Extrinsic Sensor Calibration Methods for Mobile Robots: A Short Review

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Abstract. Data acquisition is a critical task for localisation and perception of mobile robots. It is necessary to compute the relative pose between onboard sensors to process the data in a common frame. Thus, extrinsic calibration computes the sensor's relative pose improving data consistency between them. This paper performs a literature review on extrinsic sensor calibration methods prioritising the most recent ones. The sensors types considered were laser scanners, cameras and IMUs. It was found methods for robot–laser, laser–laser, laser–camera, robot–camera, camera–camera, camera–IMU, IMU–IMU and laser–IMU calibration. The analysed methods allow the full calibration of a sensory system composed of lasers, cameras and IMUs.

Keywords: Mobile robots · Calibration · Sensor · Extrinsic parameters · Laser scanners · LiDAR · Inertial Measurement Unit · IMU · Cameras

1 Introduction

A critical task in autonomous navigation is acquiring information about the environment for, e.g., localisation or perception. It can be accomplished using onboard sensors. However, it is necessary to know the relative poses between them and to the robot. Indeed, the so-called extrinsic parameters transform all the sensors measurements into a common frame. The estimation of these parameters is known as the extrinsic sensor calibration [11]. Thus, accurate extrinsic calibration can lead to improvements in the robot's perception and localisation.

This paper is a literature review on extrinsic sensor calibration methods. The sensors types considered are laser scanners, cameras and Inertial Measurement Units (IMUs). Also, the review analyses the most recent works developed on extrinsic calibration covering the most setups of sensors possible between the three types considered.

The manuscript is organised as follows. Section 2 presents the search considerations taken into account and the methods found. Section 3 analyses them by the pair of sensor types that the method intends to compute the extrinsic parameters. Section 4 presents the conclusions from this literature review.

J. A. Gonçalves et al. (Eds.): CONTROLO 2020, LNEE 695, pp. 559–569, 2021.
https://doi.org/10.1007/978-3-030-58653-9_54

2 Method

This paper analyses the research about extrinsic sensor calibration methods, and covering the most sensors setups possible between laser scanners, IMUs and cameras for ground mobile robots. Different setups of these sensors allow the implementation of multi-sensor fusion algorithms for mapping or localisation. So, the extrinsic sensor calibration can lead to improvements in these areas.

An in-depth search was performed on Scopus, Inspec, IEEE Xplore, and Google Scholar databases only considering full-text articles published in English. Given the different sensors considered and the focus on ground robots, it was used the logic operator AND to combine the following keywords: mobile robots, extrinsic calibration, extrinsic parameters, and sensor. First, the works experimented on mobile robots were prioritised. Second, the most recent ones were selected. Table 1 presents the obtained 19 methods categorised by the intended setup to be calibrated.

Table 1. Synthesis of the search results

Sensors setup	References
Robot–Laser	Gao and Spletzer [6] (2010), Underwood et al. [18] (2010)
Laser–Laser	Almeida et al. [1] (2012), Pereira et al. [17] (2016), Kühner and Kümmerle [11] (2019), Oliveira et al. [16] (2020)
Laser–Camera	Gomez-Ojeda et al. [7] (2015), Pereira et al. [17] (2016), Guindel et al. [8] (2017), Kühner and Kümmerle [11] (2019), Oliveira et al. [16] (2020)
Robot–Camera	Mueller and Wuensche [15] (2017)
Camera–Camera	Carrera et al. [3] (2011), Warren et al. [19] (2013), Ling and Shen [13] (2016), Kühner and Kümmerle [11] (2019), Oliveira et al. [16] (2020)
Camera–IMU	Yang and Shen [20] (2017), Huang and Liu [9] (2018), Kim et al. [10] (2018), Arbabmir and Ebrahimi [2] (2019), Eckenhoff et al. [4] (2019), Liu et al. [14] (2019)
Robot–IMU	Liu et al. [14] (2019)
IMU–IMU	Kim et al. [10] (2018)
Laser–IMU	Le Gentil et al. [12] (2018), Kim et al. [10] (2018)

3 Discussion

The analysis categorises the methods by the intended setup aimed for calibration. It is described briefly each method, its requirements, and the experiments made. If there are more than 2 methods for a setup, a comparison table is also presented.

