Exploiting RF-Scatter: Human Localization with bistatic passive UHF RFID-Systems

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***Abstract*—In ubiquitous computing, localization of users in indoor environments is a challenging issue. On the one hand, localization data needs to have fine granularity to provide reasonable input for intention recognition and task planning. On the other hand, effects like multi-path interference and signal scattering of RF propagation in indoor environments reduces the accuracy of traditional wireless localization techniques. However, we prove that such adversary effects can be characterized and utilized conversely to localize the source of RF-scatter with passive UHF RFID.**

Since measuring spatial correlation requires many spatially separated transmitter and receiver pairs, cost-effective and unobtrusively attachable passive RFID-tags are especially suitable for this purpose. The passive tags are spatially distributed in a manner such that it is possible to infer the spatial correlation of Received Signal Strength (RSS). The idea is to characterize the influence of user presence on RSS, and use such relationship for localization.

Three localization algorithms are investigated which consist of a Maximum Likelihood Estimator (MLE), and two Linear Least Squares variants. Algorithms are applied to measurement data which we obtained in an indoor environment. The results evidences our idea of human localization in such bistatic RFID systems.

I. Introduction

Ubiquitous systems typically contain sensors, actuators and communication modules that enable the subcomponents to exchange information. Ubiquitous computing is one of the technological advances that will probably influence everyday life as devices are connected and act as a cooperative system that is more valuable than the sum of its components.

One of the fundamental information for a ubiquitous system is the geographic location of users and devices. Developing indoor localization systems have attracted considerable research effort whereby the focus is often to guarantee sufficient accuracy (specified by the application) using simple and pervasive devices.

Some works consider passive RFID for this purpose because the tags can be applied in large numbers, are relatively cost-effective and can be attached easily. Such systems consist of one or more reader devices and many passive tags. Since the tags are powered by the impinging RF-energy of the reader, they do not need a power supply and typically consist of a thin antenna and a small integrated circuit (IC).

Besides its advantages, the complexity of indoor RF-propagation makes localization a challenging task in passive RFID systems. Especially in indoor environments, fixtures, fittings and also humans can cause reflections, diffractions and absorptions of radio signals. Therefore, some commercial products use specialized hardware and try to increase accuracy by fusing several different metrics, like angle and range measurements. Since passive RFID-tags are powered by impinging radio energy, they are especially sensitive to these effects.

Our approach observes a field of passive RFID tags, and tracks back the location of user presence according to the RSS change caused by it. Such an approach is flexible in ubiquitous environments, since it does not require the target to wear RFID tags.

II. 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 mono- or bistatic has strong impact on RSS-based localization with passive RFID because the mapping of RSS to distance is different. In bistatic systems, connectivity depends on two physically different links as will be explained in greater detail later.

Table I presents an overview about several related approaches which will be reviewed briefly in the following.

Table I
OVERVIEW OF RELATED WORK.

	Passive Tags	Measurement	Transceiverless Target	Link Type
User/Object Localization				
Landmarc [1]	No	RSS	No	monostatic
SpotOn [2]	No	RSS	No	monostatic
Ferret [3]	Yes	Connectivity	No	bistatic
Robot Self-Localization				
Schneegans [4]	Yes	Connectivity	No	bistatic
Hhnel [5]	Yes	Connectivity/LR	No	bistatic
WSN Localization using RF-Propagation Effects				
Zhang et al. [6]	-	RSS	Yes	monostatic
Patwari et al. [7]	-	RSS	Yes	monostatic
curr. approach	Yes	RSS	Yes	bistatic

In contrast to our approach, Ni et al. utilize an active RFID-system for localizing a mobile target that has RFID tags attached [1]. 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 [3]. 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 [5], [4]. However, typically the connectivity information is used for localization.

Only few work has 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 [7]. 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.

Both approaches are related to ours since the impact of user presence on RSS is used. 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, we apply a more detailed model of how user presence affect RSS and analyze extensively the localization error and its dependence on important system parameters.

III. REVIEWING PROPERTIES OF HUMAN-INDUCED RF-SHADOWING

This section reports on experiences gathered from an experimental testbed and focuses on the impact of user presence on RSS. A detailed investigation of these effects can be found in [8]. If not stated otherwise, we denote a pure sinusoid oscillation by signal.

