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AN APPROACH TO ODOMETRY CALIBRATION OF DIFFERENTIAL DRIVE MOBILE ROBOTS

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Abstract. Odometry is the most widely used method for estimation of the momentary pose of mobile robots. It provides easily accessible real-time pose information between periodic absolute position measurements. However, with time, odometric localization accumulates errors in an unbounded fashion. This paper describes an approach to odometry calibration, which is based on two simple experiments. The proposed calibration method makes a correction mostly on the mobile robot orientation since this component of the mobile robot pose is more under systematic error influence.

Keywords: Robotics, Optimisation, Electric Vehicles

1. INTRODUCTION

Localization is one of the major tasks in navigation of autonomous mobile robots [1]. In a typical indoor environment with a flat floor plan, localization becomes a matter of estimating robot position in Cartesian coordinates (x, y) and robot orientation Θ with respect to the x-axis. When we are referencing the Cartesian coordinates and orientation we use the term *robot pose*. Odometry is one of the most important means of achieving this task. This method uses encoder data and is simple, inexpensive and easy way to determine the offset from a known start position in real time. Encoder data are proceeded to the central processor that continually updates the mobile robot's pose using geometric equations. Main disadvantage of this method is unbounded accumulation of errors due to wheel slippage, floor roughness, discretised sampling of wheel speed data, and inaccessibility to the angular velocities of the wheels in some mobile robots etc. Improved odometry can significantly reduce the rate of errors accumulation, and consequently increase the autonomy range of the mobile robot. This property is vital for many applications, particularly in cases when absolute information of robot pose is temporarily unavailable.

A lot of research works have been undergone in order to improve the accuracy of odometry, i.e. to eliminate the systematic errors. It can be improved using methods for correction of mobile robot pose estimation errors [2, 3] and using better odometry or error models [4]. Sensor fusion using Kalman Filter and calibration [5] is another method to improve the pose estimation of a mobile robot. Calibration to correct the systematic errors can be made with various experiments before or during the actual use of the mobile robot [6].

Robot orientation Θ is the most significant of the localization parameters (x, y, Θ) in terms of its influence on accumulated odometry errors. For this reason, sensors that provide a measure of absolute orientation or relative angular velocity are extremely important in solving real world navigation needs of an autonomous platform. The most commonly used sensors of this type are probably the magnetic compass and the gyro. Fusion of the odometry and compass or gyro information by using Kalman Filter can provide substantial increase of robot localization accuracy, e.g. [5, 7]. However, before the fusion of odometry and any other sensor it is advisable to calibrate the odometry in order to obtain the best possible estimation accuracy. Moreover, the price of the system is a limiting factor in many commercial applications, where it is beneficial to avoid the use of compass/gyro, but at the same time to keep accuracy of the robot pose estimation as high as possible.

In this paper we propose an approach to odometry calibration based on two simple tests. In the first test the mobile robot has to perform a straight line motion for certain distance and in the second test it must turn in place for 180 degrees. On the basis of difference between actual and desired (commanded) mobile robot poses at the end of tests, three calibration parameters are optimized. Very attractive feature of this approach is that it doesn't need any expensive additional accurate instruments or any special testing space.

2. THE MOBILE ROBOT POSE MODEL

Mobile robot used in our experiments is a three-wheeled robot. Two front wheels are drive wheels with encoder mounted on them and the third wheel is a castor wheel needed for robot stability. Drive wheels can be controlled independently from each other. The encoders can measure the speed or the traveled distance of the wheel. We are using the encoders to measure the speed of the wheel. The kinematics of the mobile robot are given by the following relations (Figure 1):

$$x(k+1) = x(k) + v_t(k) \cdot T \cdot \cos\Theta(k+1) \qquad (1)$$

$$y(k+1) = y(k) + v_t(k) \cdot T \cdot \sin \Theta(k+1) \quad (2)$$

$$\Theta(k+1) = \Theta(k) + \omega(k) \cdot T \quad (3)$$

$$v_t(k) = \frac{v_L(k) + v_R(k)}{2} = \frac{\omega_L(k)R + \omega_R(k)R}{2} \quad (4)$$

$$\omega(k) = \frac{v_R(k) - v_L(k)}{b} = \frac{\omega_R(k)R - \omega_L(k)R}{b} \quad (5)$$

