# Device-Free 3-Dimensional User Recognition utilizing passive RFID walls

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*Abstract*— **User localization information is an important data source for ubiquitous assistance in smart environments and other location aware systems. It is a major data source for superimposed intention recognition systems. In typical smart environment scenarios, like ambient assisted living, there is a need for non-invasive, wireless, privacy preserving technologies. Device-free localization approaches (DFL) provide these advantages with no need for user-attached hardware.**

**A common problem of DFL technologies is the distinction and identification of users which is important for multi-user localization and tracking. Expanding the existing approaches with the 3rd dimension it becomes possible to estimate user heights and body shapes depending on the systems resolution. For that purpose we place pRFID transponders at the room's walls giving us the possibility to generate a 3 dimensional wireless communication grid within the localization area. A person moving within this area is typically affecting the RFID communication giving us the possibility to use RSS based algorithms.**

**In this work we show the basic approaches and define system and model related adaptations. We conduct first experiments in an indoor room DFL scenario for proof of concept and validation. We show that it is possible to recognize the height of a user with reasonable precision for future estimation approaches.**

***Keywords-* DFL, RFID, Indoor Navigation, Smart Environments, Pervasive Computing, Wireless**

## I. INTRODUCTION

Recognizing a user within a smart environment is a big challenge in today's ubiquitous smart technology research. Estimating the position, User Recognition and Intention Recognition are the main steps for generating intelligent assistance. Sensors which are gathering the information need to be invisible and privacy preserving. For that purpose there is much work done on the field of Device-free localization (DFL) utilize wireless radio devices which are installed in the room leaving the user without any attached hardware.

In our recent work we introduce an approach for radio based DFL by replacing most of the active radio beacons used in similar situated approaches with completely passive Radio Frequency Identification (RFID) transponders. That combines the advantages of energy efficiency, because the transponders do not need batteries, and very easy deployment. RFID transponders can very easily be placed i.e. under the carpet, on furniture or behind the wallpaper.

Another big advantage are the costs: RFID transponders can be purchased very cheap, as low as 0.20 € per item.

Based on that, multiple localization algorithms were proposed in the past providing positioning results with an error as low as 0.3 m in 2D scenarios[1–3].

The available approaches only calculate 2D results. But for superimposed intention recognition systems it is also important to know about a user's vertical position, i.e. is the user lying on the ground, sitting on a chair or even standing on the ground. Furthermore the height of a user could give information about his identity or could help separating users in multi-user scenarios.

In this paper we propose the use of 3 dimensional measurement setups (RFID walls) and adaptations for existing algorithms. Therefore we introduce the related work in section two and explain our methods in section three. The setup and the results of a first experimental validation are shown in the fourth chapter, followed by our conclusions.

## II. RELATED WORK

### A. Passive RFID Positioning

Dealing with the problem of energy efficiency and deployment complexity we invented an approach utilizing ground mounted passive Radio Frequency Identification Tags (RFID) for device-free radio-based recognition[1], [2], [4]. This work has shown that it is possible to calculate 2D user positions with remarkable accuracy [4] and low computational complexity.

Using typical RFID hardware provides less signal processing possibilities than typically used wireless sensor nodes. For this reason our measurements regards the *Received Signal Strength Indicator* (RSSI) with can be regarded as a linear transformation of the original signal strength value.

As shown in [5] the presence of the human body does strongly affect the communication between the RFID reader hardware and the passive transponders. This can be modeled as[5]:

$$\Delta P(d_{exc}) = A d_{exc}^{B} \cos\left(\frac{2\pi}{\lambda} d_{exc} + \phi_{refl}\right) \quad (1)$$

with $\Delta P$ as estimated RSSI change, wave length $\lambda$ and phase shift $\phi_{refl}$. The parameters A,B are subject to the multipath fading properties of the experimental environment[6].

Therefore the model needs to be re-adjusted for every new setup.

The path difference $d_{exc}$ between the Line-of-sight (LOS) and the Non-Line-of-sight (NLOS) path is determining the relative position of a scattering user towards a specific communication link. The influence is shown in Fig. 1.

