2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

Robust Method for Outdoor Localization of a Mobile Robot Using Received Signal Strength in Low Power Wireless Networks

Juergen Graefenstein and M. Essayed Bouzouraa
Robert Bosch GmbH, Schwieberdingen, Germany

***Abstract*— This paper deals with localization of a mobile robot using received signal strength indicator (RSSI) in low power IEEE 802.15.4 conform wireless communication in an outdoor environment. Hardware modifications are derived to reduce the radio irregularity and to increase the uniqueness of the measured RSSI to distance. A novel algorithm is elaborated allowing for sub meter accuracy. It accounts for the noise and implicitly models the uncertainty. Additionally it is robust to node failures. To further improve the accuracy a particle filter is employed to perform probabilistic sensor fusion of odometry, ultrasonic and RSSI sensors and a map. The suitability of this approach is shown with real measurements achieving a mean positioning error of 0.32m.**

I. Introduction

Due to the progress in computing technology the intelligence of the devices in our environment is continuously increasing. They start to communicate with each other, sharing their resources as services, making wireless communication a critical component. Further the intelligent devices are aware of the context, one important aspect of which is the location. A lot of research efforts have been invested into the development of localization systems to enable location based services [1]. Many of them utilize networking technology such as WLAN, Bluetooth or UWB to determine the position of a device.

Localization is also one of the fundamental problems in mobile robotics. The expense of the existing localization approaches utilizing sophisticated hardware such as laser-scanners or omnidirectional cameras, which require high computational resources, is currently not salable for consumer products. In this work the approach of the ubiquitous robot [2] is adopted. The ubiquitous robot utilizes infrastructure resources such as the networking components to accomplish its tasks and to provide services to the user. This way resources can be utilized by multiple entities in space simultaneously, decreasing the cost of the overall system. At the same time the quality of the services improves. For example using wireless networking technology for localization increases its robustness due to the absolute reference without increasing the cost, since the networking component is required for communication purposes in any case. This applies especially in the case of using the received signal strength indicator (RSSI), which signifies the power of a received radio signal. In theory the power of a radio wave decreases with the square of the distance from the transmitter under line of sight conditions. This relationship allows to deduce the position of the receiver. In practice this is impeded by radio irregularities.

This paper analyzes the suitability of the RSSI based localization for mobile robot navigation. The target environment is a common garden. Possible tasks of the robot might be irrigation, lawn mowing or fertilizing. Due to the recent advances in MEMS technology many miniature sensors are likely to be installed in the garden for plant monitoring, weather forecast or surveillance. These sensors conveniently use wireless links for communication. The employed open standard specified by the IEEE 802.15.4 defines a communication protocol with low data rate, low power and cost using the license free 2.4 GHz frequency. It also implements adhoc connectivity allowing a mobile node to connect with other nodes in its vicinity.

The paper is organized as follows. First related work is depicted in section II. Then hardware modifications are derived to reduce the radio irregularity in section III. Based on the improved radio characteristic a new algorithm is developed in IV. To further increase the accuracy of the localization, particle filter based fusion of ultrasonic data and a map is performed. This is depicted in section V. Results of experiments conducted in the target environment are presented in section VI. The paper closes with concluding remarks in section VII.

II. Related Work

Since the received signal strength is available without any additional hardware, there have been a lot of research activities during the last years, thoroughly investigating its use for localization.

A. Analysis of the RSSI variability

The main problem of localization by means of received signal strength is its high irregularity mainly caused by the nature of the radio signal. Researchers working on RSSI based localization are aware of this problem and have considered it in their algorithms. But only a few hardware measures have been proposed. Andreas Savvides et al. have identified the RF channel with its multipath and shadowing effects, the transmitter and the receiver variability and the antenna orientation as the main sources of RSSI variability [3]. As a measure to minimize multipath they propose an increase of the antenna height.

Sungwon Yang and Hojung Cha have investigated the influence of the antenna length on the radiation pattern [4]. They have found that monopole antennas with the length $\frac{5}{8}\lambda$, where λ is the wave length, have a more isotropic radiation patterns than a common $\frac{1}{4}\lambda$ antenna. Since the antennas eigen frequency does not meet the signal frequency they increase the gain by means of a loading coil. Further they raise the antenna apart from the board circuit to avoid electrical interference.

