We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,300

Open access books available

172,000

International authors and editors

190M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Distributed Estimation of Unknown Beacon Positions in a Localization Network

Mikko Elomaa and Aarne Halme
Helsinki University of Technology
Finland

1. Introduction

The localization of a mobile robot is of utmost importance for efficient task execution. The field has been well studied and many different methods have been proposed. These methods can be roughly divided into two categories: methods relying only on robot's own sensors and methods using external infrastructure such as beacons, landmarks, etc.

The most common approach to the localization of a mobile robot is the method called Simultaneous Localization and Mapping (SLAM). The idea of SLAM is to build a map by observing static features in the surrounding environment. In order to position the features correctly with respect to each other, the location of the sensors has to be estimated when making the observations. Same sensors are used for both mapping of the features and localization of the robot, thus the uncertainties in both mapping and pose estimate are correlated. The complexity of the SLAM problem has been shown to be $O(N^2)$ with N being the number of landmarks in the map (Nerurkar and Roumeliotis, 2007). Several different variations of the SLAM method exist to better address different problems. A solution based on extended Kalman filter was introduced already two decades ago (Smith et al., 1990). Newman and Ho address the loop-closing problem by combining observations of visual features with laser scanner data (Newman and Ho, 2005). In (Williams et al., 2002) submaps are used in order to keep computational burden from increasing over time. Fast SLAM algorithms have been developed to cope with a large amount of landmarks (Montemerlo, 2002) or real-time constraints (Montemerlo et al., 2003).

A robot relying only on its own sensors, such as wheel encoders, gyroscopes, laser scanner, etc., can work in environments without any external infrastructure. However, when moving in an unknown environment, the uncertainty in the robot's position estimate increases over time because the robot does not have any absolute reference for its position.

The benefit of using external infrastructure is that a robot can always estimate its position within bounded error. The robot measures its position relative to a known location, e.g. a landmark, and the resulting position estimate does not depend on the history of the robot's trajectory. The error in the robot's position estimate only depends on the measurement error and the error in the position data of the landmark. Thus the error in robot's position estimate is bounded by the limits of measurement error and landmark position error.

A well-known example of a localization system with external infrastructure is the Global Positioning System (GPS). Whenever a GPS device is turned on, it can calculate its pose in the global coordinate frame provided that at least three satellites (beacons) are visible. However, in an indoor environment the metallic structures of the building usually prohibit the use of GPS for localization. Similar kind of localization systems can be built by placing beacons inside the building. A commonly used approach is to measure the distance between robot and beacons with ultrasound sensors (Priyantha et al., 2000).

The major drawbacks of external infrastructure are deployment/maintenance costs and the need for initial localization of each beacon before it can be used. Our key interest is in developing a distributed calibration method for a localization network. The localization network is formed by sparsely deploying inexpensive beacons serving as landmarks.

2. Cooperative approach

The simplest approach to cooperative localization is to have a pair of robots moving together and improving their individual pose estimates using relative measurements between the robots. If one robot can measure its distance and relative bearing angle to a target robot, it can estimate the position of the target robot relative to its own pose. If the robot can also measure the relative heading angle of the target robot, it can estimate the relative pose of the target robot. An example of this kind of approach is a robot with a laser scanner tracking another robot with a three plane target mounted on it (Rekleitis et al., 2003). This concept can be extended to a group of robots, in which at least one robot has a suitable sensor for tracking the other robots (Kurazume et al., 1994; Howard et al., 2003; Spletzer and Taylor, 2003). Another approach based on relative measurements in a group mimics formation flying. Robots drive in a formation while each robot detects changes in the poses of the other robots. The shape of the formation affects considerably the accumulated uncertainty in the robot poses (Hidaka et al., 2005; Andersson and Nygard, 2008).

The strict constraint of robots staying visible for the sensors of the other robots may be too restricting in some scenarios. Then the robots can explore independently but can share localization information only when they meet. This method is effective if at least one of the robots sharing data has been able to keep the position uncertainty fairly low. (Howard et al., 2004; Chang et al., 2007; Zhou and Roumeliotis, 2006). Some approaches use only the landmarks on the overlapping parts of the local maps constructed by the different robots in order to align the maps (Thrun and Liu, 2003; Martinez-Cantin et al., 2007). With this kind of algorithm each robot has to have a suitable localization system in order to build a sufficiently accurate local map.

Our approach uses a group of simple and inexpensive robots for distributed localization of landmarks that form a localization network. Each robot only needs wheel encoders and one sensor that can identify a landmark and measure a bearing angle to the landmark. With these sensors, the robots should be able to estimate the positions of the landmarks and simultaneously localize themselves within bounded error. The landmarks can be deployed sparsely because only one landmark needs to be visible for our algorithm to work. When no landmarks are visible, the robot relies on its odometry sensors. For cooperation between the robots, exact identification of each landmark is required. This can be done with artificial landmarks having unique identification numbers as explained in the case study at the end of this chapter.

