Passive RFID Tomographic Imaging for Device-Free User Localization

Benjamin Wagner, Neal Patwari and Dirk Timmermann

Abstract **– Localization of users is an important part of location aware systems and smart environments. It forms a major data source for superimposed intention recognition systems. In RF device-free localization (DFL), the person being tracked does not need to wear a RF transmitter or receiver in order to be located. Instead, they are tracked using the changes in signal strength measured on static links in a wireless network. This work presents a new algorithm for RF DFL using passive RFID networks. We formulate and show how a tomographic imaging algorithm provides both low computational complexity and highly accurate position estimates. Using measurements conducted in an indoor environment with various human positions, we find the algorithm can locate the human with as low as 30 cm mean location error.**

Index Terms **– Device-free Localization, DFL, RFID, User Localization, Received Signal Strength, RSSI, Smart Environments, Positioning, Wireless**

I. INTRODUCTION

LOCATING people in indoor environments using an inexpensive, wireless, privacy preserving system is the is the aim of device-free user localization (DFL) in smart environments. Compared to the much broader research in sensor localization, very little research has been presented in locating users who do not possess any radio devices. Within the DFL research area, most proposed systems use active radio devices deployed around an area. One very encouraging approach is the *Radio Tomographic Imaging* technique (RTI) introduced by Wilson and Patwari [1–3]. This technology applies an imaging approach onto active sensor nodes around a certain area. While a person is moving in this area the received signal strength values of the single radio links are influenced and give information about the location and the movement of the user. In contrast, an alternate approach also using the human influence on RF communication and enhancing the inexpensiveness for device-free localization of users is investigated at the University of Rostock within the Graduate School MuSAMA. The architecture of mostly active beacons is replaced by using completely *passive Radio Frequency Identification* transponders (pRFID) and only a few active RFID reader antennas. This approach has two main advantages:

1. Cost: The cost for passive RFID hardware is very low: transponders can be purchased for ~ 0.20 € and only few RFID readers are required.
2. Low maintenance: Passive RFID transponders do not need power from batteries, and can be easily placed in the whole room, i.e. under the carpet or wallpaper.

However, to date, accurate localization algorithms for passive RFID-based DFL are too computationally complex for real-time operation, even though most applications of DFL require real-time operation. The new approach presented in this work maintains advantages of the different methods: the combination of low cost, low maintenance, high accuracy and real-time operation.

This paper is structured as follows: in Section II the related techniques and the state of the art of RTI and pRFID are described. Section III gives information about the methods we used, followed by the experimental validation and results in Sections IV and V. We conclude with Section VI and finally future research directions are described Section VII.

II. RELATED WORK

A. Radio Tomographic Imaging

The method *Radio Tomographic Imaging* (RTI) by Wilson and Patwari [2], [1] utilizes active wireless sensor nodes surrounding a localization area. The experimental area is defined by an image vector consisting of N pixels. When a person is affecting specific links in that network (see Fig. 1), that attenuation is regarded as the sum of attenuation each pixel contributes.

The attenuation is measured as the received signal strength for every sensor combination. The model, Wilson et al. proposed, can be written as[1]:

$$\Delta y = W \Delta x + n \tag{1}$$

where Δy is the vector of all link RSS differences in dB, W is a pre-calculated weighting matrix for every pixel-link-combination, n is a noise vector and Δx is the vector of pixel attenuations in dB creating the resulting image.

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The weighting matrix determines the contribution each pixel has to a specific link. Pixels further away have a very low contribution to a radio link, while the attenuation in the direct LOS path is very high.