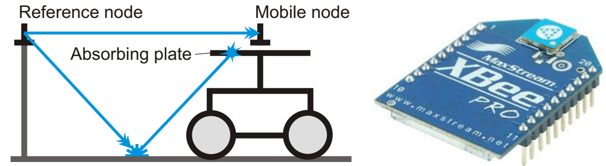
J. Ma et al found that lower communication frequency and constant battery voltage have a positive effect on the variance of the RSSI [5].

B. Algorithms to derive the position

Many different techniques have been proposed to derive the position from the RSSI measurement. In the centroid algorithm [6] the mobile node infers proximity to a collection of reference nodes, for which the respective connectivity metrics exceeds a preset threshold. The position is then calculated as the centroid of the positions of these reference nodes. Tian, H. et al. have developed the APIT algorithm[7], which uses the Point-In-Triangulation Test for all combinations of reference nodes within the communication range. The unknown position is then calculated as the centroid of the intersection of all of the triangles in which a node resides. Another approach applies the maximum likelihood estimation (MLE) incorporating a radio propagation model to deduce the distance from the measured RSSI. The estimated position is the one which minimizes the error for the multilateration of the distances. Masashi Sugano et al. use this method to derive the position of a mobile node in an indoor environment [8]. They use a high deployment density of 0.27 nodes/m^2 to obtain an accuracy between 1.5 and 2m. Hyunggi Cho et al. assume the variability of the RSSI to be gaussian [9]. They use the conjugate gradient algorithm to find the position with the maximum likelihood. Experiments in an indoor area of 8x9 m yield a mean location error of 1.6m.

A different approach is taken by Kiran Yedavalli et al. They have elaborated the Ecolocation algorithm [10] and its further development sequence-based localization (SBL) [11]. The basic idea is to use the relative distances to reference nodes defining areas with unique descending sequences. Since the RSSI relates to the distance, the position of the target node can be found forming the sequence of ascending measured RSSI values. This algorithm is robust to RSSI variability, but has an inherent limit regarding the resolution of the position. The authors report an average localization error of 1.22m for outdoor settings. They also show that their method outperforms the centroid, the APIT and the MLE algorithms.

Another methodology for localization using the RSSI is the scene analysis. This approach considers the irregularity of the radio signal strength by building databases, which assign each location a vector containing the RSSI values of all nodes within communication range. This way each position obtains a unique fingerprint. To find the position of the target node the database is searched for the closest fingerprint to the current RSSI vector. This approach is taken by the RADAR System [12], which achieves an average error of approximately 2m. Brian Ferris et al. additionally model the RSSI variability as a gaussian process [13]. They report an average localization error of 2.12 m over a large indoor area spread over different floors. The main drawback of the scene analysis is the need for an initialization phase prior to real time localization to record the fingerprints. This needs to be repeated once the environment changes. Further the size of the fingerprint database can become very large limiting the suitability of this technique for decentralized localization. A solution to this problem is presented by Konrad Lorincz and Matt Welsh [14] by distributing the database to the reference nodes. They were able to achieve a mean localization of 2m.



(a) Configuration (b) Employed RF module

Fig. 1. Hardware Setup

C. Probabilistic methods

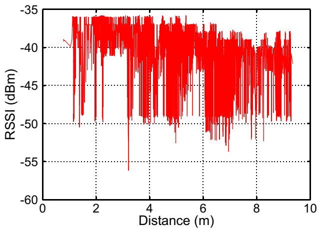
Probabilistic sensor fusion methods can be used to incorporate other informations such as sensor data or building maps to increase the accuracy of the localization. Brian Ferris et al. use a particle filter and define probabilities for different space transitions to factor the building layout into the localization [13]. They achieve an improvement of the localization accuracy of 20%. Researchers at the University of Karlsruhe have employed a particle filter to fuse RSSI data with an accelerometer and a map [15]. By this means they achieve an improvement of the localization accuracy of 30%. To our knowledge no such approaches were adopted and no comparable accuracy data is available for mobile robot localization incorporating RSSI data.

