Modeling RFID Signal Strength and Tag Detection for Localization and Mapping

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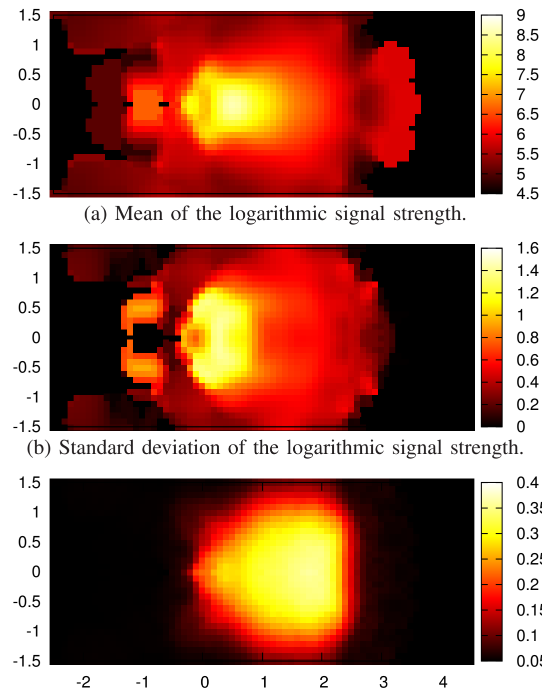
***Abstract*— In recent years, there has been an increasing interest within the robotics community in investigating whether Radio Frequency Identification (RFID) technology can be utilized to solve localization and mapping problems in the context of mobile robots. We present a novel sensor model which can be utilized for localizing RFID tags and for tracking a mobile agent moving through an RFID-equipped environment. The proposed probabilistic sensor model characterizes the received signal strength indication (RSSI) information as well as the tag detection events to achieve a higher modeling accuracy compared to state-of-the-art models which deal with one of these aspects only. We furthermore propose a method that is able to bootstrap such a sensor model in a fully unsupervised fashion. Real-world experiments demonstrate the effectiveness of our approach also in comparison to existing techniques.**

I. Introduction

Radio Frequency Identification (RFID) technology has become popular in areas such as supply chain management and inventory control, primarily because information can be attached to real-world products cheaply and can be retrieved without requiring physical contact. Recently, also robotics researchers have started to explore potential applications of the technology, focusing on the tasks of localization, mapping, and activity recognition. An RFID system consists of one or several RFID antennas and tags distributed in the environment. The antenna sends out electromagnetic waves and the passive RFID tags, consisting of a chip and a small antenna, use either load modulation or backscattering to send back their unique ID to the receiver. Ultra-high frequency (UHF) systems, one of which is also used in this work, has a reading range of up to a few meters.

According to scenarios envisioned for the near future, virtually every retail product could be equipped with an RFID tag. In addition to the *semantic* information about a given environment or situation [1], [2], such a setup also provides a rich source of *spatial* information, which can be utilized (a) to infer the location of the tags within the environment, (b) to localize the sensor relative to them, or (c) to solve both tasks jointly. A major precondition for solving all these tasks is the availability of an accurate sensor model $p(\mathbf{z} \mid \mathbf{x})$ that characterizes the relationship between locations $\mathbf{x}$ and measurements $\mathbf{z}$. The contribution of this paper is two-fold: First, we present a novel sensor model that utilizes the received signal strength indication (RSSI) as well as tag detection events to achieve superior accuracy compared to state-of-the-art models that cover one of the two aspects only (see Fig. 1 for an illustration). We use this sensor model for localizing RFID tags and for tracking a shopping cart equipped with two RFID antennas. As a second contribution, we describe how our sensor model can be learned in an fully unsupervised fashion. We also compare our model with a sensor model that has been shown to be effective for WiFi localization and we point out how this model can be further improved in the context of RFID localization and present experimental results. Real-world experiments in an office environment and a supermarket demonstrate that our system is able to robustly estimate the position of the tags and to track a shopping cart moving through an RFID-equipped supermarket.



(a) Mean of the logarithmic signal strength.

(b) Standard deviation of the logarithmic signal strength.

(c) Tag detection probability.

