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Evolution of Odometry Calibration Methods for Ground Mobile Robots

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***Abstract*—Localisation is a critical problem in ground mobile robots. For dead reckoning, odometry is usually used. A disadvantage of using it alone is unbounded error accumulation. So, odometry calibration is critical in reducing error propagation. This paper presents an analysis of the developments and advances of systematic methods for odometry calibration. Four steering geometries were analysed, namely differential drive, Ackerman, tricycle and omnidirectional. It highlights the advances made on this field and covers the methods since UMBmark was proposed. The points of analysis are the techniques and test paths used, errors considered in calibration, and experiments made to validate each method. It was obtained fifteen methods for differential drive, three for Ackerman, two for tricycle, and three for the omnidirectional steering geometry. A disparity was noted, compared with the real utilisation, between the number of published works addressing differential drive and tricycle/Ackerman. Still, odometry continues evolving since UMBmark was proposed.**

***Index Terms*—mobile robots, calibration, odometry**

I. Introduction

In ground mobile robots, localisation is one of the most critical problems associated with the navigation of an autonomous mobile robot [1]. Two basic localisation methods are absolute and dead reckoning, commonly employed together. Dead reckoning methods are usually based on odometry [2].

Odometry computes, for example, the robot's relative motion from the measurement of wheel revolutions (usually obtained from optical encoders) and/or steering angles [3]. As compared to other localisation methods, odometry allows very high sampling rates and better short-term accuracy [4]. However, odometry is based on the assumption that the revolutions of the wheels can be translated to linear displacement. This assumption may not be valid in all situations. For example, if one wheel loses traction because, say, over accelerations, the wheel revolutions do not correspond to the real linear displacement of the wheel [2].

A disadvantage of odometry is the accumulation of errors. Their source can be categorised into systematic or nonsystematic errors [2]. Systematic ones are deterministic and constantly accumulate over time, so it is possible by calibration to reduce their effect. Nonsystematic cannot be predicted, only described probabilistically. Therefore, odometry calibration is crucial to its accuracy. It is based on the identification or correction of kinematic parameters that compute the mobile robot pose with a minimum error associated with it [5].

This paper focuses on analysing the literature relative to odometry calibration. Specifically, it targets studies that estimate the physical dimensions necessary to correct the kinematic model, instead of the robot's linear displacement and orientation. The analysis covers the time period since the UMBmark [2] method was published (1996). The objective is to perform a qualitative analysis of the methods and highlight the advances made on odometry calibration.

The paper is organised as follows. Section II presents the methods found, dividing them by the steering geometry intended for each one. Section III discusses and analyses them. Section IV presents the conclusions from this analysis.

II. Method

This study aims to elicit meaningful research by analysing existing literature about odometry calibration methods. Furthermore, it intends to cover the most used steering geometries. In ground mobile robotics, the most frequent ones are differential drive, tricycle, omnidirectional of three or four wheels, and Ackerman [1]. An in depth search from January 1996 to January 2020 was performed on Scopus, Inspec, IEEE Xplore, and Google Scholar. Only full text articles published in English were considered for this analysis. To collect relevant studies, the following keywords combined with the logical operator AND were used: calibration, mobile robot(s), and odometry.

Table I presents the obtained search results. In terms of steering geometries, the results are divided into 15 for differential drive, 3 for omnidirectional, 3 for Ackerman, and 2 for the tricycle steering geometry. Further analysis and comparisons between the different methods for the respective steering geometry are made in Section III.

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TABLE I
SYNTHESIS OF THE SEARCH RESULTS

Steering geometry	References
Differential drive	Borenstein and Feng [2] (1996), Martinelli et al. [6] (2003), Caltabiano et al. [7] (2004), Antonelli et al. [8] (2005), Abbas et al. [3] (2006), Ivanjko et al. [5] (2007), Bostani et al. [9] (2008), Mondal et al [10] (2010), Lee et al. [11] (2011), Jung and Chung [12] (2012), Maddahi et al. [4] (2012), Censi et al. [13] (2013), Cantelli et al. [14] (2016), Tomasi and Todt [15] (2017), Goronzy and Hellbrueck [16] (2017)
Ackerman	Lee et al. [17] (2010), Jung et al. [18] (2016), Galasso et al. [19] (2019)
Tricycle	De Cecco [20] (2002), Kallasi et al. [21] (2017)
Omnidirectional	Han et al. [22] (2010), Maddahi et al. [23] (2013), Lin et al. [24] (2019)

