Enhancing the Performance of Indoor Localization using Multiple Steady Tags

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Abstract

Indoor localization based on signal strength fingerprinting has received significant attention from the community. This method is attractive because it does not require complex hardware beyond off-the-shelf radio transceivers. However, its main limitation is the inaccuracy caused by the variability of the signal strength. When applied to the localization of people, the signal variability can be attributed to three main sources: environmental dynamics (movement of people or objects), movement of transceiver (changes in the position and/or orientation of the transceivers) and body effects (distortion of the wireless signal due to body absorption). Our work focuses on the impact of the last two sources and provides two important contributions. First, we present an analysis to quantify the effects of antenna disorientation and transceiver misplacement. For the RFID system used in our work, these effects can decrease the localization accuracy by up to 50%. Motivated by these results, we identify parts of the human body where tags are less affected by unintentional movements and describe how multiple transceivers can be used to overcome the absorption effects of the human body. We validate our findings through an extensive set of measurements gathered in a home environment. Our tests indicate that by following a set of simple guidelines, we can increase the localization accuracy (the percentage of correct location estimations) by a factor of four (from 20% to 88%), and reduce the maximum localization error (from 7 to 4 meters).

Keywords: Indoor localization, RFID, antenna, radiation, placement

1. Introduction

The limitations of GPS [1] technology on obstructed environments has motivated a large body of research on indoor localization [2, 3]. A significant number of these efforts have focused on fingerprinting techniques based on the received signal strength (RSS) of wireless radios, e.g., [4, 5, 6, 7, 8].

Fingerprinting is an attractive solution due to its low cost and complexity. Compared to other methods, fingerprinting does not require any specialized hardware beyond off-the-shelf radios which can be easily integrated into small, lightweight, wearable tags. Unfortunately, the sole reliance on signal strength implies that fingerprinting is exposed to the well known variability of wireless channels [9]. For any fixed coordinate (x, y), the signal strength of a tag can be highly variable in time. This signal variance leads to inaccurate fingerprints, which in turn leads to localization errors that can be in the order of meters or tens of meters.

When radio tags are placed on people, localization is particularly challenging because several factors influence the variance of signal strength: dynamics in the environment (i.e. movement of people or objects), absorption and diffraction of the human body, slight misplacements of tags and the antenna design. To cope with these undesired effects, most evaluations are performed under controlled settings – where individual radio tags are placed at various predefined coordinates without disturbances in their location, e.g. [5, 10, 11, 12]. These controlled experiments minimize the variance of the signal strength. Such evaluations are valuable because they provide upper bounds on the accuracy, but they do not address the impact of (i) body effects, in particular absorption, and (ii) the natural disorientation or misplacements that tags may have when placed on the human body. Previous research has reported these pernicious effects, e.g. [13, 4]; but this paper is the first that *quantifies these two effects* and leverages the insights to derive guidelines on how to *systematically enhance the accuracy* of indoor localization.

We argue that minimizing both effects is necessary before fingerprinting techniques, based on signal strength, can be applied to accurately localize persons in indoor environments. For instance, one of the goals of WebDA, one of the Ambient Assisted Living projects running in our group, is to enable low-cost indoor localization of elderly people suffering from dementia. The gathered location is then used to provide assistance for both, the elderly and care takers. During the initial tests, we found that ordinary body actions can cause transceivers to move, rotate or to be shadowed by the body. All these effects reduce the localization accuracy.

In this paper, we describe a systematic study of the issues arising when localizing persons in an indoor environment. Using an off-the-shelf active RFID system, we quantify the effects of tag disorientation, tag misplacement and the absorption of human bodies. The following paragraphs summarize the key findings, guidelines and results of the study:

- Slight mismatches in tag orientation and tag placement have a similar negative effect. Each of them can reduce the localization accuracy by 50%. Consequently, tags should be placed on parts of the body that experience little changes over time. From a practical perspective, our findings show that the waist line is an ideal part.

- Adding more tags overcomes the effects of body absorption and increases the localization accuracy. We find that the highest accuracy improvement is obtained with four tags - two of them at the front and the other at the back.

- Following our guidelines increases the localization accuracy and reduces the localization error. We performed extensive measurements in a home environment and found that, compared to scenarios where single tags are placed carelessly, the accuracy is improved by a factor of 4, and the maximum estimation error is reduced by 40%.

2. Preliminaries

To put our work in context, we now present some preliminary information. First, we describe the hardware platform used in our experiments. Then, we provide an example that highlights the impact of signal variance on localization accuracy. Finally, we describe the methodology and metrics used in our study.

2.1. Hardware Platform

We use the LogiSphere RFID system from Sensite Solutions, which operates at a frequency of 868 MHz. The system consists of readers (HBL100) and active tags (BN208). The active tags periodically broadcast beacon frames containing their IDs, which can then be received by the readers. When the readers receive a beacon frame, they are able to determine its signal strength

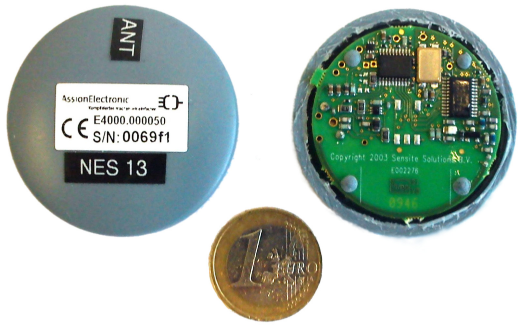


Figure 1: BN208 active RFID tags

which can then be used for fingerprinting. The reason for using this system is that the tags are small (Figure 1), lightweight (14 gr) and have a long lifetime. These characteristics make them ideal for embedding them in clothes. The output power was set to -10 dBm, which provides a transmission range of approximately 50 meters (sufficient to cover most apartments). With this transmission power, the batteries can send approximately 16 million transmissions. The beacon interval is configurable, but for the experiments described hereinafter the rate is set to 1 beacon frame every second. The tag has an accelerometer sensor which can detect (the lack of) movement, and hence, the tag can stop sending beacon frames when it is still. Given these settings, and considering that in most cases elderly users are not active more than 50% of the day, the tag has a lifetime of roughly one year.