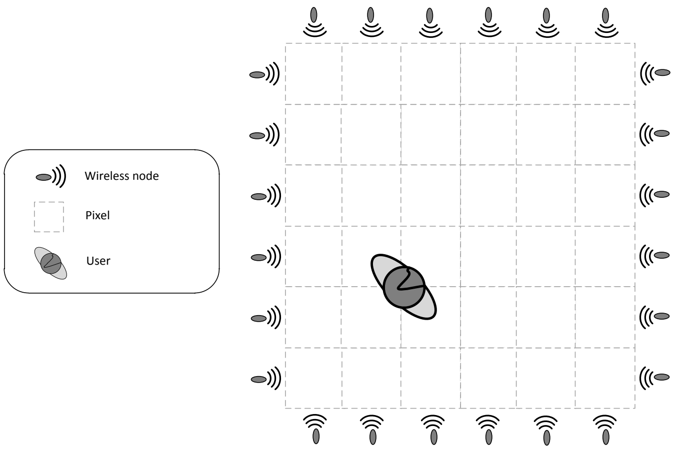

Fig. 1. Setup of a standard Radio Tomographic Imaging deployment

The authors provide a measurement based Gaussian-mixture model for the added noise. Therefore they considered the time variation in RSS measurement, without an obstacle as noise and calculated the noise model parameters from the measurements.
The most important part of the RTI method is the image reconstruction since the problem is ill-posed. The authors handle this by using regularization techniques. The resulting image estimation formula can be written as[1]:

$$\Delta x = (W^T W + C_x^{-1})^{-1} W^T \Delta y \qquad (2)$$

In this formula C_x denotes a covariance vectors providing information about the dependence of neighboring pixels.

B. Localization using passive RFID

Facing the problem of high energy consumption and high deployment costs a new approach for device-free user localization with the help of ground mounted passive Radio Frequency Identification Tags (RFID) is subject to research in the graduate school MuSAMA (see Fig. 2).

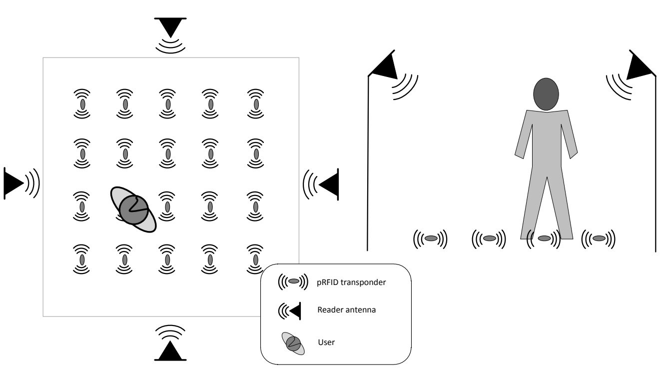

Fig. 2. Setup of the new pRFID based DFL approach

Recent work has shown that a localization of users is possible with remarkable accuracy[5]. In this research, completely passive transponders (following denoted *pRFID*) are mounted under the carpet of a room and powered over the electromagnetic communication signals transmitted by a few reader antennas in the room edges.
The RFID technology provides simple use of the *Received Signal Strength Indicator* (RSSI) of every single transponder-reader communication link. The difference between transmitted and received signal power can be used as physical measurement basis for human localization algorithms [6].
The scatterer is influencing the communication of multiple links in his environment in the way of multipath scattering. Due to that fact increased and decreased power values can appear on links near to the user´s location. That fact can be observed using a pRFID transponder field scenario: a user is moving on predefined positions on a field of several transponders. For every combination of user position, transponder and reader antenna a signal path difference can be calculated. Lieckfeldt et al. [5] define that path difference as:

$$Path\ Difference = d_{nlos,1} + d_{nlos,2} - d_{los} \qquad (3)$$

consisting of two *non line of sight* (NLOS) parts (paths from transmitter to user and user to receiver) and a *line of sight* (LOS) part (direct path between transmitter and receiver). An obstacle in the LOS path (path difference = 0) results in a strong attenuation of the RSS. Higher path differences result in smaller alternating amplifications and attenuations of the signal strength. This pattern of change in RSS vs. path difference is true both for the forward link between sending reader antenna and transponder and for the backward link. Lieckfeldt et al. provide a physical model for estimating a RSSI change depending on a signal path difference called *Executive Path Length* (D_{EXC}). That difference is only depending on the user's position within the RFID field.
Figure 3 shows the behavior of the RSSI from experimental data. Basis for this graph are 16 different user locations on a field of 69 pRFID transponders.

