Active Planning-based Extrinsic Calibration of 3D sensors on a Mobile Robot

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***Abstract*—Existing SLAM systems such as OmniMapper [1] require an extensive pre-calibration process. In non-stationary applications, pre-calibration normally involves manual calibration. Related work in automating calibration has looked at using manipulators to create patterns, while looking at specified objects to estimate the biases. We propose to use a robot to re-estimate the uncertainties of its calibration given an initial, extrinsic estimate and then move in a manner that minimizes that uncertainty. This can be performed using an entropy estimation step for the robot.**

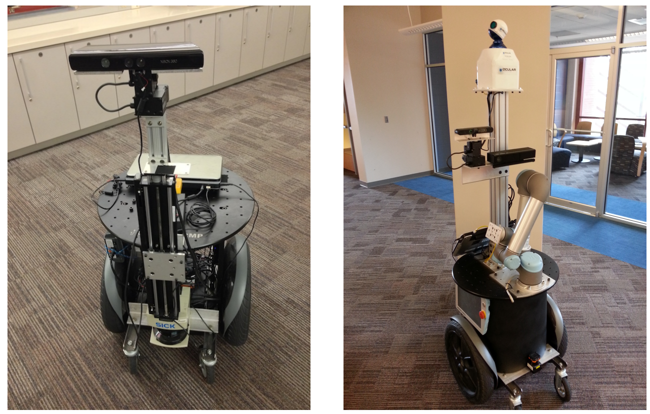

Fig. 1: Jeeves being reconfigured

I. Introduction

Performance of autonomous navigation by mobile robots can be greatly affected by the quality of extrinsic calibration of the utilised sensors. A mobile robot is often tasked to perform inference from sensor measurements, in order to build a model of the surrounding environment and to estimate variables of interest. Moreover, it has to generate a plan of actions to accomplish a given goal, such as exploration or manipulation.

In this case, the robot's goal is to self-calibrate the sensors before performing any autonomous exploration. The motivation is to reduce the amount of manual labor required and the human error introduced during calibration by offloading the task to the robot itself. Often the human is tasked with easy objectives such as repeatedly aligning the robot's field of view with the calibration grid, a process that could be sped up through automation. This would also allow the robot to be robust to sensor alignment changes between different experiments due to either intentional or accidental reconfigurations. The authors propose a novel algorithm that allows the robot to perform a self-calibration routine through autonomous investigative movements around a calibration environment that would then enable the robot to perform further autonomous tasks.

II. Related Work

In the past, the majority of range and camera setups were calibrated under traditional procedures using precisely engineered calibration targets, such as checkered calibration grids [2], or within artificially constructed environments embedded with an array of reflective landmarks [3]. In addition, such optimization techniques remained supervised, requiring a host of finely tunable parameters accompanied by lengthy computation times. For instance, Unnikrishnan et al [4] proposed a model to calibrate a 3D laser rangefinder to a pinhole camera using least-squares-based robust plane-fitting of 3D data of a calibration rig to estimate the extrinsic parameters of the pair of sensors. This and similar methods require manual measurements for the process to be robust to the estimation of the planar features.

Recent work on more autonomous approaches have come from simultaneous calibration, localization and mapping (SLAM). Kummerle et al [5] presented a method that required no prior knowledge of the environment and relied solely on a rough initial guess of the sensors' extrinsics. Specifically, this method used on-line estimation of the extrinsics by including them as states in the metric SLAM system. From these states, a hypergraph was constructed which optimized for the trajectory of the robot while also including the local offsets of the 2D LIDAR extrinsics. This method can be useful for domains that do not require precise extrinsics prior to the beginning of each mission. However for tasks that do necessitate prior calibration, or lack the capacity for the added computational load for optimizing large-scale trajectories with added extrinsic variables, simultaneous calibration during an entire mission can be costly.

Another approach with its origins in SLAM that is particularly well-suited to solving calibration problems is method manifold-based graph optimization. Wagner et al [6] provided a foundation for rapid development with the Manifold Toolkit from Matlab, and is useful when enlisting human supervised calibration methods for eventual performance comparison.

Pandey et al [7] presented a method to automatically calibrate the extrinsic parameters of a laser rangefinder and an omnidirectional camera. This was done by exploiting the relationship between the camera's pixel intensity and the laser's reflectivity measurements within unstructured environments. Although this method could be applied to any pair of range sensors supporting intensity measurements, depth sensors that rely solely on active pattern projection for disparity calculation would not be directly supported unless an image registration from a camera is already known. The approach also suffers from variant environmental elimination when using a camera due to changes in surrounding shadows and direct lighting.