III. Measures to decrease signal strength variability

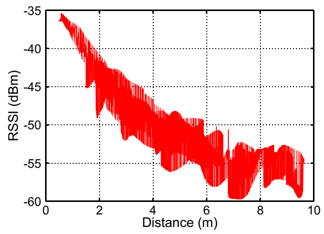
This section describes the setup of the localization system and the hardware modifications to reduce the RSSI variability.

A. Basic setup of the system

The basic setup is shown in Fig. 1(a). N transmitters serve as reference nodes. Each node n_i with $1 \leq i \leq N$ is attached to an extendable post at a known positions $\mathbf{x}_{r,i}$ in the garden in a gridlike fashion. The mobile node n_m is installed on top of the mobile robot and connected via UART interface to a mobile computer. The absorbing plate is used to cope with multipath effects and will be explained in detail below. In order to get reference data an optical tracking system measures the position and orientation of the robot with high accuracy in the range of millimeters. XBee Pro Modules shown in Fig. 1(b) are used as an integrated RF solution. The modules include MC13193 RF chip by Freescale, which is compliant to the IEEE 802.15.4 norm. In order to obtain a RSSI value R_i from a reference node n_i, the mobile node n_m transmits a message with its address. The reference nodes

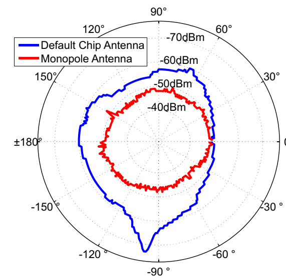


(a) Before modifications

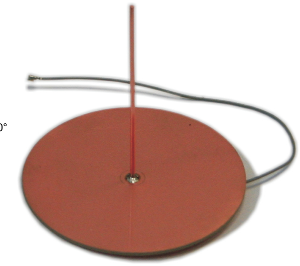


(b) After modifications

Fig. 2. RSSI Values depending on the distance



(a) Radiation patterns



(b) Antenna design

Fig. 3. Antenna Modification

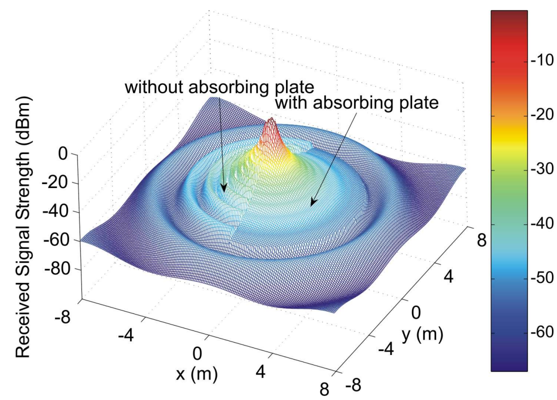


Fig. 4. Effect of an absorbing plate

are configured to simply send a return message. The mobile node receives the message, reads the RSSI associated with it and forwards it to the mobile computer for storage. 4 Ultrasonic sensors are attached to the robot and connected via I^2C interface to the mobile computer to log the data.

B. Hardware optimization measures

In a preliminary stage we have recorded the RSSI using the standard PCB antenna, which is installed on the RF board by default as shown in Fig. 1(b). The height of the nodes was set to approximately 30cm. The robot traveled a meander like path aiming for a complete area coverage. Fig. 2(a) shows the recorded RSSI values of one reference node against the distance regardless of the receiver's orientation. It shows very high noise and only slight drop with distance. Both make accurate localization almost impossible.

For this reason first the measures proposed in [3],[4] and [5] and already mentioned in section II were adopted:

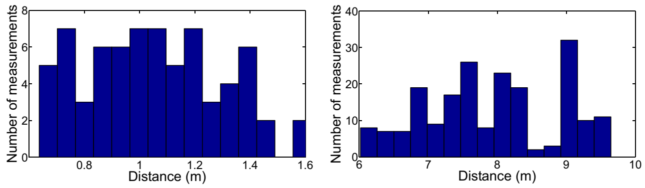
- The height of the nodes from the ground was increased to at least 1m.
- A monopole antenna with the length of $\frac{5}{8}\lambda$ was used for all nodes.
- A voltage regulator was installed on the RF board.

