Passive Tracking of Transceiver-Free Users with RFID

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Abstract. Providing location information while people move through a indoor environment is fundamental to smart environments. While many works address this problem, which is often referred to as tracking, the complex radio propagation and the need smart and unobtrusive localization system still represent challenges to current approaches.
We investigate through simulations the applicability of tracking a user with a passive RFID-System. The distinction to former approaches is that we do not constrain the user to wear any electronic devices to help localization. Our approach rather focuses on measuring the variations of signal strength which are caused by a human. For this purpose, we have spotted passive RFID to be very useful since the tags can be placed almost on any surface to measure the spatial distribution of the variations.

1 Introduction

The location of users and devices in smart environment has long been spotted as fundamental contextual information and, therefore, algorithms like intention recognition and task planning build on robust and accurate location information.

However, localization, the process of acquiring and tracking the location of users and devices using wireless communication, has to deal with several issues. Many existing approaches use the Time-of-Flight (ToF), Angle-of-Arrival (AoA) or received signal strength (RSS) to infer distances or directions to the target. However, the complex radio propagation in indoor environments represents a challenge for these methods since the aforementioned metrics are typically severely affected by multi path and interference of radio waves. For this reason, commercial localization systems use several metrics and fuse them to improve localization accuracy.

Observing that some of the negative effects on radio propagation are caused by the target to be tracked itself, an approach to track back these changes in order to localize a user has been reported to be feasible [1]. The distinction to previous approaches is that the user does not need to wear any communication devices and the resolution of the system can be adjusted by adding inexpensive passive tags.

The objective of the current paper is to investigate the applicability of this approach to tracking of the user with a particle filter. Special attention is paid to

Table 1. Overview of related work.

	Passive Tags	Measurement	Transceiverless Target	Link Type
User/Object Localization				
Landmarc [2]	No	RSS	No	monostatic
SpotOn [3]	No	RSS	No	monostatic
Ferret [4]	Yes	Connectivity	No	bistatic
Robot Self-Localization				
Schneegans [5]	Yes	Connectivity	No	bistatic
Hhnel [6]	Yes	Connectivity/LR	No	bistatic
WSN Localization using RF-Propagation Effects				
Zhang et al. [7,8]	-	RSS	Yes	monostatic
Patwari et al. [9]	-	RSS	Yes	monostatic
curr. approach	Yes	RSS	Yes	bistatic

the sampling rate of the system which is a limiting parameter of our test bed and a function of number of passive RFID-Tags. Specifically, we aim at determining the minimum sampling rate of the system for which tracking still works with acceptable accuracy.

The rest of the paper is organized as follows. Section 2 reviews related works. Sections 3 and 4 reviews the theoretical models, their applicability to the current approach and introduces the particle filter framework. In Section 5, we present the set-up and results of simulations and draw conclusions on the applicability of a particle filter for tracking

2 Related Work

Although the Global Positioning System (GPS) has been accepted as a reliable localization system for outdoor environments, its capabilities are very limited indoors since the satellite signals are typically strongly attenuated by walls and ceiling. Furthermore, in indoor environments a feasible localization system has to distinguish locations inside rooms and, therefore, an accuracy in the meter domain is expected.

The existing approaches to indoor localization can be classified in several ways: By the type of measurement, for example optical, ultrasound, infrared, pressure, RSS. Another distinction can be made concerning the system architecture, for example, whether the target can communicate over bidirectional or unidirectional links with the localization system. In some cases, the target does not need to carry a dedicated device to be located which makes these approaches especially interesting for ubiquitous environments.

Related to the distinction between uni- and bidirectional links is the distinction between monostatic and bistatic systems. In contrast to bistatic systems which use separate antennas for transmitting and receiving, monostatic systems have collocated transmitting and receiving antennas. Being either monoor bistatic has strong impact on RSS-based localization with passive RFID because the mapping of RSS to distance is different. In addition, connectivity in bistatic systems depends on two physically different links as will be explained in greater detail later.