A. Modeling of Human-induced RF-Shadowing

In Figure 1, 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*:

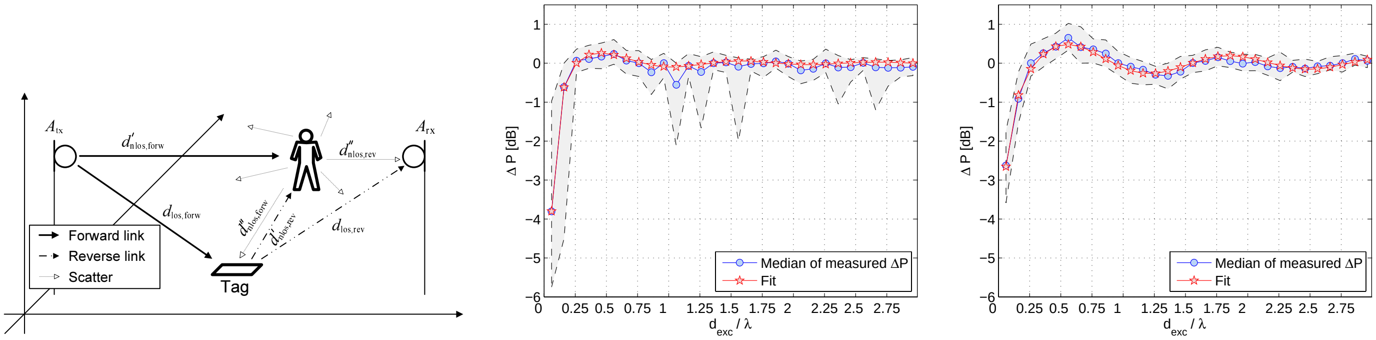
$$d_{\mathrm{exc}} = d'_{\mathrm{nlos}} + d''_{\mathrm{nlos}} - d_{\mathrm{los}} \tag{1}$$

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 $\Delta s = s_{\mathrm{obst}} - s_{\mathrm{init}}$.

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



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

Figure 1. Human influence on RFID communication and relation between RSS variations and excess path delay.

Table II
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

the *First Fresnel Zone*. Obstacles in the First Fresnel Zone typically result in attenuations of RSS [9].

In a two path scenario, it can be shown that the difference Δs has the following form [8] with the parameter values in Table II:

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

It is noted that in general there will be more than one scatterer and consequently more than one excess path. In order to characterize the impact of single scatterers, we set up the measurement that there is only one significant excess path. We demonstrate that such characteristics can be used to determine the position of the scatterer.

IV. UTILIZING RF-SCATTER FOR LOCALIZATION

In this section we focus on estimating the user location based on changes of RSSI. We propose three techniques whereas one directly uses the measurement model of (2) and the other two pursue non-parametric optimization.

A. Measurement Set-Up

We used the ALR-8800 RFID-reader from Alientechnology operating on ISM 868 MHz frequency band. Two circular polarized ($G = 5.5$ dB) and two linearly polarized ($G = 6$ dB) antennas are connected to its ports. All positions are relative to a coordinate system with its origin as depicted in figure 2.

To facilitate the following investigations, we introduce key parameters of the deployment: n_{t} and n_{a} denote the total number of RFID tags and the number of antennas used for the experiments, respectively. The experiment was conducted in an indoor room. $n_{\mathrm{t}} = 69$ passive RFID tags were deployed on the ground in a regular grid of side length $3.6\,m$. The $n_{\mathrm{a}} = 4$

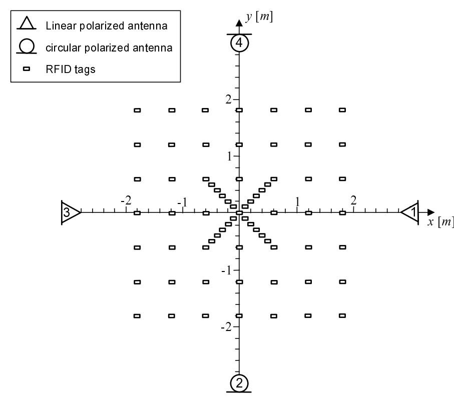


Figure 2. Measurement set-up.