where are: $x(k)$ and $y(k)$ coordinates of the center of axle [mm]; $v_t(k)$ robot translation speed [mm/s]; T sampling time [s]; $\Theta(k)$ angle between the vehicle and x-axis [°]; $v_L(k)$ and $v_R(k)$ velocities of the left and right wheel, respectively [mm/s]; $\omega_L(k)$ and $\omega_R(k)$ angular velocities of the left and right wheel, respectively [rad/s]; R radius of the two wheels [mm], and b vehicle axle length [mm]. It is assumed that the wheels have the same radius.

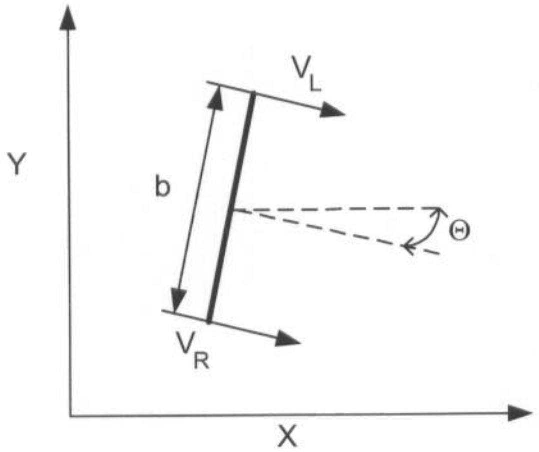

Fig. 1. The Mobile Robot kinematics

3. ODOMETRY CALIBRATION PROCEDURE

Experiments with differential drive mobile robots reveal that localization, which relies on velocities returned by the encoders, produces very large errors in the pose estimates, especially in the orientation estimation, e.g. [5]. There are many factors that deteriorate accuracy of the pose estimation, such as limited precision of the encoders, low sampling rate, and inaccessibility to raw encoders data that can give angular velocities of the wheels, but the most influential ones are unacquaintance of exact values of the wheels radiuses and axle length. These two factors contain mostly systematic errors and it is worthy to compensate their influences [5]. In order to implement these compensations we expand the equations (4) and (5) with three additional parameters:

$$v_t(k) = \frac{k_1 \cdot v_L(k) + k_2 \cdot v_R(k)}{2} \quad (6)$$

$$\omega(k) = \frac{k_1 \cdot v_R(k) - k_2 \cdot v_L(k)}{k_3 \cdot b} \quad (7)$$

where parameters k_1 and k_2 compensate the unacquaintance of the exact wheel radius and parameter k_3 the unacquaintance of the exact axle length. While parameters k_1 and k_2 affect mostly the position estimation, parameter k_3 affects mostly orientation estimation.

Calibration procedure consists of two steps: 1) appropriate experiments with the mobile robot are made and then 2) collected data are used for the parameters optimization with respect to a certain criteria.

3.1. The Experiments

Using the facts that the parameters k_1 and k_2 affect mostly the position estimation and parameter k_3 affects mostly the orientation estimation, two separate experiments are enough to collect the needed data for the parameters optimization. The first experiment is a "straight-line" experiment. It was accomplished by providing equal speed references to the both wheels. The second experiment is a "turn-experiment". The mobile robot had to turn for 180 degrees in place. During the experiments wheel speeds and sampling rate were measured and collected. These data were then used as input data for the optimization scripts. Both experiments were repeated for five times to improve the odometry calibration.

3.2. Parameters optimization

Optimal values of the compensation parameters k_1, k_2 and k_3 were calculated using *fsolve* optimization function from the MATLAB Optimization Toolbox [8]. This optimization function uses Gaus-Newton non-linear optimization method to solve any nonlinear function. Optimization of parameters k_1 and k_2 were implemented as *fsolve*("*optimize_k1_k2*", [k10, k20], options), and optimization of parameter k_3 as *fsolve*("*optimize_k3*", [k30], options), where k10, k20 and k30 are initial values of corresponding parameters, which were set to 1.0. Pseudo-codes of scripts *optimize_k1_k2* and *optimize_k3* are given in Table 1. Both scripts use the collected data and the robot model, given with equations (1)-(3) and (6)-(7), to calculate the mobile robot pose. Based on the computed mobile robot pose and actual mobile robot pose the orientation error were calculated. The goal of the optimization procedure is to minimize the orientation error by adjusting the calibration parameters. The first script is used for the calculation of the parameters k_1 and k_2 from the data collected in the straight-line experiment and the second one for the calculation of the parameter k_3 from the data collected in the turn-experiment. When the optimization procedure invokes the first script it use new value of the parameter k_3 calculated in the previous step, and consequently when it invokes the second script it use new values of the parameters k_1 and k_2 calculated in the previous step. As the stopping criteria for optimization