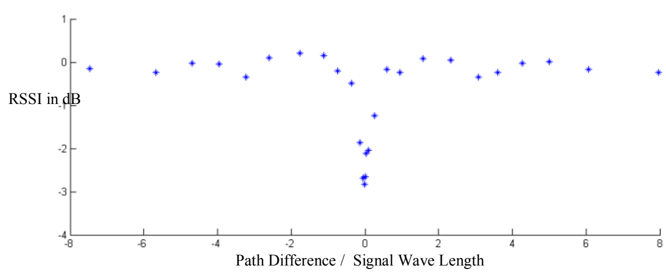

Fig. 3. Median RSS Indicator for relative User Positions [8]

The authors propose three different methods for the localization of users. The first is a database based algorithm which minimizes a log-likelihood-function out of the difference between expected change of signal strength and the measured value. This approach leads to good localization results (maximum RMSE of 0.75 m at 95% confidence level[5]), but needs significant computational power due to complicated calculations. Thus it is not useable for highly accurate online localization. Due to that reason the authors

provide secondly two geometric approaches based on *Linear Least Squares* and *Intersection Points*. These two methods achieve lower accuracies (approximately 1.61 m [5]), while having a lower time complexity. While fast, these approaches are not accurate enough for indoor intention recognition purposes. Due to the mentioned disadvantages we are searching for a localization method with low computational requirements and highest possible accuracy.
Hence our idea is to combine the idea of radio tomographic imaging with the described approach. The following section describes the work done on creating that system.

III. Methods

A. Network Layer

Utilizing wireless sensors nodes for radio frequency communication provides the possibility to implement one´s own protocol and to determine the communication links from every node pair. Using that method network-wide link measurement cycles (following denoted *spin cycle*) can be defined as static images of the RSS attenuation vector. In the domain of proprietary RFID technology the communication protocols are standardized i.e. by *EPCGlobal*[9] and every manufacturer of RFID systems provides his own implementation. Generally a number of RFID transponders is queried by an inventory command, which is based on a collision avoidance technique, i.e. slotted ALOHA[10]. Therefore the communication process between reader and the transponder field is probabilistic and we need to define spin cycles for a time discretization for the online data processing. We propose three ways for generating these spin cycles:

1. define a maximum field measurement time t_{max} or
2. define a minimum sample number per transponder $n_{samples}$ or
3. create a communication protocol over a RFID bitmasking function. That method allows the communication with one specific transponder.

The first and the third option allows the user to define a time resolution for the readings, mainly important for online localization. The second option provides a minimum data quality. In our experiments we implemented a simple bitmasking algorithm combined with a $n_{samples} = 10$ for data quality.
One main difference between a sensor node network and our pRFID field is the relation between the number of transmitters n_{tx} and receivers n_{rx}. Since sensor nodes are mostly transceivers sensor networks have the a relation of

$$n_{tx} = n_{rx} \tag{5}$$

resulting in a measurement matrix M_y with the dimension $m \times m$ with $m = n_{tx} = n_{rx}$. A typical pRFID field contains only a high number of transmitters/transponders (since the forward link between reader antenna and transponder is only regarded as power supply, the term *transmitter* is further used for the transponder and the term *receiver* for the reading antenna) and a low number of receivers/antennas. Thus that system has a relation of:

$$n_{tx} \gg n_{rx} \tag{6}$$

resulting in a measurement matrix dimension of $n_{tx} \times n_{rx}$. In this case n_{tx} is the number of RFID transponders and n_{rx} is defined by the reader antenna operating sequence AS. This sequence is adjustable since we are using a bistatic pRFID system, where powering and receiving antenna can be defined. For a consistent imaging model the change of the measurement matrix $M_y = \Delta y$ results in a new definition of the weighting matrix W with the dimension

$$\{n_{tx} \times n_{AS}, n_{Pixels}\}$$

described in the section C.

B. Signal Strength Measurement

Setting a round time for the whole field can result in a changing sum of transponder readings. A high difference between spin rounds can lead to a lack of information, since the RSS differences are calculated between the rounds. Hence a missing measurement value can occur due to a message collision, a high random parameter in the ALOHA collision protocol or a person in the direct line-of-sight. To get more information out of the measurements we proposed the minimum possible RSSI of the system. Due to provider specific regulations our pRFID system do only provide an *Received Signal Strength Indicator* (RSSI) as scale value of the original RSS and as unit less quantity. Using a simple one transponder scenario we could experimentally detect a minimum possible RSSI scale value of 150. The following experimental measurements use this value in the running experiments for not measured transponders in the measurement phase, under the condition having enough measurement data from every transponders calibration phase. Due to the high fluctuations in the pRFID communication we suggest using a calibration phase without user presence in the field as base for our attenuation measurements. At runtime we calculate the difference of calibration and measurement value[11] as

$$\Delta P = P_{meas} - P_{cal} \tag{4}$$

with P denoting the scale signal strength value and ΔP the vector of RSSI differences. The calibration value as averaged in an offline calibration phase.