Fig. 1: The proposed sensor model combines information about the expected received signal strength, (a) and (b), and about the probability of detecting a tag (c).

The paper is organized as follows. After discussing related work in the field of RFID localization as well as in the related field of WiFi localization, Sec. III then introduces the proposed sensor model. In Section IV we explain how to learn the model in an unsupervised fashion and Sec. V and VI contain a description about how this sensor model is utilized for localizing RFID tags and for tracking a shopping cart. Finally, Sec. VII presents real-world experiments that were performed in an office environment and a supermarket.

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II. Related Work

There is a variety of approaches to RFID-based localization, which can be characterized by the type of sensor information used as well as by the general approach to modeling this information. Some of the earlier systems only provided information about the ID of the detected tag while later systems also provide information about the received signal strength. Hence, some localization techniques utilize sensor models that are based only on tag detection events [3], [4], [5], [6], [7]. For some RFID readers that do not provide RSSI (signal strength) directly, this information can be emulated by means of different attenuation levels or power levels of the antenna [8], [9], [10]. Sensor models for localizing tags are usually designed to be sensor centric [3], [6], [7], [9]. A different design, that can be used for localizing a mobile agent, is to lay out the sensor model relative to the environment [5], [11], [12], [13].

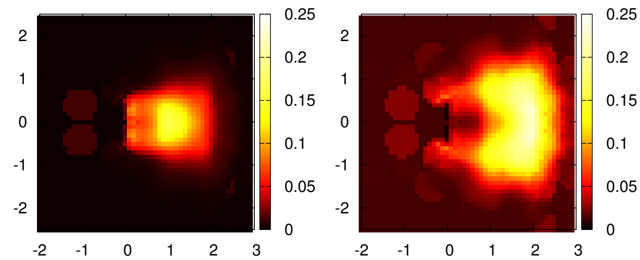
Hähnel *et al.* [3] utilized a piecewise constant tag detection sensor model to first localize the tags and then use the tag map to localize a mobile antenna. Schneegans *et al.* [5] compared histograms of tag detections with previously recorded histograms at different locations. Kleiner *et al.* [4] used a combination of pedestrian odometry and tag detections to perform graph-based RFID SLAM in a large outdoor environment. Kanda *et al.* [10] deployed RFID readers in a science museum and tracked people with attached RFID tags. Vorst *et al.* [14] showed how to learn a tag detection sensor model in a semi-autonomous fashion. Some approaches in the context of WiFi localization model the expected signal strength at different locations by using a discrete grid [11], or Gaussian process regression [12], [13].

Several approaches have addressed exclusively the tag localization problem. Ni *et al.* [8] compared the (emulated) signal strengths of tags at unknown locations with signal strengths received from reference tags at known locations. Alippi *et al.* [9] used several rotating antennas. Ehrenberg *et al.* [6] used an HF RFID system to localize books on a shelf. Liu *et al.* [7] used a tag detection model that is able to estimate the 3D position of the tag.

In contrast to the above-mentioned approaches, we model both phenomena—tag detection events as well as signal strength. The increased accuracy of the model allows us to address (a) localization of a mobile sensor relative to given tag locations and (b) mapping of tag locations when these are unknown. Furthermore, we show how to simultaneously learn the sensor model and estimate the position of the RFID tags in an unsupervised fashion. We present real-world experiments in an office environment as well as in a supermarket environment and compare our approach with state-of-the-art methods.

III. The Sensor Model

The techniques for localizing RFID tags as well as for tracking a mobile antenna both rely on a sensor model $p(\mathbf{z} \mid \mathbf{x}, \boldsymbol{\ell}_g)$ which specifies the likelihood of obtaining a measurement $\mathbf{z}$ given the pose $\mathbf{x} = (x, y, \theta)$ of the antenna and the location $\boldsymbol{\ell}_g = (x_g, y_g)$ of the detected tag with unique ID g. In our case, an observation $\mathbf{z} = (g, s)$ carries two pieces of information, namely that we have detected the tag g in the first place, and secondly that we received its signal with a signal strength s. Indeed, the event of detecting a tag is informative in itself, and this fact forms the basis for many of the previously proposed probabilistic sensor models for tag localization [3], [6], [7], [14]. Note also that the other class of existing sensor models, which consider signal strength only, implicitly condition on the tag detection event since a signal strength measurement can be obtained in this way only. We make the distinction between both sources of information explicit by denoting with d the binary variable that encodes the detection of a certain tag. Hence, the sensor model can be formalized as