Maddern et al [8] presented an unsupervised algorithm for determining extrinsic calibration between a 3D and multiple 2D LIDARs under a common mobile base frame. This technique makes minimal assumptions about the calibration environment and does not require calibration targets. The method used an entropy-based quality metric derived from Renyi Quadratic Entropy generated from observed point clouds. Thus, a planner can be provided with a continuous metric with which to evaluate how much uncertainty is reduced for a given action or motion.

These works illustrate a number of calibration methods that can be accomplished either without engineered calibration targets, outside known structured environments, or through passive on-line operation. For a more extensive list of on-line self-calibration approaches, see Maye [9]. However, none of these methods provide a truly autonomous calibration approach.

Thus, we propose an unsupervised method that reduces the calibration workload by minimizing the robot's own uncertainty in the extrinsic parameters, which serve as feedback for its navigation behavior. This capability would allow the robot to discern when an optimal number of observations has been reached, thus avoiding extensive recording times and unnecessary computation or movement.

Navigation planning with uncertainty has been approached before [10]–[13]. The work which is the most closely related to our work is by Indelman et al [10]. This work proposes a probabilistic framework using the domain of generalized belief to perform autonomous navigation with a dual-layer architecture: an inner estimation layer for generating possible actions and respective outcomes and a decision layer that identifies the optimal action considering the probable outcomes. Unlike most modern approaches that discretize either the state or control space in order to frame the computation and selection of the best plan, this novel approach allows for planning in the continuous domain. This culminates in obtaining optimal solutions that maintain bounded uncertainties as well as smoother state space trajectories.

III. Project Description

A. Problem Statement

The goal of this project is to self-calibrate the sensors by performing an autonomous and actively planned exploration strategy.

B. Research Project Justification

The primary motivation behind this is to reduce the amount of manual labor required and the human error introduced during manual calibration by offloading the task to the robot itself.

Another motivation is the development of automated calibration techniques to support the dynamic growth of our robot's setup. Our platform shown in Figure 1 is based on the Segway RMP 200 and is called Jeeves. The platform plays host to an array of sensors including the Ocular Robotics RE05, Microsoft Kinect One and an Asus Xtion Pro. All of these sensors provide 3D point clouds. This platform also serves as a frequently utilized research testbed, and thus has been plagued by sensor reconfiguration over the years.

C. Project Scope

1) All project outputs: Other than an integrated planning, calibration and mapping algorithm, we will deliver a ROS package which will be easy to integrate with ROS packages in other areas of mobile robotics.

2) Statement of success: The project will be a success if active planning based extrinsic calibration of sensors is more accurate and takes less time than the conventional way of manually calibrating the sensors.

3) Assumptions: The project assumes a static indoor world having homogeneous floor surface properties such that the calibration parameters do not change through out the run. We also assume that the robot is run in a smooth, non-jerky fashion since we will be using a simple motion model of it.

D. Project Objectives

- Integration of a simultaneous calibration, localization and mapping system with our existing SLAM framework (Omnimapper [1]) and testing it on the Jeeves robot.
- To use active planning to guide robot's motion for extrinsic calibration along with SLAM. Testing will be done again in simulation and on the Jeeves robot based on various timing and accuracy metrics.

IV. Approach

In this section, we explain the theoretical details behind simultaneous calibration, localization and mapping and propose an approach for autonomous planning in belief space for extrinsic calibration.

A. Simultaneous Localization and Mapping (SLAM)

In landmark-based SLAM a robot, while navigating, tries to localize itself and at the same time build a map of the environment (represented using landmarks). Assuming a pose of the robot at the i^{th} time step is x_i with $i \in 0 \dots M$, a landmark is l_j with $j \in 1 \dots N$ and a measurement is z_k, with $k \in 1 \dots K$, the joint probability model is given as,

$$P(X, L, Z) = P(x_o) \prod_{i=1}^{M} P(x_i | x_{i-1}, u_i) \prod_{k=1}^{K} P(z_k | x_{ik}, l_{jk})$$

where $P(x_o)$ is a prior on the initial state, $P(x_i|x_{i-1}, u_i)$ is the motion model, parametrized by a control input u_i and $P(z_k|x_{ik}, l_{jk})$ is the landmark measurement model, x_{ik} and l_{jk} corresponds to measurement z_k. Figure 2 shows the corresponding Bayes Net. Assuming the motion and measurement models are Gaussian, $P(x_i|x_{i-1}, u_i) \propto \exp -\frac{1}{2}\|f_i(x_{i-1}, u_i) - x_i\|^2_{\Lambda_i}$ and

$P(z_k|x_{ik}, l_{jk}) \propto \exp -\frac{1}{2}\|h_k(x_{ik}, l_{jk}) - z_k\|^2_{\Sigma_k}$ where $f()$ is the robot motion equation and $h()$ is a landmark measurement equation with Λ_i and Σ_k as the respective covariances.