TABLE II
TEST PATHS AND TECHNIQUES USED BY THE METHODS FOR DIFFERENTIAL DRIVE

Ref.	Method information	Path	#Runs
[2] (1996)	Closed-form equations. Needs initial and final position	4x4m bi-directional square	5 (CW) + 5 (CCW)
[6] (2003)	Augmented Kalman filter (AKF). Needs a known map (landmarks), wheels velocities along path	Single arbitrary path	1
[7] (2004)	Extended Kalman filter (EKF). Needs DPGS data, wheels velocities along path	Single arbitrary path	1
[8] (2005)	Optimisation (least squares). Needs initial and final position and orientation, wheels velocities along path	Open paths (guidelines defined in [8])	Number of suitable paths
[3] (2006)	Closed-form equations. Needs the circumference diameter of CW and CCW directions	5m diameter bi-directional circumferences	1 (CW) + 1 (CCW)
[5] (2007)	Optimisation (Gauss-Newton or Nelder-Med). Needs initial and final position, initial and final orientation, wheels velocities along path	5m straight line + 180º "on-the-spot" rotation	5 (rot. CW) + 5 (rot. CCW)
[9] (2008)	Closed-form equations. Needs initial and final position, and the position at point of rotation	Straight line + 180º "on-the-spot" rot	1 (rot. CW) + 1 (rot. CCW)
[10] (2010)	Terminal Iterative Learning Control (TILC). Needs initial and final position, initial and final orientation, wheels velocities along path	Single arbitrary path	1
[11] (2011)	Closed-form equations. Needs initial and final position	2x2m bi-directional square	5 (CW) + 5 (CCW)
[12] (2012)	Closed-form equations. Needs initial and final orientation	2x2m bi-directional square	5 (CW) + 5 (CCW)
[4] (2012)	Closed-form equations. Needs initial and final position	Straight line (length undefined)	10
[13] (2013)	Optimisation (least squares) with closed-form equations. Needs relative motion measures, wheels velocities	Segments with constant wheels velocities	Several segments needed
[14] (2016)	Extended Kalman filter (EKF). Needs DGPS, attitude and heading data, and wheels velocities	Single arbitrary path	1
[15] (2017)	Closed-form equations. Needs initial orientation (360º rot.), and final position relative to y-axis (180º rot.)	360º + 180º "on-the-spot" rotation	5 (rot. CW) + 5 (rot. CCW)
[16] (2017)	Weighted nonlinear least squares. Needs positions and wheels velocities along path	Path defined by a heuristic if is suitable or not	1

III. DISCUSSION

The methods were divided according to the steering geometry they were designed for. First, for each method is presented the technique and the path used for calibration. Second, it is described the different error sources considered by the authors. Finally, the simulations and experiments made are discussed.

A. Differential drive

1) Calibration technique and test path: Borenstein and Feng [2] was the pioneer method for odometry calibration. However, Lee et al. [11] demonstrated that the path size influences the calibrated odometry accuracy. So, [11] and [12] propose a 2x2m square path. The square size is based on experimental results, and it is not proven that effectively improves the odometry for all robots when compared to the 4m side squared path. Although Tomasi and Todt [15] is based on [12], it does not make any straight line motion, only a rotational one for calibration. [15] needs much less space than [12]. Indeed, [15] uses only the space occupied by the robot base while [12] needs a 2x2m area.

Bostani et al. [9] do not specify the path length. The distance between the three points described in Table II (initial, point of rotation, and final robot position) allows the computation of two angles (one for CW, clockwise, and another for CCW, counterclockwise) that calibrate the kinematic parameters. A method with only a straight line was proposed by Maddahi et al. [4]. Comparing it to [9], [4] is simpler in terms of the test path. However, the effort is higher because it needs 10 experiments to reduce the influence of nonsystematic errors. As an alternative to square paths, Abbas et al. [3] proposed the bi-directional circular path test (BCPT). One advantage is that the robot does not make "on-the-spot" rotations (reduces the probability of slippering). Also, [3] needs less effort compared to the [2], [11] and [12] (these need 5 trials for each direction).

