Calibration of Range Sensor Pose on Mobile Platforms

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Abstract—This paper describes a new methodology for calculating the translational and rotational offsets of a range sensor to a reference coordinate frame on the platform to which it is affixed. The technique consists of observing an environment of known or partially known geometry, from which the offsets are determined by minimizing the error between the sensed data and the known structure. Analytic results are presented which derive the necessary conditions for a successful optimisation. Practical results confirm the analysis and show that it is possible to obtain more precise results than those obtained through hand measurement.

I. INTRODUCTION

Range sensors (such as laser, radar and stereo vision), are used extensively in the field of robotics. Examples include constructing global terrain maps for obstacle avoidance, [1] and [2], globally locating features that are detected in the local sensor frame, [3] and localisation. Three dimensional maps are produced in [4] to aid in indoor robot localisation and more generally, implementations of Simultaneous Localisation and Mapping (SLAM) often use range measurement devices. In all of these examples it is critical that the sensor data be transformed from a local sensor-centric coordinate frame to a body fixed coordinate frame. The expedient solution to this problem is simply to measure the translational and rotational offsets between the two coordinate frames by hand. As will be shown in Section II, small errors in these measurements can lead to large errors in the transformed data.

It is often infeasible to accurately measure the rigid transformation between frames directly. This has been addressed in the literature in various ways. The mounting position of a laser is determined for a legged robot in [5]. The robot’s own leg is measured by the laser and compared to the kinematic calculation of the leg position. This solution is not generally applicable because it requires a part of the platform to be visible to the sensor. In [6] a laser is mounted on a movable arm. The mount point in the arm frame is found by observing a fixed plane in an unknown location. To achieve this, it uses precise control of the arm through six degrees of freedom. For the similar problem addressed by this paper, six degrees of freedom are not always available and the position of the platform is not known with such high precision. Other examples of observing planes are common for calibration. In [7] planes are observed by a camera and a laser to determine the rigid body transform between them.

To achieve this, it uses precise control of the arm through six degrees of freedom. For the similar problem addressed by this paper, six degrees of freedom are not always available and the position of the platform is not known with such high precision. Other examples of observing planes are common for calibration. In [7] planes are observed by a camera and a laser to determine the rigid body transform between them. With the sensing apparatus fixed, six degrees of freedom are used in the placement of the plane. The uncertainty due to the transformation is modeled in [2], which also mentions the possibility of reducing errors by matching data to known features, but does not describe a technique.

In this paper, the mobile platform moves through a known environment, observing it from multiple points of view. An optimisation is performed to adjust the sensor position variables to match the reconstructed data to the environment.

This paper is organised as follows: Section II describes the geometry and transformations involved in fusing the range sensor and navigation data. Section III describes the optimisation, including the theoretical reliability and requirements of the technique. Finally Section IV concludes with practical results for multiple different configurations.

II. GEOMETRY AND TRANSFORMATIONS

A. Notation and Coordinate Frames

A typical platform and sensor configuration is shown in Figure 1. The global navigation cartesian coordinate frame $n$ is fixed to a point on the earth. The $X^n$ axis is metres north of the origin, the $Y^n$ axis is metres to the east and the $Z^n$ axis is metres below the origin. The body (or platform) cartesian coordinate frame $b$ is fixed at some point on the mobile platform. For this frame, the $X^b$ axis points forward,
the \( Y^b \) axis points to the right and the \( Z^b \) axis points down. The sensor axis \( s \) is fixed to the range sensor and also has \( X^s \) forward, \( Y^s \) to the right and \( Z^s \) down. All of the coordinate frames are right handed. In this paper, a point in frame \( a \) is denoted as \( \mathbf{p}^a = [p_a^x, p_a^y, p_a^z]^T \). A rotation from frame \( a \) to frame \( b \) is described by the 3x3 rotation matrix \( C_{ab}^b \).