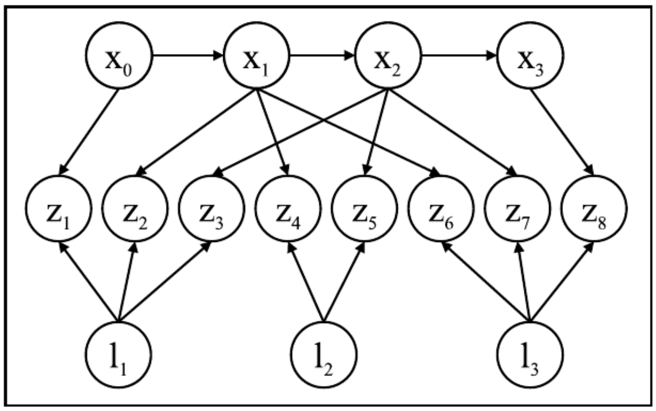

Fig. 2: Belief Net corresponding to the landmark-based SLAM problem. The pose of the robot at i^{th} time step is x_i with $i \in 0 \ldots M$, a landmark is l_j with $j \in 1 \ldots N$ and a measurement is z_k, with $k \in 1 \ldots K$.

We use a factor graph to represent the joint probability model $P(X, L, Z)$ where each factor represents either $P(x_o)$ or $P(x_i|x_{i-1}, u_i)$ or $P(z_k|x_{ik}, l_{jk})$. Therefore the joint probability model can be written as

$$P(X, L, Z) \propto g(\Theta) = \prod_i g_i(\Theta_i) \tag{1}$$

where Θ_i is the set of variables θ_j adjacent to the factor g_i. Figure 3 shows the corresponding factor graph. Given all the measurements, we obtain the maximum a posteriori (MAP) estimate by maximizing the joint probability $P(X, L, Z)$.

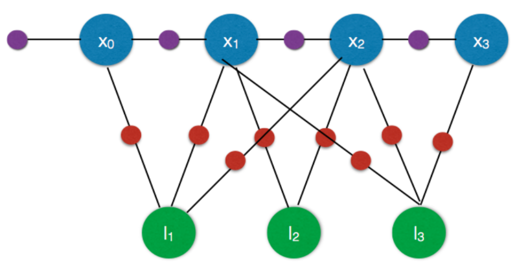

Fig. 3: SLAM factor graph

$$\Theta^* = \arg\max_\Theta P(X, L|Z) = \arg\min_\Theta (-\log g(\Theta)) \tag{2}$$

which leads to the following non-linear least squares problem:

$$\begin{aligned} \Theta^* = \arg\min_\Theta & \sum_{i=1}^{M} \|f_i(x_{i-1}, u_i) - x_i\|^2_{\Lambda_i} \\ & + \sum_{k=1}^{K} \|h_k(x_{ik}, l_{jk}) - z_k\|^2_{\Sigma_k} \end{aligned} \tag{3}$$

The non-linear least squares problem in Equation 3 is solved using a non-linear optimization method such as the Levenberg-Marquardt algorithm which solves a succession of linear approximations in order to approach the minimum.

In each iteration of the non-linear least squares problem, we linearize around a linearization point Θ to obtain a linear least squares problem of the form $\delta^* = \arg\min_\delta \|A\delta - b\|^2_2$. For a full rank matrix A, the least squares solution can be found by solving the normal equations $A^T A\delta^* = A^T b$. Cholesky factorization yields $A^T A = R^T R$ where R is an upper-triangular matrix. A forward substitution on $R^T y = A^T b$ followed by backward substitution $R\delta^* = b$ gives the update δ^*.

We use Incremental Smoothing and Mapping (iSAM2 [14]) which incrementally optimizes the resulting factor graph in order to perform SLAM.

