial distortion effects. The raw data used is the motion platform position that particular points on a planar calibration target pass through the laser plane, and the observed image location. The points used are the centroids of circular disks on the surface. The required data has to be estimated by interpolation. The planar target is scanned in two different positions to generate enough data samples.

The method described in this paper resembles that in [11], in that the raw data observed from world planes is used in the calibration process. However, it uses a nonlinear system model similar to, but more accurate than that in [12]. Fiducial marks are used as in [12] to generate initial estimates. An important contribution of this paper is the formulation of the calibration as a nonlinear least squares problem, which means that standard numerical methods can be used to solve the problem.

The rest of this paper is outlined as follows. In Section 2, the nonlinear system model is described. The details of the calibration procedure are presented in Section 3. The paper is concluded in Section 4 with a discussion of the method's performance and an indication of areas requiring further work.

2 System Description and Model

The laser stripe profiler consists of a camera viewing a scene into which a plane of laser light (generated with a cylindrical lens) is projected. The object of interest is moved through the scene along a linear trajectory. The camera and laser are arranged such that notionally the visible laser stripe appears as a vertical line in the camera's field of view, and such that the direction of motion is notionally along the camera/laser baseline. It is useful to identify several coordinate frames as shown in Figure 2. The various coordinate frames will be identified with subscripts as follows:

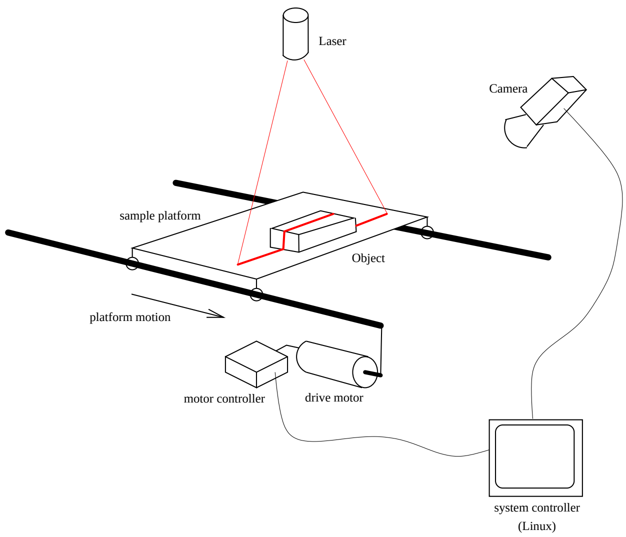

Figure 1: Overview of the laser profiling system.

w	World coordinate frame attached to object being measured (3D)
f	World coordinate frame fixed with respect to camera and laser (3D)
c	Camera coordinate frame (3D)
i	Camera image plane coordinate frame (2D)

Let $\mathbf{x}_w$ be the coordinates of a point on the surface of the object being profiled, in a world coordinate frame fixed relative to the object. The goal of using the system is to recover $\mathbf{x}_w$ for all visible points. Another coordinate frame $\mathbf{x}_f$ is introduced that is fixed with respect to the camera and laser plane. This does not move as the object is moved. The fixed and world frames are defined such that they are co-incident at the start of scanning. The object is moved by a linear translation between images of a constant step size. The relationship between $\mathbf{x}_f$ and $\mathbf{x}_w$ is given by

$$\mathbf{x}_w = \mathbf{x}_f + t\Delta\mathbf{m} \tag{1}$$

where t is the image number (starting at 0), i.e., the "time", Δ is the distance moved between images, and $\mathbf{m}$ is the unit vector representing the direction of travel between images.

A coordinate frame $\mathbf{x}_c$ associated with the camera is introduced. The Euclidian transformation between the fixed and the camera coordinate frames is specified by a rotation $\mathbf{R}$ and a translation $\mathbf{t}$, namely

$$\mathbf{x}_c = \mathbf{R}\mathbf{x}_f + \mathbf{t} \tag{2}$$

The camera model contains a nonlinear term for radial distortion [13]. The transformation from $\mathbf{x}_c$ to