C. Adaptive Bistatic Weighting Model

The weighting model generates a weighting value for every link-pixel combination. Pixels in the direct LOS path have a higher influence on the RSS shadowing, than the pixels around. Patwari et. al. proposes an elliptic model with transmitter and receiver in its foci. This method is related to the Fresnel zones in the communication path. In contrast to sensor node communication the new method has two communication links, due to the bistatic RFID technology (see Fig. 4). The forward link powers the transponder and starts the inventory round. The backward link is the communication from the transponder back to the reader. Due to that we have to mention two communication links with equal physical properties.

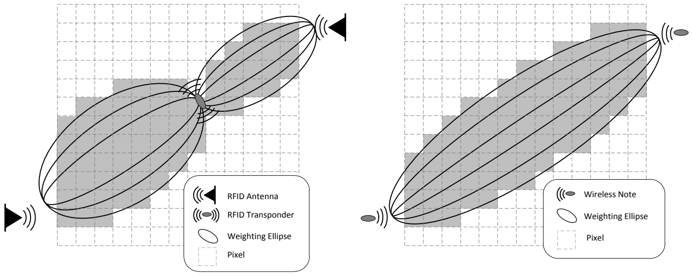

Fig. 4. Adaptive pixel weighting with a sensor node network (right) compared to bistatic pRFID (left)

Hence we have to split the weighting model on to two links with different parameters. Typically obstacles in the forward path LOS have a stronger influence on the RFID communication, because they have direct influence on the available sending power. Changing the model of [1] it can be described as

$$w_{ij} = \frac{1}{\sqrt{d_{tx(i)\,t(i)}}} \begin{cases} 1 \;\; if \; d_{tx(i)\,j} + d_{j\,t(i)} < d_{tx(i)\,t(i)} + \lambda_{forw} \\ 0 \qquad\qquad otherwise \end{cases}$$

for the forward link and as

$$w_{ij} = \frac{1}{\sqrt{d_{t(i)\,rx(i)}}} \begin{cases} 1 \;\; if \; d_{t(i)\,j} + d_{j\,rx(i)} < d_{t\,rx(i)} + \lambda_{backw} \\ 0 \qquad\qquad otherwise \end{cases}$$

for the backward link, where d_{xy} is the Euclidean distance between transmitting reader antenna tx, receiving reader antenna rx and transponder t of link i. The ellipse width is variable by the two λ parameters.

D. Link Density

One major difference between sensor node networks and the pRFID is (see IIIa) the different number of transmitters and receivers. RFID systems typically are working with a high number of transmitters and a very low number of receivers. Because of that the number of links crossing one particular point of the room is not homogeneous over the whole transponder field, even though the proposed weighting model works best with a uniformly spread of communication links. That leads to a design question, where transmitters and receivers should be placed. To get a better idea of this we suppose using the *link density* per pixel, which can be defined as the number of link lines intersecting the square pixel (see Fig. 5).

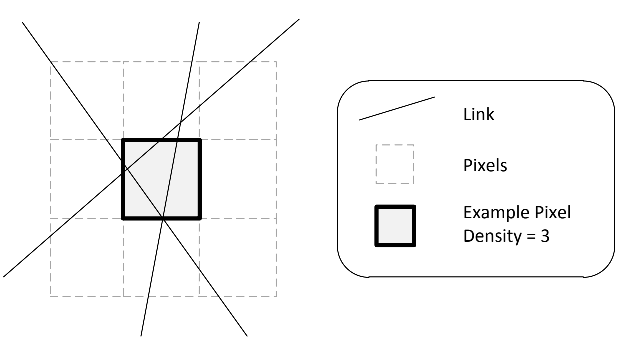

Fig. 5. Link density definition example for one pixel

The number of pixels has to be adjusted to a maximum value which leads to a sufficient resolution. That maximum value is depending on the number of nodes surrounding the area. Fig. 6 is showing sample images of the link density in different architectures described below. The pixel color is denoting the normalized density value.

Image 6a) is using an square area surrounded by 36 sensor nodes, acting as transceivers. The density image is showing a relatively uniform spread of link density. In an optimal deployment it should be perfectly uniform, little variation occur due to small variations of node positions and pixel size. Comparing to that two different pRFID field architectures are shown. Placing 4 reader antennas in the edges and 36 transponders on the room ground (see Fig. 6b) leads to a density hot spot in the middle of the deployment field and a X-shaped higher density area in direction of the reader antennas. A better density spread can be reached by the third deployment form shown in Fig. 6c). 36 pRFID transponders are placed in a rectangle form (i.e. walls of a room) at the users hip height (~ 0.85 m). The image shows, that the area within the rectangle has a more uniform density spread than the former described one.