Further antennas were build and connected by a coaxial cable and a miniature RF connector to the RF module in order to increase the isotropy of the gain and to avoid electrical interference. Therefore orientation tests were performed with the default PCB, a monopole antenna with the length of $\frac{1}{4}\lambda$ and $\frac{5}{8}\lambda$, a dipole and a loop antenna of optimal lengths. During these tests the transmitter and receiver were kept on the same position while the receiver was rotated a full turn to obtain the radiation pattern. The experiments have shown the highest isotropy for a monopole antenna with a length of $\frac{5}{8}\lambda$. Fig. 3(a) shows the results of the orientation test for the default PCB and the monopole antenna. The latter shows a significantly more isotropic and higher gain than other antennas despite the suboptimal length. For this reason the monopole antenna was installed on all RF modules. The simple and low cost antenna is shown in Fig. 3(b).

In order to minimize multipath effects, the use of an absorbing plate below the antenna was considered, to avoid interference with signals reflected by the ground. Its impact was analyzed by a simulation model in MATLAB. The free space path loss model [16] was applied to calculate the power of the direct signal. The reflection was supposed to attenuate the signal by 20 dB. A phase delay between both radio waves causes a change in the received signal strength. To further decrease the power of the reflected signal and therewith the change of the RSSI, an absorbing plate is installed below the antenna. Its influence is modeled by an absorption of 60 dB. The simulation result is shown in 4. For $x > 0$ the RSSI is calculated with consideration of the absorbing plate. Here the RSSI decreases monotonically with the distance. It is also shown, that after exceeding a certain distance, which depends on the size of the absorbing plate, the reflected signal passes the plate and interference occurs again. The diameter of the absorbing plate was set to 0.2m within the simulation. The same size was chosen for the experiments.

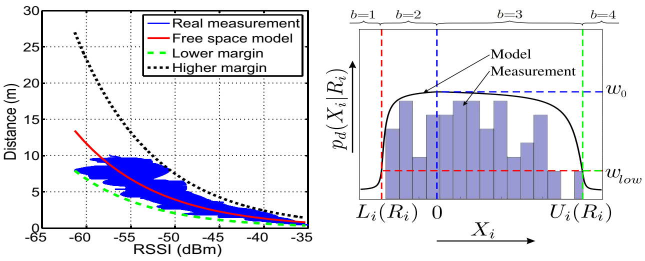
Further experiments with transmitters and the receiver on different heights were conducted. The results indicated that the lowest RSSI irregularity is achieved with nodes on the same height. This can be explained by the vertical anisotropy of the antenna gain [16]. For this reason the nodes needed to be leveled on the same height due to the slope in the test garden.

Additionally experiments with different RF modules were conducted, which have shown, that even identical RF hardware with identical antennas, position and orientation, yield different RSSI values. This can be explained by production tolerances of the low cost modules, which are not optimized for the purpose of localization.



(a) RSSI = -38 dBm (b) RSSI = -58 dBm

Fig. 5. Distance histograms for different RSSI values



(a) RF hardware characteristic (b) Pdf of the distance

Fig. 6. Distance histograms for different RSSI values

IV. Localization algorithm

To find the most appropriate algorithm to derive the position $\mathbf{x_m} = (x_m, y_m)^T$ of the mobile node from the RSSI vector $\mathbf{R} = (R_1, R_2, .., R_N)^T$, containing the RSSI values received from N reference nodes n_i with known positions $\mathbf{x}_{r,i}$ where $1 \leq i \leq N$, the characteristic of the measurements was thoroughly analyzed. The hardware modifications have yielded a significant improvement regarding the decrease of the RSSI with increasing distance from reference nodes. Therefore a sensor model was defined to derive the distance from the RSSI. Assuming that only the direct signal reaches the antenna, the free space loss model [16] is employed. Its inverse yields the distance $d_i = ||\mathbf{x_m} - \mathbf{x}_{r,i}||$ from the node n_i by the following equation:

$$d_i(R_i) = d_{i,fs} + X_i = \left(\frac{f_{1,i}}{10^{R_i}}\right)^{\frac{1}{f_{2,i}}} + X_i \qquad (1)$$

$d_{i,fs}$ is the distance given by the free space model and X_i is its deviation, modeling the RSSI irregularity. As described in [16] the parameters $f_{1,i}$ and $f_{2,i}$ are mainly influenced by the RF hardware (antenna gain and efficiency, transmit power, etc.). Although we employ the same type of RF modules the parameters can differ due to production tolerances as already stated in section III. Determining these parameters corresponds to a calibration of the RF hardware. In our case the calibration was done by means of curve fitting in a prior phase. The resulting sensor free space characteristic $d_{i,fs}$ is shown in Fig. 6(a).