3.1 Robot–Laser Scanner

Gao and Spletzer [6] relaxed the non-linear calibration problem to a Second-Order Cone Program (SOCP). The SOCP minimises the distance error of known features (retro-reflective tape on vertical poles). Due to the type of features needed, [6] requires that the lasers provide distance and remission values. Underwood et al. [18] used the MatLab function `fmincon` to solve the non-linear calibration problem by minimising the distance error of known features (vertical pole). [6] and [18] have two common requirements: the robot 6 Degrees of Freedom (DoFs) relative to the world and an extrinsic parameter initial estimation.

As for experiments made, [6] used a vehicle platform with two 2D laser scanners and the OxTS RT-3050 localisation system. Given that the SOCP is a relaxation of the original non-linear problem, [6] evaluated its computational efficiency compared with a `fmincon` implementation, and it was two orders of magnitude faster achieving similar results for the sensors extrinsic parameters. The approach [18] used a vehicle platform with four 2D laser scanners and a Novatel commercial unit for localisation. Works [6] and [18] compared their methods' accuracy to measured extrinsic parameters, in terms of mapping inconsistencies. Both methods obtained improvements over manual measurements.

3.2 Laser Scanner–Laser Scanner

Almeida et al. [1] used the 3D laser's point cloud as a reference to fit the data from a 2D laser and extract common points. The user sets the calibration object (conic-based) centre position in the point cloud readings. Then, the Visualization Toolkit computes the rigid transformation. Pereira et al. [17] implemented an Iterative Closest Point (ICP) algorithm with closed-form equations minimising the point-to-point error. This error uses the centre position of the ball calibration object. Kühner and Kümmerle [11] used a weighted least-squares algorithm to minimise the point-to-point distance error. It needs a sphere calibration object to compute the point-to-point error. Oliveira et al. [16] used the least-squares algorithm to minimise the point-to-plane distance error. The calibration object used to compute this error was a checkerboard. [16] also needs user interactions to label checkerboard readings in the sensors data, and to set initial estimations (to address the local minima problem) using the rviz tool (ROS framework).

Furthermore, [1] considered only the setup 2D–3D laser and [16] only 2D–2D. Even tough [11] proposed an error function for 2D lasers, [11] was only tested with 3D laser scanners. In contrast, [17] considers any combination between 2D and 3D lasers. The four methods need an overlapping field between the sensors.

In terms of experiments made, [1] used a vehicle platform with two 2D and one 3D laser scanner. [1] noted that its accuracy is highly dependent on the number of 2D laser measures that intersect the calibration object. It also evaluated data inconsistencies between the sensors. The approach [17] used a vehicle platform with a camera, a 3D and two 2D laser scanners, and a ToF sensor. It obtained an experimental standard deviation below 10 cm for the laser–laser setup. Work [11] used a setup with two 3D laser scanners. It made simulations using 3D laser scanners of low and high precisions showing good noise robustness for distance and angles errors. As for [16], it used a vehicle platform with two 2D laser scanners. The calibration of a laser–laser setup resulted in distance errors relative to the checkerboard plane in the order of centimeters. Table 2 summarises the comparisons made between the methods.

Table 2. Synthesis of the methods for laser–laser setups

Description		[1]	[17]	[11]	[16]
Algorithm	Iterative Closest Point (ICP)		x		
	Least-squares			x	x
	Visualization Toolkit (VKT)	x			
Requirements	Calibration object	x	x	x	x
	Overlapping field of view	x	x	x	x
	User interactions	x			x
Experiments	Simulations	x		x	
	Real data	x	x		x

3.3 Laser Scanner–Camera

Gomez-Ojeda et al. [7] used Maximum Likelihood Estimation (MLE) processes to minimise line-to-plane (rotation) and point-to-plane (translation) errors using scene corners. Pereira et al. [17] used the Levenberg-Marquardt optimisation algorithm to minimise the reprojection error (Perspective-n-Point problem) using a ball. Guindel et al. [8] used the ICP algorithm with closed-form equations to minimise the point-to-point error. It has a limitation: needs at least two cameras to compute a 3D point cloud by stereo matching. The points correspondence between sensors used the holes' centres of the calibration object (board with four circular holes). Kühner and Kümmerle [11] used a weighted least-squares algorithm to minimise the point-to-ray distance error and, similar to the laser-laser calibration, it needs a sphere object. Oliveira et al. [16] used the least-squares algorithm to minimise the error distance point-to-plane (laser) and reprojection error (camera). It has the same requirements as described in Subsect. 3.2. All five methods need an overlapping field of view between sensors.