As the landmark positions are unknown at the beginning, the robots have to work together in order to correctly localize the landmarks. At this stage, the localization problem is closely related to the SLAM problem. When the robots are configuring the system and localizing the landmarks, the main source of error is the accumulated odometry error which, in a group of robots, is assumed to have a mean close to zero. Thus, when the location estimates of several independent robots on a common object are combined, the location estimate of the object converges towards the correct position. The fusing of information in cooperative localization can be based on Kalman filter.

3. Theory

In this subchapter the robot's sensors for landmark detection are assumed to be located at the origin of the robot's coordinate frame. The positive y-axis of the robot coordinate frame points forward marking the direction of the heading angle, θ . The heading angle of the robot in global coordinate frame is expressed in compass format i.e. the heading angle increases when the robot turns clockwise. The zero heading angle is fixed towards the direction of the positive y-axis. The bearing angle measurements (λ) are expressed as an angle relative to the robots heading angle. The bearing angle increases towards clockwise direction.

3.1 Location estimate

If the robot is equipped with sensors to measure both distance and heading to a landmark, the estimate of the landmark location can be calculated after each measurement. The distance is measured directly and the absolute bearing angle can be calculated with equation 3. The relative displacement in global coordinate frame can then be solved with equation 4. However, if the robot can only measure the bearing angle to the landmark, an estimate can be calculated for the landmark location provided that the robot has basic odometry sensors. In bearing-only localization, the robot is required to make at least two bearing angle measurements to the landmark from different locations in order to calculate an estimate of the landmark's location.

Fig. 1. Landmark localization

Figure 1 shows a robot making two bearing angle measurements at locations R_k and R_{k+1} . The distance d_r between the two locations is measured with wheel encoders. The two

bearing angle measurements λ_1 and λ_2 are measured with a suitable sensor. The distance d_m can be solved as follows:

$$\gamma = \lambda_2 - \lambda_1 \quad (1)$$

$$d_m = \frac{d_r \cdot \sin(\lambda_1)}{\sin(\gamma)} \quad (2)$$

The estimated heading angle of the robot, θ , can be based on wheel encoders if no additional sensor data is available. The robot's heading angle together with a bearing angle measurement yield an azimuth angle ϕ .

$$\phi = \frac{\pi}{2} - \theta - \lambda_2 \quad (3)$$

The distance estimate d_m and the azimuth angle estimate ϕ define the displacement of the landmark in polar coordinates relative to the origin of the robot's local coordinate frame. Hence, the displacement expressed in the global Cartesian coordinates can be calculated as follows:

$$\begin{aligned} dx_m &= d_m \cdot \cos(\phi) \\ dy_m &= d_m \cdot \sin(\phi) \end{aligned} \quad (4)$$

The calculated displacement estimates in x- and y-coordinates have uncertainties, which depend on the relative distance d_m , azimuth angle ϕ and the angle difference γ between the two bearing angles. Equation 5 shows a general method for calculating the uncertainties in the landmark coordinates. C_1 and C_2 are constant parameters depending on the accuracy of the measurement system.

$$\begin{aligned} \sigma &= \phi + \frac{\lambda_1 - \lambda_2}{2} \\ r_x &= C_1 \cdot d_m \cdot |\sin(\phi)| + C_2 \left(\left(\frac{\cos(\sigma)}{\sin^2(\gamma)} \right)^2 + \sin^2(\sigma) \right) \\ r_y &= C_1 \cdot d_m \cdot |\cos(\phi)| + C_2 \left(\left(\frac{\cos(\sigma + \pi/2)}{\sin^2(\gamma)} \right)^2 + \sin^2(\sigma + \pi/2) \right) \end{aligned} \quad (5)$$

Each of the uncertainties for x- and y-coordinates consists of two parts. The first part deals with the effect of the error in the azimuth angle. The longer the distance d_m , the bigger the position error caused by the azimuth angle error will be. Also, the weight of the uncertainty in the coordinate axes, x and y, depend on the azimuth angle. The second part deals with the actual measurement uncertainty. Each bearing angle measurement has some angle uncertainty, forming a sector in which the landmark probably lies. Two bearing angle measurements form two sectors which intersect to create a diamond shaped region where the landmark probably lies. For simplicity, this region can be presented as an ellipse with its origin at the intersection of the lines representing the bearing angle measurements and with its major axis at angle σ with respect to x-axis (Figure 2). The uncertainties for x- and y-coordinates are depicted as the distances from the origin to the points where the coordinate axes intersect with the ellipse. The mutual angle γ between the two bearing angle measurements affects the ratio between the minor and major axis. For perpendicular bearing angle measurements, the ratio is one and the uncertainty is represented by a circle.

Fig. 2. Displacement measurement uncertainty

With each new angle measurement, the robot can calculate displacement estimates for the landmark using all the previous angle measurements. Thus, after two measurements the robot has one estimate for the landmark location while n measurements will give $1+2+3+\dots+(n-1)$ estimates. Figure 3 shows displacement estimates for five bearing angle measurements.