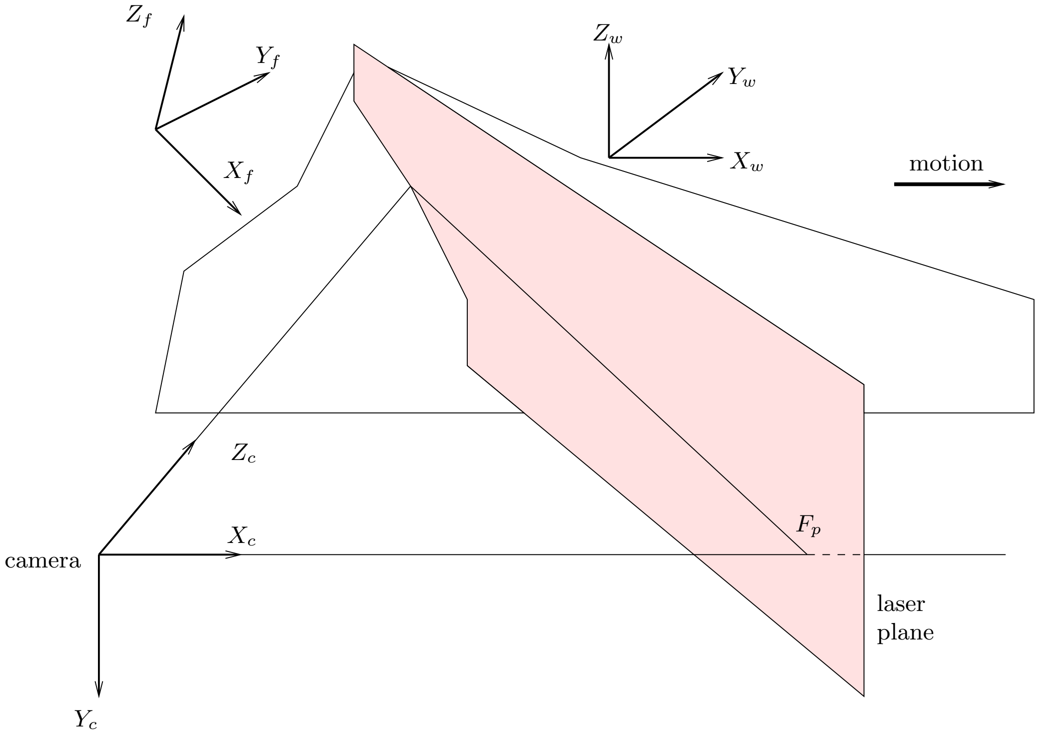

Figure 2: 3D Laser Profiler model.

$\mathbf{x}_i$ is changed as follows. Let $\mathbf{x}_u$ be undistorted image plane coordinates given by

$$x_u = \frac{x_c}{z_c}, \qquad y_u = \frac{y_c}{z_c} \tag{3}$$

These are related to distorted image plane coordinates $\mathbf{x}_d$ by

$$\mathbf{x}_u = (1 + K_1 r^2)\mathbf{x}_d \tag{4}$$

where $r^2 = x_d^2 + y_d^2$ and K_1 is a radial distortion coefficient. The observed image plane coordinates $\mathbf{x}_i$ are then

$$\mathbf{x}_i = \begin{bmatrix} s_x & k \\ 0 & s_y \end{bmatrix} \mathbf{x}_d + \begin{bmatrix} c_x \\ c_y \end{bmatrix} \tag{5}$$

The light projected by the laser lies in a plane. The plane is specified by a normal $\mathbf{n}$ and an offset d from the origin. In the fixed coordinate frame, the laser plane is thus represented by

$$\mathbf{n}_f^{\mathsf{T}} \mathbf{x}_f + d_f = 0 \tag{6}$$

Operation of the profiler generates $(\mathbf{x}_i, t)$ tuples for points on the objects surface. From these, an estimate of $\mathbf{x}_w$ is to be generated. From (5),

$$\mathbf{x}_d = \begin{bmatrix} \frac{1}{s_x} & \frac{-k}{s_x s_y} \\ 0 & \frac{1}{s_y} \end{bmatrix} (\mathbf{x}_i - \begin{bmatrix} c_x \\ c_y \end{bmatrix}) \tag{7}$$