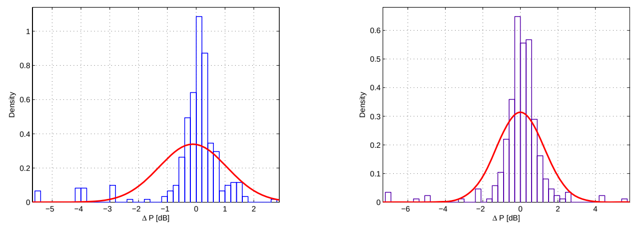
antennas were situated near the the edges of the deployment area at a height of $1.80\,m$ whereby antennas of the same type were at opposite edges. The set-up was situated in the middle of a $8.15\,m \times 6m$ room. To reduce the impact of reflection from adjacent walls, we aimed the antennas' main beam direction in an angle that all wall reflections needed to bounce on at least two walls before entering the deployment area.

The host computer was situated approximately 5 meters from the center of the deployment area. On the host computer ran a custom Java program which configured the RFID system that fetched and stored the measurement data utilizing the provided API.

To facilitate description, we introduce the following variables: The first n_{a} and the last n_{t} elements of $\mathbf{i} = [1, 2, \ldots, n_{\mathrm{a}}, n_{\mathrm{a}}+1, \ldots, n_{\mathrm{a}}+n_{\mathrm{t}}]$ represent the unique identifiers of antennas and tags.

For the measurements, we choose $n_{\mathrm{ap}} = 6$ significant antenna pairs from the possible 16 sender-receiver combinations to limit execution time of experiments. Each row of $N_{\mathrm{ap}} \in \mathbb{N}^{n_{\mathrm{ap}} \times 2}$ denotes such a pair whereby the first and the second column indicate the transmitting antenna's and the receiving antenna's identifier, respectively.

$\Delta\mathbf{s} \in \mathbb{R}^{n_{\mathrm{ap}} n_{\mathrm{t}} \times 1}$ denotes the vector of all RSSI variations, $[\cdot]_i$ denotes the i-th element of a vector. $\mathbf{p} = [x\, y]^T$ and $\mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_{n_{\mathrm{a}}}, \ldots, \mathbf{p}_{n_{\mathrm{a}}+n_{\mathrm{t}}}]^T$ denote the coordinates of each



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

Figure 3. Sample histograms for forward and reverse link depicting the characteristics of model errors.

element identified by $\mathbf{i}$. $T := \{i, 0 < i \leq n_\mathrm{t}\}$ is the set of all tags and $L := \{i, 0 < i \leq n_\mathrm{t} n_\mathrm{ap}\}$ is the set of all measured forward and reverse links between tags and antennas. $\tilde{\cdot}$ denote estimated quantities.

We assume that the operators $rx(i)$ and $tx(i)$ return the unique identifier of the receiving and transmitting antenna of link i, respectively.

It is noted that we eventually seek to estimate the 2D location of the user since the z-coordinate, i.e. the height, is of minor importance. This stems from the fact that the source of the scatter can be at any hight of the user. Consequently, the algorithms work on 2D coordinates if not stated otherwise.

B. *Maximum Likelihood Estimation (MLE)*

The Maximum Likelihood Method of parameter estimation has been widely applied to a large range of problems. Concerning the localization problem, we seek to find the location $\tilde{\mathbf{p}}$ of the user which best fits the observed change of RSSI of all links which builds the vector $\Delta\mathbf{s}$.

$$\tilde{\mathbf{p}}_\mathrm{mle} = \arg\min_{\mathbf{p}} l(\mathbf{p}|\Delta\mathbf{s}) \tag{3}$$