In contrast to our approach, Ni et al. utilize an active RFID-system for localizing a mobile target that has RFID tags attached [2]. The stationary deployed RFID-readers compare the measured power level of reference tags to improve localization performance.

Another well-known localization system using RFID is *SpotOn*. SpotOn researchers have designed and built custom hardware that serves as tags for localization. A 3D-localization algorithm uses the RSS readings between tags to determine their locations.

Ferret considers localization of nomadic objects and utilizes the directionality of RFID-readers [4]. The idea is to exploit different poses of the reader to narrow the object location down. This approach also utilizes a bistatic passive RFID-system.

The applicability of RFID to aid robot self-localization has been investigated in [6,5]. However, the connectivity information rather than the more informative RSS is used for localization.

Only few work have considered exploiting the change of RSS due to user presence for localization. Patwari et al. utilize the change of RSS to localize a person indoors [9]. The authors use a sensor network to measure the RSS and map its changes with a weighted linear least-squares error approach to estimated locations. Furthermore, Zhang et al. developed a system of ceiling mounted sensors that continuously measure the RSS between the sensor nodes. The absolute change of RSS is used to localize passing users. The authors recently proposed an extension of their original algorithm which allows for localization of multiple targets provided these are not too close [8].

Both approaches are related to ours since the impact of user presence on RSS is exploited. However, we point out the following significant differences: Our approach uses a passive bistatic RFID system which is advantageous for localization in ubiquitous environments. Such systems greatly differ in the way RSS are measured since they rely on backscattered signals. Furthermore, the resolution of our system depends on the number of inexpensive, passive RFID-Tags rather than full-fledged battery-powered transceivers.

3 Impact of Human Presence on RSSI

This section reviews findings obtained from an experimental testbed and focuses on the impact of user presence on RSS. A detailed investigation of these effects can be found in [1]. If not stated otherwise, we denote a pure sinusoid oscillation by signal.

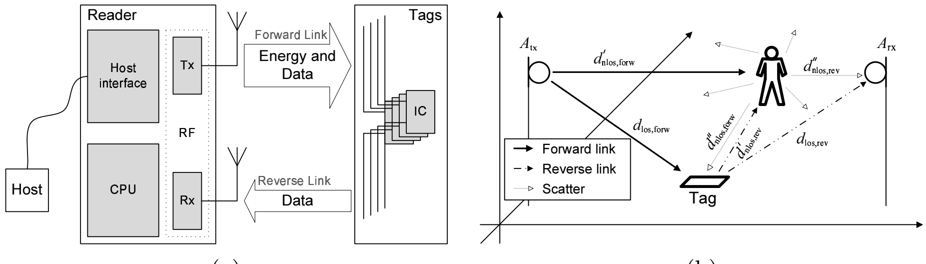
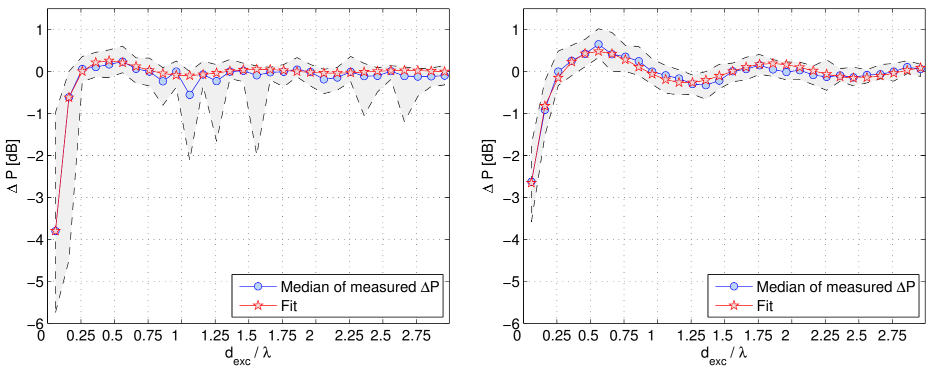


Fig. 1. a) Architecture of passive, bistatic RFID-Systems. b) Principle of radio scattering caused by human presence.