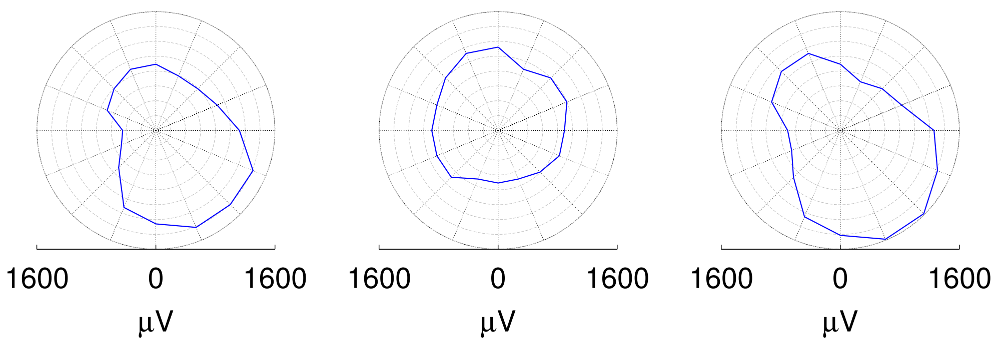
2.2. Problem Description

In order for fingerprinting to be accurate, there are two desirable characteristics that the environment should have. First, each coordinate should be uniquely identified by a fingerprint(s). Second, the signal strength should not change significantly over time. In practice, none of these conditions apply, and hence, fingerprinting methods could be – from the start or become with time – inaccurate.

Figure 2 depicts the radiation pattern of a tag located at a 1m distance along its three different axes. This figure validates the findings reported for other hardware [14], where the radiation pattern was also found to be highly anisotropic[1]. In general, the radiation pattern depends largely on the type

[1] We measured the radiation pattern of 12 tags along their three different axis (X, Y

of antenna used. In our case, the tag has a simple dipole antenna and the Y axis goes along the same direction as the antenna, and hence, it has a more symmetric coverage. To evaluate the impact of signal variances on localization, let us look at the interplay of Figure 2(c) and Figure 3, which depicts the signal strength of the tag at different distances in an aisle. We can observe that for the tag's Z axis, the highest signal strength is 1600 μV ($\approx$ 65 dBμV) and the lowest is 700 μV ($\approx$ 55 dBμV) [2]. Notice that this change on signal strength can be obtained by modifying the orientation of the antenna by 90°. A tag positioned on a limb, or over loose pieces of clothes on the torso, can easily lead to this level of disorientation. In Figure 3, we observe that a signal strength of 65 dBμV maps to a distance of 1m, while a signal strength of 55 dBμV could map to distances around 2.0, 3.0, 4.5 and 9.5 meters. Henceforth, slight movements of tags can lead to localization errors in the order of several meters. As we show later on, the absorption of a human body can have a similar effect which increases the overall error.



(a) X axis (b) Y axis (c) Z axis

Figure 2: Antenna radiation pattern measured at 1m for the different axes

2.3. Evaluation Methodology

As most studies in the area, our evaluation relies on well-known machine learning techniques. In the following, we outline these techniques and how we apply them. We also provide a rationale for the approach used for tag misplacement and disorientation.

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and Z), and all the plots showed a highly anisotropic behavior.

[2]For voltage or current ratios: $\text{dB}\mu\text{V} = 20\log_{10}\left(\frac{V_x}{1\mu V}\right)$

Gathering the Feature Vectors. Let $f_i(c)$ be a fingerprint assigned to coordinate c by reader i. We utilize four readers in all experiments, and hence, the feature vectors are given by $(f_1(c), \ldots, f_4(c))$. Due to the high variance in RSS measurements, $f_i(c)$ is usually computed as the average RSS of n consecutive packets. Unfortunately, the average can be severely biased by deep fades or high peaks caused by multi-path effects and hardware variance. To obtain a more robust fingerprint, we combine ideas from [4] and [15]. From [4] we use the concept of fingerprinting the highest values of RSS to filter deep fades, and from [15] we use the concept of trimmer-filters to filter high peaks. As a result, considering a sequence of n RSS samples, we define the fingerprint $f_i(c)$ as the RSS value corresponding to the 80^{th} percentile of that sequence [3]. As for the number of samples n to be considered in the sequence, we evaluated different values. In theory, the higher n, the more accurate the fingerprint but the less responsive the system. In practice, we found that $n > 25$ did not provide significant improvements. Hence, we consistently use $n = 25$ hereinafter.

Rationale Behind Misplacement and Disorientation. To study the effects of tag placement and orientation systematically, we used the following approach. To modify the placement, we move the tags 10 cm from their original position while keeping their orientation steady. The reason behind this choice is that misplacements of 10 cm can easily be caused by placing tags on limbs or by carelessly attaching tags to the torso. The rotation of the tags is set to 90 degrees while keeping the same position. In this case, the reason is twofold. First, when tags are placed on limbs, as proposed in other studies [16], a 90 degree rotation can be easily caused by normal body actions. Second, and more important, a 90 degree rotation leads to the largest variance in signal strength, as shown in Figure 2. To capture the combined effects of placement and orientation, we perform both modifications simultaneously.

Capturing the Signal Variance. Given that localization errors are caused by signal variances, it is important to use a metric that captures signal variability. Following the proposal in [4], we use euclidean distances to capture the signal difference between two vectors in the feature space. As we will observe later, this metric will allow us to gain deeper insights on the limitations

[3] Alternatively, the median of the sequence can be used (as it is also a robust statistic), but our experiments on the RFID system showed better results for the 80^{th} percentile. This is a hardware-specific issue.

of the localization system.

Measuring the Accuracy. The most important metric in localization is the accuracy of the system –measured as the percentage of testing samples whose classification matches the true location. Similar to other studies [4, 5, 6, 7, 8], we use a k nearest neighbor (kNN) classifier for localization. In our case we use $k = 1$, a single training fingerprint for each coordinate, in order to capture the worst case behavior[4].