The range sensor returns a range and bearing measurement of \((r, \theta)\) in a polar coordinate frame centred at the cartesian sensor frame \( s \). The bearing \( \theta \) is defined as a positive angle around the \( Z^s \) axis of the sensor frame and a measurement of zero for \( \theta \) indicates the point is on the \( X^s \) axis. Sensor returns are transformed to a point in the cartesian sensor frame using trigonometry:

\[
\mathbf{p}^s = \begin{bmatrix}
    r \cos(\theta) \\
    r \sin(\theta) \\
    0
\end{bmatrix}
\]

(1)

This point is then transformed to the navigation frame via the body frame. With the sensor offset \( \mathbf{r}_{sens}^b \) (the location of the sensor in the body frame), the 3x3 sensor to body rotation matrix \( C_s^b \) and the vehicle pose \( C_n^b \) (rotation) and \( \mathbf{p}_{body}^n \) (location of body in navigation frame), the point coordinate in the navigation frame is given by:

\[
\mathbf{p}^n = C_n^b (C_s^b \mathbf{p}^s + \mathbf{r}_{sens}^b) + \mathbf{p}_{body}^n
\]

(2)

The optimisation in this paper is to determine the three offset components of \( \mathbf{r}_{sens}^b \) and the three euler angles \( \Phi \) that can be used to form the rotation matrix \( C_s^b \). The notation for these variables is

\[
\mathbf{r}_{sens}^b \equiv [ r_{sens,x}^b, r_{sens,y}^b, r_{sens,z}^b]^T
\]

\[
C_s^b \sim (\Phi_{roll}, \Phi_{pitch}, \Phi_{yaw})
\]

(3)

and for the body frame (required later):

\[
C_b^n \sim (\Psi_{roll}, \Psi_{pitch}, \Psi_{yaw})
\]

(4)

For clarity, the rotation is defined in natural terms of roll about the forward \( X \) axis, pitch about the right hand \( Y \) axis and yaw about the down \( Z \) axis. The order of the euler angles to produce \( C_b^n \) and \( C_b^b \) is yaw, pitch, roll.

**B. Effect of Poor Calibration**

It is obvious from Equation 2 that any error in the location of the sensor will propagate to the point \( \mathbf{p}^n \) in the navigation frame. It is trivial to show from expansion that for any of the three translational offset terms in \( \mathbf{r}_{sens}^b \), the error in \( \mathbf{p}^n \) is at worst equal to the error in offset. In most applications, the offset can be directly measured with sufficient accuracy. However, errors in angle \( \Phi \) are magnified by the range of the sensor returns. For a typical outdoor robot sensing ranges up to 60m, an error of one degree translates to a metre of error in the navigation frame.

Figures 2 and 3 illustrate the effects of inaccurate sensor pose measurement on global point cloud data. In Figure 2, an upright pole is viewed in passing and appears to be leaning.

In Figure 3, the same pole is observed from two passes and appears to be duplicated due to alignment errors. The maximum error of any given point is the same in both figures, but on the return journey the sign of the error is reversed. This doubles the apparent error for a global feature and causes problems when revisiting previously mapped areas. For the data in these figures, the sensor pose on the body frame was measured as accurately as was possible by hand. In Section IV it is shown that an error of only 2 degrees in yaw caused this distortion. If precise transformed data is required, the need for accurate calibration is clear.

**III. Optimisation**

This section describes the optimisation process to find optimal values for \( \mathbf{r}_{sens}^b \) and \( \Phi \). The procedure is as follows. A simple environment of known geometry is constructed.
The robot scans this environment and builds a set of 3D points \( \mathbf{P}^n = [\mathbf{p}_1^n, \mathbf{p}_2^n, \ldots, \mathbf{p}_N^n] \) using Equation 2. The error between the known geometry and the data is minimised using an optimisation with respect to the six sensor offset variables of \( r_{sens}^b \) and \( \Phi \).

A. The Constructed Environment

The approach taken in this paper is to use a simple environment, both in terms of algorithms and physical apparatus that is appropriate for successful optimisation. This is because calibration must be done each time the sensor configuration is changed due to remounting or repositioning. Further experimentation could be done to determine a more optimal structure.