Moreover, [7] and [16] only considered 2D laser scanners. [8] needs a stereo-pair system and a 3D laser to produce two point clouds. As for [17], it can calibrate both 2D and 3D lasers with a camera. The 3D laser–camera calibration was not tested. It was only tested the 2D–2D/3D laser and 2D laser–camera setups, although the authors justify that the 2D laser was the reference sensor because of its accuracy. Work [11] experimented only with 3D laser scanners and cameras. Still, the 2D laser was considered in the development of the method.

In terms of experiments made, [7] used a rig with a 2D laser scanner and a camera. It performed Monte Carlo simulations to analyse the method's accuracy using a different number of features correspondence. A higher number of correspondences showed better results, analysing the extrinsic parameters rotational and translational error. Also, the accuracy of [7] using a low number of correspondences outperformed other state-of-art methods referred to in the article. With real data, analysing the reprojection error by increasing the camera's exposure time, the method showed good results in evaluating these visually. Approach [17] used a vehicle platform with a camera, a 3D and two 2D laser scanners, and a ToF sensor. It evaluated its performance analysing the mean reprojection error. This error was less than 4 pixels error in the experiments made. Work [8] used a vehicle platform with a 3D laser scanner and a trinocular camera. It only performed simulations in order to have ground-truth data for the extrinsic sensors parameters. It was compared with other state-of-art methods referred to in the article obtaining lower rotational and translational error. Although real experiments are mentioned in [8], no results were presented. The approach [11] used a setup with two cameras and two 3D laser scanners. It simulated the sphere detection error and evaluated the impact of the sensors noise model. The results were compared to an euclidean approach and the [11] showed better results. With real data, it obtained standard deviations below 0.1 cm and 0.01° for translation and rotational parameters, respectively. As for [16], it used a vehicle platform with two cameras and two 2D laser scanners. Work [16] compared the initial estimation with the extrinsic calibration, and the distance errors to the checkerboard and the reprojection errors decreased in most of the experiments. Table 3 summarises the comparisons made between the methods.

Table 3. Synthesis of the methods for laser–camera setups

Description		[7]	[17]	[8]	[11]	[16]
Algorithm	Iterative Closest Point (ICP)			x		
	Levenberg-Marquardt optimisation		x			
	Maximum Likelihood Estimation (MLE)	x				
	Least-squares				x	x
Requirements	Calibration object		x	x	x	x
	Overlapping field of view	x	x	x	x	x
	User interactions					x
Experiments	Simulations	x		x	x	
	Real data	x	x	x	x	x

3.4 Robot–Camera

Mueller and Wuensche [15] was the only method found for the robot–camera setup. By using an Extended Kalman Filter (EKF), it estimates the twelve extrinsic parameters of robot's left and right cameras, and the position of the tracked Scale-Invariant Feature Transform (SIFT) features. The Inertial Navigation System (INS) used allowed to estimate the vehicle's motion, and, so, predict the position of the tracked features (static relative to the world frame). In order to [15] be executed in dynamic environments, a convolutional neural network was used to label the features as dynamic or static rejecting the dynamic ones. As for experiments made, [15] used a vehicle platform with a high-end INS and two cameras. Work [15] evaluated its performance in urban environments, and it did converge (corrected the false initial estimative for the extrinsic parameters) demonstrating that it could run online. It was noted that the extrinsic parameters could be computed in straight-line motion because these were sensitive to the road small imperfections. Lastly, [15] is not analysed in Subsect. 3.5 because [15] did not performed specific tests for the camera–camera setup. Indeed, the EKF considers always the robot–camera extrinsic parameters in its state.

