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# Pose Tracking and Sensor Self-Calibration for an All-terrain Autonomous Vehicle ⋆

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**Abstract:** In this work we address the simultaneous pose tracking and sensor self-calibration problem by applying a pose-graph optimization approach. A factor-graph is employed to store robot pose estimates at different time instants and calibration parameters such as magnetometer hard and soft iron distortion and gyroscope bias. Specific factors are developed in this paper to handle Ackermann kinematic readings, inertial measurement units, magnetometers and global positioning systems. An experimental evaluation supports the viability of the approach considering an autonomous all-terrain vehicle, for which we perform calibration and real-time pose tracking during navigation.



*Keywords:* Sensor fusion, Navigation, Calibration, Multisensor integration, Autonomous mobile robots

## 1. INTRODUCTION

Long range autonomous navigation is the key capability of unmanned vehicles in outdoor operations (e.g., agriculture, search & rescue, surveillance), and robust pose tracking is the cornerstone of such capability as clearly known since the 90s (Borenstein et al., 1996). Indeed, the proper execution of common tasks, such as trajectory planning or trajectory control, heavily rely on the robot knowledge about its current pose, i.e., position and orientation, with respect to a known fixed reference frame.

Accurate positioning has been highly investigated in the literature, and, currently, most successful solutions exploit the presence, on the robot, of multiple sensors (e.g., wheel encoders, inertial measurement units, GNSS receivers, etc.) through sensor fusion techniques such as extended (Chen, 2003) and unscented (Julier and Uhlmann, 1997) Kalman filters or Monte Carlo methods such as particle filters (Gordon et al., 1993).

Sensor fusion algorithms need to deal with heterogeneous, asynchronous, and possibly faulty, information sources which are affected by biases, distortions, and noise. The latter effects (i.e., biases, distortions, and noise) are usually faced by means of proper modeling and compensation procedures: a set of parameters need to be carefully estimated to preserve estimation accuracy. Examples of such calibration parameters are hard and soft iron distortion coefficients in magnetometers, time-varying biases in gyroscopes, intrinsic and extrinsic camera calibration matrices, and kinematic parameters such as wheel radii, and interaxis distance. While some of these parameters are fixed during operations, and they can be determined offline once and for all by ad-hoc calibration procedures, others, such as the gyroscope bias, slowly drift during operations and they have to be estimated online.

While pose tracking by means of sensor fusion has been extensively studied, and many general solutions exist in the literature, the problem of determining unknown calibration parameters from sensor readings only, i.e., without relying on external information such as sensor position ground truth or environment structure, is still an active research field. Many ad-hoc techniques have been developed to target specific combinations of platform and sensors; among the others we cite the work by Censi (Censi et al., 2013), who considered the case of differential drive robots equipped with laser range-finders, or specific algorithms for magnetometer calibration (Vasconcelos et al., 2011). Only recently, approaches appeared in the literature which aim at generalizing the pose tracking (Indelman et al., 2012) and self-calibration (Cucci and Matteucci, 2014b; Weiss et al., 2012) problems with respect to sensor configuration and/or robotic platform.

In the realm of generalized simultaneous pose tracking and parameter self-calibration, this paper investigates the use of pose-graph optimization, which nowadays is a quite popular technique in Simultaneous Localization and Mapping (SLAM). Indeed, mainstream SLAM algorithms use a factor-graph formulation to represent the joint probability distribution of odometry and environmental features readings (e.g., world fixed landmarks, visual features, etc.), and

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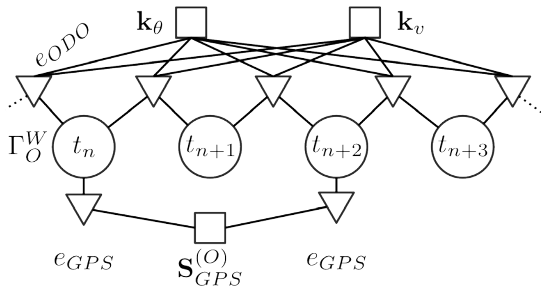


Fig. 1. An instance of a hyper-graph for pose tracking and self-calibration with four pose nodes $\Gamma_{O;t}^W$ (circles), odometry edges $e_{ODO}$ (triangles), having two shared calibration parameters $\mathbf{k}_v$ and $\mathbf{k}_\theta$ (squares), and two GPS edges $e_{GPS}$ sharing the GPS geometric placement parameter $\mathbf{S}_{GPS}^{(O)}$.

they apply non-linear optimization to find the assignment for the state variables that maximizes the likelihood of sensor readings. The pose-graph SLAM formulation was extended to Simultaneous Localization, Mapping and Calibration by (Kümmerle et al., 2012) where the wheels radii and the baseline of a differential drive robot, together with laser range-finder geometric displacement parameters, were added to a pose-graph SLAM algorithm to be estimated online. This was in a 2D setting.