A single vertical pole was placed on relatively flat ground, as can be seen in Figure 4. The base of the pole is perpendicular and no special equipment was used to place it. The pole was covered with a retro-reflective material, which is distinguishable from the ground by the SICK LMS-291 laser scanner used for the results in this paper. This enabled automatic segmentation of pole and ground data. Similar techniques may be possible for other sensors or the data could be manually segmented using an initial approximation for the sensor location.

B. The Environment-Data Similarity Equation

An equation for the similarity of the point cloud to the environment is required. The data is split into pole points \( \mathbf{P}_{pole}^n \) and ground points \( \mathbf{P}_{ground}^n \).

The similarity measure for \( \mathbf{P}_{pole}^n \), \( c_{pole} \), is defined to be the average squared perpendicular distance to the pole. The pole is assumed to be vertical so the equation is the average squared 2D distance of each pole point to the mean of the pole data.

\[
\begin{align*}
    c_{pole} &= \frac{\sum_i (P_{pole,x,i}^n - P_{pole,x}^n)^2}{N_{pole}} + \frac{\sum_i (P_{pole,y,i}^n - P_{pole,y}^n)^2}{N_{pole}} \\
    c_{pole} &= \sigma_{pole,x}^2 + \sigma_{pole,y}^2
\end{align*}
\]

where \( N_{pole} \) is the sample size and \( P_{pole,z}^n \) is the set of \( x \) coordinates in the point cloud \( \mathbf{P}_{pole}^n \). This is the sum of the variances of the two non-vertical dimensions of the pole data.

The similarity measure for \( \mathbf{P}_{ground}^n \), \( c_{ground} \), is defined to be the average squared distance to the ground plane. This is assumed to be horizontal, so the equation is the average squared 1D distance of each ground point to the mean of the ground data.

\[
    c_{ground} = \frac{\sum_i (P_{ground,x,i}^n - P_{ground,x}^n)^2}{N_{ground}}
\]

This is the variance of the vertical dimension of the ground data. Finding optimal values for the sensor pose is equivalent to minimising the cost function:

\[
    c = \sigma_{pole,x}^2 + \sigma_{pole,y}^2 + \sigma_{ground,z}^2
\]

This can be be minimised through optimisation of the six scalar values in \( \Phi \) and \( r_{sens}^b \) from Equations 2 and 3. The optimisation technique is described in Section III-D.

C. Parameter Sensitivity

In this section a simple sensitivity analysis is performed to determine how successful the optimisation is likely to be for the six parameters. The specific case that the platform is constrained to the ground plane (as is the case for most ground vehicles) is considered. This restricts the roll and pitch of the vehicle to zero:

\[
\begin{align*}
    \sin(\Psi_{roll}) &= \sin(\Psi_{pitch}) = 0 \\
    \cos(\Psi_{roll}) &= \cos(\Psi_{pitch}) = 1
\end{align*}
\]

While considering this constraint it is assumed that data is obtained from varying yaw and theta angles. This means the data is obtained with a scanning range sensor and the vehicle observes the environment from different headings. It is shown here that with the ground plane constraint, it is possible to determine \( \Phi, r_{sens,x}^b \), and \( r_{sens,y}^b \), but that \( r_{sens,z}^b \) requires non-zero platform roll or pitch. It will also be shown that only the pole data is strictly required.

The optimisation will work well if there are non-trivial partial derivatives of the cost function with respect to the parameters of interest. This cost function depends on the data \( \mathbf{P}^n \), so the derivatives are different for any specific set of data.