(a) RSSI=$\log(2000)$ (b) RSSI=$\log(500)$

Fig. 2: Two instances of the inverse sensor model that describes the likelihood of relative offsets between antenna and tag given a certain level of received signal strength (RSSI). We plot (a) RSSI=$\log(2000)$ and (b) RSSI=$\log(500)$. The antenna is located at $(0, 0)$ and oriented towards the positive x-axis.

$$
\begin{aligned}
p(\mathbf{z} \mid \mathbf{x}, \boldsymbol{\ell}_g) &= p(s, d \mid \mathbf{x}, \boldsymbol{\ell}_g) \\
&= p(s \mid d, \mathbf{x}, \boldsymbol{\ell}_g) \cdot p(d \mid \mathbf{x}, \boldsymbol{\ell}_g). \qquad (1)
\end{aligned}
$$

In the most general form, these two conditional distributions are intractable to learn in practice since, for example, $p(d \mid \mathbf{x}, \boldsymbol{\ell}_g)$ specifies a tag detection probability for every possible combination of antenna pose $\mathbf{x}$ and tag location $\boldsymbol{\ell}_g$. Therefore, we make the common assumption that only the *relative* location $\delta(\mathbf{x}, \boldsymbol{\ell}_g)$ of a tag with respect to the antenna is relevant (see [3], [6], [7], [14]). This assumption certainly is a strong one, since the propagation of an RFID signal is also influenced by *location-dependent* factors, such as the materials the tags are attached to, the orientation of the tags relative to the antenna, or obstacles that reflect or absorb electro magnetic waves. The gain in efficiency, however, is large in comparison to other simplifications that could be made. As we will show in the experimental evaluation, the accuracy of a *location-dependent* sensor model for RFID tags is slightly higher than of our model, but that gain comes at a high computational cost already for small environments.

Committing ourselves to *sensor-centric* sensor modeling, which considers relative tag positions only as outlined above, we get

$$
p(\mathbf{z} \mid \mathbf{x}, \boldsymbol{\ell}_g) = p(s \mid d, \delta(\mathbf{x}, \boldsymbol{\ell}_g)) \cdot p(d \mid \delta(\mathbf{x}, \boldsymbol{\ell}_g)) \,. \qquad (2)
$$

In words, this models the likelihood of an observation as the likelihood of receiving signal strength s at position $\delta(\mathbf{x}, \boldsymbol{\ell}_g)$ relative to the antenna multiplied by the probability of detecting a tag at this relative position.

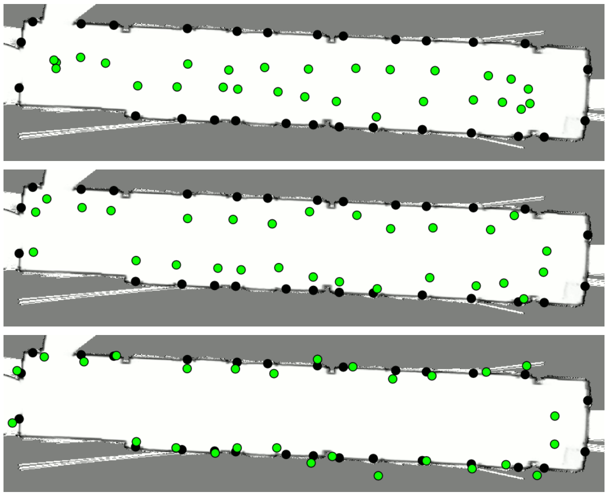


Fig. 3: Ground truth tag locations (black) and tag locations estimated (green / gray) with the initial sensor model (top), and with the learned models at bootstrapping iterations 2 (middle) and 25 (bottom).