(a) Forward link. (b) Reverse link.

Fig. 2. Human influence on RFID communication and relation between RSS variations and excess path delay.

3.1 Modeling of Human-induced RF-Shadowing

We consider a bistatic, passive RFID-System consisting of a receiving and transmitting antenna and a RFID-Tag as depicted in Figures 1. These passive systems differ from active ones as the small tags are powered by impinging radio energy and thus do not need a battery. In the following, we seek to find a mathematical model for the RSS at the receiving antenna given a specific user location. Due to the characteristics of radio propagation, it is feasible to first describe the user location as the set of coordinates having the same excess path delay. Later, we will show how the excess path delays of several links can be combined for actual localization.

In Figure 1b, a user is situated in the deployment area and acts as scatterer to the ongoing wireless communications. As a result, radio signals reach the receiving antenna over several paths of different length and, therefore, show an *excess path delay*:

$$d_{\text{exc}} = d'_{\text{nlos}} + d''_{\text{nlos}} - d_{\text{los}} \tag{1}$$

The figure shows that for bistatic RFID systems we need to consider both forward and reverse links as the measured RSS depends on both. Furthermore, we are only able to observe a function of the actual RSS which is typically referred to as Received Signal Strength Indicator (RSSI). In the following, we assume that the RSSI is proportional to RSS that we only need to consider the change of RSSI to characterize the change of the true RSS.

To facilitate further considerations, we define the following quantities in dB

s_{init} is the initial RSSI measured without user presence in the deployment area.
s_{obst} is the RSSI measured with user presence at a specific location in the deployment area.
Δs denotes the difference or variation of RSSI $\Delta s = s_{\text{obst}} - s_{\text{init}}$.

To characterize the change of RSSI compared with the initial RSSI, we need to consider the relative excess path delay d_{exc} of the direct line-of-sight (LOS) and the scattered non-line-of-sight (NLOS) path. The ratio between excess path delay and signal wave length determines whether two interfering signals' amplitudes add or subtract. It is noted that lines of equal excess path delay form ellipsoids with A_{tx} and A_{tx} as focii. For example the region $d_{\text{exc}}/\lambda \leq 0.25$ is called the *First Fresnel Zone*. Obstacles in the First Fresnel Zone typically result in attenuations of RSS [10].

Table 2. Parameters of fitting the measurements.

Parameter	Forward link	Reverse link
A	0.025	0.14
B	-1.32	-0.79
$\tilde{\lambda}$	0.37	0.43
Φ_{refl}	3.20	3.25

In a one excess path scenario, it can be shown that s_{obst} has the following form [1] with the parameter values in Table 2:

$$\Delta s_(d_{\text{exc}}) \approx A d_{\text{exc}}^{B} \cos\left(\frac{2\pi}{\tilde{\lambda}} d_{\text{exc}} + \phi_{\text{refl}}\right) \tag{2}$$

It is noted that in general there will be more than one scatterer and consequently more than one excess path. However, since we focus in this paper on system parameters, we constrain the investigations to the single-target case.

Figure 3 depicts simulated variation of RSSI. It is shown that there is ambiguity when we try to determine the location of the user given a specific Δs

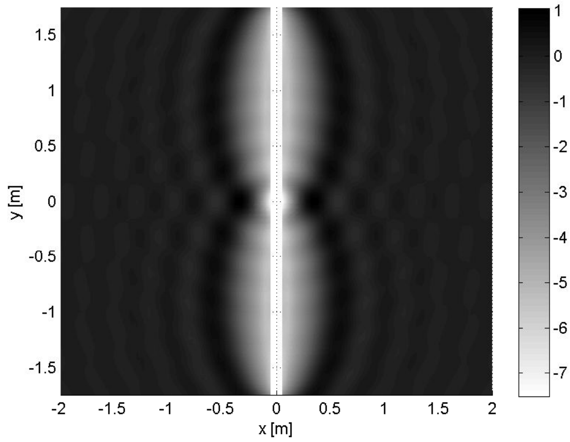


Fig. 3. Simulated s_{obst} for different user locations. Dark areas indicate no influence or amplification and white areas indicate attenuations. Receiving and transmitting antenna and the tag are situated at $(0, -1.75)$, $(0, 1.75)$ and $(0, 0)$ respectively.