For a single sensor return, consider the partial derivative \( \frac{\partial c}{\partial p_i} \) of the coordinate \( p_i^n \) with respect to some parameter \( f \). If it is trivial for all platform angles \( \Psi \) and scan angles \( \theta \), changing \( f \) will not affect the point cloud. If \( \frac{\partial c}{\partial f} \) is constant for all \( \Psi \) and \( \theta \), the entire point cloud will move together, with constant variance. For the optimisation to perform as desired for parameter \( f \), a vehicle pose and sensor return is required that yields:
\[
\frac{\partial p^n}{\partial f} \neq 0, \quad \forall \Psi, \exists \theta, \forall \Phi, \forall r_{sens}^n \nonumber
\]
\[
\frac{\partial^2 p^n}{\partial f \partial \Psi} \neq 0, \quad \exists \theta, \forall \Phi, \forall r_{sens}^n \tag{9}
\]

The partial derivatives for \( r_{sens}^b \) are calculated by expanding Equation 2. Cos and sin are abbreviated to \( c \) and \( s \); roll, pitch and yaw are abbreviated to \( r \), \( p \) and \( y \) respectively:

\[
\frac{\partial p^n}{\partial r_{sens,X}} = \cos(\Psi_{yaw}) \cos(\Psi_{pitch}) \nonumber
\]
\[
\frac{\partial p^n}{\partial r_{sens,Y}} = \sin(\Psi_{yaw}) \cos(\Psi_{pitch}) \nonumber
\]
\[
\frac{\partial p^n}{\partial r_{sens,Y}} = -\sin(\Psi_{pitch}) \nonumber
\]
\[
\frac{\partial p^n}{\partial r_{sens,Z}} = -s(\Psi_y)c(\Psi_r) + c(\Psi_y)s(\Psi_p)s(\Psi_r) \nonumber
\]
\[
\frac{\partial^2 p^n}{\partial r_{sens,Y}} = c(\Psi_y)c(\Psi_r) + s(\Psi_y)s(\Psi_p)s(\Psi_r) \nonumber
\]
\[
\frac{\partial^2 p^n}{\partial r_{sens,Z}} = \cos(\Psi_{pitch}) \sin(\Psi_{roll}) \nonumber
\]
\[
\frac{\partial^2 p^n}{\partial r_{sens,X}} = \sin(\Psi_{yaw}) \cos(\Psi_{pitch}) \nonumber
\]
\[
\frac{\partial^2 p^n}{\partial r_{sens,Z}} = \cos(\Psi_{pitch}) \cos(\Psi_{roll}) \nonumber
\]
\[
\tag{10}
\]

With the ground plane constraint in Equation 8 substituted into Equation 10 above, \( r_{sens,Z}^b \) fails the requirements in Equation 9. So \( r_{sens,Z}^b \) can only be determined if the vehicle undergoes some roll or pitch. This makes intuitive sense; if the vehicle is limited to a planar surface, changing the \( z \) offset will move the entire point cloud up or down. Also of interest is that the partial derivatives of \( r_{sens,X}^b \) and \( r_{sens,Y}^b \) with respect to \( z \) are zero in this case, so the calibration of these offsets can be achieved using the pole data, independent of the ground data.

The same process can be applied to the sensor pitch.

\[
\frac{\partial p^n}{\partial \Psi_{pitch}} = \nonumber
\]
\[
-\cos(\Psi_y) \cos(\Psi_p) \cos(\Phi_p) \sin(\Phi_p) r \cos(\theta) \nonumber
\]
\[
+ \cos(\Psi_y) \cos(\Psi_p) \cos(\Phi_p) \cos(\Phi_p) \sin(\Phi_p) r \sin(\theta) \nonumber
\]
\[
+ \sin(\Psi_y) \cos(\Psi_p) \sin(\Phi_p) \cos(\Phi_p) \sin(\Phi_p) r \cos(\theta) \nonumber
\]
\[
- \sin(\Psi_y) \cos(\Psi_p) \sin(\Phi_p) \cos(\Phi_p) \sin(\Phi_p) r \sin(\theta) \nonumber
\]
\[
- \cos(\Psi_y) \sin(\Psi_p) \sin(\Phi_p) \sin(\Phi_p) r \cos(\theta) \nonumber
\]
\[
- \cos(\Psi_y) \sin(\Psi_p) \cos(\Phi_p) \sin(\Phi_p) r \sin(\theta) \nonumber
\]
\[
+ \cos(\Psi_y) \sin(\Psi_p) \sin(\Phi_p) \cos(\Phi_p) \sin(\Phi_p) r \sin(\theta) \nonumber
\]
\[
\tag{11}
\]

Subject to the ground plane constraint in Equation 8, only the first four lines of Equation 11 and the first two lines of Equation 12 remain.