Function: *optimize_k1_k2* (k1, k2)	Function: *optimize_k3* (k3)
Input: new k1 and k2 values **File Input:** measurement data (wheel velocities and time data, exact start and final mobile robot poses) **Output:** difference between exact and computed mobile robot orientation **load** collected data of straight-line experiment **load** the parameter k3 value **compute** the final pose using the expanded robot model and the measurement data **return** difference between exact and computed mobile robot orientation	**Input:** new k3 value **File Input:** measurement data (wheel velocities and time data, exact start and final mobile robot pose) **Output:** difference between exact and computed mobile robot orientation **load** collected data of turn experiment **load** the parameter k1 and k2 value **compute** the final pose using the expanded robot model and the measurement data **return** difference between exact and computed mobile robot orientation

Tab. 1. Pseudo-codes of optimization scripts

procedure we set the number of iteration for the *fsolve* optimization function to 50.

4. EXPERIMENTAL RESULTS

The described experiments where performed using a Pioneer 2DX mobile robot from ActivMedia Robotics (Figure 2). Two front wheels are drive wheels with encoders mounted on them and the third wheel is a castor wheel to ensure stability. Drive wheels can be controlled independently from each other. The mobile robot has the following measures: axle length b is 32 [cm], wheel width is 3.7 [cm], wheel diameter R is 16.5 [cm], maximal translation speed is 1.6 [m/s] and maximal rotational speed is 300 [degrees/s]. Traversable terrains are all wheelchair accessible. The sampling time T is 100 [ms].

Figure 2. Mobile Robot Pioneer 2DX

Calibration experiments described in previous section were performed in a corridor with a translation speed of 0.2 [m/s]. Applying the proposed optimization procedure, optimal values of parameters k_1, k_2 and k_3 were found. They are: $k_1 = 0.9963$, $k_2 = 1.0037$ and $k_3 = 1.057$. In order to evaluate proposed calibration procedure, we performed additional experiments with optimal values of parameters k_1, k_2 and k_3. Two trajectories were used to test the calibrated odometry. The first one is a straight-line of 5 m length, and the second one is a straight-line of 5 m with return to the start position. Results of these two experiments are shown in Figures 3 and 4, respectively.

In order to recognize the influence of the systematic errors, reference velocities for both drive wheels were equal for the straight-line trajectory. Figures 3 and 4 show that the mobile robot drifts to the left due to systematic errors. They also show results of three different robot pose estimation methods. The first one, called "Saphira", is the pose estimation returned by the mobile robot control application. The second one, called "Odometry", is the pose estimation using uncalibrated odometry, i.e. applying the robot model given with equations (1)-(5). The third one, called "Calibrated Odometry", is the pose estimation using calibrated odometry, i.e. applying the robot model given with equations (1)-(3) and (6)-(7) with optimal values of parameters k_1, k_2 and k_3. The exact final mobile robot position is denoted by a black cross and the calculated final position for each tested method by a black dot. Table 2 summarizes the results of two evaluation experiments. Final mobile robot poses obtained by different estimation methods are given. It can be seen that the calibrated odometry gives the best results. The accuracy is improved for all three pose variables. The improvement in orientation estimation is of particular importance. Table 3 summaries the results of two evaluation experiments using a percentage error comparison. The percentage error is computed as:

$$Error = \frac{Pos_{act} - Pos_{est}}{Dist} \cdot 100\% \qquad (8)$$

where Pos_{act} is the actual final position, Pos_{est} is the estimated final position and $Dist$ is the total distance traversed by the mobile robot. The traveled distance is about 5 [m] for the straight-line experiment and 10 [m] for the straight-line with return experiment.