To quantify how well a potential location agrees with the measurements, we calculate the vector of expected RSSI variations $\Delta\tilde{\mathbf{s}}$ and assume that the model of (2) is subject to Normal noise. Hence, we can calculate the negative log-likelihood $l(\mathbf{p}|\Delta\mathbf{s})$:

$$l(\mathbf{p}|\Delta\mathbf{s}) = \sum_i -\log\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{([\Delta\hat{\mathbf{s}}(\mathbf{p})]_i - [\Delta\mathbf{s}]_i)^2}{2\sigma^2}\right) \tag{4}$$

$$[\Delta\tilde{\mathbf{s}}(\mathbf{p})]_j = \Delta\tilde{s}([\mathbf{D}_\mathrm{exc}(\mathbf{p})]_j) \tag{5}$$

$$\begin{aligned}[\mathbf{D}_\mathrm{exc}(\mathbf{p})]_j =& ||\mathbf{p} - [\mathbf{P}]_{rx(j)}|| + ||\mathbf{p} - [\mathbf{P}]_{tx(j)}|| \\ &- ||[\mathbf{P}]_{tx(j)} - [\mathbf{P}]_{rx(j)}||\end{aligned} \tag{6}$$

It is noted that the algorithm uses a 3D coordinates for the calculation of (4) and discards height information for finding the minimum in (3). This is necessary since the assumed model is susceptible to even small changes of distances and, therefore, discarding height information during calculation of the excess path delay would increase localization error. Furthermore, we reduce the computational burden and compute (4) on a grid of size $20 \times 20 \times 20$.

Considering (4), we observe that our method's applicability is subject to the accuracy of the model and the validity of the Normal noise assumption. Previous work has shown that the model agrees well with measurements [8]. Therefore, we elaborate on the Normal noise assumption in the following.

Figure 3 shows two typical histograms of Δs for $d_\mathrm{exc} \in [0.21, 0.31]$. It is shown that the Normal distribution can not explain all data values. However, the strong central tendency of measurements render the Normal distribution a feasible assumption.

C. *Weighted Linear Least Squares (WLLS)*

Due to its independence from model assumptions and computational feasibility, localization using a linear least squares approach has been intensively studied in the literature. The idea to pronounce some data values using weighting stems from the fact, that often some measurements are known to be more reliable than others.

Specifically, we consider the forward and backward links and regard them as straight lines which can be described by $\mathbf{A}\mathbf{p} = \mathbf{b}$. Assuming a diagonal weighting matrix $\mathbf{W}$, the Weighted Linear Least-Squares solution of the system of equation is the point $\tilde{\mathbf{p}}_\mathrm{wlls}$ which minimizes the weighted squared distance to all links.

$$\tilde{\mathbf{p}}_\mathrm{wlls} = (\mathbf{A}^T\mathbf{W}\mathbf{A})^{-1}\mathbf{A}^T\mathbf{W}\mathbf{b} \tag{7}$$

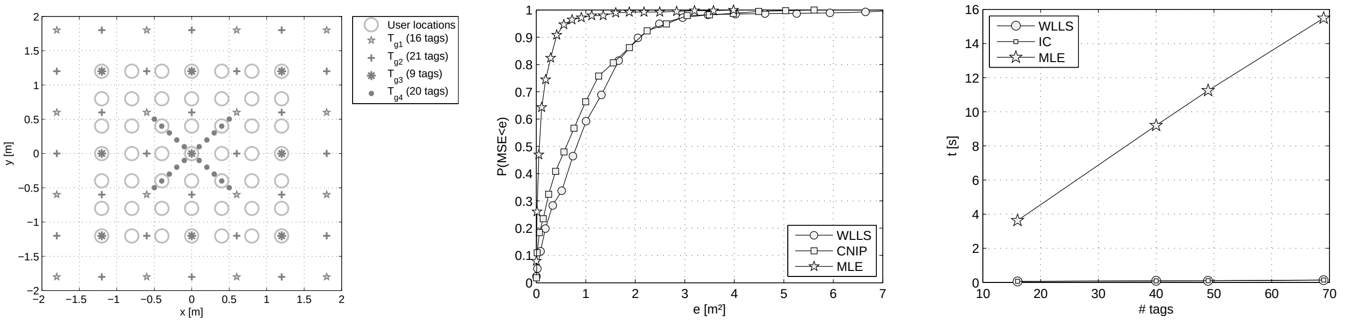
We adopt the basic approach and incorporate knowledge about the significance of the specific measurements from [8] for the weighting. In particular, we apply thresholds T on Δs and discard links with $|\Delta s| < 2.25$ on the forward link and $|\Delta s| < 1.45$ on the reverse link to reduce the impact of noise and maximize mutual information. Furthermore, we use the absolute value of $|\Delta s|$ of a specific link as its weighting. Thereby, we emphasize links which are highly affected by user presence.