Measuring the Maximum and Average Error. Other important metrics in localization are the maximum and average error of the system, that is, when we do not estimate the right location, how far is the estimation from the true value? In our evaluation, we obtain the maximum and average distance error for all the testing samples that were classified incorrectly.

3. Quantification of Variability Effects

In this section, we quantify the effects induced by tag misplacements, disorientation and body absorption. Based on this, we propose a set of guidelines to minimize them. To filter the effects of channel dynamics due to movement of people or objects, all experiments are conducted in a controlled setting (explained below). The next section evaluates our approach in a realistic scenario (a medium size apartment).

3.1. Laboratory Environment and Setup

The controlled experiments were performed in a room with the layout shown in Figure 4. We defined four coordinates (C_i) located at the corners of a 4m×4m square and positioned one reader (R_i) close to each of the four corners.

Before conducting the experiments, we obtained the radiation pattern of each tag, 12 tags in total, in a similar way to Figure 2. The radiation patterns allow us to identify the main lobe of the antenna, that is, the direction of the strongest signal strength. Identifying the main lobe is important to quantify the rotation effects with respect to a single point of reference[5].

In these controlled experiments, our goal is to quantify only the effects of tag movements and body effects. We took care of minimizing the variability

[4]Some studies report that $k = 3, 4$ provide better results [4], but our goal is to stress the system and capture the relative performance of the different effects.

[5]For several types of antennas, the strongest and weakest lobe are orthogonal (90°).

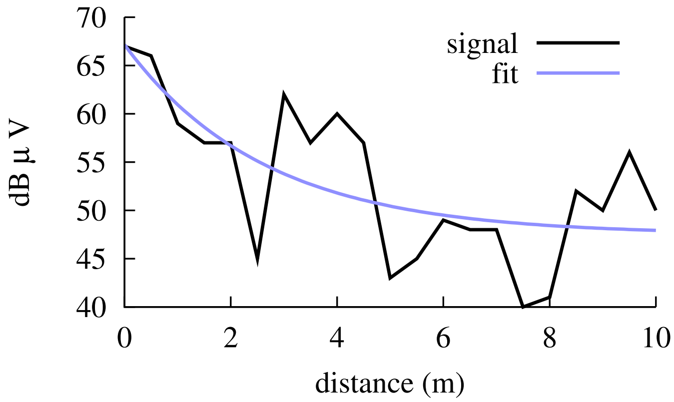


Figure 3: Signal strength vs. distance in an aisle

caused by dynamics in the environment (movement of people or objects). The test room remained closed and unchanged for the complete duration of the experiments. Furthermore, the experiments were controlled remotely (outside the room) to further minimize the dynamics.

3.2. Effects of Disorientation and Misplacement

In order to capture the effects of antenna disorientation and tag misplacement, we performed two sets of experiments. In the first set, we measured the signal variability without the disturbing effects of the human body. To do this, we placed the tags on top of wooden stands at approximately 1m height. In the second set, the tags were attached to the body. To guarantee for a stable tag placement and orientation, we attached the tags to a tightly fitted belt and asked the person not to move for the time of the experiments.

First Set of Experiments (Without Human Body). For each one of the 12 tags, and for each coordinate, we collect three different sets of measurements.

- **Baseline**: the main lobe of the tag faces North (with respect to the compass in Figure 4)
- **Disoriented**: the tag is rotated 90° to the right with respect to the baseline. The main lobe faces East.
- **Misplaced**: the tag is moved 10cm to the right with respect to the baseline. The main lobe still facing North.

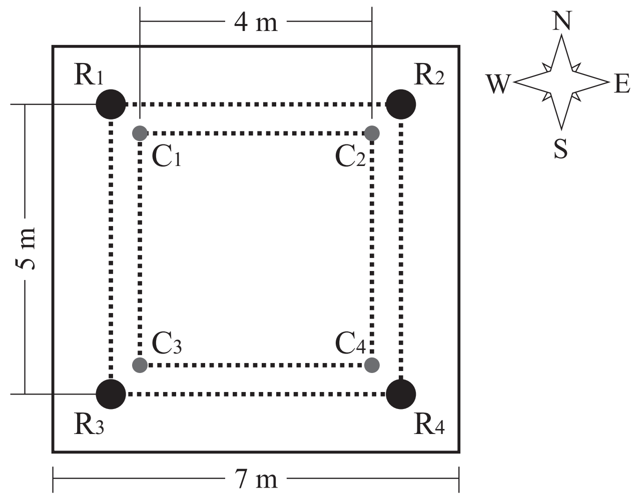


Figure 4: Laboratory layout with readers (R_i) and coordinates (C_i)

At each position we collected two minutes of data, which leads from 100 to 120 samples (due to clock skew and collisions). According to the methodology described in section 2.3, a sequence contains 25 samples, and hence, two minutes of data lead to four fingerprints. The baseline measurements are collected twice, one is used as a training set and the other as a testing set. The disoriented and misplaced measurements are collected once, and both are used only as testing sets.

As indicated in Section 2.3, the signal variance is captured by the euclidean distance among vectors. For each coordinate, we have four training vectors and four testing vectors. A cross product of these two sets leads to 16 comparisons that capture the variability in signal strength at each coordinate. This process is repeated for the four coordinates and 12 tags, which leads to 768 comparisons. Figure 5 depicts the distribution of these comparisons. The candlestick plots show the minimal and maximal signal differences, as well as, the interval between the 25th and 75th percentile (box). The circles represent the mean. The plot provides two important insights. First, the variability of the baseline comparison is minimal. This is due to two reasons, the controlled settings, which minimizes signal variance, and the robustness of the fingerprints defined in Section 2.3. Second, disorientations and misplacements have a similar effect on signal variance, and this effect is large. As explained earlier in the paper, large variances in signal strength are the main reason for inaccurate localization.