3.5 Camera–Camera

Carrera et al. [3] used a bundle adjustment to minimise the weighted reprojection error. The MonoSLAM was used to construct a Speeded Up Robust Features (SURF) 3D map and to match the features between cameras. The cameras need to be synchronised, and it was noted that high-texture scenes helped generate more features. [3] was the only method of the selected that did not require an overlapping field of views for the camera–camera calibration. Warren et al. [19] is similar to [3], but it did not use MonoSLAM. The calibration algorithm is executed at any time if a specific heuristic defined in [19] is not met. After the calibration, the method continues to perform a visual odometry also proposed in [19]. It also needs an initial estimation for the extrinsic parameters. Although [19] did not specify if the method needs synchronised cameras or high-texture scenes, the experimental setup used synched cameras, and the tests were performed in an outdoor environment (high-texture scenes). Ling and Shen [13] proposed an optimisation-based algorithm that minimises the overall epipolar error using Binary Robust Independent Elementary Features (BRIEF) matching. However, it only computes 5 DoFs between the cameras. [13] considers only a stereo configuration for the cameras where the distance between them is known. Kühner and Kümmerle [11] used a weighted least-squares algorithm to minimise the ray-to-ray distance error. It requires a sphere object for the calibration procedure. Oliveira et al. [16] used the least-squares algorithm to minimise the reprojection error. It has the same requirements as described in Subsect. 3.2.

As for the experiments made, [3] used a robot with two and four cameras. Also, it was used the commercial photogrammetry solution Photomodeler to model the calibration room and provide ground-truth data. Work [3] accomplished good results in terms of reprojection error. Also, it was noted that adding more cameras improved the accuracy because it added more constraints to the optimisation process. Approach [19] used a vehicle platform wit two cameras. It performed simulations for different stereo-pair cameras poses always converging. Also, [19] experimented in outdoors and evaluated its online capability by comparing the visual odometry with an INS. It had similar localisation results in comparison to the INS. Approach [13] used a setup with two cameras on a front-parallel stereo configuration. [13] compared its accuracy using a checkerboard or BRIEF features to an offline-checkerboard-based calibration method available in OpenCV. The proposed method using a calibration object or BRIEF features obtained similar performance to the OpenCV method in terms of the experimental mean and standard deviation. Approach [11] used a setup with two cameras. It compared low-resolution to high-resolution cameras (the last as ground-truth). The method showed noise robustness in the simulations by estimating the extrinsic parameters accurately when observation noise was associated with the cameras. Work [16] used a vehicle platform with two cameras. It evaluated the reprojection error difference between an initial estimative and a calibrated setup. Although in one of the cameras was reduced the reprojection error, for the other camera, it increased. So, [16] could not be suited for camera–camera calibration. Table 4 summarises the comparisons made between the methods.

Table 4. Synthesis of the methods for camera–camera setups

Description		[3]	[19]	[13]	[11]	[16]
Algorithm	Bundle adjustment	x	x			
	Least-squares				x	x
	Optimisation			x		
Requirements	Calibration object				x	x
	High texture environment	x	x			
	Overlapping field of view		x	x	x	x
	Synched cameras	x	x			
	User interactions					x
Experiments	Simulations		x		x	
	Real data	x	x	x		x

3.6 Camera–IMU

Yang and Shen [20] used a probabilistic optimisation-based approach to minimise the Mahalanobis norm. Huang and Liu [9] used an optimisation-based algorithm integrated with ORB_SLAM. Kim et al. [10] used an optimisation-based algorithm to minimise residual functions defined in [10]. It requires 3D landmarks with known localisation. Arbabmir and Ebrahimi [2] opted for a hybrid optimisation algorithm based on particle swarm optimisation and genetic algorithm. [9] and [2] require a synched camera–IMU setup. Eckenhoff et al. [4] used a Multi-State Constraint Kalman Filter that also computes the time offsets between camera and IMU readings, and could be executed online. Liu et al. [14] proposed a Visual-Inertial System (VINS) coupled with encoder performing a online extrinsic calibration based on optimisation. It requires the encoder's data and landmarks (not their localisation). [10,20] and [14] did not specify if synched data is a requirement. Only [14] requires initial estimations.