Hence $\mathbf{x}_u$ can be calculated from (4), and $\mathbf{x}_c$ expressed as

$$\mathbf{x}_c = z_c \begin{bmatrix} \mathbf{x}_u \\ 1 \end{bmatrix} \tag{8}$$

in terms of the unknown z_c. Substituting this into (2),

$$\mathbf{x}_f = z_c \mathbf{A} - \mathbf{B} \tag{9}$$

where

$$\mathbf{A} = \mathbf{R}^{\mathsf{T}} \begin{bmatrix} \mathbf{x}_u \\ 1 \end{bmatrix} \tag{10}$$

$$\mathbf{B} = \mathbf{R}^{\mathsf{T}} \mathbf{t} \tag{11}$$

Substituting this into (6) then gives

$$z_c = \frac{\mathbf{n}_f^{\mathsf{T}} \mathbf{B} - d_f}{\mathbf{n}_f^{\mathsf{T}} \mathbf{A}} \tag{12}$$

Thus, $\mathbf{x}_f$ has been determined, and $\mathbf{x}_w$ can be determined from (1).

3 System Calibration

Calibration is the determination of optimal values for the model parameters. This is accomplished by scanning a calibration target about which world information is apriori known. The target used consists

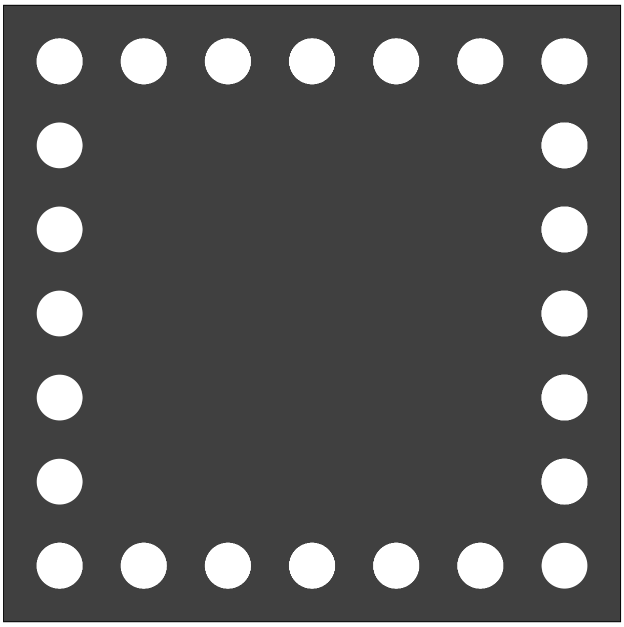

Figure 3: The pattern used on each face of the calibration target.

of several planar surfaces having the pattern shown in Figure 3 printed on them. A three surface target is shown in Figure 4. The data obtained from scanning the calibration target is presented to an operator as the intensity recorded along the laser stripe for each scan, as shown in Figure 5. The operator then identifies the regions corresponding to the circular fiducial marks and the rectangular planar regions. This data is used in the parameter estimation process.

In Section 3.1, the calibration process is formulated as a nonlinear regression problem which can be solved using standard tools. The numerical solution technique requires a good starting condition. This is provided by ignoring the nonlinear part of the model and solving the resulting linear system of equations. This is described further in Section 3.2.

3.1 Nonlinear Estimation

The planar surfaces of the calibration target are specified in a world coordinate frame associated with the target as

$$\mathbf{p}_w(k)^\mathsf{T}\mathbf{x}_w + q_w(k) = 0, \qquad k = 1 \ldots N \tag{13}$$

The raw data acquired from the target consists of sets of tuples (x_i, y_i, t) for each plane k, which record when the stripe at time t lies on plane k such that the stripe is measured to intersect row y_i at column x_i^o. Thus, if φ represents the system parameters ($\mathbf{R}$, $\mathbf{t}$, s_x, etc.),

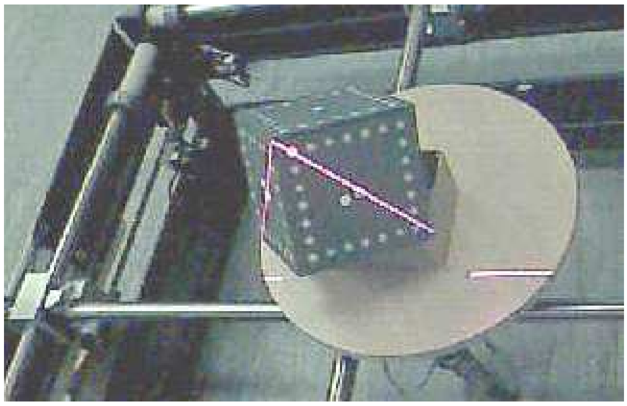

Figure 4: A calibration target consisting of three planar faces.