since lines of equal excess path delays form ellipsoids. In addition, Δs can not be attributed to either forward or backward link. To mitigate ambiguity, we need to consider several links between tags and antennas. This has the additional advantage of further narrowing down the possible location of the user the more tags are used. At this point it becomes clear that the inexpensiveness and small scale of passive RFID-Tags make such systems especially appropriate.

Following this approach, classical estimators like the method of least squared errors or the maximum likelihood method have been applied to the problem [11].

4 Tracking Transceiver-Free Users

This section considers tracking a moving user and introduces the framework which will be used for tracking.

Concerning the localization problem, we desire to estimate the state sequence $\{\theta_k, k \in \mathbb{N}\}$ of the user which consists of its location and possible other parameters describing its movement. Here we assume a time discrete representation where k denotes the current time slot. Due to physics, the location of an object can not change abruptly but typically can be modeled by a set of state transition equations

$$\theta_k = \mathbf{f}_k(\theta_{k-1}, \mathbf{v}_{k-1}) \tag{3}$$

where $\mathbf{f}_k$ is a possibly nonlinear function, $\mathbf{v}$ is the an i.i.d. process noise and $\mathbb{N}$ are the natural numbers. The objective of tracking is to estimate the sequence

$\{\theta_k, k \in \mathbb{N}\}$ given noisy measurements $\mathbf{z}_k$

$$\mathbf{z}_k = \mathbf{h}_k(\theta_{k-1}, \mathbf{n}_{k-1}) \quad (4)$$

Classical estimation methods regard the parameters to be estimated as deterministic yet unknown variables. In contrast thereof, Bayesian estimators assume that the parameters are random and, hence, can be described by probability distributions [12].

In this work, we consider the application of the Extended Kalman Filter (EKF) and the Particle Filter to the tracking problem. Since both algorithms have been extensively studied in the literature [13,14,15], we omit the mathematical details here.

5 Simulation

We conducted computer simulations to investigate the following:

- Relation between tracking error and number of RFID-Tags
- Compare tracking error of Particle Filter and Extended Kalman Filter.

We consider an indoor deployment of $N_{\text{ant}} = 4$ antennas and N_{tag} passive RFID-Tags. The tags are deployed in a regular, quadratic grid on the floor. The antennas are located at the four corners of the deployment area in a height of 1.8 meters. A target is assumed to move through the deployment area while the RFID system measures the vector of RSS of all tags in discrete time steps with sampling period T.

5.1 Simulation Set-Up

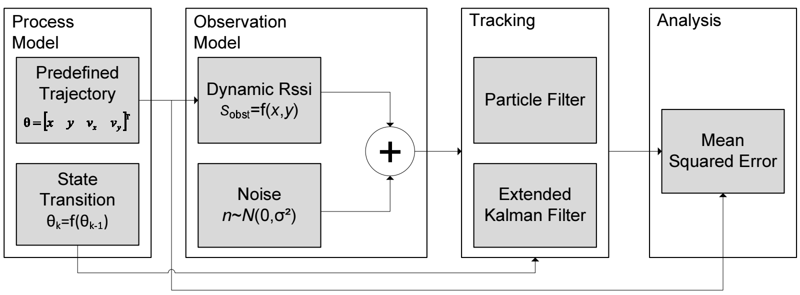


Fig. 4. Data flow of computer simulations.