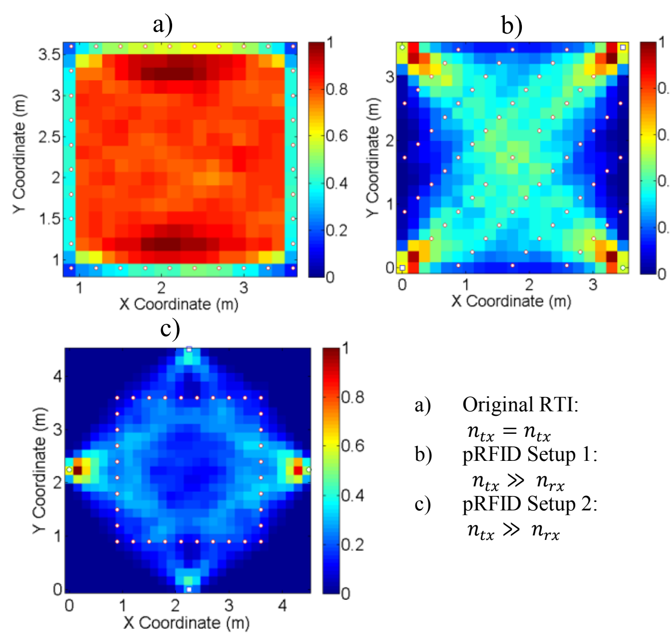

Fig. 6. Link density images based on the original RTI setup and two different pRFID setups

E. Image Calculation

Our calculation approach for the resulting image matrix is based on the original attenuation-based RTI approach by Wilson et. al.[1][2] as described earlier in (2). The pixel weighting matrix is calculated according to (7) and (8) and C_x is the covariance matrix of Δx.

$$\Delta x = (W^T W + C_x^{-1})^{-1} W^T \Delta P \tag{9}$$

ΔP is the vector of signal strength differences for one spin cycle as in (4).

IV. Experimental Validation

For the experimental validation we designed an experimental setup meeting three requirements:

1. Creating a uniform link spread (see Section IIID)
2. Highest possible energy consumption at the transponders
3. Using the backward link for the localization, because it contains more information[5]

Therefore we used a passive bistatic UHF RFID system from *Alien Technology*[13] working on ISM 868 MHz frequency band. We connected four linearly polarized antennas (G = 6 dB) to the ALR-8800 reader. We did not use circular polarized antennas, because they have a higher attenuation and all transponders are placed in the same orientation. Hence all tags are readable in the same quality.

We placed 36 transponders in a square with the length of 2.7 m on the height of 0.85 m. In the middle of that square we defined 13 possible user locations. Fig. 7 shows the experimental setup. In this deployment every reader antenna is powering the transponder-line in front of it. This ensures a maximum power transmission to the transponders.

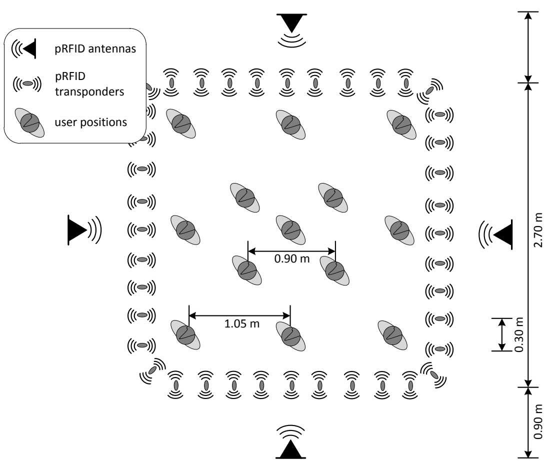

Fig. 7. Experimental pRFID setup for validation

The transponders are sending their data to each of the other reader antennas. Hence the operating sequence is defined as follows:

$$AS = \left\{\begin{matrix} [1,2],[1,3],[1,4], \\ [2,1],[2,3],[2,4], \\ [3,1],[3,2],[3,4], \\ [4,1],[4,2],[4,3] \end{matrix}\right\} \quad (10)$$

with the following annotation:

[Transmitting Antenna, Receiving Antenna].