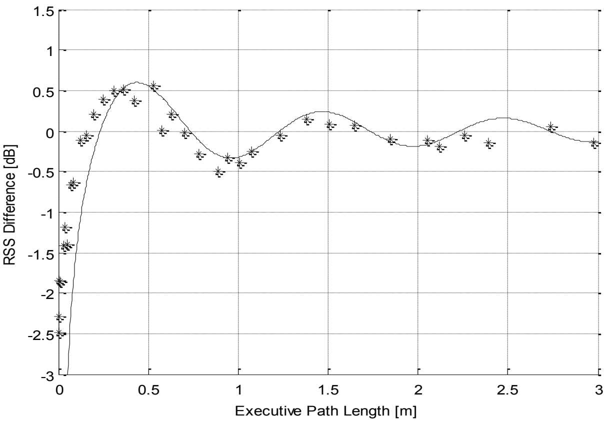


**Figure 1. Theoretical model regression and experimental data points from multiple transponder scenario**

Based on this model different methods for the localization of users were investigated in the past:

- Database based localization: minimizing a log-likelihood-function from the difference between an expected change of signal strength and the measurement. The results provide a maximum RMSE of 0.75 m[2].
- Geometric localization based on Linear Least Squares and Intersection Points applied on the measured signal strength differences. The results provide lower accuracy at approximately 1.61 m, while having a lower computational complexity[2].
- Training based approaches, e.g. Multi-layered Perceptrons (MLP) [5], [6]. A three layered MLP getting the RSSI differences into its input layer and providing a 2D user position out of the output layer. Evaluating different training functions and layered transfer functions it is possible to achieve accuracies as low as 0.01m MSE in a ground mounted pRFID scenario.

## B. Passive RFID Tomography

In our recent work [4] wireless sensor network based radio tomographic imaging [7], [8] and RFID DFL were combined. The setup consists of waist-high mounted passive transponders placed around the discretized measurement area. The RFID antennas are placed directly behind the transponder lines to guarantee a maximum power transfer.

The imaging result is calculated by using the model of Wilson et.al.[8]:

$$\Delta y = W \Delta x + n \qquad (2)$$

with $\Delta y$ as matrix of RSS differences in dB, $W$ as pre-calculated weighting matrix for every pixel-link-combination, $n$ as zero mean gaussian noise vector and $\Delta x$ as matrix of pixel attenuations generating a tomographic picture of the measurement area.

The algorithm can locate human with as low as 0.3 m mean location error. In [3] we propose multiple improvements for performance and online operation.

# III. METHODS

For adding the height as 3rd result dimension both the measurement setup and the model need to be adapted.

## A. Measurements

For the measurement we built “RFID-Walls” with a wall mounted RFID transponder grid. Discretizing the height coordinate we can define $l_z$ 2-dimensional layers within the squared measurement area. As mentioned in [4] these systems have a sender-receiver relation of:

$$n_{tx} \gg n_{rx} \qquad (3)$$

because a RFID field typically contains a high number of transponders (regarded as senders) and a relatively low number of receivers (RFID antennas).

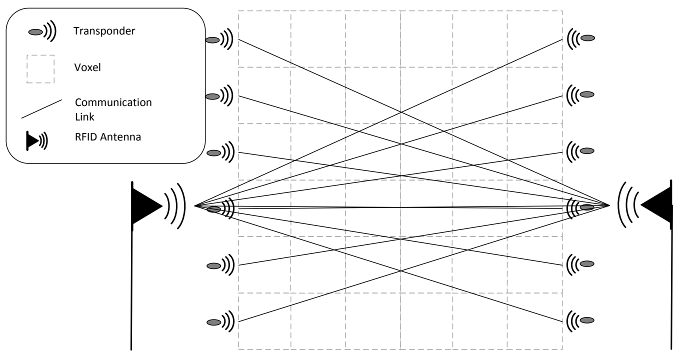


**Figure 3. Principle link structure in sectional view**

Because simply integrating more antennas would increase the systems costs and reduce the advantage of cost efficiency we just use one receiver layer with 4 antennas situated at every mid-wall.