A schematic of the computer simulations is shown in Figure 4. The movement of the target is described by the process model. We assume 2D coordinates and the associated velocities, i.e. the state $\theta = [x, y, v_x, v_y]^{\mathrm{T}}$ and the state transition function are given by:

$$\theta_k = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \theta_{k-1} + \mathbf{v}_{k-1} \tag{5}$$

Where $(\cdot)^{\mathrm{T}}$ denotes the transpose. To facilitate simulation, we predefined a S-shaped trajectory and calculated the evolution of the state accordingly.

The observation model describes the relation between the vector of measured RSS $\mathbf{z}$ and the state. We define the matrix of antenna sequence (AS) $\mathbf{S}_{\mathrm{ant}} \in \mathbb{N}^{N_{\mathrm{as}} \times 2}$. The first and second element of the i-th row of $\mathbf{S}_{\mathrm{ant}}$ denote the i-th transmitting and receiving antenna, respectively. Theoretically, there are $\binom{N_{\mathrm{ant}}}{2}$ possible antenna pairs. However, we choose for the simulation $N_{\mathrm{as}} = 2$ antenna pairs to limit the complexity of calculations. Consequently, the vector of observations is given by

$$\mathbf{z} = \left[\Delta s^{(1,1)}, \ldots, \Delta s^{(N_{\mathrm{tags}},1)}, \Delta s^{(1,2)}, \ldots, \Delta s^{(N_{\mathrm{tags}},N_{\mathrm{as}})}\right]^{\mathrm{T}} + \mathbf{n} \tag{6}$$

We assume a lognormal fading model and add iid Gaussian noise with distribution $N(0, 1)$ to the RSS given in dezibels. It is noted that each measured RSS, i.e. each element of $\mathbf{z}$, corresponds to the link between sending and transmitting antenna and tag. Consequently, the measurement vector has a size of $\mathbf{z}_k \in \mathbb{R}^{N_{\mathrm{as}} N_{\mathrm{tag}} \times 1}$.

We point out that this observation model assumes knowledge of the static RSS s_{init} associated with the absence of the target. Recognizing that it is possible to measure s_{init} during run-time, e.g. during nights when their is no activity, we regard this assumption as tractable.

Equation (1) and (2) are used to calculate the obstacle-dependent RSS which is a function of the current target position. For the calculation of the excess path length d_{exc} we need several quantities (see eq. (1) and Figure 1b). However, since the complexity of the human body prohibits an analytical calculation, we apply a simplified model and regard it as a cylinder of radius 0.1 m and height 1.9 m. This way, the path length of each NLOS line segment in Figure 1b can be determined using simple ray tracing.

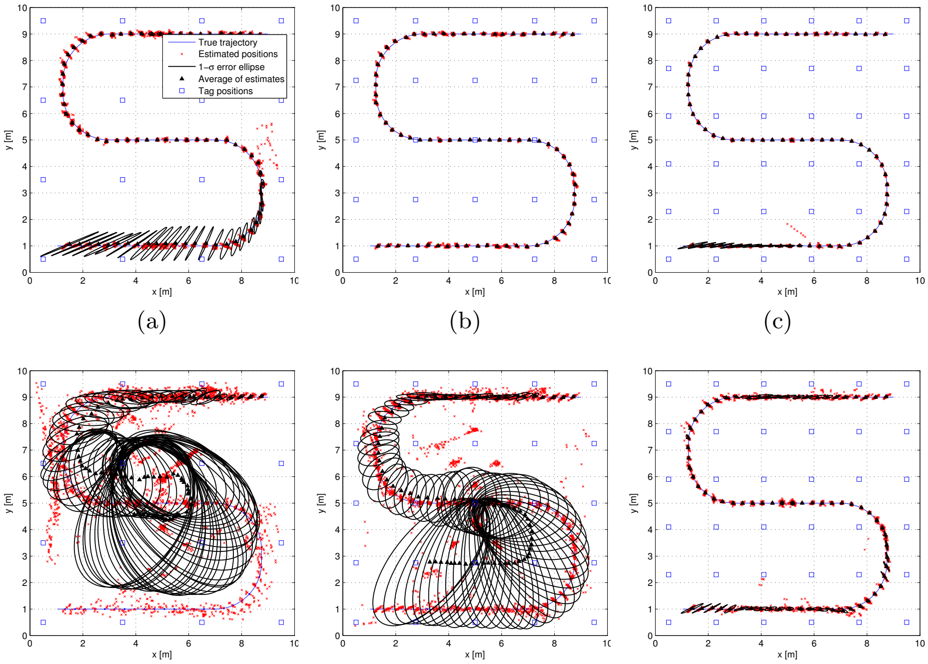
To facilitate a simple implementation of the computer simulations we further assume that all tags are in range of every antenna.