Location-dependent sensor models, that characterize the distribution of signal strength relative to the environment rather than to the sensor (see [11], [12], [13]), can be understood as a different approximation that stays more faithful to the true signal strength distribution. Instead of conditioning the signal strength on the relative tag position, they learn a separate signal strength distribution $p_g(s \mid \mathbf{x})$ for each tag individually, which is conditioned only on the antenna location. The resulting signal strength *maps* implicitly contain all environment-specific factors. On the downside, they do not model the location of the tag explicitly and, thus, cannot be used to estimate the location of the tags directly.

IV. Learning the Model from Data

We first describe how the components of (2) can be learned in a semi-autonomous way and then extend this procedure to an unsupervised bootstrapping method.

A. Semi-Autonomous Learning

Vorst *et al.* [14] proposed a method for learning a tag detection sensor model in a semi-autonomous fashion, which we will adopt and extend towards also learning the signal strength distribution. Building on this, we show how to learn both models in an fully autonomous way. The semi-autonomous way of learning a tag detection model is to assume a list of tag positions given as well as the trajectory of a mobile antenna moving through the environment. At every tag detection event, we transform the positions of tags into the antenna's local coordinate system and register the tag detection at the tags relative position as a positive event while registering the non-detected tags as negative events. We then discretize the space relative to the antenna according to a two-dimensional grid and count for every grid cell (x, y) the positive events $n^+_{x,y}$ and the negative events $n^-_{x,y}$. Given these counts, the maximum likelihood estimator of the tag detection probability is $p_{x,y} = n^+_{x,y} / \left(n^+_{x,y} + n^-_{x,y}\right)$. Likewise, we maintain a second grid that contains statistics about the average received logarithmic signal strength $\mu_{x,y}$ and the empirical variance $\sigma_{x,y}$ for each grid cell. Under the assumption that the logarithmic signal strengths within each grid cell are normally distributed, we can estimate the likelihood of an observation $\mathbf{z} = (g, s)$ at the antenna relative position $\delta(\mathbf{x}_t, \boldsymbol{\ell}_g) = (x, y)$ as

$$p(\mathbf{z} \mid \mathbf{x}, \boldsymbol{\ell}_g) = p(s \mid d, \delta(\mathbf{x}, \boldsymbol{\ell}_g)) \cdot p(d \mid \delta(\mathbf{x}, \boldsymbol{\ell}_g)) \quad (3)$$
$$\propto \frac{1}{\sigma_{x,y}\sqrt{2\pi}} \exp\left(-\frac{(\log(s) - \mu_{x,y})^2}{2\sigma^2_{x,y}}\right) \cdot p_{x,y} \ .$$

B. Bootstrapping the Sensor Model

So far, learning the sensor models required knowledge about the true tag positions, which might be tedious or impossible to acquire. We can sidestep this, by bootstrapping the sensor models. We start with a basic, yet plausible tag detection model similar to the one proposed by Hähnel *et al.* [3] and iterate the following steps:

1) Use the current model to estimate the tag locations (as described in the next section) and
2) learn a new sensor model based on the estimated tag locations (as described above).

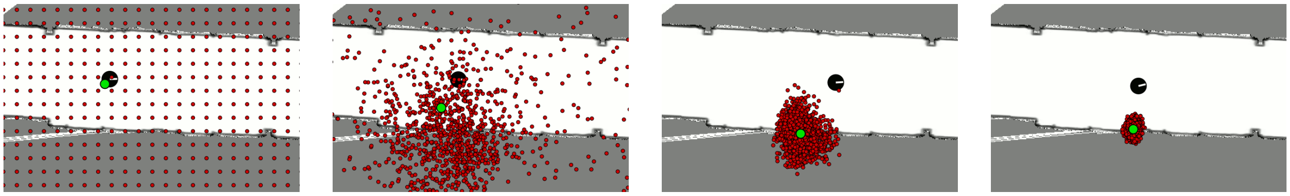
In the experimental section, we present results that indicate that alternating tag location estimation and sensor model learning converges in terms of tag location error and the similarity of the bootstrapped sensor model to a model learned in a semi-autonomous way. Fig. 1 shows an example for a sensor model learned this way in an office environment. Fig. 2 visualizes two instances of the corresponding *inverse* sensor model, that is, the likelihood of relative poses *given* a certain level of received signal strength. This model has been calculated analytically from the three components of the sensor model depicted in Fig. 1. The improvement of the estimated tag locations during the bootstrapping procedure is illustrated in Fig. 3.