Figure 6 depicts the localization accuracy of this simple scenario. The accuracy is calculated using a nearest neighbor classifier. As explained in section 2.3, we set $k = 1$ and we divide the Baseline training set into four smaller sets (each set with one fingerprint per coordinate). The accuracy is presented in two ways: on a per-tag basis (candlesticks) and in an overall basis i.e. all-tag performance (connecting line). First, let us analyze the overall accuracy. We have 192 sample vectors for each testing set ($192 = 4$ fingerprints$\times$4 coordinates$\times$12 tags) and, as explained earlier, each testing set is evaluated 4 times (once with each one of the four training subsets). The overall accuracy is hence represented by the fraction of correct localizations out of 768 attempts. The accuracy of the baseline is one because the variance in signal strength is not high enough to confuse neighboring coordinates. On the other hand, misplacements and disorientations decrease the accuracy by 20% and 30% respectively.

The overall accuracy hides an important characteristic: hardware variance. Not all tags are born equal. Given the same output power, the shape and strength of their radiation patterns are different[6]. This implies that tags may have different performances. The candlestick plots in Figure 6 capture the per-tag performance. The plot shows the tags with best, worst and average performances (tags between the 25th and 75th percentile). The per-tag accuracy is given by the fraction of correct localizations out of 64 attempts (4 fingerprints$\times$4 coordinates$\times$4 training subsets). We observe that misplaced tags have a wide performance range $[0.65, 1.00]$, while disoriented tags have a narrower range $[0.60, 0.85]$. We hyphotesize that the wider range of values for the misplacement experiments is due to differences in the width of the main lobe (recall that in our study the main lobe is the point of reference for changes in positions and directions). If a lobe is wide, a tag is more robust to misplacements on the direction of that lobe, while narrower lobes are more sensitive to the orientation between the tag and the reader. On the other hand, disorientation has a smaller effect because tags have similar signal strengths at their weakest directions, and this leads to less variability in the results.

It is important to notice that the grid is large (4m), and this contributes to the perfect accuracy of the baseline set, smaller grids may cause errors,

[6]This is due to imprecise manufacturing processes and also affects hardware designs that strive for precise RSS measurements [17].

but our goal is to highlight the *relative* impact of tag misplacements and disorientations.

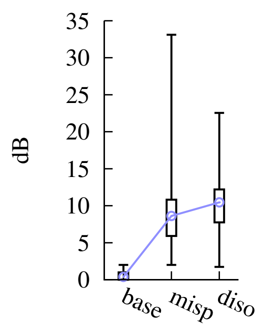


Figure 5: Signal strength variability (without human body)

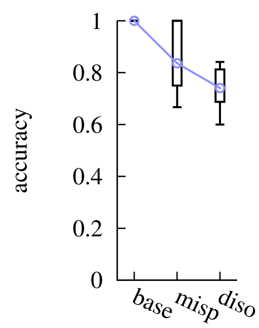


Figure 6: Impact on localization accuracy (without human body)

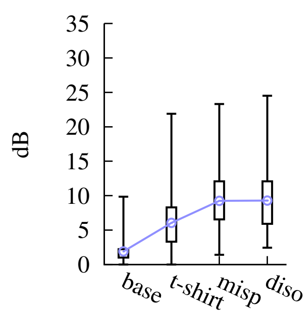


Figure 7: Signal strength variability (with human body)

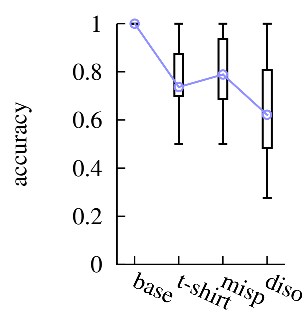


Figure 8: Impact on localization accuracy (with human body)

Second Set of Experiments (With Human Body). The framework is analogous to the first set of experiments, but the tag was located on the front middle torso of a person facing North. For each tag and each coordinate we collected 4 sets of experiments:

- **Baseline**: the tag is fixed to a belt with the main lobe facing up.
- **T-shirt**: the tag has the same position and direction of the baseline, but it is placed directly on the clothes (loosely attached).
- **Disoriented**: the tag is fixed to a belt and rotated 90° clockwise with respect to the baseline.

- **Misplaced**: the tag is fixed to a belt and moved 10 cm to the right with respect to the baseline.

The collection and processing of data is the same as in the first set of experiments. Figure 7 shows the distribution of the signal variance (based on the comparisons of the euclidean distances). Similarly to the first set of experiments, disorientations and misplacements cause a large variance. But in this case, the baseline has a wider variance. This is because of the slight unconscious movements of people (as compared to the completely static setup with a stand). We can also observe that the *t-shirt* tag has a wider variance than the baseline. This is because it was loosely attached, and hence, it has slight misplacements and rotations.

Figure 8 depicts the per tag (candlesticks) and overall localization accuracy (connecting line). The results follow the same trend as the first set of experiments, but the effects are aggravated (worse accuracy). The ranges of the t-shirt, misplaced and disoriented sets are rather similar among themselves because minor movements of the person intertwined these effects, that is, a small movement can cause both disorientation and misplacement.

3.3. Effects of Body Absorption

Besides tag disorientation and misplacement, another important factor increasing signal variability is the human body itself [7]. We quantify the impact of this effect by placing one reader at R_1 and 12 tags at C_4 following the layout depicted in Figure 4. The experiments were conducted as follows:

- **Baseline**: All 12 tags are attached to a thin cardboard and the cardboard is then attached to a thin wooden stand with a height of 1.5m. The main lobes of all tags are facing up.

- **Body**: The cardboard, with the 12 tags, is attached to the back of a person facing the reader (5 persons in total). The persons are of different stature and mass. While attaching the cardboard, we ensured that we keep the height and orientation of the baseline.

As in the previous experiments, we asked the persons to avoid movements in order to minimize the dynamics. We took two baseline measurements and

[7]The human body consists of 65 percent of water which is well-known to have a high radiation absorption.