The methods based on optimisation need more information than just the end-points. Antonelli et al. [8] formulated the odometry calibration as a linear problem defining the robot's velocities (linear and angular) and wheels angular velocities by a matrix 2x2. Due to the use of least squares, it must be performed several calibrations runs with different trajectories to compute an unbiased estimator for the algorithm. In contrast, Ivanjko et al. [5] needs less effort compared

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to [8] (5 calibration sets for [5], while [8] can be greater if the trajectories aren't suitable). [5] optimises corrective factors to the kinematic parameters. Mondal et al. [10] also requires more information than just the end-points by using a terminal iterative learning control (TILC) algorithm. The advantages over [8] and [5] are ideally only one run to perform a calibration, and the test path is arbitrary (less effort compared to [8] and [5]). However, the odometry accuracy depends on the trajectory chosen. Censi et al. [13] simultaneously calibrates the odometry and the extrinsic sensor parameters. The method differs from [8], [5] and [10] by using the robot relative motion (scan matching of laser scanner measurements) over the entire trajectory. Even though [13] does not impose a particular trajectory, its calibration accuracy is dependent on the trajectory chosen. Lastly, Goronzy and Hellbrueck [16] differs from [8], [5], [10] and [13] by using the robot position over the entire trajectory. Although the method only takes 1 run, the absolute localisation system needed for calibration results in a more complex procedure.

Lastly, the methods based on a Kalman filter have the advantage of being able to be executed when the robot is performing tasks. Martinelli et al. [6] developed an augmented Kalman filter (AKF) which estimates the robot pose and the odometry adjustment parameters to correct the wheels diameters and the wheelbase over time. However, [6] needs a known map (e.g., landmarks) to fuse the laser with odometry data and update the filter. Caltabiano et al. [7] developed an extended Kalman filter (EKF) estimating the odometry parameters directly. The main difference relative to [6] is the DGPS data required to update the filter, instead of a known map. Although Cantelli et al. [14] is similar to [7], the data fusion considers also measurements from an inertial and magnetometer unit. This unit provides attitude and heading measurements to update the filter. Also, the augmented state takes into account the magnetometer offset over time. Comparing [6], [7] and [14] in terms of hardware needed, [7] requires less hardware. Table II summarises the description of the techniques, the test paths and the number of runs for each method.

2) Error sources considered: Methods [2], [3], [9], [11], [12], [15] considered the unequal wheel diameters and wheelbase uncertainty. Method [2] did not considered the scaling error (ratio of the actual average and the nominal wheel diameter), and considered the wheel radius and wheelbase errors as independent from each other. [3] differs from [2] by reducing the influence of nonsystematic errors in calibration (because of the test path). [11] proven that the wheelbase uncertainty and unequal wheel radius have a coupled effect. [11] considered it except on straight motion, but made trigonometric approximations ($\sin\alpha = \alpha$, $\cos\alpha = 1$) to compute the calibration equations. Given that [12] used the final robot orientation, trigonometric approximations used by [2] and [11] were no longer needed. [15] is based on [12] reducing the same error sources. In contrast, [9] considers the unequal wheel diameters, wheelbase uncertainty, and the scaling errors.

The five methods ([5], [8], [10], [13], [16]) that use optimisation and the three methods ([6], [7], [14]) based on Kalman filters are classified as "Not specific to any error source". Indeed, these methods do not consider the individual contribution of each specific error source. Lastly, [4] has the same classification given that it defines corrective factors that englobe the contribution of errors in general.

3) Simulations/experiments performed: Methods [3] and [9] did not experiment with robots. Although [11] makes comparisons with [3] and [2], no direct comparison was possible to make between these two. [12] compared [2] and [9] in the same experiment showing that [9] improves the odometry accuracy over [2]. Also, [12] shows that its method is more accurate in calibrating the robot than [11]. Lastly, [15] do not specify the robot used. Although [15] is based on [12], only compares it with [2] showing better odometry accuracy.

Work [8] compares different performances by analysing the final robot pose errors statistically (mean and max errors, and standard deviation estimation). Using a Khepera II robot, the performance of [8] and [2] were similar. For the Magellan Pro robot, the results were worse than with the odometry provided by the manufacturer.