Fig. 3. Displacement estimates of five bearing angle measurements

The estimates based on almost parallel bearing angle measurements have considerable error, but their uncertainties are also large so the effect of such measurements on the final landmark position estimate is small.

3.2 Kalman filter

In (Maybeck, 1979), Maybeck defines Kalman filter as an optimal recursive data processing algorithm. Kalman filter is an application of the Bayesian probabilistic estimation method. In Bayesian scenario, we are estimating, from our prior information and data, the unknown constant value that the parameter had when the data were taken. Kalman filter is a recursive estimator, so all the prior information is contained in the previous estimate. The standard Kalman filter can be used with linear models. Non-linear models can be linearized using the extended Kalman filter. The Kalman filter maintains the first two moments of the state distribution (Welch and Bishop, 1995)

$$E[x_k] = \hat{x}_k \quad (6)$$

$$E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T] = P_k \quad (7)$$

When using a discrete Kalman filter the motion model is presented with a discrete time state-space representation, where ω_k and $\mathbf{v}_k$ represent the process and measurement noises respectively.

$$\mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{B}_k \mathbf{u}_{k+1} + \boldsymbol{\omega}_k \quad (8)$$

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k \quad (9)$$

In the case where matrices $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{H}$ are constants the general form for Kalman filter equations for the estimate are shown in Table 1. $\mathbf{Q}_k$ represents the process noise covariance and $\mathbf{R}_k$ represents the measurement noise covariance.

a priori state	$\hat{\mathbf{x}}_k^- = \mathbf{A} \hat{\mathbf{x}}_{k-1} + \mathbf{B} \mathbf{u}_k$
a priori estimate error covariance	$\mathbf{P}_k^- = \mathbf{A} \mathbf{P}_{k-1} \mathbf{A}^T + \mathbf{Q}_k$
a posterior state	$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H} \hat{\mathbf{x}}_k^-)$
a posterior estimate error covariance	$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}) \mathbf{P}_k^-$
Kalman gain	$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}^T (\mathbf{H} \cdot \mathbf{P}_k^- \mathbf{H}^T + \mathbf{R}_k)^{-1}$

Table 1. Discrete Kalman filter equations

3.3 Extended Kalman filter

In bearing only localization, the only measurement is the bearing angle to the target. The robot displacement between measurements can be considered as external control, so it is not calculated as a function of the state vector $\mathbf{x}$. When calculating the position of the robot or the landmark based on bearing angle measurements, non-linear equations are needed. The Extended Kalman Filter (EKF) can use the non-linear measurement equation, h , but the measurement matrix $\mathbf{H}$ has to be the Jacobian matrix composed of partial derivatives of h with respect to the state vector $\mathbf{x}$. In addition the a priori estimate is calculated with a non-linear function f , which involves the heading angle of the robot. The a priori covariance matrix is calculated using the matrix $\mathbf{A}$, which is a Jacobian matrix of partial derivatives of f with respect to the state vector $\mathbf{x}$. The equations for Extended Kalman filter are shown in Equations 10-14

$$\hat{\mathbf{x}}_k^- = f(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_k, 0) \quad (10)$$

$$\mathbf{P}_k^- = \mathbf{A} \mathbf{P}_{k-1} \mathbf{A}^T + \mathbf{Q}_k \quad (11)$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\mathbf{z}_k - h(\hat{\mathbf{x}}_k^-, 0)) \quad (12)$$

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}) \mathbf{P}_k^- \quad (13)$$

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}^T (\mathbf{H} \cdot \mathbf{P}_k^- \mathbf{H}^T + \mathbf{R}_k)^{-1} \quad (14)$$

3.4 Localization

In robot positioning, the state-space model can estimate the robot's position based on the motion measured by wheel encoders. Due to wheel slippage and measurement errors, the model gives increasingly bad position data i.e. position error increases over time. With Kalman filter, a correction to this position data can be applied if external positioning data such as triangulation or trilateration to beacons is available. The Kalman filter combines the data from the encoders (the motion model) and external measurements to beacons or landmarks. The process noise covariance matrix $\mathbf{Q}$ and the measurement noise covariance

matrix $\mathbf{R}$ are used to tune the Kalman filter for best possible performance in the operation environment. The process noise increases the uncertainty of the robot's position estimate on each step the Kalman filter is updated. The amount of the process noise depends on the quality of the sensors, such as wheel encoders, used for measuring the movement of the robot directly. The measurement noise depends on the quality of the sensors used for obtaining the external positioning data.