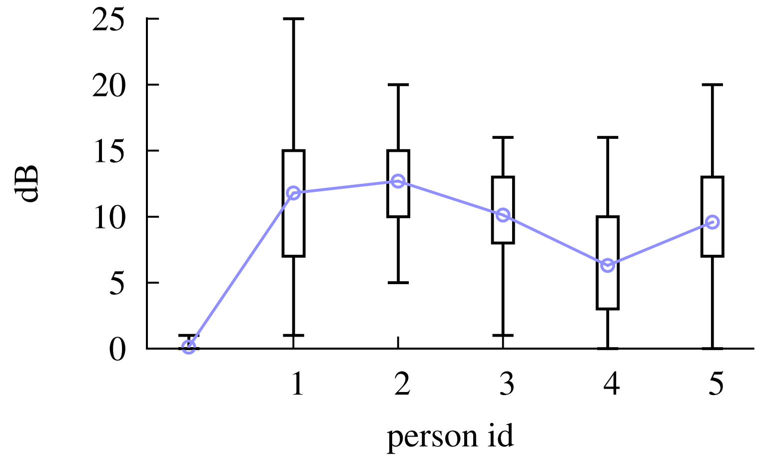


Figure 9: Absorption and signal strength variability of human body

one testing measurement for each person (two minutes for each measurement). Following the same methodology of the previous section we obtained the euclidean distances. However, in this case we had only 16 comparisons because we used a single coordinate. The results are depicted in Figure 9. We observe that body effects cause a variance between 5 and 15 dB. These variances are significant and comparable to those of tag misplacement and disorientation (Figure 7).

As reported in previous studies [4], body absorption leads to ambiguous information. By simply rotating 180 degrees, a person could be mistakenly located several meters further (or closer). In [4], the authors propose to take samples at different cardinal directions to overcome body effects. In contrast, we propose to attach multiple tags to a person in order to overcome these effects. To do this, we construct *wide fingerprints* from the individual fingerprints by simply concatenating them. This allows us to apply the machine learning method without any modifications.

The resulting fingerprint not only copes with body absorption and contains information about the orientation of the person, but it is also more robust to multi-path effects. This last point is particularly important compared to single-tag approaches. To quantify the effects of using the *wide fingerprints* of multiple tags, we attach 12 tags steadily to a belt in the waist line of a person (main lobe facing up). The tags are evenly spaced along the belt to cover the different sides of the body. For the training and testing

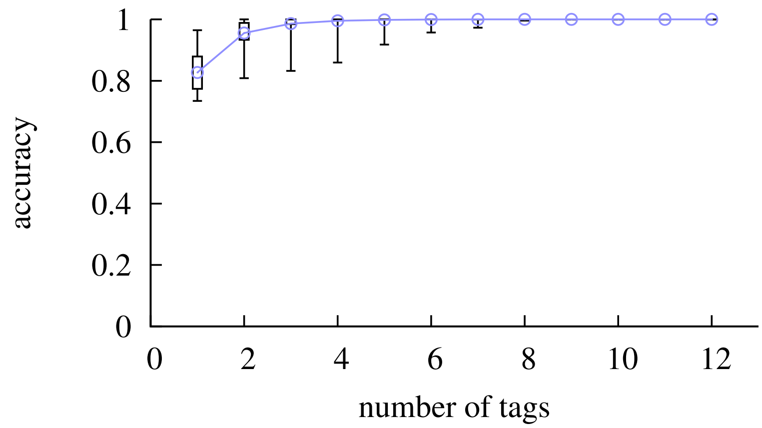


Figure 10: Localization accuracy of multiple tags on human body

sets, we obtain four fingerprints for each of the four coordinates and each of the four cardinal directions, which results in 64 fingerprints per tag (4 coordinates $\times$ 4 orientations $\times$ 4 fingerprints). The training set is divided into four subsets each containing one fingerprint per pair of coordinates and locations. The overall and per-tag accuracy is calculated analogous to the previous experiments.

Figure 10 shows the resulting accuracy distribution of the different tag combinations. For example, the value 2 in the x-axis represents all the potential combinations of 2 tags (out of 12). This figure provides two important trends. First, more tags provide better accuracy, but with diminishing returns - meaning that the gain per tag decreases as more tags are added. Second, and more important, four tags seem to provide a good trade off between cost an accuracy. In the next section, we will observe that this insight is validated in a realistic environment.

3.4. Tag Placement Guidelines

Given the results discussed in the previous sections, we derive a set of practical guidelines to minimize the negative effects that occur when tags are placed on a human body. For simplicity, we refer to them as **PMMS** (**p**recisely **m**ount **m**ultiple tags and keep them **s**teady).

Guideline 1 (Tag Orientation). *The rotation of the antenna has an impact on the variability of the signal strength.* ***Keep the orientation of the tag steady.***

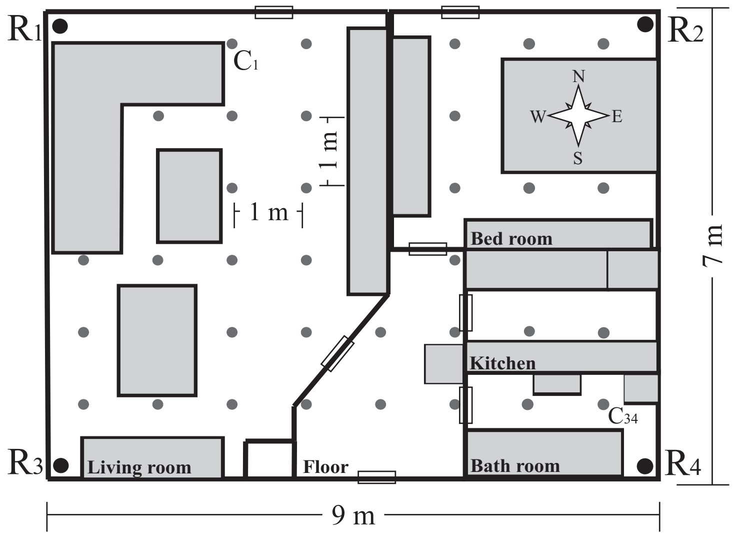


Figure 11: Apartment layout with readers (R_i) and coordinates (C_i)

