Mobile Robot Localization Using Beacons and the Kalman Filter Technique for the Eurobot Competition

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Abstract. The objective of this work was the development of a positioning system for the Eurobot contest, which enhance the positioning accuracy compared to the odometry. In order to achieve this goal, we measured angles to three unique landmarks with known positions. These angles, we determined the position of the robot. For the position determination, we examined two approaches: The trilateration and an positioning system based on an enhanced kalman filter (EKF). The trilateration determines cycles from the angles between the landmarks and then intersects these cycles to determine a position. The EKF based system, fuse the measured angles with the position provided by the odometry. Measurement drives proved that the EKF based system is the most suited for localization task at the Eurobot contest and that is also more accurate than the odometry.

1 Introduction

The localization problem is one of the most challenging tasks for all mobile robots, because the knowledge about the own position is the basic requirement for high level tasks. Due to the Eurobot contest the robot's localization on the playground is necessary for path planning and navigation. Thus high level tasks like collision avoidance with alternative path planning or the depositing of collected objects at predefined targets are possible. Generally there are two practical approaches to locate the robot's position on the playground. On the one hand there is dead reckoning and on the other hand there are landmark based localization methods. Our approach combines both methods by a Kalman filter to get an improved position estimation.

Dead reckoning systems usually use the measurements of wheel encoders to estimate the rotation of the wheels. Based on these measurements the calculation of the cover distance is straight forward and also called odometry. The disadvantage of this method is the unbounded accumulation of the errors. To reduce this errors an exact estimation of the wheel diameter and the wheel distance are necessary. An approach to precisely collect these parameters and calibrate the robot to reduce these errors is presented in [1]. But errors like wheel slip can not be handled with this method and so much research is done to improve dead reckoning systems by adding acceleration and gyroscope sensors [2–6].

Another approach to estimate the robot's position is to use landmarks. A standard method is to place landmarks in the robot's workspace at known positions. In this case the robot needs sensors to detect these landmarks and to measure the distance or the angle to these. For many sensors such as cameras or wireless hardware the bearing is easier to measure than the distance. Thus, we focus on these approaches which use the bearings for localization. *If the robot is able to measure the angle to at least three landmarks every time then the position estimation in the plane is possible using a triangulation algorithm as shown in [7–12].* An approach for an omni directional camera which only needs two landmarks is presented in [13]. They use additionally a distance measurement to the landmark based on the visual information. All these approaches have two major difficulties to deal with. The first one is the imprecise measurements based on the senors inaccuracy and the second one is the arrangement of the landmarks. The effect of the landmarks arrangement is analyzed in detail in [14].

Based on the repeating rules of the Eurobot contest, we present a landmark based localization approach. The rules define that every team has the possibility to put three beacons around the playground at known positions. We use active infrared markers with an unique id as landmarks. As sensor an omni directional camera array with an infrared filter is used. The design of this sensor is presented in [15]. The sensor provides an angle measurement between the robot and the landmarks with an accuracy of about ±0.6 degree. Based on these measurements we have analyzed two methods for the position estimation. First a triangulation method which only uses the angle information is presented. This method needs the angle to all three beacons at times to estimate the robot's position.

In a second step we have improved this method by applying an Extended Kalman filter to combine the angle measurements with the odometry. An advantage of this approach is that the position can be estimated at all times even if the landmarks are not detected. A second benefit is that the robot's position can be improved by the angle measurement even if only one beacon is detected. The idea of the Kalman filter is presented in [16] and a practical introduction to the discrete and Extended Kalman filter is given in [17].

2 Triangulation Method

The coordinate system fixed with the Eurobot playground is called the global coordinate system. We assume three beacons at the positions $B_i = (x_i, y_i)$ for $i = 1, 2, 3$ (see fig. 1). The local coordinate system is fixed with the robot, where the x-axis is aligned with the robot's orientation The robot measures three angles $\phi_i, i = 1, 2, 3$, between the beacons B_i and its local x-axis. The goal is to find the unknown robot position (x_R, y_R) and its orientation θ_R.

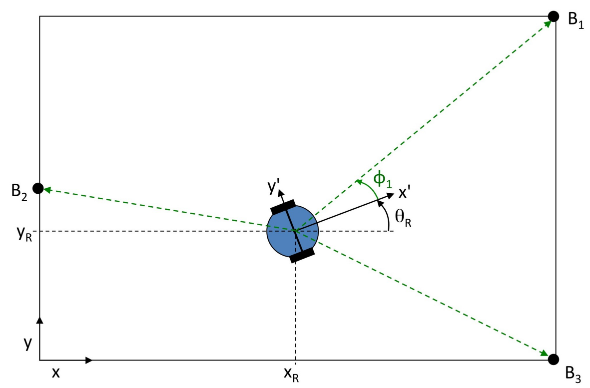

Fig. 1. Robot at position (x_R, y_R, θ_R) and the beacons $B_1 = (3m, 2.1m), B_2 = (0m, 1.05m)$ and $B_3 = (3m, 0m)$. The robot measures the three angles ϕ_1, ϕ_2 and ϕ_3. In the figure, angles ϕ_2 and ϕ_3 are omitted.