Similarly to (Kümmerle et al., 2012), in the following, we show how proper sensor models can be developed for heterogeneous information sources such as vehicle kinematics, inertial measurement units, and GNSS, in a way such that calibration parameters explicitly appear as state variables in the pose-graph formulation of a 6DoF simultaneous pose tracking and parameter self-calibration problem. The estimation problem can then be solved by means of non-linear graph-optimization techniques, online, yielding real-time pose estimates for trajectory control, or offline, for determining unknown calibration parameters. Online tracking of time varying quantities, such as gyroscope and accelerometer biases, is also possible with the proposed approach as we show in the experimental evaluation.

In Section 2 we briefly review the pose-graph optimization framework and we describe how such framework can be used to formulate a simultaneous pose tracking and sensor calibration problem. General hyper-edges to introduce kinematic constraints in pose-graph optimization are described in Section 3, while an experimental evaluation of the approach is presented, by means of the Quadrivio all-terrain autonomous vehicle (Bascetta et al., 2009) (Bardaro et al., 2014), in Section 4.

## 2. POSE-GRAPH OPTIMIZATION

This work addresses the problem of 6DoF simultaneous position and attitude determination and sensor parameter self-calibration by means of pose-graph optimization (Lu and Milios, 1997). Pose-graph optimization uses a factor-graph (Dellaert, 2012) in which nodes store robot poses at different time instants, while factors are hyper-edges encoding sensor readings constraints. More precisely, each factor is associated to a sensor reading and it evaluates the measurement likelihood given the current estimates of the state variables stored in incident nodes.

The resulting graph represents the full joint probability of sensor readings with respect to state variables, representing its factorization in terms of single measurement likelihoods. Pose estimates are usually obtained by means of max-likelihood estimation over this distribution, which can be efficiently done by means of non-linear optimization algorithms such as Gauss-Newton or Levenberg-Marquardt.

In this work we employ auxiliary nodes to store calibration parameters, such as magnetometer distortion coefficients and gyroscope bias. In this way, measurement likelihoods become also function of the relevant calibration parameters, allowing us to simultaneously obtain estimates for both robot poses and sensor calibration. An example of the resulting hyper-graph is visible in Figure 1 where two types of factors are present, i.e., odometry hyper-edges, $e_{ODO}$, and global positioning system hyper-edges, $e_{GPS}$. The factors are incident both in robot pose nodes, $\Gamma_O^W(t_n)$ and in calibration parameters, such as the GPS antenna placement $\mathbf{S}_{GPS}^{(O)}$.

The advantages of the factor-graph formulation are manifold. First of all, it is general and flexible with respect to the nature, and multiplicity, of information sources; indeed, if we need to add a new sensor to the architecture, this reduces to insert further edges into the pose-graph, once a proper likelihood function has been defined for such measurement domain. Second, it allows to apply non-linear optimization algorithms that are aware of the manifold state variables belong to. Moreover, it allows to solve both the offline parameter calibration and the real-time pose tracking problems; the latter case indeed simply restricts the max-likelihood estimation, i.e., the non-linear optimization, to a subset of the robot poses. Finally, out-of-sequence and delayed measurements do not constitute an issue, as it might be the case in filtering approaches; they are simply associated to the proper pose nodes, according to their timestamps.

To formulate and solve the pose-graph optimization problem, in this paper, we extend ROAMFREE [1] (Cucci and Matteucci, 2014b)(Cucci and Matteucci, 2014a), an open source framework for 6DoF pose tracking and sensor parameter self-calibration, which, in turn, is based on the g$^2$o graph optimization framework (Kümmerle et al., 2011). ROAMFREE provides a general, turn-on-and-go, solution for the pose tracking and parameter self-calibration problems; it comes with a comprehensive library of sensor models, which can be easily extended to target specific properties of the robot platform in use and to characterize actual hardware sensors in terms of measurement functions and calibration parameters.

## 3. SENSOR MODELS

In this section we present the definitions of specific factors, i.e., pose-graph hyper-edges, that allow to handle Ackermann steering geometry readings, Inertial Measurement Units (IMUs), magnetometer sensors and a Global Positioning System (GPS). These factors, with the associated

[1] `https://github.com/AIRLab-POLIMI/ROAMFREE`