We did a calibration measurement for every transponder-AS combination with a minimum of 20 data samples to get a reliable mean signal strength value.

For the measurement phase we implemented a bitmasking algorithm, which allows us to communicate with each single transponder. Thus we defined one spin round by having data samples from every transponder. We emphasized the length of each measurement round, to get a minimum of 10 data samples per transponder-reader antenna combination.

For getting better results we applied two different pixel bases, because taking the full area surrounded by the pRFID reader antennas can lead to solutions outside the transponder square. While we state the assumption that the test person is only moving within the square we add this information while trimming the pixel area. Afterwards we did offline processing with *Matlab* and applied the described algorithms on to the fetched data. The results can be seen in section V.

V. Results

Figure 8 depict the results of the pRFID imaging scenario. It can be seen, that the localization results are having a reasonable accuracy. It is also obvious, that the technique has only few problems with users standing in the edges, than users standing near the middle of the room.

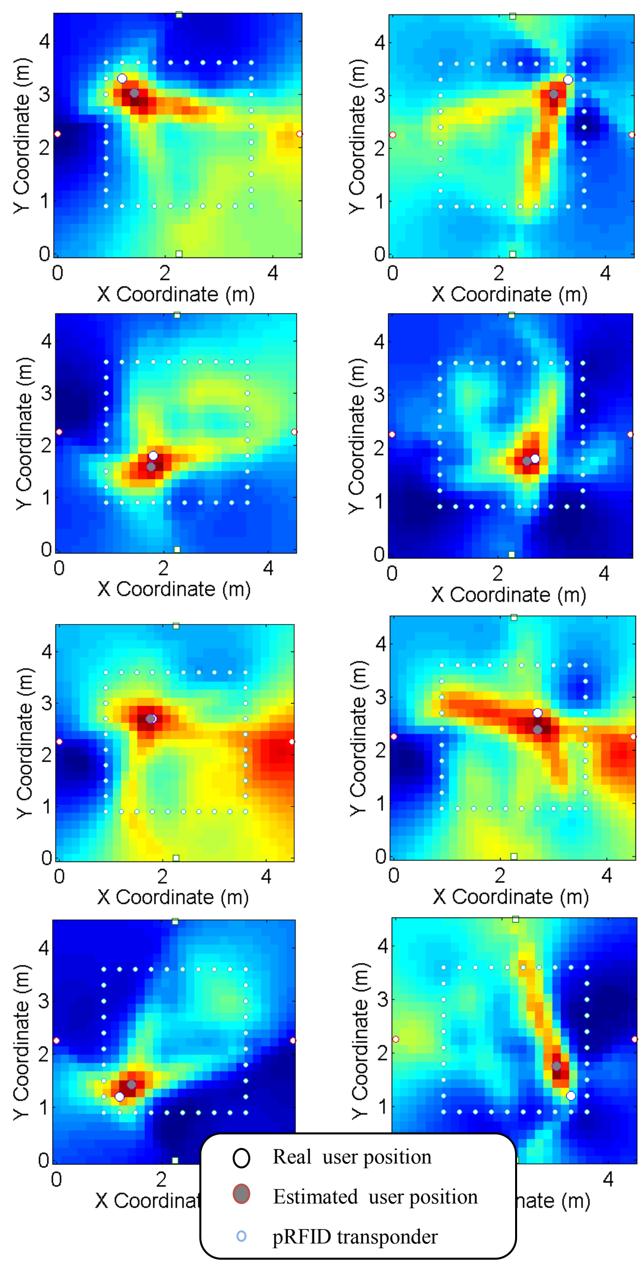

Fig. 8. Example resulting images for pRFID based tomography

It can be observed that the image shape differs, although the setup is completely symmetrical. This is probably due to environmental disturbances or missing data in single spin rounds.

TABLE I
MEAN ERROR OF LOCALIZATION ALGORITHMS

Complete field	0.45 m
Squared field	0.30 m

Table I is showing the mean localization errors for the two different versions. Regarding that the shoulder width of a test person can be assumed with ~0.3 m, the results depicting the center of the maximum pixel have a high accuracy for a device-free localization approach.