In terms of experiments made, [20] used a sensor suite with a camera and an IMU. [20] compared its performance with the Kalibr [5] method. It achieved an experimental standard deviation lower than 1 cm (3 cm for [5]). A calibrated VINS was also compared to a ground-truth provided by the OptiTrack system achieving similar localisation results. [9] used the EuRoC dataset acquired from a micro aerial vehicle with two cameras and an IMU. The extrinsic parameters had rotational errors lower than 1° and translation errors lower than 15 cm. [10] used a sensor suite with one camera and two IMUs. [10] compared its performance to [5] by performing two experiments: 45° rotation of part of the sensor suite, and 5 cm change in translation. It had lower translation and rotational error than [5] comparing the second experiment with the first. [2] performed simulations using the KIITI dataset and compared the results with a state-of-art method. It obtained similar results in terms of the parameters accuracy, even though it has fewer requirements (e.g., no calibration object, no calibration scenarios). Also, executing [2] on a VINS and comparing its accuracy to a GPS/INS system, it showed good navigation results in outdoors. [4] used a Snapdragon Flight with onboard IMU and two/three cameras. [4] evaluated its online convergence and obtained similar accuracy relative to [5]. [14] used a car with a camera, an IMU, and a wheel encoder on the left rear wheel. It compared its VINS with a similar one that does not perform the online calibration. [14] improved the positioning and reconstruction accuracy of the system. Table 5 summarises the comparisons made between the methods.

Table 5. Synthesis of the methods for camera–IMU setups

Description		[20]	[9]	[10]	[2]	[4]	[14]
Algorithm	Multi-state constraint Kalman filter					x	
	Optimisation	x	x	x	x		x
Requirements	Landmarks			x			x
	Synched camera–IMU		x		x		
Experiments	Real data	x	x	x	x	x	x

3.7 Robot–IMU

Liu et al. [14] proposed a VINS coupled with wheel encoder that performs an online extrinsic calibration based on optimisation. It requires the use of landmarks and the encoder's data. The experimental setup is the same as described in Subsect. 3.7. [14] showed that the online calibration of robot–IMU–camera has better reconstruction and positioning accuracy than only camera–IMU.

3.8 IMU–IMU

Kim et al. [10] defined residual functions minimised by nonlinear least-squares solvers. It estimated the extrinsic parameters, and the initial gravity and velocity vectors of the IMUs. [10] was tested with two IMUs performing the same experiments as for the camera–IMU setup. The results compared to the expected ones were 1.03° for rotational and 5.88 cm for translational errors.

3.9 IMU–Laser Scanner

Le Gentil et al. [12] is an optimisation-based algorithm that minimises the point-to-plane distance associated with the 3D laser and the residuals associated with the IMU. Kim et al. [10] defined residual functions to be minimised by an optimisation-algorithm. Both methods require a scene corner and only [12] addressed the synched data problem by modelling the inertial data continuously.

Approach [12] used a 3D laser–IMU setup. It performed Monte Carlo simulations to analyse the rotation and translational errors. Athough ideal IMUs resulted in accurate extrinsic parameters, the translation and rotational errors increased (0.57 to 34 cm and 0.02 to 0.96°, respectively) when the IMU had perturbations. [12] showed accurate results in terms of reprojection error when compared to a chained calibration method (Kalibr [5] for camera–IMU, and point-to-plane optimisation for laser–camera). Even though it is referred in [12] experiments with real data, no conclusions were taken. Work [10] used a 2D laser–IMU setup, and evaluated the relative errors between two experiments. It achieved a 0.32 cm translational and a 0.94° rotation errors.

4 Conclusions

This paper analysed the most recent works on extrinsic sensor calibration. Its accuracy is determinant for transforming the sensor readings into a common frame and it can improve localisation, mapping performances and robot perception.

Thus, it was analysed 19 methods. In the in-depth search, it was noted that the laser-camera and the camera-IMU were the setups most well studied, and the robot–camera and robot–IMU are the less studied. In terms of the most general methods, [11,17] and [16] calibrate two or more setups of lasers and cameras, and [10] setups with IMUs except for robot–IMUs. For robot–laser, [6] seems to be accurate but also computationally efficient. [15] is the only method found for the robot–camera setup. Lastly, [14] was the only method found for robot-IMU.

This literature review presents some methods that allow the calibration of a sensory system composed by lasers, IMUs and cameras. So, we aim that this paper, apart from analysing some of the most recent work on extrinsic calibration, helps the scientific community to propose new methods to improve this field.

Acknowledgement. This work is financed by the ERDF – European Regional Development Fund through the Operational Programme for Competitiveness and Internationalisation - COMPETE 2020 Programme, and by National Funds through the Portuguese funding agency, FCT - Fundação para a Ciência e a Tecnologia, within project SAICTPAC/0034/2015- POCI-01-0145-FEDER-016418.

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