The same concept works for bearing only measurements to a single landmark. We can also estimate the location of the landmark relative to the location of the robot. Instead of calculating directly a position estimate for the landmark as described in section 3.1, we calculate an estimate for the bearing angle to the landmark given the current estimates of the robot and landmark positions. Then we compare the estimated bearing with the latest bearing angle measurement and correct both robot and landmark position estimates. In this scenario the state vector $\mathbf{x}$ has five elements: the x- and y-coordinates of the robot (x_r, y_r), the heading angle of the robot θ and the x- and y-coordinates of the latest visible landmark (x_t, y_t). Only one landmark at a time can be visible for the robot. The zero angle of robot's heading is towards the global positive y-axis and it increases in the clockwise direction. The robot is assumed to be stationary while measuring bearing angle to the landmark. The robot movement between measurements is obtained from the odometry sensors. The movement can be represented by a control vector $\mathbf{u}$, and no actual motion model is needed. That simplifies the equations of the a priori state. The landmarks are static, thus they do not have a motion model and their control vector is zero.

$$\mathbf{x} = \begin{bmatrix} x_r \\ y_r \\ \theta \\ x_t \\ y_t \end{bmatrix} \quad \mathbf{P} = \begin{bmatrix} \text{var}_{rx} & \text{cov}_{rxy} & \text{cov}_{rx\theta} & \text{cov}_{rxtx} & \text{cov}_{rxt y} \\ \text{cov}_{rxy} & \text{var}_{ry} & \text{cov}_{ry\theta} & \text{cov}_{rytx} & \text{cov}_{ryty} \\ \text{cov}_{rx\theta} & \text{cov}_{ry\theta} & \text{var}_{\theta} & \text{cov}_{\theta tx} & \text{cov}_{\theta ty} \\ \text{cov}_{rxtx} & \text{cov}_{rytx} & \text{cov}_{\theta tx} & \text{var}_{tx} & \text{cov}_{txy} \\ \text{cov}_{rxt y} & \text{cov}_{ryty} & \text{cov}_{\theta ty} & \text{cov}_{txy} & \text{var}_{ty} \end{bmatrix}$$

Prediction equation $x_k^- = f(\hat{x}_{k-1}, u_k, 0)$ and Jacobian matrix $\mathbf{A}$ are

$$\hat{\mathbf{x}}_k^- = \hat{\mathbf{x}}_{k-1} + \begin{bmatrix} d_r \cdot \sin(\theta_{k-1}) \\ d_r \cdot \cos(\theta_{k-1}) \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} 1 & 0 & d_r \cdot \cos(\theta_{k-1}) & 0 & 0 \\ 0 & 1 & -d_r \cdot \sin(\theta_{k-1}) & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (15)$$

The measurement equation is

$$h(\hat{\mathbf{x}}_k^-, 0) = \text{atan2}(x_t - x_r, y_t - y_r) - \theta_r \quad (16)$$

The Jacobian matrix $\mathbf{H}$ is

$$\mathbf{H} = \begin{bmatrix} -\Delta y & \Delta x & -1 & \Delta y & -\Delta x \\ \Delta y^2 + \Delta x^2 & \Delta y^2 + \Delta x^2 & & \Delta y^2 + \Delta x^2 & \Delta y^2 + \Delta x^2 \end{bmatrix} \quad (17)$$

where $\Delta x = x_t - x_r$ and $\Delta y = y_t - y_r$.

Combining the measurements of a robot with the Kalman filter results in better estimate of the relative position of the landmark since the effect of measurement errors decreases. However, position estimate of the landmark in the global coordinate frame is based on the estimate of the robot's own pose. The error in robot's pose is thus directly inherited by the

position estimate of the landmark. To cope with this, we need measurements from multiple independent sources, e.g. from different robots. A single robot can always turn back when its pose uncertainty grows too big. However, even if it would return back to the starting point and start localization again its pose estimate would be subjected to the same structure related error as in previous runs. Thus, calibration runs made by one robot are not completely independent.

3.5 Distributed landmark localization

When a single robot estimates the position of a landmark the estimate is biased by the errors in the robot's own position and heading angle estimate. Filtering the different measurements of a single robot helps to decrease the effect of measurement errors but not the effect of the error in the robot's own pose estimate. However, if different robots are estimating the position of a landmark, the position estimate is based on several independent groups of measurements. When multiple robots pass a landmark, they each have different error and uncertainty in their own position estimate. This is due to the mechanical differences between the robots and due to the differences in the actions they have taken so far.

The robots have to use the same global coordinate frame in order to cooperate. If the robots start at a common location, they would share a common view of the global coordinate frame right from the start. Otherwise, the robots need to use a hierarchical method to determine which global coordinate frame they should adapt to when detecting landmarks that have already been located by robots using different global coordinate frame. The previous estimate of the position of the landmark and the related uncertainty have to be available for a robot in calculating new estimates. This can be done by storing the information to the memory of the landmark or by broadcasting all new estimates to other robots. The landmark position estimate contains all the information provided by the robots that have already passed the landmark. Thus, each robot passing the landmark benefits from the position information of all the previous robots.

4. Simulation

A simulation model for the multi-robot localization system was built in order to get an idea of the effects of different measurement errors. The simulations were run on Matlab. The system presented here simulates a scenario where a single landmark is localized by a group of robots passing the landmark one by one. All the robots estimate their own pose in a common (global) coordinate frame. Each robot has random error in its own position and heading angle estimate. Each bearing angle measurement also contains a random error. After each bearing angle measurement, the Kalman filter calculates new estimates for the location of the landmark and the pose of the robot.