Experiment	Coordinate	Exact Pose	Saphira	Odometry	Calibrated Odometry
Straight Line	X [mm]	4995	5150	5130	5132
	Y [mm]	184	-17	-196	104
	Θ [°]	4	0	358	5
Straight Line with return	X [mm]	15	-35	46	39
	Y [mm]	-575	-14	884	-614
	Θ [°]	190	180	171	194

Tab. 3. Final position comparison of different position estimation techniques

Experiment	Saphira	Odometry	Calibrated Odometry
Straight Line	6.3 %	10 %	4 %
Straight Line with return	6.2 %	14 %	1 %

5. CONCLUSIONS AND FUTURE WORK

A simple approach to odometry calibration has been presented. It is shown that the proposed calibration can give an improvement of the pose estimation of a differential drive mobile robot. Our calibration method doesn't require any additional sensors or measurements. Calibrated odometry can be used for pose updates in cases when absolute positions from sensors like GPS are not regularly available or for pose updates in pose tracking methods which are using local maps based on sonar or laser range finder sensors.

However, in high-demanding applications, it can be necessary to fuse calibrated odometry with compass or gyro for better estimation of robot orientation. Another competing approach is development of an on-line odometry calibration method based on information from perception sensors, like sonars or laser range finders. The later approach will be in focus of our further research, because it can substantially increase accuracy of odometry without applying compass or gyro.

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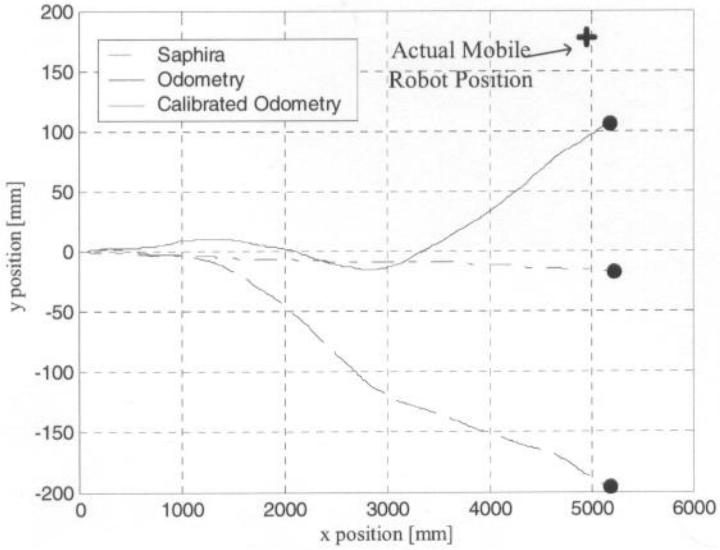

Fig. 3. The Straight Line Experiment

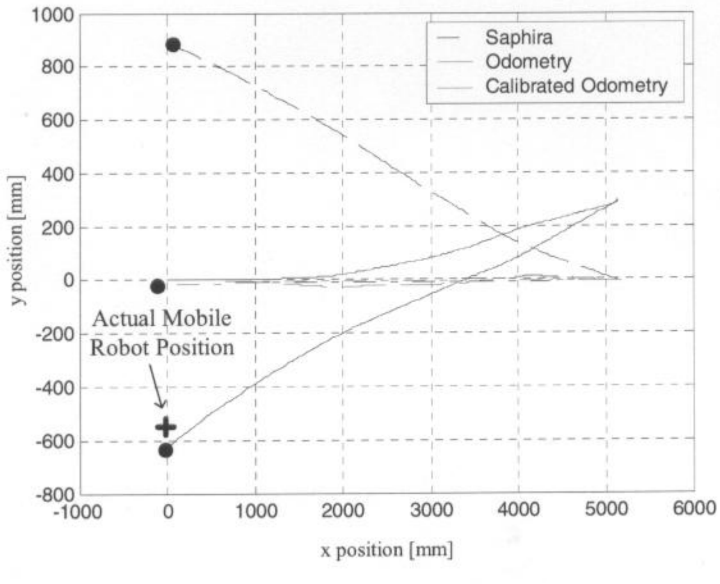

Fig. 4. The Straight Line with return Experiment