Guideline 2 (Tag Placement). *The placement of the antenna has an impact on the variability of the signal strength.* ***Keep the position of the tag steady.***

Guideline 3 (Body Absorption). *The absorption of the body has an impact on the variability of the signal strength.* ***Use multiple tags to overcome body absorption effects.***

These guidelines limit the parts of the human body where tags could be attached. The first two guidelines exclude the limbs, as ordinary body movements (such as walking or hand motions) will likely cause both, disorientation and misplacements. Although tags could be attached to caps or hats, this might be inconvenient for many persons. Consequently, the placement of tags are restricted to the torso. Furthermore, considering that tags should be tightly attached, a belt on the waist line appears as the most convenient and practical position.

4. Evaluation

In order to validate the results gathered in the laboratory environment, and to test the validity of our guidelines in a realistic scenario, we performed an experiment in a medium size apartment. The layout of the apartment is

Figure 12: Tag placement on t-shirt (loose) and with belts (tight)

shown in Figure 11. The doors and larger pieces of furniture are primarily made of wood, metal and fabric. We distributed 4 RFID readers (R_1-R_4) in the apartment by placing them in each of the outermost corners at a height of 180 cm. After discarding the areas blocked by furniture and walls, we identified 34 accessible coordinates (C_1-C_{34}) in a 1×1m grid (c.f. Figure 11).

We equipped a person with 10 tags as shown in Figure 12. To capture realistic temporal changes, we collected the testing set seven hours after collecting the training set. During the experiment, the tags were split into the following test-groups:

- **Loosely attached:** 4 tags were loosely attached to the t-shirt of the person. After the training set was collected, one of the tags was moved by 10 cm to the right, one of them was rotated by 90 degrees, one of them was moved and rotated, and the last one stayed as it was.
- **Tightly attached:** 2 tags were attached to a belt. After the training set was collected, one of them was moved by 10 cm to the right and the other one was rotated by 90 degrees.
- **PMMS guidelines:** 4 tags were attached to a second belt (2 on the front and 2 on the back). Following our own guidelines, we neither move nor rotate them.

For each set (testing and training), and for each coordinate, we collect one-minute samples at each cardinal direction (N,E,S,W). A one-minute sample leads to two fingerprints. This results in 272 fingerprints for each tag (34 coordinates $\times$ 4 directions $\times$ 2 fingerprints/minute). Also, as described in the previous section, we divide the training data into two sets (each set having only one fingerprint per <coordinate, direction> tuple).

We evaluate the accuracy and the maximum and average error of the system. The accuracy captures the fraction of test samples that correctly match their location, and the average error captures the expected distance to the ground truth. It is important to highlight that the average error considers *only* the test points that were not mapped correctly. For example, considering ten test samples, where eight of them are mapped correctly, one of them is mapped to a neighboring cell (error = 1) and the other is mapped to a point that is two-cells away (error = 2), the accuracy of this set would be 80% and the average error equal to 1.5 cells.

The accuracy and error of the system are evaluated in two ways, in a per-location basis and in an overall basis. In the per-location evaluation, we consider the 16 attempts made at each particular coordinate (2 training sets $\times$ 4 directions $\times$ 2 fingerprints). If one or more of those 16 attempts are erroneous, we calculate their average errors. The overall accuracy reflects the fraction of correct guesses across all coordinates, a total of 544 attempts (272 fingerprints $\times$ 2 training sets), and the overall average error considers all the erroneous attempts.

4.1. Impact of Keeping a Tag Steady

First, we will focus on the performance of individual tags and the impact of the first two guidelines: keeping the orientation and position of a tag steady. Figure 13 and Figure 14 show the accuracy and error in candlestick plots, respectively. The plots show the minimal and maximal values for all coordinates, as well as, the interval between the 25th and the 75th percentile (box). The connecting line represents the average accuracy and error. Based on the depicted results, we can draw three important conclusions:

Misplacement and disorientation play a central role on localization accuracy. The tightly attached tags {misp},{diso} are used to *enforce* the maximum possible deviations due to misplacements and disorientation throughout our evaluation, and in Figure 13, we observe that, when compared to the loosely attached tags {misp},{diso},{misp+diso}, the two tightly attached tags seem to indeed capture a lower bound behavior on the localization accuracy. This observation is important because, as we mentioned in the introduction, signal variance have several sources, some of them out of our control (like the movement of pieces of furniture). Misplacement

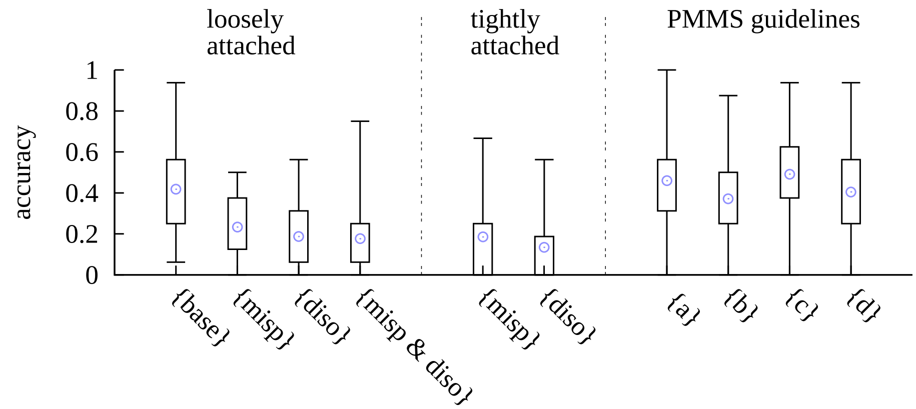


Figure 13: Localization accuracy for single tags

and disorientation are, however, to some extent under our control, and they seem to account for most of the performance degradation. Hence, they must be considered in order to maximize the accuracy of an indoor localization system that applies RSS fingerprinting.