B. Simultaneous Calibration, Localization and Mapping

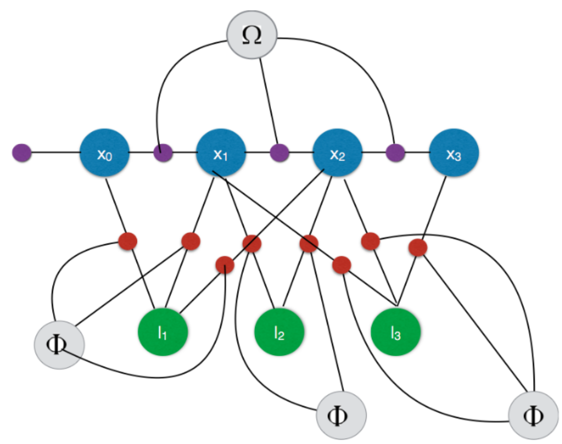

Fig. 4: Simultaneous calibration, localization and mapping factor graph

In order to perform simultaneous calibration, localization and mapping we explicitly represent the additional calibration parameters in the joint probability model as

$$\begin{aligned} P(X, L, Z, \Omega, \Phi) = \; & P(x_o) \prod_{i=1}^{M} P(x_i|x_{i-1}, u_i, \Omega) \\ & \prod_{k=1}^{K} P(z_k|x_{ik}, l_{jk}, \Phi) \end{aligned}$$

where Ω represents odometry bias parameters and Φ represents the extrinsic transformation between the robot base and a corresponding sensor used in the particular landmark measurement model. Figure 4 shows the corresponding factor graph. Each sensor will have a different extrinsic transformation Φ but for simplicity we use a single Φ corresponding to a single sensor. Optimization can be done in a similar manner as discussed above. One possible way to improve calibration beyond this optimization is to use Expectation-Maximization for optimizing the additional calibration parameters by running normal SLAM optimization in the Maximization step followed by calibration parameters estimation in the Expectation step.

C. Autonomous Extrinsic Calibration using Active Planning

We propose to use planning for an autonomous, extrinsic, and odometry bias calibration. Planning is done such that it actively reduces calibration parameter uncertainty at each instant in the previously unknown environment. To achieve that end, we will integrate simultaneous calibration, localization and mapping with an active planning framework resulting in planning for calibration.

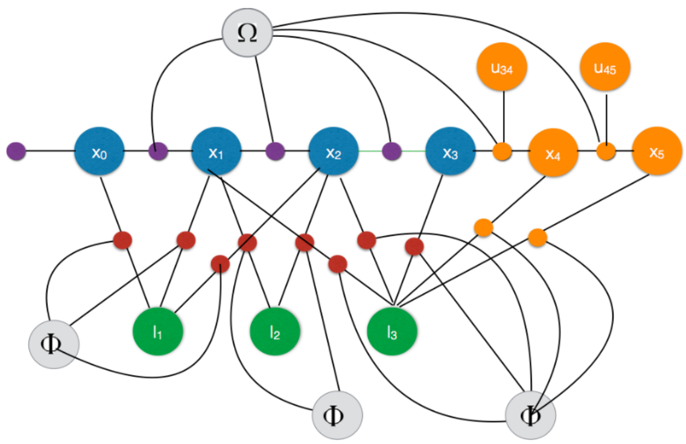

Fig. 5: Planning to calibrate factor graph

In order to compute the optimal control action over L look ahead steps, we have to compute the predicted belief over the time horizon. However since we don't know the observations ahead of time, observations $Z_{M+1:M+l}$ are added as random variable, where M is the current time step. Given the calibration parameters Ω_M and Φ_M, estimated poses and landmarks up to time M, predicted poses and landmarks from $M+1$ to $M+l$, the control inputs $U_{M+1:M+l}$, the predicted calibration belief Ω_{M+l}, and Φ_{M+l} at a future time step l is given as:

$$gb(\Omega_{M+l}, \Phi_{M+l}) =$$
$$\sum_{X,L,Z} P(\Omega_{M+l}, \Phi_{M+l} | X_{1:M+l}, L_{1:M+l}, Z_{1:M+l}, U_{M+1:M+l})$$

The control action minimizes the general object function over L look ahead steps

$$J_k(U_{M+1:M+L}) = \Sigma_{l=0}^{L} c_l(gb(\Omega_{M+l}, \Phi_{M+l}))$$

where c_l is defined as the uncertainty determinant of the calibration parameters. Figure 5 shows the corresponding factor graph. The above minimization is run until the uncertainty determinant of the calibration parameters is below a certain threshold.