D. *Centroid of Nearest Intersection Points (CNIP)*

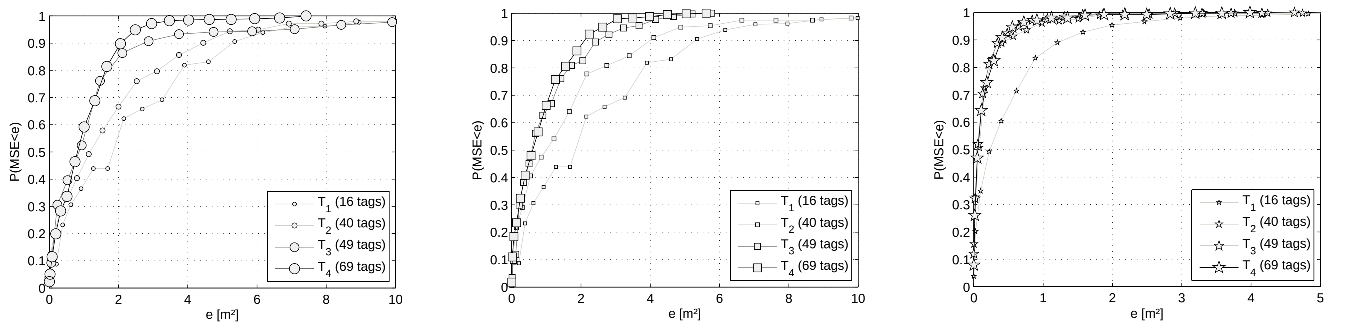
It is known that the linear least-squares approaches are susceptible to noise. Consequently, we seek to improve the robustness of location estimates while maintaining the computational feasibility. Therefore, we investigate a combination of a centroid based localization and a WLLS approach. The idea is to consider the *intersection points* (IPs) of links as potential user locations and find the centroid of a spatially adjacent subset of these points.

Having calculated the n_ip intersection points $\mathbf{p}_{\mathrm{ip},i} \quad i = 1, 2, \ldots, n_\mathrm{ip}$, we determine the $\binom{n_\mathrm{ip}}{2}$ euclidean distances $\mathbf{d}_{\mathrm{ip},i}$ between all pairs of IPs. Since we observed that IPs concentrate in the vicinity of the user, we determine the lower 5% percentile of distances $\mathbf{d}_{\mathrm{ip},5\%}$ and discard the rest of IPs. $C := \{i, \mathbf{d}_{\mathrm{ip},i} \leq \mathbf{d}_{\mathrm{ip},5\%}\}$ is the set of IPs that belong to the 5% IPs that have smallest distance to each other. We calculate the user location as the centroid of the IPs in C:

$$\tilde{\mathbf{p}}_\mathrm{cnip} = \frac{1}{|C|}\sum_{i\in C}\mathbf{p}_{\mathrm{ip},i} \tag{8}$$



(a) User locations and tag groups. (b) CDF all tags. (c) Time complexity.



(d) CDF of WLLS Localization. (e) CDF of CNIP Localization. (f) CDF of MLE Localization.

Figure 4. Performance of algorithms.

V. Experimental Evaluation

This section considers the evaluation of the localization algorithms of Section IV using RSSI measurements form an experimental testbed and the Matlab software for analysis. The performance of algorithms is compared using the *Mean Squared Error* (MSE) of localization e_{mse} and the related Root *Mean Square Error* (RMSE) e_{rmse}

$$e_{\mathrm{mse},i} = E\{(\tilde{x}_i - x_i)^2 + (\tilde{y}_i - y_i)^2\} \tag{9}$$

$$e_{\mathrm{rmse},i} = \sqrt{e_{\mathrm{mse},i}} \tag{10}$$

$E\{\cdot\}$ denotes expectation. We consider the *cumulative distribution function* (CDF) of the MSE of all location estimates for all measurements which fully describes its characteristics.