4.1 Simulation parameters

The simulation model permits setting of several parameters. The robot pose error depends on remaining error after previous localization i.e. when robot passed the previous landmark and the accumulated error while robot has been moving. Both are set separately for each robot as random numbers, but the upper bounds of the errors can be set with parameters.

When a robot arrives near a landmark, the uncertainty in the robot’s pose estimate (var_{rx} , var_{ry} , var_{θ}) is initialized with a calculated pose uncertainty. The pose uncertainty and the accumulated error depend on a random number representing the distance the robot has travelled since previous localization. The position and heading angle errors inherited from previous localization have small, fixed uncertainties.

E_{prev}	8 cm	Upper limit for random error in robot’s position after previous localization
E_{accu}	24 cm	Upper limit for driving distance related random error in robot’s position
θ_{prev}	$\pm 2^\circ$	Upper limit for random error in robot’s heading after previous localization
θ_{accu}	$\pm 4^\circ$	Upper limit for driving distance related random error in robot’s heading
var_{xy_init}	1000 cm ²	Upper limit for robot’s initial position uncertainty
var_{θ_init}	0.14 rad ²	Upper limit for robot’s initial heading uncertainty

Table 2. Robot odometry parameters

D_{landmark}	80 cm	Landmark detection distance. Within this distance the robot can always detect the landmark
D_{step}	10 cm	Bearing angle measurement interval i.e. distance between two angle measurements
λ_{limit}	$\pm 5^\circ$	Upper limit for random error in bearing angle measurement
w_{xy}	0.5 cm	Robot position related model noise for Kalman filter
w_{θ}	0.04°	Robot heading angle related model noise for Kalman filter
r	5.7°	Measurement noise for Kalman filter

Table 3. Localization parameters

The landmark detection is only possible in certain range. This range can be defined with a parameter. Other parameters are the distance the robot moves between bearing angle measurements, the upper limit of the error in the bearing angle measurement, model noise for the robot and the measurement noise. In these simulations, we consider a scenario where the landmark is a passive Radio Frequency Identification (RFID) tag and the bearing angle is measured by a turning antenna mounted on the robot. These constraints give us estimates of the realistic detection range and bearing angle measurement error.

While a robot is within the detection distance from the landmark, it measures bearing angles to the landmark and calculates new estimates for the position of the landmark as well as for its own pose. Simulations were run in order to discover how different error sources affect the accuracy of the landmark and robot position estimates. Each simulation consisted of 1000 independent runs, each having 20 robots passing a landmark. As a result, we get the average errors in the landmark and robot position estimate. The different plots in Figure 4 show the error in the position estimate of the landmark after ten robots have passed (landmark10) and after 20 robots have passed (landmark20). They also show the error in the position estimate of the 10th and 20th robot after they have passed the landmark (robot10 and robot20). The fifth line shows the heading angle error of the tenth robot (heading10). The scale for the heading angle error is on the right side of the plot.

4.2 Simulation results

For each simulation, one error parameter was chosen as a variable while the rest had the values defined in Table 2. Figure 4a shows the effect of the error in the bearing angle measurement. The maximum error on the x-axis represents the upper limit of the bearing angle error in degrees to either direction i.e. maximum error of 5 degrees means that the measured bearing angle is within $\pm 5^\circ$ of the correct angle. As can be seen, the error in the measured bearing angle has very little effect on the landmark or robot localization. The simulated error in the bearing angle measurement has zero mean. Thus, when the number of measurements increases, the mean of the measurement errors approaches zero. While passing the landmark each robot makes approximately 14 bearing angle measurements to the landmark, when the detection distance of the landmark is set to 80 cm. The position estimate of the landmark after ten robots have passed is based on 140 measurements but each robot's own pose correction is based on approximately 14 measurements. This explains why the robot pose estimate is more sensitive to the measurement error than the landmark position estimate.

The accumulated heading angle error has a significant effect on the robot's pose estimate as can be seen in Figure 4b. When localizing with only one landmark, the error in the heading angle of the robot impairs considerably the position estimate of the robot. The x-axis shows the upper limit for the accumulated heading angle error. For example, with upper limit of 10 ($\pm 10^\circ$ to be exact), the expected accumulated heading angle error is $\pm 5^\circ$. In addition, the robot is expected to have initial heading angle error of $\pm 1^\circ$ after previous localization. With these values, the 10th robot had an average heading angle error of 3° after passing the landmark. This shows that only a small correction to the robot's heading angle error can be made while passing a single landmark. However, the position estimate of the landmark depends on the estimates of several different robots with independent heading angle errors. Thus, the position estimate of the landmark is not so sensitive to the errors in the heading angles of individual robots.