As for methods based on the Kalman filter, [6] performed two experiments and added tape to the wheels in the second one. Although it was noted in the second experiment an expected increase of the wheels diameters, there are not presented any evaluations relative to the estimations error of the odometry parameters. Method [7] did not make any comparisons with [6]. However, [7] simulated DGPS failure comparing itself to the EKF classic (system state does not take into account odometry parameters, only the robot localisation) initialised with wrong odometry parameters, and to [2]. The calculated trajectories of each method were computed, and [7] obtained better results over the other two methods, in terms of the final position error. Work [14] did not make any comparisons with other methods proposed in the literature. The method compared its performance with gaussian noise added to the DGPS to the true position of the robot (given by the DGPS system). When the robot went through a rectangular, circle and an arbitrary path, the algorithm did reconstruct the robot's path accurately, in comparison with the DGPS measures. The final estimations of the odometry parameters were similar to their manual measurements.

For the other methods, [5] did not make any comparison with other methods. It improved odometry accuracy over the uncalibrated robot. [10] only compared its method with [2]. The results demonstrate an improvement in odometry accuracy over [2]. Similarly, [4] only compares its odometry accuracy to [2]. Even tough [16] did not make any comparisons to other methods in terms of accuracy, it evaluated the algorithm susceptibility to measurement noise (from the absolute localisation system). For the two cases, QRPos and UWM localisation systems, lead to similar results for the kinematic parameters. Lastly, [13] compared its accuracy with manual measurements and [2] estimations. It obtained similar results for the odometry while also calibrating the extrinsic sensors parameters. Table III summarises the simulations and experiments performed by each method.

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TABLE III
SIMULATIONS/EXPERIMENTS PERFORMED BY THE METHODS FOR DIFFERENTIAL DRIVE

Ref.	Simulations and experiments made
[2] (1996)	No simulations performed. Experiment with a LabMate robot moving slowly (0.2m/s to avoid slippering). Comparison with raw odometry using the measure of odometric accuracy for systematic errors as reference
[6] (2003)	No simulations performed. Experiments with a Donald Duck robot. Comparison with tape on both robot wheels
[7] (2004)	Simulations with DGPS failure. Experiments with a Robovolc robot. Comparison with EKF classic and [2]
[8] (2005)	No simulations performed. Experiment with a Khepera II and Magellan PRO robots. The first compared with raw odometry and [2]. The other with the odometry of the manufacturer
[3] (2006)	Simulations with kinematic parameters different from the real ones. Added gaussian noise to wheelbase and measurement values. No experiments with robots were performed
[5] (2007)	No simulations performed. Experiment with a Pioneer 2DX robot. Comparison between 2 or 3 corrective coefficients, and raw odometry using the final pose normalised error
[9] (2008)	Simulations with wheelbase and wheels radius different from real ones. Comparison with [2]. No experiments with robots were performed
[10] (2010)	Simulation with MATLAB. Comparison with the actual robot path. Experiment with a Pionner-DX3 robot. Comparison with [2] calibrated robot path and raw odometry
[11] (2011)	Simulations without non-systematic errors. Different size tracks also simulated. Experiment with a TETRA_DS(II) robot. Experiments with different size tracks. Comparison with raw odometry, [2], [3] and [9]
[12] (2012)	Simulations without non-systematic errors. Different size tracks also simulated. Comparison with [2] and [11]. Experiment with a TETRA_DS(II) robot. Comparison with raw odometry, [2], [9] and [11]
[4] (2012)	No simulations performed. Experiments with Six prototyped robots. Comparison with raw odometry and [2]. Validated on unseenpath bi-directional square
[13] (2013)	Experiments with a Kephera III robot. Comparison with manual measurements and [2]
[14] (2016)	Experiments with a tracked mobile platform. Addition of gaussian noise to DGPS measurements and testing of DGPS failure. Comparison with robot real position
[15] (2017)	No simulations performed. Experiment with a unknown robot. Comparison with raw odometry and [2] using the measure of odometric accuracy as reference
[16] (20017)	Simulations with a straight line, square path, and a complex/random path. Measurement noise also simulated. Comparison with raw odometry. Experiment with a Roomba 520 robot. QRPos and UWB position systems tested and their measurement noise influence analysed. Comparison with raw odometry

B. Ackerman and Tricycle

1) Calibration technique and test path: De Cecco [20] proposed a self-calibration algorithm for tricycle Automated Guided Vehicles (AGVs). The algorithm only needs one run and does not require an initial vector for the kinematic parameters. Also, for the tricycle steering geometry, Kallasi et al. [21] proposed a method based on least squares technique to calibrate the odometry. Several runs are needed to satisfy the condition of well-conditioned data acquired by measuring. In comparison to [20], the effort needed is higher because it requires several runs, and it is not a self-calibrated method.