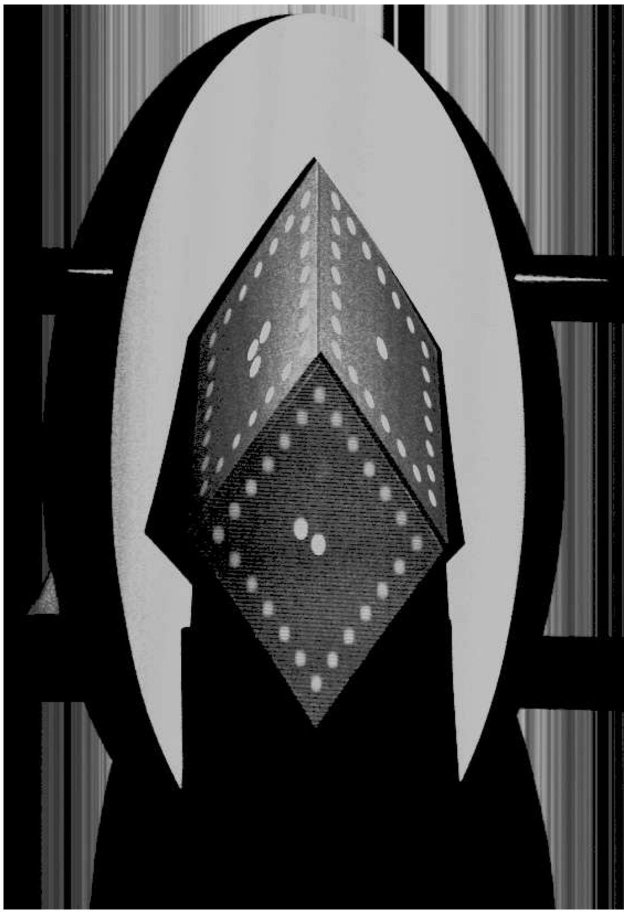

Figure 5: Image constructed from intensity recorded along the laser stripe in each scan.

and the system model can be expressed as

$$x_i = f_k(y_i, t; \varphi) \tag{14}$$

then the system parameters can be estimated by non-linear least squares minimisation of

$$E = \sum_k \sum_{y_i} (x_i^o - f_k(y_i, t; \varphi))^2 \tag{15}$$

The rest of this section shows how f_k can be derived. The kth calibration target plane (13) can be expressed in camera coordinates as

$$\mathbf{p}_c^\mathsf{T} \mathbf{x}_c + q_c = 0 \tag{16}$$

where the k arguments have been dropped for clarity, and

$$\begin{aligned} \mathbf{p}_c &= \mathbf{R}\mathbf{p}_w(k) && (17) \\ q_c &= q_w(k) + t\Delta \mathbf{p}_w(k)^\mathsf{T} \mathbf{m} - \mathbf{p}_c^\mathsf{T} \mathbf{t} && (18) \end{aligned}$$

If we define

$$\begin{aligned} \mathbf{n}_c &= \mathbf{R}\mathbf{n}_f && (19) \\ d_c &= d_f - \mathbf{n}_c^\mathsf{T} \mathbf{t} && (20) \end{aligned}$$

then (6) can be expressed in the camera coordinate system as

$$\mathbf{n}_c^\mathsf{T} \mathbf{x}_c + d_c = 0 \tag{21}$$

and (12) can be rewritten as

$$z_c = \frac{-d_c}{(n_1 x_d + n_2 y_d)(1 + K_1 r^2) + n_3} \tag{22}$$

where the n_i are the components of $\mathbf{n}_c$. Substituting this into (16) gives

$$\begin{aligned} (1 + K_1 r^2)[q_c(n_1 x_d + n_2 y_d) - d_c(p_1 x_d + p_2 y_d)] \\ + q_c n_3 - d_c p_3 = 0 \quad (23) \end{aligned}$$

where the p_i are the components of $\mathbf{p}_c$. Substituting for r, x_d, and y_d from (7) gives a cubic polynomial for x_i in terms of t, y_i, the system parameters, and the calibration target plane parameters:

$$A x_i^3 + B x_i^2 + C x_i + D = 0 \tag{24}$$

where

$$\begin{aligned} A &= K_1 \beta^3 \alpha_1 && (25) \\ B &= K_1 \beta^2 (3\alpha_1 \gamma + \alpha_2 y_d) && (26) \\ C &= \beta \alpha_1 + K_1 \beta(\alpha_1 y_d^2 + 2\alpha_2 \gamma y_d + 3\alpha_1 \gamma^2) && (27) \\ D &= \alpha_3 + \alpha_1 \gamma + \alpha_2 y_d \\ &\quad + K_1(\alpha_2 y_d + \alpha_1 \gamma)(y_d^2 + \gamma^2) && (28) \\ \alpha &= q_c \mathbf{n}_c - d_c \mathbf{p}_c && (29) \\ \beta &= \frac{1}{s_x} && (30) \\ \gamma &= -\beta(k y_d + c_x) && (31) \\ y_d &= \frac{y_i - c_y}{s_y} && (32) \end{aligned}$$

3.2 Initial Parameter Estimates

The calibration target consists of several non-coplanar fiducial marks $\mathbf{c}_w(k), k = 1 \ldots N$. The target is placed into the system and scanned. The raw data acquired from the target consists of the points $\begin{bmatrix} c_i^o(t) & r_i \end{bmatrix}^\mathsf{T}$ where the image of the laser stripe intersects row r_i at sample times $t = 0 \ldots T$, and the image intensity $I(r_i, t)$ at the stripe location. It is also assumed that the distance moved between images, Δ, is known. From this data, the image plane location $\begin{bmatrix} \tilde{x}_i(j) & \tilde{y}_i(j) \end{bmatrix}^\mathsf{T}$ and time $\tilde{t}(j)$ when fiducial mark j is in the laser plane can be estimated. This is described in Section 3.3. Given these measurements, the calibration parameters can be estimated by least squares minimisation, as described in Section 3.4.

By ignoring the radial distortion, the system model can be converted into a linear system of equations in terms of homogeneous coordinates. By ignoring some of the internal structure of the matrices (which effectively over-parameterises the model), a linear system of equations for determining the matrix elements can be formed. These involve (x_i, y_i, t) triples for some fiducial marks. The circular white disks on the target are used as fiducial marks. Section 3.3 describes how the (x_i, y_i, t) is estimated from the observed raw data. The equations are solved by least squares minimisation, as described in Section 3.4. Given the matrix elements, the original system model parameters can be estimated, as shown in Section 3.5.

3.3 Fiducial Mark Estimation

The fiducial marks used in this initialisation phase are the white disks on the targets. The required data is the (x_i, y_i, t) of each mark's centroid. This is estimated from the observed data using a centroid operator. Let $\mathcal{N}(j)$ be the set of all data triples (c_i^o, r_i, t) identified to be in the vicinity of fiducial mark j, and such that $I(r_i, t) > \tau$. Then the estimate of the fiducial mark position is given by

$$\tilde{x}_i(j) = \frac{\sum_{(c_i^o, r_i, t) \in \mathcal{N}(j)} I(r_i, t) c_i^o}{\sum_{(c_i^o, r_i, t) \in \mathcal{N}(j)} I(r_i, t)} \tag{33}$$

$$\tilde{y}_i(j) = \frac{\sum_{(c_i^o, r_i, t) \in \mathcal{N}(j)} I(r_i, t) r_i}{\sum_{(c_i^o, r_i, t) \in \mathcal{N}(j)} I(r_i, t)} \tag{34}$$

$$\tilde{t}(j) = \frac{\sum_{(c_i^o, r_i, t) \in \mathcal{N}(j)} I(r_i, t)t}{\sum_{(c_i^o, r_i, t) \in \mathcal{N}(j)} I(r_i, t)} \tag{35}$$

In practice, $\mathcal{N}(j)$ is identified as follows, in an interactive manner. The user is shown an image in which each row shows the intensity recorded along the laser stripe for a particular scan, and the scans are stacked on above another to form the columns, as shown in Figure 5. The operator identifies the location of several such points so that an approximate estimate of the calibration parameters can be generated. This is used to project all of the fiducial marks onto the image. Then all image points that are within a elliptic region centred on these estimates and having an intensity larger than a threshold form $\mathcal{N}(j)$.

3.4 Parameter Estimation

By assuming that $K_1 = 0$ (so that $\mathbf{x}_d = \mathbf{x}_u$), the camera model can be written succinctly in terms of a 3×4 perspective transformation matrix $\mathbf{P}$ as

$$\begin{bmatrix} \mathbf{x}_i \\ 1 \end{bmatrix} = \lambda \mathbf{P} \begin{bmatrix} \mathbf{x}_f \\ 1 \end{bmatrix} \tag{36}$$

where

$$\mathbf{P} = \mathbf{K} \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix} \tag{37}$$

and

$$\mathbf{K} = \begin{bmatrix} s_x & k & c_x \\ 0 & s_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{38}$$

The map from fixed to world coordinates (1) can be written as

$$\mathbf{X}_w = \mathbf{T} \mathbf{X}_f \tag{39}$$

where

$$\mathbf{T} = \begin{bmatrix} \mathbf{I}_3 & t\Delta\mathbf{m} \\ \mathbf{0} & 1 \end{bmatrix} \tag{40}$$

The laser plane equation (6) can be written as

$$\begin{bmatrix} \mathbf{n}_f^\top & d_f \end{bmatrix} \begin{bmatrix} \mathbf{x}_f \\ 1 \end{bmatrix} = 0 \tag{41}$$

Thus, the whole system model can be written as

$$\begin{aligned} \begin{bmatrix} \mathbf{x}_i \\ 1 \\ 0 \end{bmatrix} &= \lambda \begin{bmatrix} \mathbf{P} \\ \mathbf{n}_f^\top \quad d_f \end{bmatrix} \mathbf{T}^{-1} \begin{bmatrix} \mathbf{x}_w \\ 1 \end{bmatrix} & (42) \\ &= \lambda \mathbf{M} \begin{bmatrix} \mathbf{x}_w \\ 1 \end{bmatrix} & (43) \end{aligned}$$

where

$$\begin{aligned} \mathbf{M} &= \left(\begin{bmatrix} \mathbf{P} \\ \mathbf{n}_f^\top \quad d_f \end{bmatrix} - t\Delta \begin{bmatrix} \mathbf{0}_{4\times 3} & \mathbf{a} \end{bmatrix} \right) & (44) \\ \mathbf{a} &= \begin{bmatrix} \mathbf{KR} \\ \mathbf{n}_f^\top \end{bmatrix} \mathbf{m} & (45) \end{aligned}$$

By subtracting the third row multiplied by x_i from the first, and the third row multiplied by y_i from the second, (43) is reduced to three equations which do not contain λ. These can be rearranged into two independent sets of equations in the linear model parameters (one for the camera and one for the laser plane).

$$\begin{bmatrix} x_w & y_w & z_w & 1 & 0 & 0 & 0 & 0 & -x_i x_w & -x_i y_w & -x_i z_w & -x_i & -t\Delta & 0 & t\Delta x_i \\ 0 & 0 & 0 & 0 & x_w & y_w & z_w & 1 & -y_i x_w & -y_i y_w & -y_i z_w & -y_i & 0 & -t\Delta & t\Delta y_i \end{bmatrix} \mathbf{l}_1 = 0 \tag{46}$$

$$\begin{bmatrix} x_w & y_w & z_w & 1 & -t\Delta \end{bmatrix} \mathbf{l}_2 = 0 \tag{47}$$

where

$$\mathbf{l}_1 = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{21} & p_{22} & p_{23} & p_{24} & p_{31} & p_{32} & p_{33} & p_{34} & a_1 & a_2 & a_3 \end{bmatrix}^\top \tag{48}$$

$$\mathbf{l}_2 = \begin{bmatrix} n_1 & n_2 & n_3 & d & a_4 \end{bmatrix}^\top \tag{49}$$

These can be used to solve for the unknown calibration parameters as shown in the following sections. Note that these are linear in the parameters a_i but not in the original parameters m_i.

3.4.1 Camera Parameters

Let $\mathbf{A}_1$ be the $2N \times 15$ matrix formed by stacking (46) for each of the available data points one above the other, given that there are N fiducial marks. Thus, the estimate for the parameters $\mathbf{l}_1$ is the solution to

$$\min_{\mathbf{l}_1} \|\mathbf{A}_1 \mathbf{l}_1\|^2 \tag{50}$$

subject to a constraint, say $\|\mathbf{l}_1\| = 1$, to avoid the trivial solution $\mathbf{l}_1 = 0$. The estimate of $\mathbf{l}_1$ is then the singular vector associated with the smallest singular value of $\mathbf{A}_1$ [14].

3.4.2 Laser Stripe Parameters

Let $\mathbf{A}_2$ be the $N \times 15$ matrix formed by stacking (47) for each of the available data points one above the other. Thus, the estimate for the parameters $\mathbf{l}_2$ is the solution to

$$\min_{\mathbf{l}_2} \|\mathbf{A}_2 \mathbf{l}_2\|^2 \tag{51}$$

subject to a constraint to avoid the trivial solution $\mathbf{l}_2 = 0$. The most natural constraint to impose is that the sum of squares for the first three components of $\mathbf{l}_2$ equal 1, since these represent the unit vector $\mathbf{n}_f$. If we define

$$\mathbf{B} = \begin{bmatrix} \mathbf{I}_3 & 0 \\ 0 & 0 \end{bmatrix} \tag{52}$$

then the estimate of $\mathbf{l}_2$ is the solution to

$$\min_{\mathbf{l}_2} \|\mathbf{A}_2 \mathbf{l}_2\|^2 \text{ subject to } \|\mathbf{B}\mathbf{l}_2\|^2 = 1 \tag{53}$$

This is a constrained minimisation of a quadratic form with quadratic constraints and has a solution as follows. Let

$$\mathbf{l}_{21} = \begin{bmatrix} n_1 & n_2 & n_3 \end{bmatrix}^\top \tag{54}$$

$$\mathbf{l}_{22} = \begin{bmatrix} d & a_4 \end{bmatrix}^\top \tag{55}$$

so that $\mathbf{l}_2 = \begin{bmatrix} \mathbf{l}_{21} & \mathbf{l}_{22} \end{bmatrix}^\top$. Let $\mathbf{A}_{21}$ be the first three columns of $\mathbf{A}_2$ and let $\mathbf{A}_{22}$ be the last two columns. Define

$$\mathbf{C} = \mathbf{A}_{21}^\top(\mathbf{I}_N - \mathbf{A}_{22}(\mathbf{A}_{22}^\top\mathbf{A}_{22})^{-1}\mathbf{A}_{22}^\top)\mathbf{A}_{21} \tag{56}$$

Then, $\mathbf{l}_{21}$ is the eigenvector of $\mathbf{C}$ associated with the smallest eigenvalue of $\mathbf{C}$, and $\mathbf{l}_{22}$ is given by

$$\mathbf{l}_{22} = -(\mathbf{A}_{22}^\top\mathbf{A}_{22})^{-1}\mathbf{A}_{22}^\top\mathbf{A}_{21}\mathbf{l}_{21} \tag{57}$$

3.5 Recovery of Intrinsic and Extrinsic Parameters

The previous two sections show how the parameters $\mathbf{P}$, $\mathbf{n}_f$, d_f, and a_i can be estimated from calibration target data. Standard techniques are available to decompose $\mathbf{P}$ into the camera extrinsic parameters $\mathbf{R}$ and $\mathbf{t}$, and the camera intrinsic parameters s_x, s_y, k, c_x, and c_y.

The remaining system parameter is the motion direction $\mathbf{m}$. This satisfies (45), from which $\mathbf{m}$ can be estimated using the puesdo-inverse.

4 Summary and Conclusions

In this paper, a nonlinear least squares based method for calibrating a laser stripe profiling system has been presented. A non-linear model of the system is used, which allows for radial distortion in the camera lens. A calibration target consisting of a set of planar surfaces is used. An explicit function for the error in the stripe observations off this target is developed. This is then used in a non-linear least squares algorithm. A separate linear calibration method is used to generate initial estimates of the system parameters.

A number of areas have been identified for future work. The use of centroid estimates in the preliminary calibration phase is a major source of errors. They will be replaced with corner features, and ultimately, a linear calibration method that uses the same raw data as the non-linear phase. Another useful step will be to incorporate the relative position of the planar faces into the set of unknown system parameters, which will mean that an expensive calibration target will be unnecessary. The extension of the technique to using an arbitrary surface via ray-tracing will also be investigated.

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