But although the hardware modifications have shown significant improvements, the recorded RSSI is still highly irregular resulting in high noise in Fig. 6(a) modeled by X_i in equation (1). This needs to be considered in the localization algorithm to make it robust to irregularities. To analyze the distribution of the noise, histograms of the distance at which the same RSSI was recorded were examined. Fig. 6 shows exemplary histograms for two different RSSI values received from the same node at different positions and orientations. The figures allow for two conclusions:

- The distance for the same RSSI can span over a wide range which depends on the RSSI. Fig. 5(b) indicates, that this range increases for lower RSSI values.
- The histogram cannot be approximated by a normal distribution as was assumed in [9]. The same observation was already made in [3].

Therefore the heuristically determined distribution shown in Fig. 6(b) was chosen. The resulting probability density function of the deviation X_i is described piecewise by the following equation:

$$p_d(X_i|R_i) = a_b \arctan(\tilde{X}_i) + w_{low};\ 1 \leq b \leq 4 \qquad (2)$$

Here $\tilde{X}_i$ maps the deviation into the domain of the $\arctan$ function. w_{low} is equal for all nodes. It defines the probability of $w_{low} = p(X_i = L_i) = p(X_i = U_i)$. The coefficient a_b depends on the range. The ranges are defined by the lower and upper bounds L_i and U_i, which are described by the following equations:

$$L_i(R_i) = \left(\frac{l_{1,i}}{10^{R_i}}\right)^{\frac{1}{l_{2,i}}} - d_i(R_i) \qquad (3)$$

$$U_i(R_i) = \left(\frac{u_{1,i}}{10^{R_i}}\right)^{\frac{1}{u_{2,i}}} - d_i(R_i) \qquad (4)$$

The parameters need also to be determined in a calibration phase. Ideally this is done in an environment similar to the one in the application to also capture the variability due to multipath. The calculation is done by curve fitting the parameters $l_{1,i}$, $l_{2,i}$, $u_{1,i}$ and $u_{2,i}$ to the upper and lower distance deviations respectively measured for the same RSSI in a prior phase. Fig. 6(a) shows the lower and upper bounds for the employed RF hardware.

Assuming that the deviations of the measurements are independent for different nodes and given the RSSI vector $\mathbf{R}$, the probability $p(\mathbf{x}_m = \mathbf{x}|\mathbf{R})$ of the mobile node being at position $\mathbf{x}$ with distance vector $\mathbf{d} = (d_1, d_2, ..., d_N)$, containing the distances to the reference nodes, is given by the following product:

$$p(\mathbf{x}_m = \mathbf{x}|\mathbf{R}) = \prod_{i=1}^{N} p_d(d_i - d_{i,fs}|R_i) \qquad (5)$$

To find the position with the highest probability, a grid of the size $n_x \times x_y$ is spanned over the localization area defining the grid points $\mathbf{x}_{ij} = (x_i, y_j)^T$ with $1 \leq i \leq n_x$ and $1 \leq j \leq n_y$. Given a RSSI vector the probability $p_{ij} = p(\mathbf{x_m} = \mathbf{x}_{ij}|\mathbf{R})$ is calculated for each point. Since a geometrical interpretation of the probability distribution in the grid results in a torus around each node, the new algorithm is named as probability torus localization (PTL). The position of the mobile node can then be determined as the best grid point with the highest probability:

$$\mathbf{x}_m^* = \mathbf{x}_k|_{p_k = \max(p_{ij})} \qquad (6)$$

In another approach the expected mean with normalized probabilities $\hat{p}_{ij} = \frac{p_{ij}}{\sum p_{ij}}$ represents the position of the mobile node by

$$\mathbf{x}_m^{**} = \sum \mathbf{x}_{ij}\hat{p}_{ij} \,. \tag{7}$$

A third method uses the robust mean, which considers only points in space with distance ϵ from the best grid point (also called robust mean).