The 3D measurement area is discretized into $n_{Pixels} \times l_z$ voxels generating a measurement picture for every height layer.

In contrast to the 2D approach of [4] the transponder layers and the antenna layer are spatial separated. This has a great effect on the model, especially on the voxel-communication link allocation and weight matrix calculation. Figure 3 is showing the principle problem. The link density above and under the antenna layer is declining. This has effect on the weighting matrix.

## B. Adapted Model

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[4].

The attenuation is measured as the received signal strength for every transponder-antenna combination. Due to the RFID protocol[9] it is difficult to set a stable power value for every transponder. Therefore a 2 phase measurement was conducted: a calibration phase with no user presence and a measurement step with scatterer in the field. The measurement vector is built by

$$\Delta y = y_{meas} - y_{cal} \tag{4}$$

with signal strength y and RSSI difference vector Δy.

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]:

$$\Delta x = (W^T W + C_x^{-1})^{-1} W^T \Delta y \tag{5}$$

In this formula $C_x$ denotes a covariance vector providing information about the dependence of neighboring pixels due to a zero-mean Gaussian random field [10]:

$$C_x = \sigma_x^2 e^{-d/\delta} \tag{6}$$

with the voxel-voxel distance d and a correlation term $\delta$ determining the impact of dependence of neighboring pixels.

We have to use a weighting model only regarding the backward link between transponder and antenna because due to the experimental scenario a user can only effect this path. The forward link is regarded only as sending power supply. Regarding the model of [11] it can be described as

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

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 surrounding each link is variable by $\lambda$.

Dealing with the problem of inter-layer variation as mentioned in *III.A* we define the main imaging scale by

$$x_{image} = \{\min(\Delta x_l) : s : \max(\Delta x_l)\} \tag{7}$$

over all layers with constant step size s.

## C. Error Model

Most authors dealing with user recognition in the 2D area assume a cylindrical human model with radius $R_x$ [5], [11]. This is not suitable for the 3D area because the human body has a different shape with different reflection properties at every height layer. Typically the body center has the greatest effect on a horizontal communication, although the influence if the users head or legs is less.

Therefore we define an extended ellipsoid of rotation with a height dependent radius $R_x(h)$ as a 3D human model. The reference image can be described as:

$$x_{ref} = \begin{cases} 1\ if\ |V_{ijl} - C| < R_x(h) \\ 0 \end{cases} \tag{8}$$

with the center of the reference object $C$ and every voxel $V_{ijl}$. Assuming this model we can define the picture dependent mean-squared error for comparison purposes to be [11]

$$\varepsilon_x = \frac{|x_{ref} - x_{calc}|^2}{N_v} \tag{9}$$

with the calculated image $x_{calc}$ and the number of all voxels $N_v$.

# IV. Experimental Validation

## A. Experimental Setup

For the experimental validation of our approach we used a passive bistatic UHF RFID system from *Alien Technology* 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 40 transponder at every of 4 walls at the layer heights of

$$l = [1.0; 1.3; 1.6; 1.9]$$

meters resulting in a total of 160 transponders. Each wall has a length of 2.7 meters and in the center of the measurement area we define 13 possible user positions. Fig. 4 shows profile and topview of the setup.

The antennas are situated 1.0m behind the wall to guarantee a best possible energy transmission. This is done due to the specific antenna lobes.

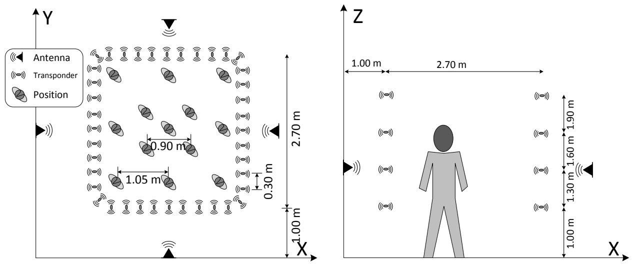


**Figure 3. Top and sectional view of measurement setup**

The RFID reader hardware is connected to a workstation where a Java program is fetching the data. The calculation of the described approach is done in a post processing step with the help of Matlab®.