From figure 1 the following equations can easily be deduced:

$$\phi_i = atan2(y_i - y_R, x_i - x_R) - \theta_R, i = 1, 2, 3 \tag{1}$$

Thus, we get a nonlinear equation system, which can be solved for the unknown (x_R, y_R, θ_R) numerically (e.g. the trust-region dogleg algorithm [18]) . It should be noted, that exactly three angle measurement are needed in order to determine the unknowns.

This localization system is very easy, but unfortunately it is not reliable enough for solving one of the Eurobot tasks. There are two reasons.

1. The occlusion of one of the beacons (e.g. by the opposing robot) or some error in the sensors do not allow to compute a position. We estimate that each of the beacons can not be recognized about 20% of the time.
2. Due to the geometric constellations of the beacons there are regions on the playground where localization is very deficient. This can be seen by the following property of the triangulation method. For each pair of angle measurements ϕ_i and ϕ_j the angular difference $\phi_i - \phi_j$ determines an unique arc, where the robot must lie on (see fig. 2). The position of the robot can be determined by computing the intersection of all arcs as can be seen in figure 3. Figure 4 depicts the extreme case where all beacons and the robot lie on the same circle. Therefore the intersection point is not unique. If an error in the angle measurements is assumed, we also get an positioning error, which depends on the position on the playground (figure 5).

Therefore, we combine our triangulation method with the well known odometry by applying the Kalman filter technique. This leads to an accurate and highly available positioning system.

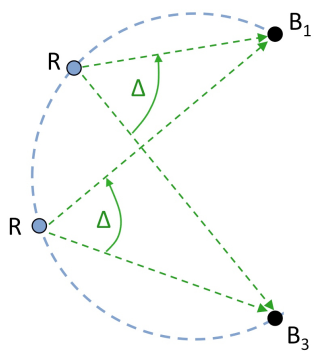

Fig. 2. The angle difference $\Delta = \phi_1 - \phi_3$ determines an unique arc from B_1 to B_3 where the robot must lie on. This results from the inscribed angle theorem.

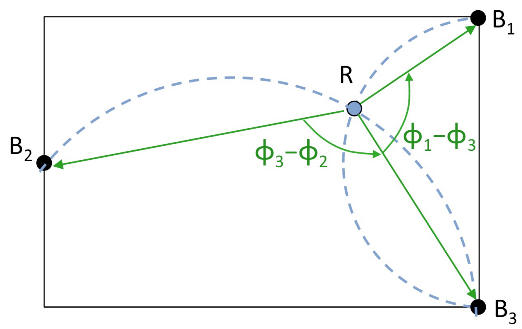

Fig. 3. The angle difference $\Delta = \phi_1 - \phi_3$ determines an unique arc from B_1 to B_3 where the robot must lie on. This results from the inscribed angle theorem.

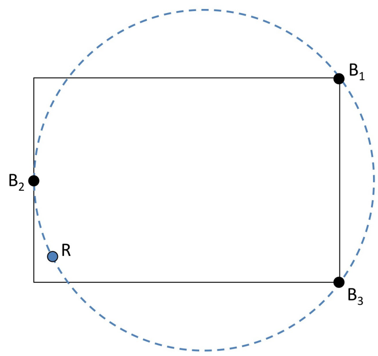

Fig. 4. In this extreme case the robot and all beacons lie on the same circle. No unique intersection point between the arcs is possible. Therefore, localization is ambiguous.

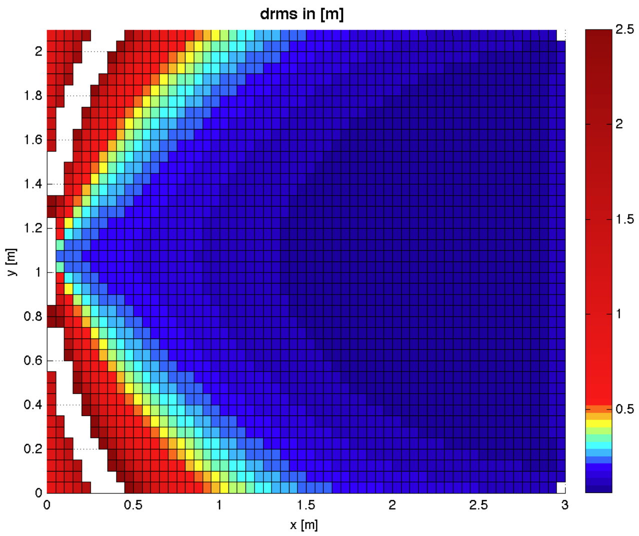

Fig. 5. drms (distance root mean square) $= \sqrt{(\sigma_x^2 + \sigma_y^2)}$ in m at all positions on the playground. σ_x and σ_y are standard deviations of the robot position and are computed by doing some error error propagation in equation 1. For the angle measurements we assume a standard deviation of $\sigma_\phi = 1^o$. Only the right half of the playground guarantees accuracy better than 5 cm.