V. Particle Filter Sensor Fusion

Due to the high irregularity of the radio signal the localization accuracy achieved by the RSSI based localization is not sufficient for mobile robot navigation. Therefore a particle filter is applied to estimate the posterior conditioned on additional information, given by odometry, ultrasonic sensors and a map of the environment. The particle filter represents the posterior belief of the robot's state at time t by a finite set of samples $\mathcal{X}_t := \mathbf{x}_t^{[1]}, \mathbf{x}_t^{[2]}, ...\mathbf{x}_t^{[M]}$ [17], where each of the M samples represents a hypothesis of the true state. An importance weight $w_t^{[m]}$ is assigned to each particle during the filtering process signifying its quality based on the received measurements.

A. Prediction phase

The state of the robot is described by the state vector $\mathbf{x}_t := (x, y, \varphi)_t^T$, where x and y denote the position and φ the orientation. Given the most recent control $\mathbf{u}_t := (\omega_l, \omega_r)_t^T$ with the rotational speeds ω_l and ω_r of the left and right wheels respectively and the particle $\mathbf{x}_{t-1}^{[m]}$ from the particle set $\mathcal{X}_{t-1}$, the hypothetical $\bar{\mathbf{x}}_t^{[m]}$ of the state at time t is generated by

$$\bar{\mathbf{x}}_t^{[m]} = \mathbf{x}_{t-1}^{[m]} + \mathbf{B}(\varphi_{t-1})(\mathbf{u}_t + \mathcal{N}(0, \mathbf{Q})) \tag{8}$$

The matrix $\mathbf{B}(\varphi_{t-1})$ modesl the differential drive of the robot and depends on its orientation. Gaussian noise with zero mean and the covariance $\mathbf{Q}$ is added to the control input to model the uncertainty.

B. Update

In the update phase the sensor measurements are incorporated to generate the posterior belief of the robots position. For each sensor a model is defined, which assigns each particle a weight denoting the probability to obtain the given sensor measurement.

1) RSSI measurement model: As described in section IV the PTL algorithm implicitly assigns a probability to each position. Therefore each particle $\bar{\mathbf{x}}_t^{[m]}$ is simply processed through the algorithm yielding the weights $w_{t,r}^{[m]}$.

2) Ultrasonic measurement model: To incorporate the ultrasonic sensors in conjunction with a map of the environment, the probability to detect an obstacle with robot being at pose $\bar{\mathbf{x}}_t^{[m]}$ needs to be determined. Therefore the ultrasonic sensor beam is modeled by a two dimensional cone with an angle of $60°$. If the sensor produces the measurement $z_{u,t}$ all particles having an obstacle in this range are good hypotheses for the true pose reflected by a high weight $w_{t,u}^{[m]}$. Positions with different distances are assigned a lower weight, but not excluded completely allowing for unknown objects.

3) Map measurement model: Under the assumption that the environment of the robot is partially known, a particle $\bar{\mathbf{x}}_t^{[m]}$ obtains a low weight $w_{t,m}^{[m]}$ if the position is occupied by other objects in the map such as buildings or obstacles.

Assuming independence of all sensor data the overall weight is given by the product of the single weights by

$$w_t^{[m]} = w_{t,r}^{[m]} w_{t,u}^{[m]} w_{t,m}^{[m]} \,. \tag{9}$$

Analogue to the localization algorithm the weighted mean, the best particle or the robust mean can be chosen to estimate the position of the robot.

VI. Experimental Results

To evaluate the performance of the localization algorithm and the accuracy gain achieved by particle filtering based sensor fusion, experiments were conducted in the test garden. 11 reference nodes were placed to span an area of approximately 140 sqm. The robot was controlled remotely. All sensor measurements, including odometry, ultrasonic and RSSI data were recorded along with the real pose of the robot given by the optical tracking system.