Based on this bootstrapping procedure, we can learn both the sensor model and the tag locations in a fully unsupervised fashion. This greatly simplifies sensor modeling in practice, compared to the manual acquisition of calibration data. In contrast to the semi-autonomous method, it does not require knowledge about the true tag positions.

V. Mapping Tags from Known Sensor Poses

For localizing RFID tags, we move a mobile antenna through the environment and integrate the measurements iteratively so that the estimates of tag locations improve gradually over time. We assume that the antenna is localized, e.g., applying laser-based FastSLAM [15], so that we have accurate estimates of the positions at which observations have been made.

Formally, we are given a sequence of tag readings $\mathbf{z}_{1:t} = \{(g_i, s_i)\}^t_{i=1}$ denoting the unique ID g of the detected tag and the received signal strength s, as well as a sequence of antenna poses $\mathbf{x}_{1:t} = \{(x_i, y_i, \theta_i)\}^t_{i=1}$, denoting the antenna's position and orientation at which these observations have been made. We are interested in the posterior $p(\boldsymbol{\ell}_g \mid \mathbf{x}_{1:t}, \mathbf{z}_{1:t})$ of the tag location $\boldsymbol{\ell}_g = (x_g, y_g)$ given the



(a) Initial filter state. (b) After second filter update. (c) After 5th filter update. (d) After 30th filter update.

Fig. 4: Localizing RFID tags in an office corridor: The green circle indicates the estimated tag location and the black circle the pose of the shopping cart.

information up to time t. Using Bayes' rule and assuming independence between measurements, we get the recursive update formula

$$p(\boldsymbol{\ell}_g \mid \mathbf{x}_{1:t}, \mathbf{z}_{1:t}) = \eta \cdot p(\mathbf{z}_t \mid \delta(\mathbf{x}_t, \boldsymbol{\ell}_g)) \cdot p(\boldsymbol{\ell}_g \mid \mathbf{x}_{1:t-1}, \mathbf{z}_{1:t-1}), \quad (4)$$

where $p(\mathbf{z}_t \mid \delta(\mathbf{x}_t, \boldsymbol{\ell}_g))$ is the sensor model described in the previous section and η is a normalization factor (see also [3]).

To estimate this posterior sequentially as new data arrives, we apply a particle filter for each tag and use its unique ID for data association. Each filter is initialized with a uniform particle distribution bounded by the maximum reading range of the antenna and centered around the antenna's position during the first encounter of the tag [visualized in Fig. 4 (a)]. We resample whenever the so-called number of effective particles $n_{\text{eff}} = \left(\sum_i w_i^2\right)^{-1}$ falls below a threshold κ, which we set to half the number of particles of the filter. Here, w_i denotes the weight of particle i. Following Liu and West [16], we disturb the individual particle locations by resampling them from a normal distribution with mean $ap^{[i]} + (1-a)\overline{p}$ and variance $h^2\mathbf{V}$. Here, $\overline{p}$ and $\mathbf{V}$ are the mean and covariance matrix of the particle set and $a = \frac{3\gamma-1}{2\gamma}$ and $h^2 = 1 - a^2$ only depend on a discount factor γ, which we set to 0.95. This procedure causes the particle-based estimates of the tag locations to converge to the true locations even for crudely initialized estimates within a few filter iterations, as can be seen in Fig. 4.