The dependence of \( \frac{\partial p^n}{\partial \Psi_{pitch}} \) on \( \Psi_{yaw} \) means it satisfies Equation 9; varying platform heading will alter the derivative. If any of the sensor angles cause \( \frac{\partial p^n}{\partial \Psi_{pitch}} \) to become trivial, the optimisation will not perform well for pitch with just the pole data. Only one of the partial derivatives of \( x \) or \( y \) is needed as they only differ by the sign of the platform angles \( \Psi \). Analysing Equation 11 provides a list of sensor configurations that will work for pitch, shown in Tables I and II. In these tables, if the sensor angles \( \Phi \) conform to the logic in any row, then \( \Phi_{pitch} \) can be calibrated successfully. Conversely, Table III shows the only configuration that cannot yield successful calibration of \( \Phi_{pitch} \).

**Table I**

<table>
<thead>
<tr>
<th>Sensor Configuration Required for Calibration of Sensor Pitch</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Phi_{roll} )</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>( \neq 0 )</td>
</tr>
<tr>
<td>any</td>
</tr>
</tbody>
</table>

**Table II**

<table>
<thead>
<tr>
<th>Condensed Requirement for Calibration of Sensor Pitch</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Phi_{roll} )</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>( \neq 0 )</td>
</tr>
<tr>
<td>any</td>
</tr>
</tbody>
</table>

**Table III**

<table>
<thead>
<tr>
<th>Unique Failing Configuration for Calibration of Sensor Pitch</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Phi_{roll} )</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>0</td>
</tr>
</tbody>
</table>

The same process applied to \( \frac{\partial p^n}{\partial \Phi_{roll}} \) shows roll calibration fails under the same unique condition as pitch. There is no failing configuration for yaw. With zero sensor roll and pitch, the partial derivatives of \( Z \) are non-trivial, but it is impossible to obtain ground data with a sensor mounted parallel to the ground plane. In this case, \( \Phi_{roll} \) and \( \Phi_{pitch} \) can be constrained to zero in the optimisation, allowing the other parameters to be determined.

It has been shown that the pole data is sufficient to determine all parameters other than \( r_{sens,Z}^b \). The only way to determine this is for the platform to undergo non-zero roll or pitch while observing the pole (or the ground if that data is used). Despite not being strictly required, use of the ground
data is recommended for practical reasons. It is easier to
gather large data sets from a wider range of roll and pitch if
the ground is included.

Success in this analysis relies on the assumption that the
sensor scans through $\theta$ and that the platform has either six
degrees of freedom or is constrained to the ground plane.
Other specific constraints may be present in a particular
application. (For example a wall climbing robot may be
constrained to a different plane, or a non-scanning laser may
be used). The general process shown here can be used to
calculate requirements for any such configurations and the
calibration method can still be used.

D. Numerical Optimisation

The cost function in Equation 7 uses the point cloud
data generated from Equation 2. The goal of the numerical
optimisation is to choose values for the sensor location
variables $\Phi$ and $r_{sens}^b$ such that the final output of Equa-
tion 7 is minimised. Once collected, the range sensor and
navigation data remain constant in their local frames. Each
time a change is made to $\Phi$ or $r_{sens}^b$, the point cloud must
be recalculated with Equation 2 and the cost recalculated
with Equation 7. A sequential quadratic programming (SQP)
method implemented in [8] is used for the numerical opti-
misation.