TABLE II
MEAN PROCESSING TIME

Complete field matrix precalculation	2.43 s
Complete field image calculation	0.32 s
Squared field matrix precalculation	1.46 s
Squared field image calculation	0.29 s

Table II is showing the mean processing times using a Intel® Core™2 CPU @ 1.66 Mhz. The values are showing a precalculation time which is for the matrix generation for calibration data, pixel covariance, weighting and projection matrices and is needed only once at the beginning of the localization process. The image calculation time is needed for every new spin cycle (i.e. when the user has moved to a new position) and only the measurement matrix has changed.

VI. CONCLUSION

This paper presents a new approach for device-free indoor user localization utilizing *Radio Tomographic Imaging* and *Passive RFID*.

To achieve this goal we describe the measurement characteristics of a passive RFID field in detail and propose an adaptive bistatic weighting model. Different field designs are compared by defining the pixel link density for the whole field and a pRFID based imaging approach is presented.

Experimental data is fetched from a deployment based on a new field design with RFID transponders on hip height. The data is post processed with the proposed approach and the results are presented. The new technique is able to achieve a high accuracy with low computational complexity.

VII. FUTURE WORK

In future we will work on the improvement of this concept in several ways. The method discussed in this paper is working with mean RSS differences. Former RTI studies have shown that the use of variances can lead to better results for through wall motion detection. We also suggest using geometric analysis of the resulting image with the help of calibration data. By now just the middle of the maximum pixel is taken as the user´s location, although variations due to room characteristics are reproducible. Another field for future studies is the proposed link density analysis. The influence of transmitter- and receiver pair numbers and deployment architectures on the localization results indicates that there could be an optimal deployment structure for a given number of nodes. Furthermore we will investigate the 3D applicability of our RTI-pRFID system in future experiments.

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REFERENCES

[1] J. Wilson and N. Patwari, “Radio Tomographic Imaging with Wireless Networks,” *IEEE Transactions on Mobile Computing*, vol. 9, no. 5, pp. 621-632, May 2010.

[2] J. Wilson and N. Patwari, “Through-Wall Motion Tracking Using Variance-Based Radio Tomography Networks,” *arXiv. org, Oct*, pp. 1-9, 2009.

[3] J. Wilson, N. Patwari, and F. Vasquez, “Regularization methods for radio tomographic imaging,” in *2009 Virginia Tech Symposium on Wireless Personal Communications*, 2009.

[4] J. Wilson and N. Patwari, “Radio Tomographic Imaging with Wireless Networks,” *IEEE Transactions on Mobile Computing*, vol. 9, no. 5, pp. 621-632, May 2010.

[5] D. Lieckfeldt, J. You, and D. Timmermann, “Exploiting RF-Scatter: Human Localization with Bistatic Passive UHF RFID-Systems,” *2009 IEEE International Conference on Wireless and Mobile Computing, Networking and Communications*, no. Ic, pp. 179-184, Oct. 2009.

[6] H. Liu, H. Darabi, P. Banerjee, and J. Liu, “Survey of Wireless Indoor Positioning Techniques and Systems,” *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067-1080, Nov. 2007.

[7] D. Lieckfeldt, “Efficient Localization of Users and Devices in Smart Environments,” *Dissertation, University of Rostock*, 2010.

[8] B. Wagner and D. Timmermann, “Investigations on User Positioning Effects in a device-free Localization System for Smart Environments,” *8th International Conference & Expo on Emerging Technologie for a Smarter World (CEWIT)*, vol. 8, 2011.

[9] EPCGlobal Inc., “Specification for RFID Air Interface EPC ™ Radio-Frequency Identity Protocols Class-1 Generation-2 UHF RFID Protocol for Communications at 860 MHz – 960 MHz,” no. October, 2008.

[10] Y. Kawakita, “Anti-collision performance of Gen2 Air Protocol in Random Error Communication Link,” *International Symposium on Applications and the Internet Workshops (SAINTW’06)*, pp. 68-71, 2005.

[11] D. Lieckfeldt, J. You, and D. Timmermann, “Characterizing the Influence of Human Presence on Bistatic Passive RFID-System,” *2009 IEEE International Conference on Wireless and Mobile Computing, Networking and Communications*, pp. 338-343, Oct. 2009.

[12] Y. Zhao and N. Patwari, “Robust Estimators for Variance-Based Device-Free Localization and Tracking,” *Arxiv preprint arXiv:1110.1569*, pp. 1-23, 2011.

[13] “Alien Technology Inc.” [Online]. Available: http://www.alientechnology.com/.