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# Automatic 2-D LiDAR geometric calibration of installation bias

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## HIGHLIGHTS

- Automatic calibration algorithms for 2-D LiDARs on board aerial vehicles.
- No a priori knowledge of the trajectories or the terrain are necessary.
- Use of geometric optimization techniques on SO(3).
- Extensive characterization of the proposed methods using simulated data.
- Validation of the proposed methods using experimental data.

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ABSTRACT

This paper proposes two estimation algorithms for the determination of the attitude installation matrix for 2-D light detection and ranging (LiDAR) systems on board unmanned aerial vehicles (UAVs). While a comparative calibration algorithm assumes the existence of a known calibration surface, an automatic calibration algorithm does not require any prior knowledge of the trajectories of the vehicle or the terrain where the calibration mission is performed. The proposed calibration algorithms rely on the minimization of the errors between the measured point cloud and a representation of the known calibration surface or, alternatively, the errors between several acquired point clouds, by comparing each measured point cloud with a surface representation of the others. The resulting optimization problems are addressed using two techniques: (i) nonlinear optimization, where the attitude installation rotation matrix is parameterized by the *ZYX* Euler angles, and (ii) optimization on Riemannian manifolds, enabling the estimation of the attitude installation matrix on the group of special orthogonal matrices $\mathcal{SO}(3)$. The proposed calibration techniques are extensively validated and compared using both simulated and experimental LiDAR data sets, demonstrating their accuracy and performance.



## 1. Introduction

Light detection and ranging (LiDAR) technology is nowadays widely used in the industry as well as by the robotics and the remote sensing research communities. The development of airborne laser ranging sensors started in the 1970s in North America, mainly for topographic applications. Later, with the development of affordable inertial navigation systems (INS) and global positioning system (GPS) units, other applications captured the attention of the research community, such as monitoring ice sheets [1] or measuring canopy heights [2]. The robotics research community is nowadays employing autonomous vehicles equipped with LiDARs to perform automatic acquisition and 3-dimensional (3-D) reconstruction of terrain, buildings, large infrastructures, and to obtain semantic descriptions of complex environments [3,4], using this information to safely and accurately navigate through unknown environments [5,6]. Data accuracy is essential for all these applications, as there are several sources of inaccuracy that can lead to considerable nonlinear reconstruction errors.

The calibration of 2-D LiDARs on board an autonomous vehicle capable of complex 3-D motion, is one of the most challenging problems in the extrinsic calibration of LiDAR sensors. There is comprehensive work in the literature that is dedicated to the analysis of the intrinsic and extrinsic LiDAR error sources, such as in [7,8] and references therein. Namely, the identified error sources include the attitude and position installation biases, range detection errors, scanning angle errors, vehicle attitude and position errors, time synchronization errors, etc. While most intrinsic

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errors can be identified and accounted for with laboratory experiments using the sensor, the installation biases are highly dependent on the vehicle and mounting apparatus. It is argued by these authors that the attitude installation bias, also simply referred to as the mounting bias, is a particularly important source of error in LiDAR systems. For instance, an airborne LiDAR acquiring terrain elevation 300 m above the ground, with 1° of roll mounting bias will generate points with more than 5 m of error. Moreover, when working with rough terrain with high slopes the distortions can become highly nonlinear, which further motivates the necessity of the calibration of these errors, in particular, the attitude installation bias, to meet the desired accuracy requirements.

### *1.1. Relevant work*

Most applications requiring a three-dimensional (3-D) reconstruction of the surrounding environment use one or several LiDARs installed on board a vehicle equipped with an INS/GPS unit, which provide measurements of the relative distances to the terrain and the trajectory of the vehicle, respectively. To obtain consistent and accurate 3-D maps it is possible to formulate a problem that makes use of some characteristics of the environment to adjust potential errors in the obtained point cloud and vehicle trajectory, as in [9,10], or address the calibration of LiDAR sensors as a separate problem prior to the intended 3-D environment data acquisition.

The most common calibration procedures require particular terrain features and specific vehicle trajectories in order to calibrate a subset of the parameters, as found in [11]. For instance, a standard procedure in the literature for airborne LiDAR calibration would be to fly over a known flat surface while performing pitch or roll maneuvers, separately, which would enable the calibration of only these two parameters. Nonetheless, several difficulties render the problem of 2-D LiDAR attitude installation calibration special, including the absence of any matching information between the measured point clouds and a known calibration surface, and also the fact that, with each calibration correction step, the reconstructed clouds of points will change their shape in a nonlinear fashion, accordingly to the vehicle trajectory and the terrain.