E. Summary of Experimental Method

1) Place a pole and gather range sensor and navigation
data from different points of view.
2) Segment the data into two groups. One for the pole
and one for a flat ground region.
3) Combine Equations 2, 3 and 7 to produce the complete
cost function.
4) Numerically minimise the output of the cost function
with respect to $\Phi$ for $C_b$ and $r_{sens}^b$ from Equation 2.
5) The final values for $\Phi$ and $r_{sens}^b$ can be used for all
future data provided the geometric configuration does
not change.

IV. RESULTS

The range sensor used in the tests is a SICK LMS-291
2D laser range scanner, configured with a maximum range
of $80m$ and $\pm 50^\circ$ and a resolution of $1cm$ and $0.25^\circ$.
The navigation system is a Novatel Synchronized Position
Attitude Navigation (SPAN) system that combines global
positioning (GPS), an inertial measurement unit (IMU) and
differential GPS corrections. This equipment is mounted on
an unmanned ground vehicle (UGV) as shown in Figure 1.

A large set of data (over 415,000 samples) was gathered
and the optimisation was run to produce the optimal sensor
pose. The experiment was repeated using only the pole data
and with both the pole and ground data. The results are sum-
marrised in Table IV. The optimised results are similar with
or without the ground plane data $P_{ground}$, confirming that the
pole geometry is sufficient for calibration. This is expected
from the analysis in Section III-C. The optimised values are
similar to the measured values, but with approximately 2
degrees difference in yaw, which was not measurable by
hand. The resulting cost metric is substantially reduced, from
an error standard deviation of $12cm$ down to $3cm$. Figure 5
shows the 3D data from the hand measured sensor pose and
Figure 6 shows the same data after calibration. The optimised
pose has clearly reduced the error in the reconstructed 3D
point cloud.

In the analysis of Section III-C, several requirements
on the data were given, but the analysis did not show how much
data would be needed for successful calibration. To empirically
determine how much data is required, the optimisation was run on different sized random sub-sections
of the complete data-set. To ensure that the assumption of
multiple viewing angles was not violated, random selections
of points were taken from every 30 degree slice of platform
yaw $\Phi_{yaw}$. The resulting pose from each subset was then
used to calculate the cost metric in Equation 7 for all the
data. The results are shown in Table V and a plot of the cost
metric for increasing amounts of data is shown in Figure
7. Ideally an infinite quantity of data would be used for
TABLE IV
MEASURED AND OPTIMISED SENSOR POSE

<table>
<thead>
<tr>
<th>$N_{samples}$</th>
<th>Cost</th>
<th>$r^b_1$ (m)</th>
<th>$r^b_2$ (m)</th>
<th>$r^b_3$ (m)</th>
<th>$\Phi_y$ (°)</th>
<th>$\Phi_p$ (°)</th>
<th>$\Phi_r$ (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measured</td>
<td>415447</td>
<td>0.1161</td>
<td>0</td>
<td>$-0.359$</td>
<td>1.0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Optimised (pole + ground)</td>
<td>415447</td>
<td>0.0305</td>
<td>$-0.029$</td>
<td>$-0.360$</td>
<td>$-0.996$</td>
<td>$-2.017$</td>
<td>$-8.182$</td>
</tr>
<tr>
<td>Optimised (pole)</td>
<td>22506</td>
<td>0.0355</td>
<td>$-0.025$</td>
<td>$-0.357$</td>
<td>$-0.997$</td>
<td>$-2.070$</td>
<td>$-8.496$</td>
</tr>
</tbody>
</table>

$N_{samples}$ is the total number of samples in the set. Cost is the cost metric in Equation 7, calculated for the sensor pose shown in the table.