A. Performance of the localization algorithm

Fig. 7 shows the real path driven by the robot. Further it shows the positions estimated by the PTL and SBL algorithms. For the PTL algorithm the grid point with the maximum probability was chosen to represent the estimation. To quantify the accuracy, the locilization error $LE := ||\mathbf{x}_{est} - \mathbf{x}_{true}||$ is defined, where $\mathbf{x}_{est}$ represent the estimated and $\mathbf{x}_{true}$ the true position, provided by the optical tracking system. The mean error for the PTL algorithm was $\overline{LE}_{PTL} = 0.95m$. The estimation given by the SBL algorithm averagely deviates by $\overline{LE}_{SBL} = 2.17m$. Fig. 8 shows the cumulative probability of the error for both algorithms. It makes clear that the PTL algorithm is more accurate than the SBL and has a significantly lower maximum error. Since the SBL algorithm represents the state-of-the-art, we see that our approach outperforms the current RSSI based localization techniques for the outdoor environment.

To prove the robustness of the approach we have tested it for the failure of reference nodes. Removing 2 nodes from the calculation increased the mean error by only 10cm. This is due to the redundancy and its optimal utilization by the PTL algorithm.

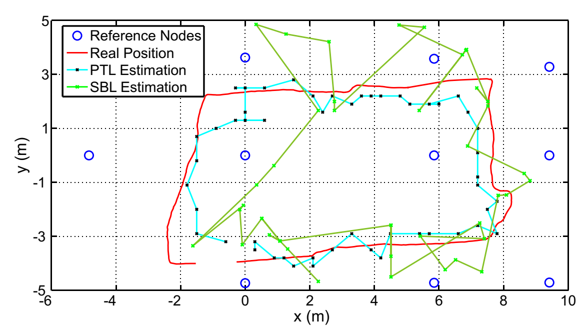


Fig. 7. Estimated and real positions

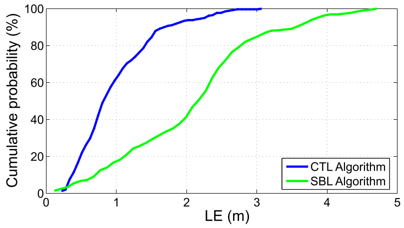


Fig. 8. Cumulative probability of the error

B. Performance of the Sensor Fusion

The result of the particle filter based sensor fusion is shown in Fig. 9. The number of particles was $n_p = 2000$ and the covariance $\mathbf{Q} = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \frac{1}{s}$. Fig. 9 also depicts the objects of the employed map. The mean error for the shown path was $\overline{LE}_{pf} = 32$cm. This means an improvement of the accuracy by 67% compared to the sole PTL algorithm. To demonstrate the suitability of the sensor fusion the path calculated by dead reckoning based on the odometry data is also depicted. The initial position was set to the true position given by the optical tracking system. The mean error here was $\overline{LE}_{od} = 68$cm. Not only that it is half as accurate, dead reckoning is also not capable to provide a global position and the error will increase with time.

VII. Conclusions

An accurate prediction of the position based on the received signal strength turned out as a complex problem, especially in low cost and low power RF hardware, since it is not optimized for this purpose. Therefore the first step to consider before implementing localization algorithms is to employ the hardware modifications described in this paper. These are an absolute prerequisite for enabling high accuracy.

The developed algorithm optimally calculates the position considering the uncertainty. Experimental results have shown sub meter accuracy, which is higher than other state of the art methods. Further it has proven to be robust to node failures. It also needs to store only 6 parameters for each node to define its characteristic. This makes it suitable for a decentralized localization architecture.

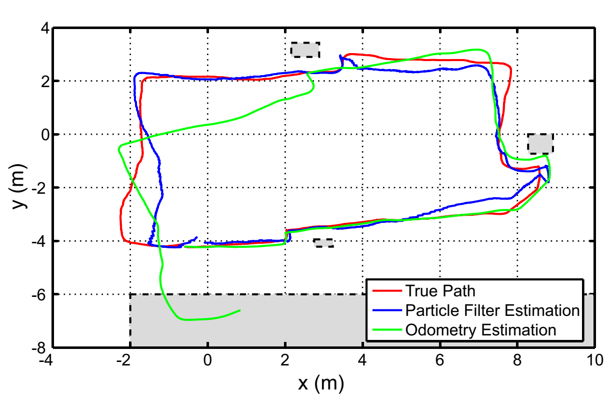


Fig. 9. Result of the sensor fusion

Since it implicitly models the uncertainty, it can be easily integrated in probabilistic sensor fusion as was shown in this article by means of a particle filter. The sensor fusion minimizes the mean error to 32cm and make the approach applicable for mobile robot navigation.