VI. Localizing a Mobile Agent

Given that we know the locations of the RFID tags, we can use the very same sensor model to track a mobile agent equipped with an RFID antenna. We apply Monte Carlo Localization (MCL) [17], which utilizes a particle filter to maintain the posterior over the agent's location

$$\operatorname{bel}(\mathbf{x}_{t+1}) = \eta\ p(\mathbf{z}_{t+1} \mid \delta(\mathbf{x}_{t+1}, \boldsymbol{\ell}_g)) \cdot \int p(\mathbf{x}_{t+1} \mid \mathbf{x}_t) \cdot \operatorname{bel}(\mathbf{x}_t) d\mathbf{x}_t\,. \quad (5)$$

While the sensor model $p(\mathbf{z} \mid \delta(\mathbf{x}, \boldsymbol{\ell}_g))$ remains the same, the crucial part here is the motion model $p(\mathbf{x}_{t+1} \mid \mathbf{x}_t)$, from which we sample the next particle distribution. As we are tracking a shopping cart, which does not provide odometry information, we used a velocity based motion model that tries to capture the typical motion patterns of people pushing the cart. For this, each particle $p^{[i]}$ is constrained in a seven-dimensional space

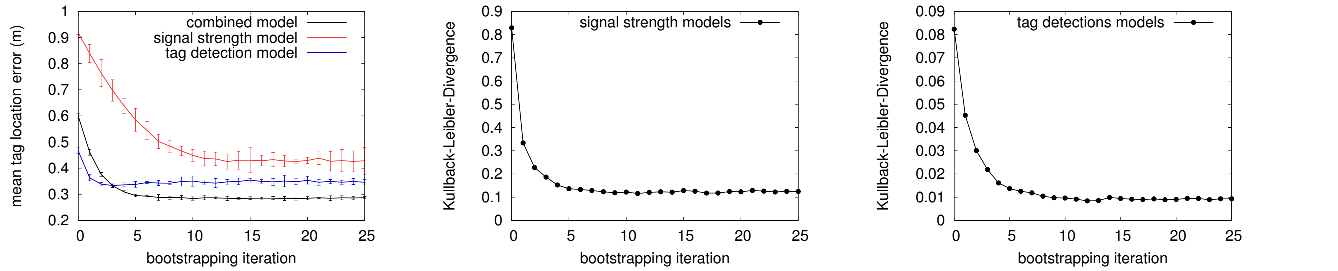
$$p^{[i]} = (\mathbf{x}, \dot{\mathbf{x}}, m) = (x, y, \theta, \dot{x}, \dot{y}, \dot{\theta}, m)\,, \quad (6)$$

that consists of the current pose $\mathbf{x} = (x, y, \theta)$ of the cart, its velocity $\dot{\mathbf{x}}$—parameterized by the translational velocity $\dot{x}$ in direction of the cart, a lateral drift velocity $\dot{y}$, and a rotational velocity $\dot{\theta}$—and a discrete motion state m, which can be one of the following seven states: *standing*, *moving forwards (backwards)*, *turning left forwards (backwards)*, or *turning right forwards (backwards)*.

The transition from one particle state $p_t^{[i]}$ to the state $p_{t+1}^{[i]}$ at the next point in time is modeled as follows: first, we sample a new motion state m_{t+1} according to a state transition probability $p(m_{t+1} \mid m_t)$. If the motion state changed, we sample new velocities $\dot{\mathbf{x}}_{t+1}$ from three motion state specific normal distributions $\mathcal{N}(\mu_{m,\dot{x}}, \sigma_{m,\dot{x}})$, $\mathcal{N}(\mu_{m,\dot{y}}, \sigma_{m,\dot{y}})$, $\mathcal{N}(\mu_{m,\dot{\theta}}, \sigma_{m,\dot{\theta}})$ that capture the velocity distributions of the particular state. If the sampled motion state is the same as in the time step before, we do not sample new velocities, but keep the velocities of the previous point in time. Once the new velocities are determined, we deterministically compute the new pose of a particle based on the velocities and the time passed during one filter update step. As during tag localization, we resample whenever the number of effective particles is less than half of the particle set size. To account for physical constraints imposed by walls and other obstacles, we set the weight of a particle close to zero, whenever it enters an occupancy grid cell that is likely to be occupied. The transition probabilities and the velocity distributions of the motion model were learned from recorded trajectories with hand-labeled motion states.