Maintaining the orientation and placement of tags prevents accuracy degradations of up to 50 percent. To clarify this, consider the following two sets of tags show in Figure 13: the first set contains {base},{misp},{diso},{misp+diso} and the second contain {a},{b},{c},{d}, i.e. tags following the guidelines. Figure 13 shows that in the first set, only the *base* tag provides an accuracy similar to the second set[8]. The key lesson to take away is that a tag *may* remain still and have a good performance, but it might as well rotate or move, which could degrade the overall accuracy from approximately 40% to 20%. Following our guidelines guarantees a fairly constant and good performance.

Keeping a single tag steady does not seem to have an impact on the localization error. Figure 14 depicts the localization error of each tag. The units of the y-axis represent the length of cells (approximately 1 m). We observe that keeping a tag steady does not reduce the localization error. For all tags, the maximum error fluctuates between 5.5 and 7, and

[8]Note that the {base} tag has a good performance, in spite of being directly on the clothes, because it is relatively steady between two belts (Figure 12).

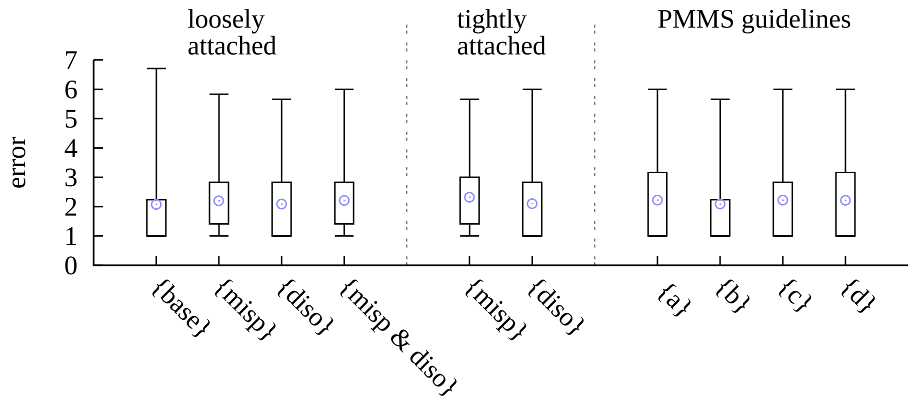


Figure 14: Localization error for single tags

the average error fluctuates between 2 and 2.5. In the next section, we will observe that our third guideline (using multiple tags) overcomes this limitation. It is important to recall that in Figure 14, the minimum error is one because we only consider test points that have not been matched correctly (approximately 80% of test points for {misp} and/or {diso} tags, and 60% of test points for the steady tags {a},{b},{c},{d}).

4.2. Impact of Using Multiple Tags

Our evaluation now focuses on the impact of our third guideline – using multiple tags. As we will observe, utilizing several steady tags not only leads to a further increase in localization accuracy, but it also reduces the localization error of faulty estimations.

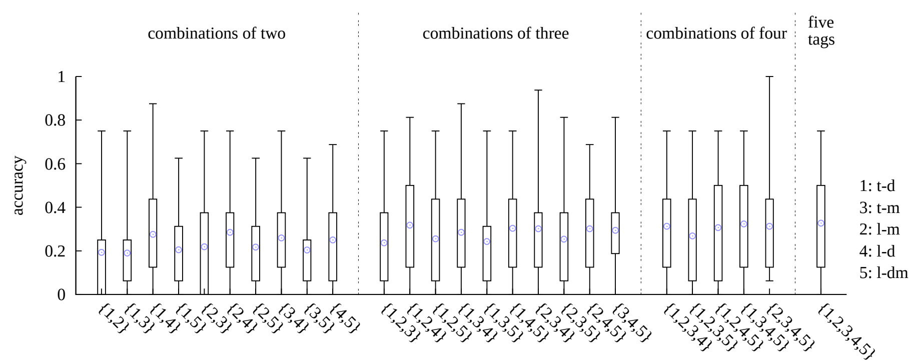
Unless tags are placed in a steady way, adding more tags does not improve the localization accuracy. Figure 15(a) depicts the localization accuracy of using multiple tags that are disoriented and/or misplaced. For the sake of clarity, we use numbers to identify the five types of such tags in our evaluation, the tightly coupled {diso} and {misp}, and the loosely coupled {misp},{diso} and {misp+diso}. We notice that the average localization accuracy of multiple disoriented or misplaced tags fluctuates between 20% and 30%. These values are lower than the 40% accuracy achieved by a single steady tag (Figure 13). This observation is important because it indicates that the first two guidelines, regarding tag steadiness, are necessary conditions for the third guideline to have a strong positive effect.

Placed properly, multiple tags effectively mitigate body effects and increase the accuracy by a factor of 4. Fixing a tag to avoid misplacements and disorientations is necessary, but it may not be sufficient to achieve a high localization accuracy. For a fine grain scenario like ours (1×1m grid), single tags {a},{b},{c},{d} lead to a rather moderate accuracy (40%). This relatively low performance is due to external effects such as multipath and body absorption that create ambiguities (locations having similar fingerprints). Figure 15(b) shows that utilizing two fixed tags improves the localization accuracy to values around 70%, and four *fixed* tags can improve the average accuracy to values around 88% (4 times more than single tags that are carelessly attached). It is important to highlight that the diminishing returns pattern validates the laboratory results.