3 Kalman Filter

Odometry data is usually obtained by integrating some wheel encoder. From odometry data the robot computes $u_t = (d_t, \delta_t)^T$ at each time step, where d_t is the driven distance and δ_t is the change in orientation in the time intervall $(t, t+1]$. We consider odometry data as if it were control signals [19]. The robot advances from position (x_t, y_t, θ_t) to $(x_{t+1}, y_{t+1}, \theta_{t+1})$ by integrating the control signal $u_t = (d_t, \delta_t)^T$, which leads to the following nonlinear system model:

$$\begin{pmatrix} x_{t+1} \\ y_{t+1} \\ \theta_{t+1} \end{pmatrix} = \begin{pmatrix} x_t + d_t \cos(\theta_t + \delta_t/2) \\ y_t + d_t \sin(\theta_t + \delta_t/2) \\ \theta_t + \delta_t \end{pmatrix} \tag{2}$$

As described in the previous section the robot measures angles $\phi_i, i = 1, 2, 3$, to the three beacons at each time step t.

$$\phi_{i_t} = atan2(y_i - y_t, x_i - x_t) - \theta_t, i = 1, 2, 3 \tag{3}$$

With the given system equation 2 and the mesurement equation 3 the extended Kalman Filter technique [16] can now be applied. The Kalman filter receives a series of control and measurement data and yields an optimal estimation of the robot position. The technical details can be found in [20, 17]. It should be noted that the availablilty of all three measurements in each time step is not necessary. In the extreme case that there is no sensor data available, odometry only is used. It should also be mentioned that an error model for the control data and the measurement data is assumed as zero-mean Gaussian with some variance, which easily can be determined by some measurements with the sensors and the odometry. Some simulations in Matlab are made for the true path shown in fig. 6 with several sensor outage scenarios (fig. 7).

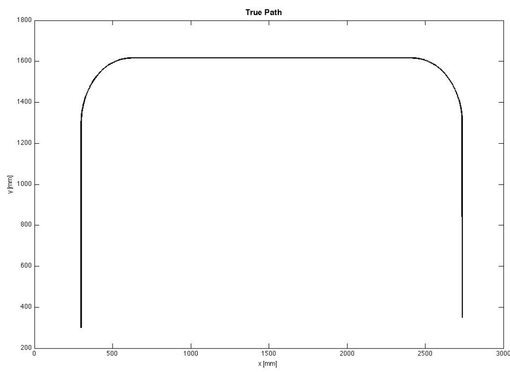

Fig. 6. True path of the robot in the Matlab Simulation. The robot starts in left lower corner and ends in the right lower corner in about 10 seconds.

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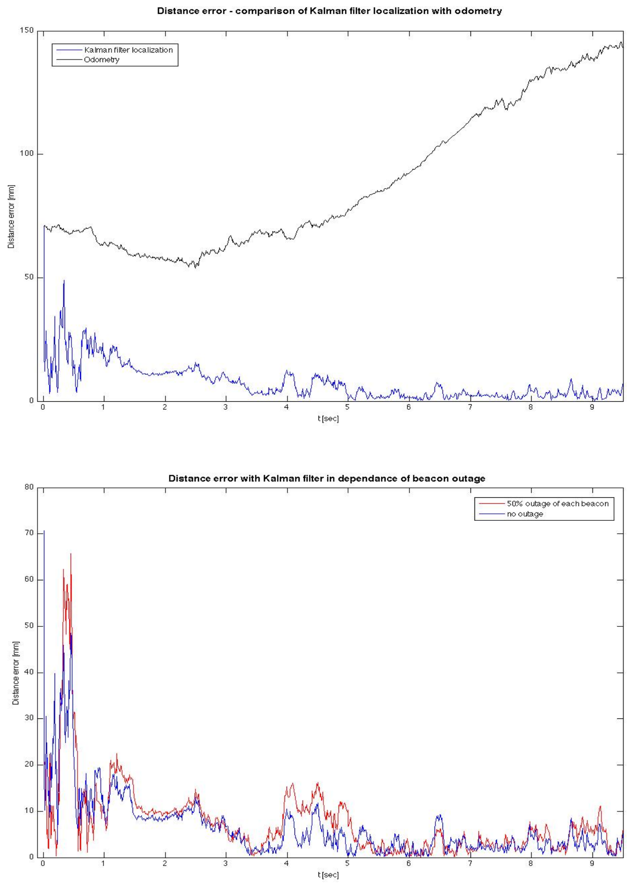

Fig. 7. The position distance error in [mm] is shown for several scenarios. In the figure above we compare pure odometry (i.e. complete outage of beacon signals) with our Kalman Filter approach. The picture below shows how robust our approach is against beacon outage. In that case beacon outage of about 50% for each beacon is supposed. In all simulations we start with an initial position error of about 7 cm. Unlike the Kalman filter approach pure odometry can not compensate for it. In all simulations we assume $\sigma = 1^o$ for the angle measurement, $\sigma = 1cm/m$ for the odometry distance error, $\sigma = 1^o/m$ for the drift error and $\sigma = 1^o/360^o$ for the turning rate error.

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