The accumulated position error of the robot depends on the distance the robot has been driving after the position update. The accumulated error is the product of the upper limit and two random numbers between one and zero. The first random number represents the distance the robot has been driving after the last position update. The second random number represents an unknown factor causing error in the robot's odometry system. The two random numbers together cause the average accumulated error to be one fourth of the maximum error. The error is calculated separately for both coordinate axes. For maximum error of 20 cm, the expected error is ± 5 cm in both position coordinates.

Fig. 4. (a) Effect of bearing angle measurement error. (b) Effect of accumulated heading angle error. (c) Effect of robot's initial position error. (d) Effect of robot's accumulated position error

Figures 4c and 4d show that the position error has a more significant effect on the error in the landmark position estimate than the aforementioned angle errors. The error in the robot's position estimate after passing the tag also increases with increasing initial position error, but the heading angle error seems to be a more significant factor. The correction of the robot's heading angle is slightly slower with bigger initial position error.

Figure 5 shows the convergence of the landmark position as the number of contributing robots increase. The different plots in Figure 5a show the effect of the magnitude of the accumulated error in robot's heading angle. In Figure 5b the effect of accumulated error in robot's position estimate is presented. As before the indicated accumulated error (e.g. 0, 5, 10, 15 or 20 degrees in Figure 5a) is the upper limit of the error, i.e. with a limit of $\pm 20^\circ$ the expected accumulated heading angle error is $\pm 10^\circ$.

The error in landmark position estimate is significant after the initial estimate of the first robot passing it, because the error in the robot's position estimate is inherited by the landmark. However, when more robots contribute to the estimate, the average error decreases rapidly and after five robots, it is already at quite reasonable level. As the number of robots contributing to the estimate and thus, the number of measurements, increases, the

uncertainty of the landmark position estimate decreases. When the uncertainty of the landmark position decreases each new measurement has smaller and smaller effect on the landmark position estimate and the estimate becomes more stable.

Fig. 5. Effect of accumulated (a) heading angle, (b) position error on landmark position estimate

5. Case Example

This case example is not a real multi-robot experiment, but gives an idea how the concept would work in practice. Only two robots are used for the measurements, each one making several independent runs. The case example uses RFID technology for the localization system. Passive RFID tags serve as landmarks and the robot is equipped with an RFID interrogator (reader). A turning antenna is connected to the RFID interrogator. The bearing angle to the landmark is estimated by turning the interrogator antenna and recording the direction in which the RFID tag responded.

5.1 Experimental setup

For this experiment we are using an UHF RFID system which operates at the 867 MHz frequency. The system is EPC Class 1 GEN 2 compatible. One RFID tag is used as a landmark. It is attached to a wall along a two meter wide corridor. The dimensions of the tag sticker are 97 × 15 mm. The detection distance of the tag is usually around one meter, but it can be up to two meters in an optimal environment.

The RFID interrogator is mounted on a robot. The dimensions of the interrogator are 66 × 33 × 6 mm and it has a Compact Flash connector for interfacing to a USB or a serial port. A three element Yagi-Uda antenna is connected to the interrogator. The antenna has one main lobe with a beam width of 68 degrees on the horizontal plane and 115 degrees on the vertical plane. The main lobe gain is 8 dBi and the front-to-back ratio is -14 dB. The dimensions of the antenna are 149 × 138 × 7 mm. In this prototype the antenna is mounted on a hobby servo which can turn the antenna 360 degrees.

The robots are equipped with wheel encoders. The encoders are connected to a microcontroller, which constantly integrates the relative pose of the robot. The two robots

are not alike. One is a relatively small with wheel base of 17 cm. It moves slowly, but has an accurate odometry system. The other robot has a 30 cm wheel base. It is fast, but the odometry is less accurate.

A reference point (0, 0) is marked on the floor of the corridor. The landmark position is measured to be (2.26, 0.74). For each run a robot is manually placed at the reference point with its heading angle approximately parallel to the global x-axis. After the manual placement there is a small initial error on the robot's pose estimate.

The robot drives forward on small steps (10-30 cm) and stops to detect the landmark. The antenna is turned a full circle on steps of 0.1 rad. The first and the last angle at which the landmark is detected are recorded and the bearing to the landmark is estimated as half way between these two angles. On each successful bearing angle estimate the robot's current pose and the estimated bearing angle to the landmark are recorded.

Fig. 6. (a) RFID interrogator and the antenna, (b) antenna gain pattern

5.2 Sensor accuracy

The measurement accuracy of the RFID system is determined by making 20 bearing angle measurements to a stationary tag from a single location. This procedure was repeated for three different angles; tag on the left side of the robot, the robot facing the tag and the tag on the right side of the robot. In all three cases the standard deviation was approximately 0.09 rad. In all the measurements the tag antenna was perpendicular to the line between the tag and the robot, so the polarisation was optimal when the reader antenna was pointing towards the tag. When a robot moves with respect to the tag the polarisation is not always optimal. This is expected to deteriorate the measurement accuracy as the energy transfer from the reader antenna to the passive tag gets more uncertain.