References

[1] J. Hightower and G. Borriello, "Location systems for ubiquitous computing," *Computer*, vol. 34.

[2] J. Kim, Y. Kim, and K. Lee, "The Third Generation of Robotics: Ubiquitous Robot," *6th IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA)*, 2005.

[3] D. Lymberopoulos, Q. Lindsey, and A. Savvides, "An Empirical Characterization of Radio Signal Strength Variability in 3-D IEEE 802.15.4 Networks Using Monopole Antennas," *Proc. of the 3 rd Workshop on European Wireless Sensor Networks (EWSN'06)*, 2006.

[4] S. Yang and H. Cha, "An Empirical Study of Antenna Characteristics Toward RF-Based Localization for IEEE 802.15.4 Sensor Nodes," *LECTURE NOTES IN COMPUTER SCIENCE*, 2007.

[5] J. Ma, Q. Chen, D. Zhang, and L. Ni, "An Empirical Study of Radio Signal Strength in Sensor Networks Using MICA2 Nodes," Technical Report, Department of Computer Science and Engineering, Hong Kong University of Science and Technology, Tech. Rep., 2006.

[6] N. Bulusu, J. Heidemann, and D. Estrin, "GPS-less low-cost outdoor localization for very small devices," *Personal Communications, IEEE*, vol. 7, no. 5, pp. 28–34, 2000.

[7] H. Tian, H. Chengdu, B. Blum, *et al.*, "Range-free Localization Schemes in Large Scale Sensor Networks," *Proceedings of the 9th Annual International Conference on Mobile Computing and Networking, MOBICOM*, pp. 2003–81, 2003.

[8] M. Sugano, T. Kawazoe, Y. Ohta, and M. Murata, "Indoor Localization System using RSSI Measurement of Wireless Sensor Network based on ZigBee Standard," *Proceeding of Wireless Sensor Networks*, vol. 7, pp. 54–69, 2006.

[9] H. Cho, M. Kang, J. Park, B. Park, and H. Kim, "Performance Analysis of Location Estimation Algorithm in ZigBee Networks Using Received Signal Strength," *Proceedings of the 21st International Conference on Advanced Information Networking and Applications Workshops*, vol. 2, pp. 302–306, 2007.

[10] K. Yedavalli, B. Krishnamachari, S. Ravula, and B. Srinivasan, "Ecolocation: a sequence based technique for RF localization in wireless sensor networks," *Proceedings of the 4th international symposium on Information processing in sensor networks*, 2005.

[11] Y. K. and K. B., "Sequence-based localization in wireless sensor networks," *IEEE Transactions on mobile computing*, 2007.

[12] P. Bahl, V. N. Padmanabhan, and A. Balachandran, "Enhancements to the radar user location and tracking system," Microsoft Research, Tech. Rep., 2000.

[13] B. Ferris, D. Haehnel, and D. Fox, "Gaussian Processes for Signal Strength-Based Location Estimation," *Proc. 2006 Robotics: Science and Systems Conf., MIT Press*, 2006.

[14] K. Lorincz and M. Welsh, "MoteTrack: A Robust, Decentralized Approach to RF-Based Location Tracking," *Proceedings of Intl. Workshop on Location and Context-Awareness*, 2005.

[15] H. Wang, H. Lenz, A. Szabo, J. Bamberger, and U. Hanebeck, "WLAN-Based Pedestrian Tracking Using Particle Filters and Low-Cost MEMS Sensors," *Procedings of Workshop on Positioning, Navigation and Communication, 2007.*, pp. 1–7, 2007.

[16] R. Vaughan and J. Andersen, *Channels, propagation and antennas for mobile communications*. Institution of Electrical Engineers, 2003.

[17] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. The MIT Press,, 2005.