In turn, the resulting planning algorithm will ensure that the robot moves in a direction that will reduce the associated calibration uncertainty.

V. Evaluation

For evaluation, we propose two separate methods by which to validate our approach (1) synthetic quantitative findings through control simulations as well as (2) real experiments with our mobile-based platform.

In simulation, we can directly compare our autonomous calibration algorithm against known extrinsic parameters for each sensor. This will also allow us to control for any additional variables when scrutinizing analytical performance within a truly static environment.

In the real-world robot experimentation, we intend to present the differences in extrinsic calibration estimates of the several 3D sensors (including 2-D and 3-D LIDARs and RGBD cameras) with respect to each other using our own approach vs manual calibration.

VI. Deliverables

These two calibration techniques will also be evaluated in terms of the gage of repeatability and reproducibility, GR&R [15], by taking into consideration the variation in measurements in trials in order to best interpret the significance of our contribution. The deliverables include:

- A simultaneous calibration, localization and mapping system integrated with our existing SLAM framework (Omnimapper [1]) and tested on Jeeves robot.
- Active planning based robot's motion guidance for extrinsic calibration along with SLAM. Testing again will be done in simulation and on Jeeves robot based on various timing and accuracy metrics. It will be compared against manual calibration techniques.

References

[1] A. J. Trevor, J. G. Rogers, and H. I. Christensen, "Omnimapper: A modular multimodal mapping framework," in *Robotics and Automation (ICRA), 2014 IEEE International Conference on.* IEEE, 2014, pp. 1983–1990.

[2] Q. Zhang and R. Pless, "Extrinsic calibration of a camera and laser range finder (improves camera calibration)," in *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, vol. 3, Sept 2004, pp. 2301–2306 vol.3.

[3] C. Gao and J. Spletzer, "On-line calibration of multiple lidars on a mobile vehicle platform," in *Robotics and Automation (ICRA), 2010 IEEE International Conference on*, May 2010, pp. 279–284.

[4] R. Unnikrishnan and M. Hebert, "Fast extrinsic calibration of a laser rangefinder to a camera," 2005.

[5] R. Kummerle, G. Grisetti, and W. Burgard, "Simultaneous calibration, localization, and mapping," in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, Sept 2011, pp. 3716–3721.

[6] R. Wagner, O. Birbach, and U. Frese, "Rapid development of manifold-based graph optimization systems for multi-sensor calibration and slam," in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on.* IEEE, 2011, pp. 3305–3312.

[7] G. Pandey, J. R. McBride, S. Savarese, and R. Eustice, "Automatic targetless extrinsic calibration of a 3d lidar and camera by maximizing mutual information." in *AAAI*, 2012.

[8] W. Maddern, A. Harrison, and P. Newman, "Lost in translation (and rotation): Rapid extrinsic calibration for 2d and 3d lidars," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, May 2012, pp. 3096–3102.

[9] J. Maye, "Online self-calibration for robotic systems," Ph.D. dissertation, ETH Zürich.

[10] V. Indelman, L. Carlone, and F. Dellaert, "Planning under uncertainty in the continuous domain: a generalized belief space approach."

[11] C. Stachniss, D. Hahnel, and W. Burgard, "Exploration with active loop-closing for fastslam," in *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, vol. 2, Sept 2004, pp. 1505–1510 vol.2.

[12] C. Stachniss, G. Grisetti, and W. Burgard, “Information gain-based exploration using rao-blackwellized particle filters,” in *Proc. of Robotics: Science and Systems (RSS)*, Cambridge, MA, USA, 2005.

[13] R. Valencia, M. Morta, J. Andrade-Cetto, and J. Porta, “Planning reliable paths with pose slam,” *Robotics, IEEE Transactions on*, vol. 29, no. 4, pp. 1050–1059, Aug 2013.

[14] M. Kaess, H. Johannsson, R. Roberts, V. Ila, J. J. Leonard, and F. Dellaert, “iSAM2: Incremental smoothing and mapping using the bayes tree,” *The International Journal of Robotics Research*, vol. 31, no. 2, pp. 216–235, Feb. 2012. [Online]. Available: http://ijr.sagepub.com/content/31/2/216

[15] D. C. Montgomery and G. C. Runger, “Gauge capability and designed experiments. part i: Basic methods,” *Quality Engineering*, vol. 6, no. 1, pp. 115–135, 1993.