## B. Procedure

Due to the high amount of transponders we have to limit the data measurements. Therefore we define major operating antenna sequences as follows:

$$AS = \{[1,2]; [2,1]; [3,4]; [4,3]\}$$

with the following annotation:

[*Powering Antenna; Receiving Antenna*]

We did our measurements for every transponder-AS combination with a minimum of 80 data samples to get a reliable mean signal strength value.

For experimental validation of 3D user recognition we placed a test person on every of the 13 defined test positions in three ways:

1. *User is sitting on a chair*
2. *User is standing on the ground*
3. *User is standing on a chair*

## *C. Results*

Fig. 5 depicts a sample result of the test person located in the middle of the room.

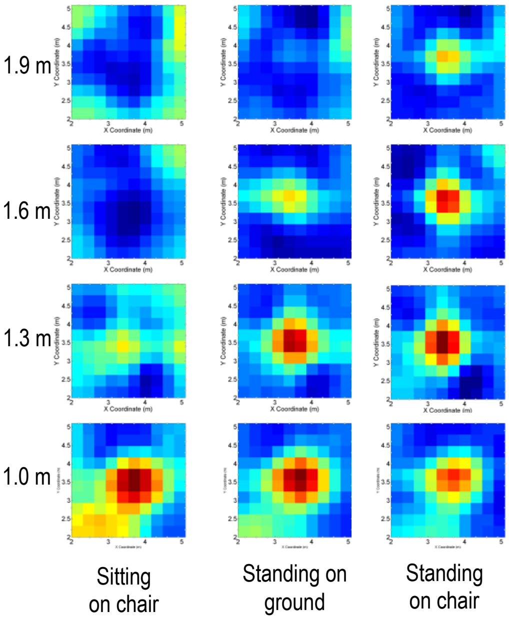


**Figure 5. Sample results by layer - center**

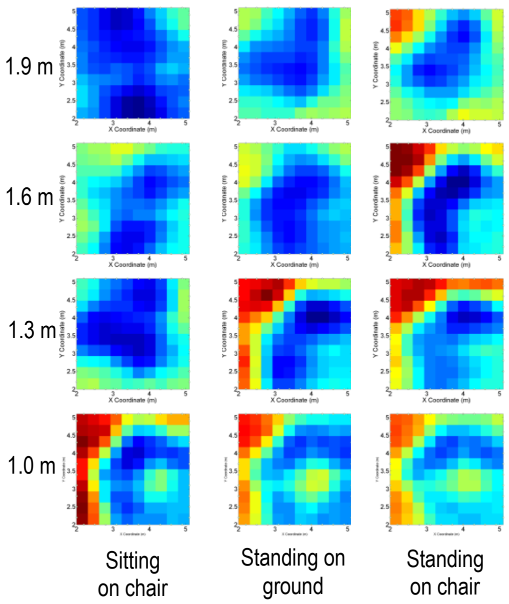


**Figure 6. Sample results by layer – edge**

It can be stated, that the recognition of the users height within the testbed could be recognized with reasonable accuracy. Fig. 6 depicts a sample result of the testperson located in the upper left edge of the room.

It has to be said, that the technique has some problems with the positioning precision in the field edges, because the density of communication links is even lower, but the height information is also recognizable very clearly.

# V. Conclusion & Future Work

In this work we did a proof of concept for 3D user recognition with passive RFID walls. To achieve this goal we described adaptations for the mathematical model and the measurement system. Within the model the adaptive bistatic weighting matrix and the covariance matrix needed to be adapted for a 3D scenario. Furthermore we defined a 3D error model, which application would go beyond the scale of this work.

In future work estimation algorithm should be developed and applied on to the results. With them the height of a user within a room could be estimated, that could be a valuable data source for user distinction in a multi user scenario.

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