The robot pose estimate is based on wheel encoders only. The big robot has encoder resolution of 500 pulses per rotation of the wheel. The wheel diameter is 150 mm, so the odometry resolution is 0.942 mm/pulse. The encoder is directly connected to the wheel axle. There is no free play between the encoder and the wheel, but the number of pulses per rotation is relatively small. The small robot has encoder resolution of 2688 pulses per rotation of the wheel. The wheel diameter is 159 mm, so the odometry resolution is 0.186 mm/pulse. The encoder is connected to the motor shaft. This gives more pulses per one

rotation of the wheel, but backlash between the wheel and the motor shaft may cause inaccurate readings.

5.3 Results

Both robots made ten runs storing the measurement data into files. Matlab was then used to calculate position estimate for the landmark. The algorithms used were the same as in the simulation runs. The initial uncertainty in the robot position estimate was fixed to 0.05 m^2 . The model noise was 0.005 m and measurement noise 0.3 rad .

When the first robot detects the landmark for the first time there is no estimate of the position of the landmark and the Kalman filter cannot be used. The initial estimate is simply based on the first bearing angle and the expected detection range of one meter. This is a very rough estimate and has an uncertainty of 1 m^2 . With the rest of the measurements the extended Kalman filter is used to correct the estimate.

The order in which the measurements are used affects the position estimate of the landmark. The 20 measurement runs were used in random order to estimate the position of the landmark. This procedure was repeated 1000 times. Figure 7 shows the average error in the landmark position estimate as a function of the number of robots contributing on the estimate. After 10 robots the average error of the position estimate of the landmark was 5.1 cm and the maximum error was 18.4 cm . After 20 robots the average error was less than 2 cm and the maximum error was 5.6 cm . The average distance between two bearing angle measurements was longer than in the simulation runs where it was fixed to 10 cm . In the simulation runs each robot made approximately 14 bearing angle measurements while passing the landmark. In this laboratory experiment the average number of measurements was 7.7 per robot.

Fig. 7. Convergence of the landmark position estimate

Using the recorded poses of the robot and the known position of the landmark, estimates for correct bearing angle measurements were calculated and compared with the recorded

bearing angle measurements. The calculated root mean squared error of the bearing angle measurements was 0.27 rad. This is based on the assumption that the pose estimates for a robot are accurate. The pose of a robot is based on odometry as no another reference was available.

The bigger root mean squared error in the bearing angle measurements and the smaller number of measurements per robot explains why the landmark position estimate converges somewhat slower in the case example than in the simulation. In the case example the total number of measurements after 18 robots is about the same as the number of measurements in a simulation run after 10 robots. Then the position error of the landmark position estimate is approximately 2 cm in both cases. Altogether the case example behaves as can be expected based on the simulations.

6. Conclusion

In this chapter, a multi-robot approach to the calibration of a localization system has been introduced. The bearing-only measurements are shown to be sufficient for single landmark localization. The simulations indicate that the algorithm is fairly robust. Localization of the landmarks can be achieved even in the presence of considerable errors in bearing angle measurements or in the position estimate of an individual robot. A significant error in the heading angle estimate of a robot was noticed to cause problems with the simultaneous localization of the robot, but the landmark localization was still accurate.

The case example shows that the concept can be used with real robots. The RFID technology provides a possibility to use passive landmarks which are maintenance free, easy to deploy and inexpensive. Nonetheless they provide unique identification of the landmark and a possibility to store some information for other entities passing by.

The results achieved in the simulation study as well as in the case example encourage us to further test the concept. Next we plan to use three robots to localize multiple consecutive landmarks in order to determine how fast the localization network starts to support the robots in practice. A reference system will be used to record the error in the robots' own position estimates. This will tell us how well the robots can correct their own position while simultaneously localizing the landmarks.

7. References

- Lars A. A. Andersson and Jonas Nygard. On utilizing geometric formations for minimizing uncertainty in 3 robot teams. Technical report, Robotics & Autonomous Mechanical Systems, Linköping University, 2008.
- H. J. Chang, C. S. G. Lee, Y. C. Hu, and Yung-Hsiang Lu. Multi-robot slam with topological / metric maps, *International Conference on Intelligent Robots and Systems*, 2007.
- Y. S. Hidaka, A. I. Mourikis, and S. I. Roumeliotis. Optimal formations for cooperative localization of mobile robots, *International Conference on Robotics and Automation*, 2005.
- A. Howard, M. J. Mataric, and G. S. Sukhatme. Putting the 'i' in 'team': an egocentric approach to cooperative localization, *International Conference on Robotics and Automation*, 2003.