VII. Experimental Evaluation

To evaluate our approach, we equipped a shopping cart with a SICK RFI 641 UHF RFID reader with two antennas mounted perpendicular to each side of the cart (see Fig. 6). The reader also reports which antenna detected the tag, and we know their positions relative to the center of the cart. As the antennas are identical in construction we assume the same sensor model for both. The reader is configured to run in continuous mode, reporting a tag as soon as it is detected. The typical tag detection rate of the system is about 10 Hz. We used passive UHF tags ("DogBone" by UPM Raflatac). In order to acquire a ground truth trajectory and an occupancy grid of the environment we additionally equipped the cart with a SICK LMS 291 laser scanner and processed the data with the GMapping algorithm [15], which is an efficient laser-based realization of the FastSLAM approach. In the remainder of this section we present experimental results about the tag localization approach and the localization of a mobile agent.



(a) Average tag localization error. (b) Divergence of the signal strength models. (c) Divergence of the tag detection models.

Fig. 5: The bootstrapping process: (a) The process converges in terms of the average tag location error. The error bars depict the 2σ confidence interval. (b) and (c) show that the bootstrapping procedure also converges in terms of sensor model similarity to a semi-autonomously learned model.

A. Localizing the RFID Tags

We distributed 28 RFID tags in an office corridor as depicted by the black circles in Fig. 3. Neighboring tags had an average distance of about two meters. We knew the true locations of the tags and therefore could evaluate the accuracy of tag localization quantitatively. We bootstrapped the sensor model by moving the shopping cart up and down the corridor several times—performing 360° turns at several locations. This took about 4 minutes and resulted in roughly 4100 tag detections. Fig. 5 (a) shows the evolution of the average error of the estimated tag locations after each iteration of the bootstrapping process. As can be seen, the error converges to a final value of about 29 cm. We also give the estimation results for (a) the signal strength-based model alone and (b) the tag detection-based model alone evaluated on the same trajectory. The proposed combined sensor model is significantly better than either the signal strength-based model or the tag detection-based one alone.

If we learn the sensor model semi-autonomously based on the true tag locations, we achieve a localization accuracy of about 27 cm. This indicates, that the bootstrapping process yields a sensor model that is comparable to a semi-autonomously learned sensor model. This was also confirmed by visually comparing the individual components of the two models. To confirm this finding quantitatively, we calculated the average symmetric Kullback-Leibler divergence between all grid cells of the two models after each bootstrapping iteration. The results illustrated in Figs. 5 (b) and (c) show that the bootstrapping process also converges in terms of model similarity to a semi-autonomously learned model.

B. Localizing a Mobile Agent

We distributed about 350 tags along the shelves in a supermarket at an average distance of approximately one meter. Then we bootstrapped the sensor models and the tag

Fig. 6: We equipped a shopping cart with an RFID reader and a laser range scanner and deployed about 350 passive UHF tags in a supermarket.

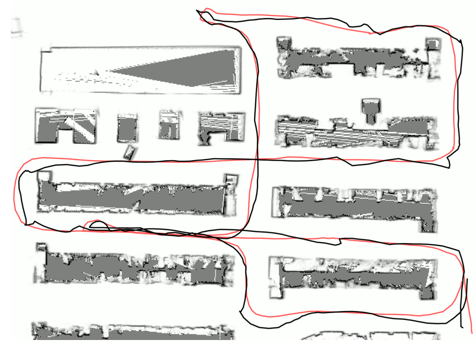
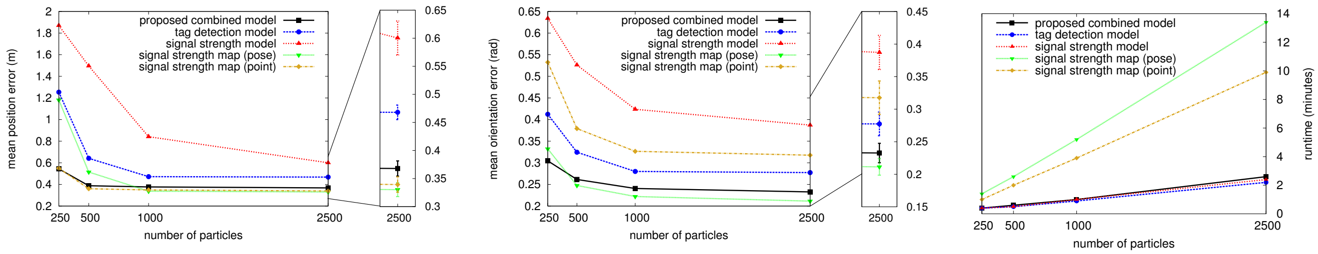