Furthermore, we consider the dependence of MSE on the number of tags used for the RSSI measurements. Therefore, we define in addition to the set of all tags T four other sets or group of tags, namely T_{g1}, T_{g2}, T_{g3} and T_{g4}, that are depicted in Figure 4a. Regarding calculation of MSE, we consider then four different situation as either $T_1 = T_{g1}$, $T_2 = T_{g1} \cup T_{g2}$, $T_3 = T_{g1} \cup T_{g2} \cup T_{g3}$ or $T_4 = T$ are used for localization.

A. Results

Figure 4b depicts the MSE of localization algorithms when all tags are used. The MLE method achieves best performance yielding a maximum RMSE of 0.75 m at 95% confidence while WLLS and CNIP perform similarly and achieve approximately 1.61 m. The superiority of MLE is not unexpected since the method uses the full information of Δs instead of assuming a linear relation as associated with the WLLS and CNIP methods. Considering WLLS and CNIP, we observe that CNIP can improve its median and maximum MSE. This stems from the more robust computation of location estimates compared to WLLS which avoids very large errors and also seems to improve middle MSEs.

However, the MLE method involves extensive calculations compared to WLLS and CIP which make the current implementation of MLE unfeasible for real time localization. Figure 4c depicts the time complexity, i.e. the execution time, of algorithms versus the number tags. Although MLE's time complexity scales linearly, its slope is much larger than that of WLLS and CNIP.

Figure 4 (d)–(f) depict detailed analysises of MSE regarding the number of tags used for localization. It is shown that all algorithms benefit from increasing the number of tags, though, the MLE method performs the best for all tag numbers. CNIP and WLLS have similar localization errors whereas CNIP appears to perform slightly better for all but 16 tags. When considering only T_1 consisting of 16 tags for localization, CNIP and WLLS show equal MSE because in this case there are often only two links significantly affected by user presence and, therefore, only one IP. In this situation, calculating either (7) or (8) yield identical estimates.

B. Discussion

This section is dedicated to discussing the advantageous and drawbacks of the proposed approach.

While the MLE method achieved superior localization accuracy, the assumed model it uses for calculating the likelihood was determined using the same data as for the actual localization. Consequently the question arises, whether presuming the availability of such models impairs the applicability of the approach. However, there are many localization strategies utilizing a often-termed offline phase in which the system learns the the measurement model and the MLE can be regarded as an localization technique requiring offline learning.

Another important issue is applicability of our approach to real-time localization. Since RFID systems have to cope with collisions of tag responses, different techniques can be used to read a specific tag in a dense tag population. However, applying these techniques lead to an increased delay of responses. The current system configuration provides measurements in sub-second intervals. However, considering application of thresholds for WLLS and CNIP, time intervals are longer for these methods. Further investigations concerning fine-tuning of system parameters to improve timing are needed to determine the applicability of the current system for real-time localization.

Concerning our model of human influence on RSS, we considered only one human. As pointed out earlier, this assumption will not hold in general situations. Therefore, we are currently investigating this issue.

Finally, it is noted that we have excluded from investigations the identification of the user which is one advantageous property of using RFID. Furthermore, knowing the location of an object without knowing its identity might not suffice for many scenarios of ubiquitous environments. However, the current approach can be supplemented by user wearing RFID tags. Localizing these tags and fusing these information with our approach appears to be a good way to provide both reasonable location estimates and identities of users.

VI. Conclusion

This paper presents a new approach for localization using passive UHF RFID. The idea is to characterize the change of Received Signal Strength Indicator (RSSI) caused by the presence of a person inside an RFID augmented deployment area.

We characterize the model of the influence of user location on RSSI and apply the Maximum Likelihood Estimator (MLE) to the localization problem. Additionally, two variants of Linear Least-Squares localization are proposed in this paper.

Applying these techniques to the measurement data obtained in an indoor environment reveals that the MLE achieves superior performance while requiring extensive calculations. The Linear Least-Squares variants have low computational complexity, though, their location estimates are considerably larger and might only suffice to determine the coarse location of the user.

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