- Andrew Howard, Lynne E. Parker, and Gaurav S. Sukhatme. The sdr experience: Experiments with a large-scale heterogenous mobile robot team. In *9th International Symposium on Experimental Robotics*, 2004.
- R. Kurazume, S. Nagata, and S. Hirose. Cooperative positioning with Multiple robots, *International Conference on Robotics and Automation*, 1994.
- R. Martinez-Cantin, J. A. Castellanos, and N. de Freitas. Multi-robot marginal-slam. *IJCAI Workshop on Multi-Robotic Systems for Societal Applications*, 2007.
- P. S. Maybeck. *Stochastic Models, Estimation and Control*, pages pp. 1–16. Academic Press, New York, 1979.
- Michael Montemerlo. Fastslam: A factored solution to the simultaneous localization and mapping problem. In *Proceedings of the AAAI National Conference on Artificial Intelligence*, pages 593–598. AAAI, 2002.
- Michael Montemerlo, Sebastian Thrun, Daphne Koller, and Ben Wegbreit. Fastslam 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. In *Proceedings of the Int. Conf. on Artificial Intelligence (IJCAI)*, pages 1151–1156, 2003.
- E. D. Nerurkar and S. I. Roumeliotis. Power-slam: A linear-complexity, consistent algorithm for slam. In *International Conference on Intelligent Robots and Systems, 2007. IROS 2007*, pages 636–643, 2007.
- P. Newman and Kin Ho. Slam-loop closing with visually salient features, *International Conference on Robotics and Automation*, 2005.
- Nissanka B. Priyantha, Anit Chakraborty, and Hari Balakrishnan. The cricket location-support system. *Sixth Annual ACM International Conference on Mobile Computing and Networking*, 2000.
- I. Rekleitis, G. Dudek, and E. Milios. Probabilistic cooperative localization and mapping in practice, *International Conference on Robotics and Automation*, 2003.
- R. Smith, M. Self, and P. Cheeseman. *Estimating uncertain spatial relationships in robotics*, pages 167–193. Autonomous robot vehicles. Springer-Verlag New York, Inc., 1990. ISBN 0-387-97240-4.
- J. R. Spletzer and C. J. Taylor. A bounded uncertainty approach to multi-robot localization, *International Conference on Intelligent Robots and Systems*, 2003.
- S. Thrun and Y. Liu. Multi-robot slam with sparse extended information filters. In *Proceedings of the 11th International Symposium of Robotics Research (ISRR'03)*, Sienna, Italy, 2003. Springer.
- G. Welch and G. Bishop. An introduction to the kalman filter. University of North Carolina at Chapel Hill, Chapel Hill, NC, 1995.
- S. B. Williams, G. Dissanayake, and H. Durrant-Whyte. An efficient approach to the simultaneous localisation and mapping problem, *International Conference on Robotics and Automation*, 2002.
- X. S. Zhou and S. I. Roumeliotis. Multi-robot slam with unknown initial correspondence: The robot rendezvous case, *International Conference on Intelligent Robots and Systems*, 2006.

Contemporary Robotics - Challenges and Solutions

Edited by A D Rodi

ISBN 978-953-307-038-4

Hard cover, 392 pages

Publisher InTech

Published online 01, December, 2009

Published in print edition December, 2009

This book is a collection of 18 chapters written by internationally recognized experts and well-known professionals of the field. Chapters contribute to diverse facets of contemporary robotics and autonomous systems. The volume is organized in four thematic parts according to the main subjects, regarding the recent advances in the contemporary robotics. The first thematic topics of the book are devoted to the theoretical issues. This includes development of algorithms for automatic trajectory generation using redundancy resolution scheme, intelligent algorithms for robotic grasping, modelling approach for reactive mode handling of flexible manufacturing and design of an advanced controller for robot manipulators. The second part of the book deals with different aspects of robot calibration and sensing. This includes a geometric and threshold calibration of a multiple robotic line-vision system, robot-based inline 2D/3D quality monitoring using picture-taking and laser triangulation, and a study on prospective polymer composite materials for flexible tactile sensors. The third part addresses issues of mobile robots and multi-agent systems, including SLAM of mobile robots based on fusion of odometry and visual data, configuration of a localization system by a team of mobile robots, development of generic real-time motion controller for differential mobile robots, control of fuel cells of mobile robots, modelling of omni-directional wheeled-based robots, building of hunter- hybrid tracking environment, as well as design of a cooperative control in distributed population-based multi-agent approach. The fourth part presents recent approaches and results in humanoid and bioinspirative robotics. It deals with design of adaptive control of anthropomorphic biped gait, building of dynamic-based simulation for humanoid robot walking, building controller for perceptual motor control dynamics of humans and biomimetic approach to control mechatronic structure using smart materials.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Mikko Elomaa and Aarne Halme (2009). Distributed Estimation of Unknown Beacon Positions in a Localization Network, Contemporary Robotics - Challenges and Solutions, A D Rodi (Ed.), ISBN: 978-953-307-038-4, InTech, Available from: <http://www.intechopen.com/books/contemporary-robotics-challenges-and-solutions/distributed-estimation-of-unknown-beacon-positions-in-a-localization-network>

INTECH
open science | open minds

InTech Europe

University Campus STeP Ri
Slavka Krautzeka 83/A

InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China

www.intechopen.com

51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

IntechOpen

IntechOpen

© 2009 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](https://creativecommons.org/licenses/by-nc-sa/3.0/), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen