# Calibration of Wrist-Mounted Profile Laser Scanning Probe using a Tool Transformation Approach (RAAD 2009) 

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#### Abstract

This paper describes a method for calibrating a 3D laser scanning device mounted on the wrist of a 6 -DOF robot arm, by computing a tool transformation for the laser sensor reference frame. The calibration procedure involves scanning a spherical object fixed in the robot workspace, and it makes possible aligning many individual scans taken from different orientations. Another advantage of this approach is that further applications are made possible, such as using the laser sensor for accurate robot guidance and alignment.


Keywords. 3D scanning, sensor calibration, tool transformation

## 1. Introduction

This article presents a technique for calibrating a 2D laser profile sensor mounted on the arm of a 6-DOF robot arm in order to be able to reconstruct 3D models of existing parts from range data. An overview for the scanning system is presented in Fig. 1. This approach will consider that the laser probe is the tool used by the robot arm, and therefore it will compute a tool transformation so that all the contour data from the profile sensor can be expressed in the reference frame of the robot.


Fig. 1. Overview of the laser scanning system

In a previous paper (Borangiu et al., 2008a), there was presented a calibration method for the $7^{\text {th }}$ degree of freedom of the scanning system, which is the rotary table holding the scanned part. However, it was assumed that the transformation matrix between the robot wrist and the laser probe is already known, which was not true in practice. This paper focuses on the method for determining the tool transformation for the laser sensor, which includes the orientation and the tool center point.

The data from the laser sensor is a set of unorganized 2D points, which can be mapped to the 3D reference frame of the laser sensor by considering $X=0, Y=x_{2 \mathrm{~d}}$ and $Z=y_{2 \mathrm{~d}}$. The scanned data has to be aligned into a common 3D reference frame, which is attached to the object of interest, and this is done using the alignment equation. This equation premultiplies the laser measurements with the following matrix equation:

$$
\begin{equation*}
T_{\text {align }}=T_{L}^{R}=T_{0}^{R}\left(\theta_{R}\right) \cdot T_{6}^{0}\left(\theta_{1 \ldots 6}\right) \cdot T_{6}^{L} \tag{1}
\end{equation*}
$$

where $T_{6}^{0}$ represents the direct kinematics of the robot arm (Spong, 2005), $T_{0}^{R}$ is the transform between the table and the robot, and $T_{L}^{6}$ (also called $\left.T_{L}^{W}\right)$ is the transform from the robot wrist to the field of view (FOV) of the sensor $X_{L} Y_{L} Z_{L}$ (Fig. 2).


Fig. 2. Tool transformation for the laser probe.
The direct kinematics function of the robot was considered ideal, and there are two transformation matrices that are determined using two calibration procedures:

- robot - laser probe calibration
- robot - rotary table calibration

The calibration between the robot and the table was presented in detail in (Borangiu et al., 2008a), and this paper will only address the robot - laser probe calibration.

The software which controls the laser probe has a calibration routine for the linear stages of the scanning system ( $X, Y$ and $Z$ ), which is performed using a tooling ball placed in the workspace, in a fixed, but not precisely known position. The laser sensor is translated over the tooling ball, scanning with a sweeping motion. The acquired data is then fitted to a sphere, and its center is computed and used for calibration. The sphere is placed in various locations in the field of view (FOV) of the laser probe; for determining the orientation of the FOV, at least 3 locations are needed. For better accuracy, a higher number of locations is used (by default 9), because the errors will be averaged, increasing the accuracy of the calibration.

Aside from the orientation, this procedure, which is named ball matching, computes also the parameters for internal calibration of the sensor itself, which include the offsets between the two cameras, the scaling factor and also a nonlinear (quadratic) correction for the 3D data.

This method of calibration does not compute the origin of the sensor reference frame; only its orientation is determined. However, because the implementation of this method is mature, stable and provides good results, the calibration process will not
be rewritten from scratch; instead, the existing method will be reused. Therefore, the first step of the calibration will be executed using the existing ball matching method, but the calibration results will have a slightly different interpretation. A second calibration step will be necessary in order to determine the origin of the sensor, i.e. the cartesian offsets $d x, d y$ and $d z$.

## 2. Calibration equations

The procedure for finding the TCP (tool center point) $P=\left(x_{P} ; y_{P} ; z_{P}\right)$ is presented by (Hallenberg, 2007). The user has to teach at least 3 robot locations, $L^{(1)} \ldots L^{(n)}$, with $n \geq 3$, by placing the tool tip in the same physical location, with different orientations. The method will find the point which has the same World coordinates, when expressed in the tool reference frames for the taught robot locations.
The point $P$ can be expressed in World reference frame using:

$$
\begin{gather*}
P_{W}^{(1)}=L_{1} P \\
\vdots  \tag{2}\\
P_{W}^{(n)}=L_{n} P
\end{gather*}
$$

Since all points $P_{W}^{(i)}, i=1: n$, represent the same physical location, which is unknown to the calibration routine, the conditions for finding the tool center point $P$ become:

$$
\begin{equation*}
P_{W}^{(i)}=P_{W}^{(j)}, \forall i \neq j \tag{3}
\end{equation*}
$$

If 3 locations are taught, the point $P$ can be can be computed by solving linear system $A x=b$. Eq (2) and (3) will be rewritten using homogeneous transforms as:

$$
P_{W}=\left[\begin{array}{c}
x_{W}  \tag{4}\\
y_{W} \\
z_{W} \\
1
\end{array}\right]=\left[\begin{array}{cc}
R^{(i)} & T^{(i)} \\
0 & 1
\end{array}\right]\left[\begin{array}{c}
x_{P} \\
y_{P} \\
z_{P} \\
1
\end{array}\right]
$$

where $R^{(i)}$ and $T^{(i)}$ are the rotation and translation components of $L^{(i)}$ :

$$
R^{(i)}=\left(r_{i j}\right), i=1: 3, j=1: 3, \text { and } \quad T^{(i)}=\left[\begin{array}{c}
x_{L}^{(i)}  \tag{5}\\
y_{L}^{(i)} \\
z_{L}^{(i)}
\end{array}\right]
$$

Decomposing the rotation and translation, Eq. (4) is rewritten as:

$$
P_{W}=\left[\begin{array}{c}
x_{W}^{(i)}  \tag{6}\\
y_{W}^{(i)} \\
z_{W}^{(i)}
\end{array}\right]=R^{(i)}\left[\begin{array}{l}
x_{P} \\
y_{P} \\
z_{P}
\end{array}\right]+\left[\begin{array}{c}
x_{L}^{(i)} \\
y_{L}^{(i)} \\
z_{L}^{(i)}
\end{array}\right]
$$

Since $P_{W}$ is an unknown, but its value is not required in the calibration process, only $P=\left(x_{P} ; y_{P} ; z_{P}\right)$ will be computed. Therefore, from Eq.(6) for $i=1$, will be subtracted Eq.(6) for $i=2$ and $i=3$, multiplied by 0.5 , in order to remove the $P_{W}$ term. The result is:

$$
\left(R^{(1)}-\frac{R^{(2)}+R^{(3)}}{2}\right)\left[\begin{array}{l}
x_{P}  \tag{7}\\
y_{P} \\
z_{P}
\end{array}\right]=-\left(T^{(1)}-\frac{T^{(2)}+T^{(3)}}{2}\right)
$$

which is a $3 \times 3$ linear system in $A x=b$ format.
If the calibration is performed with more than three points, Eq. (3) can be solved in a least squares sense (Dumitrescu, 2006), or it can be regarded as a minimization problem. A possible quadratic criteria for minimization is:

$$
\begin{equation*}
e=\operatorname{var}\left[x_{W}^{(1 \ldots . . n)}\right]+\operatorname{var}\left[y_{W}^{(1 . . n)}\right]+\operatorname{var}\left[z_{W}^{(1 . . n)}\right] \tag{8}
\end{equation*}
$$

where $\operatorname{var}(a)$ is the variance of $a$ :

$$
\begin{equation*}
\operatorname{var}\left[a^{(1 . . n)}\right]=\sum_{i=1}^{n}\left[a^{(i)}-a_{m}\right]^{2} \tag{9}
\end{equation*}
$$

and $a_{m}$ is the arithmetic mean of $a$.
For the laser calibration problem, the $n \geq 3$ robot locations are also taught using the ball matching method. If the ball is in the field of view, it will be seen as a circle having the radius less than or equal to the real radius $R$ of the ball, and the circle will be in the $Y Z$ plane of the tool coordinate system. The center of the circle in $Y Z$ can be determined easily, but the $X$ coordinate is not known, since the laser plane does not intersect the center of the ball. The ball matching method will perform a sweep on the $X$ direction of the tool reference frame, from $-R$ to $+R$ with respect to the current position, and from the 3D point cloud acquired, the center of the ball can be computed by a sphere fitting procedure (Fig. 3).


Fig. 3. Sphere identification and fitting from 3D point cloud data.

The sphere is fitted using the Riemann method, by projecting the data points on a 4D paraboloid, the result being a hyperplane. A similar method was presented in (Frühwirth et.al, 2003) for fitting a
circle, and it was straightforward to extend the method for fitting the sphere. This method is advantageous because the hyperplane fitting problem is linear, and can be solved by well-known robust fitting methods based on weighted least squares (Fox, 2002). The robust fitting method is iterative and slower than the classical least squares fitting technique, but the results (center and radius) are not affected by outliers in data.

## 3. Simulation results

The method for computing the tool center point from three or more robot locations taught with different orientations was simulated using ideal data affected by random Gaussian noise, employing a Monte Carlo approach for determining the standerd deviation of the estimation errors.

The first test used three simulated robot locations, the first one being vertical and downlooking, the second being rotated around $X$ with an angle $\alpha$, and the third one rotated around $Y$ with the same angle $\alpha$. The position of the three taught locations was altered with a Gaussian noise on each axis, having a standard deviation of $\sigma=0.1 \mathrm{~mm}$, zero mean and zero cross-correlation. The orientation of the locations was not altered.


Fig. 4. Estimated standard deviation of the translation errors in the tool transformation, for the three axes.

The error function was considered the difference between the ideal and estimated position of the Tool transformation. The ideal position was chosen $(60,10,200)$, which is very close to the actual (physical) position. Using the Monte Carlo approach, for each constant value of $\alpha, 200$ tests were performed, from which the standard deviation of the error was estimated for each axis ( $X, Y$ and $Z$ ).

The conclusion from this simulation is that the angle between the $Z$ axes of any two robot locations used for calibration has to be higher than $45 \square$, if only 3 points are used, since for lower values the accuracy decreases rapidly, and for higher values there are no significant gains. Also, the error is biased, so the position on the $Z$ axis has the least standard deviation. Further experiments revealed that the bias is heavily dependent on the set of orientations used for calibration, so a balanced solution should include more than 3 points, which cover the entire range of orientations which will be used in the application.

## 4. Experimental results

The calibration routine has been implemented successfully on the scanning system, and it allows scanning the parts with any orientation of the laser sensor that can be achieved physically with the mechanical setup. The scanning procedure can be completed in two modes:

- The laser probe follows a complex 3D path, changing simultaneously the position and orientation.
- The laser probe follows a sequence of simple linear sweep motions (scan passes), keeping its orientation constant. The orientation is changed before beginning the next scan pass.


Fig. 5. Reconstruction of a decorative object
(a) - photography; (b), (c), (d) - scans from different orientations; (e) - the scans merged into a single mesh; (f) - 3D surface model created using the Poisson filter in MeshLab.

While the second approach is simpler to implement, the first method is more elegant, but also more complex, and it requires a very high absolute accuracy for the mechanical subsystem that moves the laser sensor. Since in the current setup, a vertical robot arm was used, and its kinematic structure has only rotary joints, the transformation to Cartesian space is performed using the direct and inverse kinematics routines. They are nonlinear functions,
and may introduce nonlinear errors if the physical kinematic model of the robot has slightly different parameters, with respect to the nominal (ideal) values, and the calibration method presented in this paper does not account for nonlinearities. Therefore, it is expected that the calibration method will be better suited to a Cartesian mechanical structure, such as a coordinate measurement machine (CMM) with a 3-DOF spherical wrist.

The best results were obtained using the second approach, with many scan passes, each pass maintaining constant orientation. The result of every scan pass is a point cloud, and the point clouds obtained from all the scan passes are already almost aligned, with very small differences, i.e. up to 0.5 mm distance between two overlapping surfaces. These differences are corrected using the Iterative Closest Point (ICP) algorithm, and the method was successfully tested using the open-source mesh processing software MeshLab. An example of reconstruction of a small decorative object is presented in Fig. 5.

While it is true that the alignment of individual meshes is still not perfect, it provides a good initialization for the ICP algorithm, very close to the optimal result, and the user is not required to manually align the meshes before executing the automatic alignment procedure.

## 5. Other applications of the calibration method

The calibration method presented in this paper has a much wider applicability in other tasks, different from 3D reconstruction using the laser scanner. For example, the laser probe can be used as a highly accurate distance sensor, which can be used for delicate tasks such as manipulating very small parts, or as a tool for teaching robot locations with high accuracy.

The simplest application is learning a reference frame for a tilted plane on which the robot has to work. Instead of manually teaching at least 3 robot locations on the tilted plane, the laser sensor can be used as a distance sensor in order to teach the location with an automatic procedure.

A more complex application involves 3D path following around a given workpiece, when the 3D data is not available. The 3D path is defined along an edge of the workpiece (e.g. Fig. 6), which can be identified by the laser sensor. The robot has to move a tool along the edge of the workpiece in order to perform various technological operations, such as sealant dispensing, edge deburring, or welding.

After the user teaches the edge model into the vision software, the robot uses the laser sensor in order to automatically identify the 3D path, adjusting its position and orientation, and learning the trajectory with a resolution specified by the user, e.g. 1 mm . After the trajectory is learned, since the tool transformation for the sensor is known, the locations
are expressed in the robot's reference frame. Therefore, the robot can use the tool specific to the technological operation needed, change the tool transformation matrix to the one for the physical tool, and replay the learned path with high accuracy.


Further applications with the laser sensor are possible using the tool transformation defined. For example, since the laser sensor can measure distances with very high accuracy (tens of micrometers or even micrometers for very short range devices), the sensor can be used for robot guidance in order to manipulate very small parts and to perform precise operations. Another possibility is to use the laser sensor for guiding the robot along a visible edge of an existing part, in order to learn and follow a complex 3D path, even if a CAD model for the part is not available.

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The 3D data was postprocessed using MeshLab, an open-source tool developed by the VCG group with the support of the Epoch NOE.

Fig. 6. Sample 3D path following problem.
The 3D contour learning and following application is presented in detail in (Borangiu, 2009).

## 6. Conclusions

This article presented a calibration method for a wrist-mounted laser scanning probe, which is able to reconstruct 3D surfaces of existing objects by having a 6-DOF robot arm move the probe around the objects with different orientations. The method computes a tool transformation which moves the tool center point of the robot in the origin of the laser's field of view and aligns the axes of the wrist reference frame to the ones of the laser sensor, thus making possible for the data from the laser scanner to be expressed in the robot reference frame only by premultiplying it with the direct kinematics of the robot at the moment of the data acquisition.
Having the tool center point in the origin of the reference frame, the position of the laser sensor in the workspace is also much easier to control, since the user can move the probe on its own axis, i.e. $X$ is normal to the laser plane, and $Y-Z$ define the laser plane, with positive $Z$ approaching the scanned part. The rotations of the probe around the part can be performed either around the center of the laser's field of view, or around any point defined by the user, for example, the "center" of the data visible in the sensor. This is a big improvement to the usability of the scanning system, since the scanned part will remain visible while rotating the probe around it.

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