5.2 Simulation Results

In order to analyze tracking performance, we calculate the Mean Square Error (MSE) of each estimated position $(\tilde{x}, \tilde{y})$ for each point of the simulated trajectory.

$$MSE = E\left[(x - \tilde{x})^2 + (y - \tilde{y})^2\right] \tag{7}$$

$$RMSE = \sqrt{E\left[(x - \tilde{x})^2 + (y - \tilde{y})^2\right]} \tag{8}$$



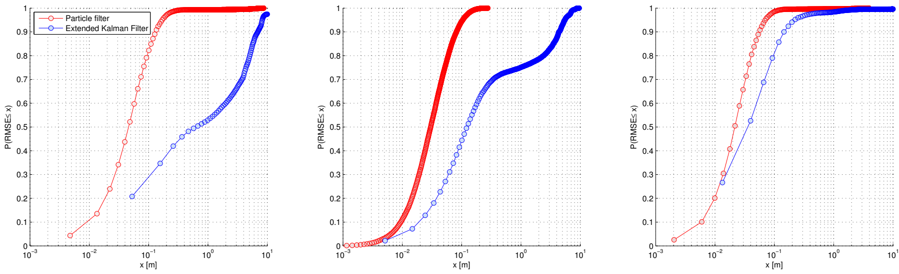
(a) (b) (c)

(d) (e) (f)

Fig. 5. MSE tracking error of a)-c) Particle Filter and d)-f) Extended Kalman Filter. The four antennas are situated at the corners at (0,0), (0,10), (10,10) and (10,0).

Figures 5 show the tracking error. Estimated positions are depicted by red crosses and the black ellipses and triangles denote the $1-\sigma$-area of position errors and the average estimated positions. It is shown that the accuracy of tracking using the approach presented strongly depends on the number of tags. To further elaborate on this point, the capability to correctly follow the true trajectory is indicated by the distance between average estimated position and true position. The figures show that, especially for the EKF, this capability strongly depends on the number of tags deployed.

In contrast thereof, the Particle Filter shows good tracking performance for all tag numbers investigated. This is also supported by the cumulative histograms of Root Mean Square Error (RMSE) in Figure 6. It is shown that the tracking error of EKF slowly approaches that of the Particle Filter. In particular, the EKF achieves only for 36 tags feasible position estimates while the accuracy of the Particle Filter only marginally improves when the number of tags is increased.



(a) 16 tags. (b) 25 tags. (c) 36 tags.

Fig. 6. Cumulative histogram of RMSE tracking error.

6 Conclusions

We have investigated the applicability of both Particle Filter and Extended Kalman Filter to tracking a user by merely measuring the changing received signal strength with passive RFID. The simulations indicate that the tracking error strongly depends on the number of passive tags.

In contrast to the Particle Filter which showed good tracking accuracy for all tag numbers, the Extended Kalman Filter proved to be very susceptible to the tag number and its estimates were only feasible when using 36 tags.

Future work will consider relaxing the assumption of a-priori known static RSS to make the approach applicable to changing environments. Although the observation model has been calculated using real measurements, we will investigate the tracking performance using our test-bed.

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