There are two fundamental approaches in the literature to compare two clouds of points when there is no matching information between them. The first approach is to use a point-to-point metric, as in the by-now classic iterative closest point (ICP) algorithm [12], and assign to each point of one cloud a matching point of the other cloud. An alternative approach is to use a point-to-plane metric and, thus, to measure the closest distance between each point of one cloud to a surface approximation of the other cloud [13]. As the surface information is not taken into account in point-to-point based techniques, they suffer from the inability to slide overlapping clouds to find a better fit between them, demonstrating slower convergence rates than the point-to-plane alternatives [14].

To reduce the conservativeness of the calibration procedures of 2-D LiDAR sensors, new algorithms were proposed in [15,16], where the measured point cloud is compared with a plane-wise representation of the known calibration surface to obtain the calibration parameters. These authors consider the linearization of the error model to obtain a Gauss–Helmert model and then obtain the least-squares estimate of the installation bias. This approach was refined in [17] by considering the full nonlinear model of the reconstruction error and, consequently, resorting to nonlinear optimization techniques to obtain the optimal calibration parameters. More recently, specially with the use of expensive 3-D LiDARs installed on ground vehicles, several strategies have been proposed, such as those presented in [18,19], for LiDAR calibration that rely on the detection and association of artificial features in the point clouds. Nonetheless, the major drawback of these techniques is that they make strong assumptions about the environment where the calibration procedure takes place, either assuming complete knowledge of the calibration surface or adding artificial marks to enable feature based association.

An alternative for the pose calibration of sensors is the joint formulation of the calibration, localization, and mapping problems into a single problem. In this approach, the typical state of a simultaneous localization and mapping problem (SLAM), such as [6,20,21], is augmented to include the intrinsic or extrinsic variables to be calibrated. For instance, in [22] the authors proposed a method rooted on graph-based SLAM to obtain the robot position in the mapped environment, the LiDAR position on the robot, as well as the kinematic variables of the robot. For the case of camera calibration, a method based on the unscented Kalman filter (UKF) SLAM is proposed in [23] for obtaining the map of the environment, the pose of the vehicle, and the pose of the camera relative to the vehicle.

Within the field of mobile robotics, the calibration of 3-D LiDARs on board ground vehicles has been addressed in [24,25]. The former uses a point-to-plane metric to define a cost function, based on Euler angles for the attitude installation bias, and a heuristic search in several directions to avoid local minima. The later resorts to an entropy-based point cloud quality metric, which allows for the calibration of a 3-D LiDAR sensor using several overlapping 3-D scans, and based on this calibrated point cloud, any 2-D LiDAR on board the vehicle can also be calibrated. However, noting that both these methods rely on the use of 3-D LiDAR data, the proposed calibration methods would not be appropriate if only one statically mounted 2-D LiDAR was used for data acquisition. Furthermore, using an entropy-based point cloud quality metric might not be the best approach to use all the available information (see Appendix A) provided by the type of point clouds obtained with airborne 2-D LiDARs, as two uncalibrated point clouds might only be close to each other within a small boundary close to their intersection (as can be seen in Fig. 12(a)).

### *1.2. Proposed approach*

The algorithms proposed in this work can cope with arbitrary vehicle 3-D motion and terrain topology, yielding accurate calibration of airborne 2-D LiDAR sensors. It is assumed that there is enough information on the calibration terrain and vehicle trajectories to enable the full attitude installation bias calibration. One obvious counter-example would be a flat terrain, thus, with no relevant topological features, for which there would always be one uncalibrated degree of freedom. The proposed methods use a point-to-plane metric to compare each acquired point cloud with either a known calibration surface or a surface approximation of all the remaining acquired point clouds, by measuring the minimum distance of each point to the approximated surface. A fully nonlinear model of the calibration errors is also defined, either using Euler angles or rotation matrices, thus avoiding the linearization problems of many works in the existing literature. In addition, by using rotation matrix representation of the attitude installation bias, optimization tools on the special orthogonal group can be used.

Two different approaches are considered for the calibration procedures addressed in this paper: the (i) *Comparative Calibration*, which considers arbitrary vehicle trajectories and assumes the existence of a known calibration surface that will be compared with the measured data during the calibration algorithm; and the (ii) *Automatic Calibration*, for which no a priori information on the terrain or trajectory is required and, at least, two measured data sets of the same terrain obtained from different vehicle trajectories are necessary. The former approach was introduced by the authors in [17] and is included in this paper for comparison purposes, as it represents the classical approach to this calibration problem. Regarding the automatic calibration, where a known calibration surface