Fig. 7: Comparison of the estimated trajectory (black) and the ground truth trajectory (red / gray) on one of the supermarket log files.

positions by using data from six log files, which we collected by moving the shopping cart through the environment. The log files contained 34 200 tag detections and lasted about 74 minutes in total. We used the agent localization technique described above and defined as the localization result the trajectory of the most likely particle. An example of an estimated trajectory and its corresponding ground truth trajectory is depicted in Fig. 7 as well as in the accompanying video.

To evaluate the accuracy of the localization technique quantitatively, we localized the agent on seven different log files which lasted 24 minutes in total and contained 13 400 tag detections. We repeatedly localized the cart for each log file ten times and averaged the measured error values. The error was quantified in terms of the average position error and the average orientation error. Results are given in Fig. 8.

Using only the tag detection model can be considered equivalent to the approach by Vorst *et al.* [14]. For further comparison, we implemented a model similar to the one presented by Ferris *et al.* [13], which used Gaussian process regression [18] to model the signal strength distributions of WLAN access points in 2D space. We used Gaussian process regression for modeling the log-signal strength of the RFID tags in the supermarket. We observed that the estimation of the cart's orientation can be significantly improved [Fig. 8 (b)], if the antenna's orientation is taken into account, and hence the signal strength is mapped in pose space rather than in 2D. The proposed combined sensor model outperforms both of its components—the tag detection model and the signal strength model—and performs comparable to the signal strength map. Both methods can be executed online for 2 500 particles, but the proposed model needs only 2.6 minutes on average to process all log files, while the signal



(a) Average position error. (b) Average orientation error. (c) Runtime.

Fig. 8: Evaluating several sensor models for agent localization: the proposed combined model, and its two components alone. For comparison, we show the results of a signal strength map, similar to the model by Ferris *et al.* [13], mapping the signal strength either in pose space ("pose") or in 2D ("point").

strength map, which uses Gaussian process regression instead of a grid, requires 13.4 minutes, as can be seen in Fig. 8 (c).

In both tasks—localization and mapping—the signal strength model alone was consistently less accurate than the tag detection model. This is an unexpected finding, since the received signal strength should intuitively be more informative than a simple detection event. Close inspection of the recorded data reveals, however, that the relationship between signal-strength and sensor location is more noisy than it is the case for tag detections. Thus, the particle filter as a sophisticated way of integrating information over time, is able to recover the (real-valued) pose information accurately from the stream of (binary) tag detection events.

VIII. Future Work

There are several directions for future work. Our results showed that considering signal strength information along with tag detection events lead to an improved sensor centric model. Therefore, it would be interesting to see if the accuracy of signal strength maps could be improved in just the same way by combining them with "tag detection maps". Another direction would be to extend the model to a 3D sensor model. Moreover, the assumption made that the tag map remains static could be alleviated—a technique for mapping "nomadic" tags (static tags which change locations from time to time) was presented in [7].

IX. Conclusions

In this paper, we presented a novel combined sensor model that utilizes both (a) the received signal strength and (b) tag detections of RFID systems for robot localization and mapping of tags. We also presented a technique to learn such a model in an unsupervised way. This greatly simplifies the task of sensor modeling in practice compared to the manual acquisition of calibration data. For comparison, we implemented a sensor model that has been shown to be effective for WiFi localization. We furthermore described how this model can be improved in the context of RFID localization. As our experiments in several real-world settings showed, our approach achieves the computational efficiency of existing sensor-centric models and an accuracy of a state-of-the-art approach that learns a location-dependent model for each tag.

Acknowledgement

This work has been supported by the Deutsche Forschungsgemeinschaft (DFG) under contract number SFB/TR 8 Spatial Cognition (R6-[SpaceGuide]).

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