TABLE IV
TEST PATHS AND TECHNIQUES USED BY THE METHODS FOR TRICYCLE/ACKERMAN

Ref.	Method information	Path	#Runs
[20] (2002)	Closed-form equations. Self-calibration. No initial guess needed. Needs intermediate and final positions and orientations	Initial curvilinear + straight line + turn left + turn right (lengths undefined)	1
[17] (2010)	Closed-form equations. Needs initial and final position	Bi-directional path: 2 straight lines + 2 semicircles (∼3x1.75m space)	5 (rot. CW) + 5 (rot. CCW)
[18] (2016)	Closed-form equations. Needs initial and final orientation	Bi-directional path: 2 straight lines + 2 semicircles (∼3x1.75m space)	5 (rot. CW) + 5 (rot. CCW)
[21] (2017)	Optimisation (Least Squares) with Closed-form equations. Needs steering angle and thick count, and relative motion for each path segment	Circular segments with increasing steering angle (CW + CCW)	Several
[19] (2019)	Optimisation (Least Squares) with Closed-form equations. Needs steering angle, thick count, and relative rotation for each path segment	Circular segments with increasing steering angle (CW + CCW)	Several segments needed

Lee et al. [17] proposed a method that by measuring the position errors and performing the path 5 times for CW and CCW directions, the kinematic parameters are adjusted using the position error centre of gravity. Instead, Jung et al. [18] uses the final orientation error (similar to [12] for the differential drive geometry). Lastly, Galasso et al. [19] method needs not only the steering angle and thick count along a segment path but also the relative rotation given by an exteroceptive sensor (laser range finder). A least square algorithm is applied to compute the calibrated kinematic parameters. Table IV summarises the description of the techniques, the test paths and the number of runs for each method.

2) Error sources considered: In terms of the tricycle configuration, [20] considers the steering angle offset, wheel radius and distance between wheel rotation axis as possible error sources. On the contrary, [21] does not consider the distance between wheel rotation axis as an error source. As for Ackerman robots, [17] and [18] considers the same error sources: wheel radius and distance between rear wheels. In comparison to these methods, [19] considers the wheel radius and the steering angle offset as error sources.

3) Simulations/experiments performed: In contrast to experiments with differential drive geometries, the articles referred did not make any comparison with other existing methods, except for [18]. However, [21] and [19] made a critical comparison. That is, AGVs have manual procedures

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TABLE V
SIMULATIONS/EXPERIMENTS PERFORMED BY THE METHODS FOR TRICYCLE/ACKERMAN

Ref.	Simulations and experiments made
[20] (2002)	No simulations performed. Experiment with a three-wheeled industrial robot. Compared with an uncalibrated odometric, uncalibrated inertial, calibrated inertial, and a calibrated odometric robot
[17] (2010)	Simulations with tread and wheel diameters error, and evaluated the region of convergence. Experiment with a prototype CLMR. Artificial errors induced using winding tape to change wheel radius. Compare with raw odometry. Experiment with EKF for odometry fusion
[18] (2016)	No simulations performed. Experiment with a prototype CLMR. Compared with raw odometry and [17]
[21] (2017)	No simulations performed. Experiments with CB16 and CB25 industrial AGVs. Comparison between STC and ATC procedures. Comparison between ATC and manual calibration (expert operator)
[19] (2019)	No simulations performed. Experiments with AGV17 (Ackerman) and AGV12 (Dual Drive) industrial robots. Experiments on calibration stability and position precision. Compared with manual calibration (expert operator) and 2 different calibration trials

that usually take much time (1 hour, as referred by [21] and [19]). Thus, these two methods have the advantage of only taking approximately 15 minutes, reducing the effort need to perform the AGV calibration (regardless if it is an Ackerman or a tricycle robot). [20] also focused on the industrial environment by doing experiments with industrial robots. Furthermore, since this is a self-calibration method, it takes much less effort than methods [21] and [19].

Lastly, [17] and [18] focuses on the automobile industry. Indeed, the surge of automatic parking systems led to the necessity of improving odometry accuracy of the Ackerman geometry. As a comparison, [18] obtained better odometry accuracy than [17] ([18] does not make any trigonometric approximations). Table V summarises the simulations and experiments performed by each method.