TABLE V
OPTIMISED SENSOR POSE FOR SUB-SECTIONS OF POLE AND GROUND DATA

<table>
<thead>
<tr>
<th>$N_{samples}$</th>
<th>Cost</th>
<th>$r^b_1$ (m)</th>
<th>$r^b_2$ (m)</th>
<th>$r^b_3$ (m)</th>
<th>$\Phi_y$ (°)</th>
<th>$\Phi_p$ (°)</th>
<th>$\Phi_r$ (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>215</td>
<td>0.0421</td>
<td>0.016</td>
<td>$-0.373$</td>
<td>$-1.022$</td>
<td>$-1.228$</td>
<td>$-7.796$</td>
<td>$-0.099$</td>
</tr>
<tr>
<td>428</td>
<td>0.0389</td>
<td>0.012</td>
<td>$-0.351$</td>
<td>$-1.003$</td>
<td>$-1.544$</td>
<td>$-8.767$</td>
<td>$-0.309$</td>
</tr>
<tr>
<td>1056</td>
<td>0.0378</td>
<td>0.009</td>
<td>$-0.348$</td>
<td>$-1.005$</td>
<td>$-1.615$</td>
<td>$-8.617$</td>
<td>$-0.278$</td>
</tr>
<tr>
<td>2072</td>
<td>0.0355</td>
<td>$-0.007$</td>
<td>$-0.349$</td>
<td>$-1.002$</td>
<td>$-1.706$</td>
<td>$-8.659$</td>
<td>$-0.293$</td>
</tr>
<tr>
<td>4072</td>
<td>0.0338</td>
<td>$-0.013$</td>
<td>$-0.344$</td>
<td>$-0.997$</td>
<td>$-1.831$</td>
<td>$-8.973$</td>
<td>$-0.344$</td>
</tr>
<tr>
<td>10064</td>
<td>0.0336</td>
<td>$-0.018$</td>
<td>$-0.345$</td>
<td>$-0.992$</td>
<td>$-1.839$</td>
<td>$-8.892$</td>
<td>$-0.322$</td>
</tr>
<tr>
<td>17979</td>
<td>0.0327</td>
<td>$-0.021$</td>
<td>$-0.342$</td>
<td>$-0.979$</td>
<td>$-1.937$</td>
<td>$-8.890$</td>
<td>$-0.382$</td>
</tr>
<tr>
<td>56350</td>
<td>0.0309</td>
<td>$-0.026$</td>
<td>$-0.360$</td>
<td>$-0.994$</td>
<td>$-1.972$</td>
<td>$-8.381$</td>
<td>$-0.464$</td>
</tr>
<tr>
<td>90864</td>
<td>0.0306</td>
<td>$-0.028$</td>
<td>$-0.363$</td>
<td>$-0.995$</td>
<td>$-2.011$</td>
<td>$-8.265$</td>
<td>$-0.476$</td>
</tr>
</tbody>
</table>

$N_{samples}$ is the total number of samples in the set. Cost is the cost metric in Equation 7, calculated for the sensor pose shown in the table.

Fig. 7. Cost metric calculated from Equation 7 plotted against number of samples in data set $N_{samples}$.

calibration. However, the asymptote in this figure shows that little reduction in cost is achieved after 60,000 samples are obtained, so this is a sufficient amount for this set of data. Note that the cost metric asymptotes to a non-zero number. This is because the pole has non-zero radius and there are measurement errors in both the sensor readings and the platform pose.

V. CONCLUSION

This paper has presented a new technique for determining the offset and rotation of a range sensor on a mobile platform. A sensitivity analysis has shown the requirements of the algorithm and this is confirmed by the practical results, which show that the position can be calculated more accurately than is possible by hand.

Accurately measuring the mounted position of a range sensor on a platform can be very difficult and transformation of the sensor data to the platform frame magnifies the error. After calibration with this technique, global point clouds represent the environment much more accurately than when the best possible measurement is used. More generally, for any application that requires this transformation, results will be improved after using this calibration technique.

Ongoing work includes extending the process for multiple sensors and automating the entire calibration process. An automated platform can traverse a pre-defined route until enough data is gathered. For use in the optimisation, the data can then be segmented into pole and ground regions using reflectivity measurements. Success can be evaluated with a threshold on the final cost metric or the rate of cost improvement.

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