C. Omnidirectional

1) Calibration technique and test path: First, Han et al. [22] proposed a kinematic equation adjustment for a four-wheel omnidirectional robot. The algorithm adjusts the three kinematic parameters (associated with slippage, bearing and/or axle friction, and point contact friction respectively) to reduce the error associated with the robot's velocity. Next, based on [4], Maddahi et al. [23] also proposed a straight line path but to calibrate an omnidirectional. As in [4], the authors alert that the number of runs depends on the positioning accuracy in the calibration process. Lastly, Lin et al. [24] proposed a method similar to [8] but intended for omnidirectional geometry. Table VI summarises the description of the techniques, the test paths and the number of runs for each method.

2) Error sources considered: Only [22] specifies which error sources intends to reduce it, namely errors from slippage, bearing and/or axle friction, and point contact friction. Still, [23] and [24] reduce systematic errors independently of its error source. Lastly, none of these three methods compared between each other.

TABLE VI
TEST PATHS AND TECHNIQUES USED BY THE METHODS FOR OMNIDIRECTIONAL

Ref.	Method information	Path	#Runs
[22] (2010)	Optimisation (Least Squares). Needs wheel velocities and robot relative position along path	Movement along x-axis + y-axis + Θ direction	10 for each movement
[23] (2013)	Closed-form equations. Need initial and final position	Straight line (length undefined)	10
[24] (2019)	Optimisation (Least Squares). Needs initial and final robot pose	Open paths (guide-lines defined in [8])	Number of trajectories

TABLE VII
SIMULATIONS/EXPERIMENTS PERFORMED BY THE METHODS FOR OMNIDIRECTIONAL

Ref.	Simulations and experiments made
[22] (2010)	No simulations performed. Experiment with PODIMOR v1.0: custom-made four-wheeled omnidirectional robot. Uses RMS errors as reference. Comparison with the desired path
[23] (2013)	No simulations performed. Experiment with a prototype three-wheeled omnidirectional robot. Comparison with raw odometry. Validated on unseen paths (bi-directional square, triangle, and a combination between straight and curved)
[24] (2019)	No simulations performed. Experiment with a prototype three-wheeled omnidirectional robot. Validated on L-shaped and square paths. Comparison with raw odometry

3) Simulations/experiments performed: In Table VII are presented the simulations and experiments made by each method for omnidirectional robots. Analysing the results of each method, all improved the odometry accuracy over an uncalibrated robot.

IV. CONCLUSIONS

This article analysed the evolution of odometry calibration methods in ground mobile robots. If odometry is not accurate, the cost of localisation systems can increase due to the need for more measures from the absolute positioning systems.

Therefore, we surveyed 23 odometry calibration methods developed over time. Analysing the results, a disparity between differential drive versus tricycle/Ackerman was high: 15 and 5 results, respectively. Also, most methods for the differential drive, given its simplicity, use closed-form equations. However, for Ackerman, tricycle, and omnidirectional geometries, the latest methods developed used some sort of optimisation technique. This trend could be related to the fact that these geometries are more complex than the differential drive, being more difficult to compute closed-form equations.

In terms of the differential drive geometry, only [11] and [12] performed comparisons with other methods than [2]. Indeed, [12] improves odometry accuracy over [2], [9], and [11]. Overall, [12] seems to be the most accurate, taking into account the comparisons made with other methods. In terms of

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the procedure simplicity, [9] is simple in terms of the path and runs needed. Even though [4] requires 10 runs, the test path used is a straight line needing less space than other methods. However, the methods based on Kalman filter are useful to calibrate the robot without the need of taking the robot out of normal operation. The work presented in [7] is the only one based on a Kalman filter that compared its accuracy with other methods. As for tricycle/Ackerman methods, although [18] improved over [17], [21] and [19] compared themselves with a calibration method performed by an expert. So, [18], [21] and [19] seem to be the most odometric accurate. In terms of simplicity, [20] is the simplest method because it is self-calibrated. Lastly, [23] is the simplest of the three methods for omnidirectional robots, due to the only straight line path. Also, it is because of a similar number of runs relative to the other two methods. In terms of odometry accuracy, no experiments were made to compare the methods between them.

This analysis led us to conclude that odometry is still evolving (by improving its accuracy or simplifying the calibration procedure). Thus, we hope the analysis helps the scientific community evaluates existing methods and propose new ones.

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