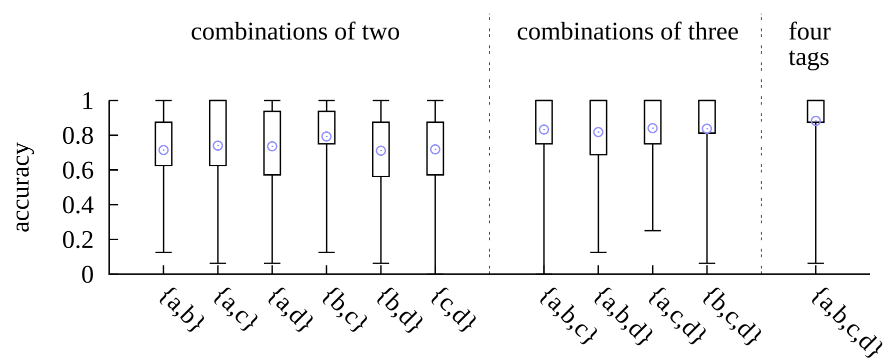
Multiple steady tags not only increase the localization accuracy, but they also decrease the localization error. In the previous subsection we observed that a single steady tag enhanced the accuracy of the system but did not reduce the average error. Figure 16(b) shows that, when 4 steady tags are used, the maximum error is 4 and the average error is 1.4, compared to the ranges [5.5, 7] and [2, 2.5] for single tags. The reduction of the 75th percentile error to values below 1.5 is an important result because it indicates that when an estimation is incorrect, 75% of the time, the PMMS guidelines estimate a location that is one of the eight neighboring cells close the ground truth. On the other hand, if multiple loose tags are used (Figure 16(a)), the maximum and average errors do not decrease much compared to the single tag case.

4.3. Impact on Applications

Until now, we have focused on the technical outcomes of our study. In this subsection, we describe the importance of these outcomes within the context of WebDA, one of the Ambient Assisted Living projects running in our group. As indicated previously, one of the goals of WebDA is to enable the localization of people suffering from dementia in order to provide services for them and their care takers. One of the use cases targeted by WebDA is the early detection of agitation and distraction during which people are repeatedly changing from one place to another and back. A second use case is the automated issuing of context-dependent reminders and notifications when the user is at a certain location. As a simple example, the elder might be reminded to drink something when he has been sitting on the couch for

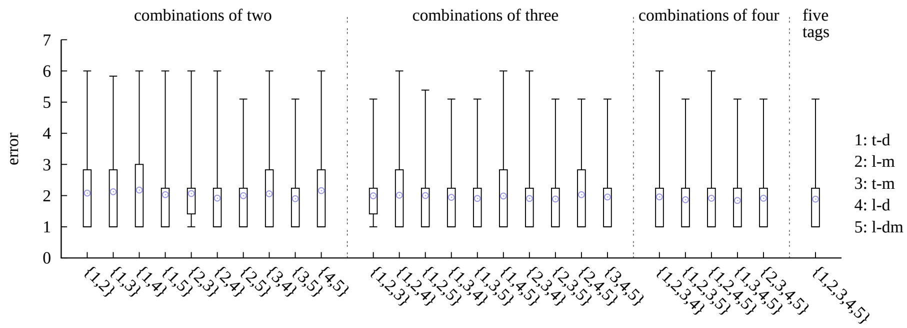


(a) Accuracy for multiple tags that are misplaced and/or disoriented

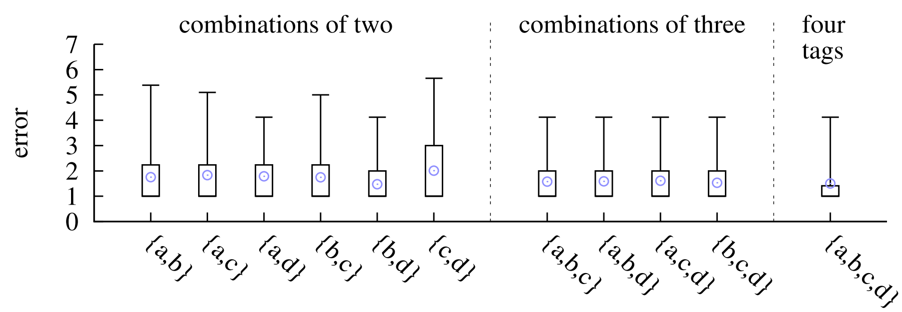


(b) Accuracy for multiple steady tags following the PMMS guidelines

Figure 15: Accuracy for multiple steady tags



(a) Localization error for multiple tags that are misplaced and/or disoriented



(b) Localization error for multiple steady tags following the PMMS guidelines

Figure 16: Localization error for multiple tags

more than an hour. Similarly, a care taker might be notified via SMS when the elder person is leaving the apartment at 3 am.

If a single loose tag is placed on a person, 20% of the time the system will give the correct location (Figure 13), 60% of the time the system will provide a location that is up to three cells away from the true location (Figure 14) - which could lead to a different room, and the remaining 20% of the time the error could be between 4 and 7 cells, which means that the person can be erroneously located at the opposite side of the apartment. Consequently this will lead to a significant number of improperly issued reminders and notifications. In real-world deployments, the resulting distraction for both – the elders as well as the care takers – will quickly outweigh the overall system's benefits.

In a system with four steady tags following our placement guidelines, 88% of the time the estimation will be correct, 9% of the time the person will be located on cells contiguous to the ground truth - which in several cases would be still valuable information, and only 3% of the time the person will be erroneously located to a position that is 2 to 4 cells away from the ground truth. Although this may not be an accurate piece of information for small rooms or areas such as a bathroom, given this low percentage, it is possible to avoid almost all false reminders and notifications by applying trivial aggregation.

5. Related Work

Location is an important part of a person's context which, in turn, represents a cornerstone of pervasive computing. Outdoors, GPS [1] provides a cost-effective solution to determine the location of persons on a global scale. When GPS is not available, or if energy and latency are a concern, it is possible to provide supplementary solutions using WLAN [18], GSM [19], CDMA [20], or WiMax [21], to name a few. Over the last decade, the ubiquity of accurate location information in outdoor settings has led to the development of a plethora of location-based services and applications.

Transferring the results from outdoor to indoor environments is a challenging task that has spawned an enormous body of research. For the sake of brevity, we would like to refer the reader to [2] and [3] for recent surveys on existing applications, algorithms, systems, and metrics. To overcome the effects of multi-path signal propagation, RADAR [4] was among the first systems that applied the idea of signal strength fingerprinting. This seminal work used 802.11 as basis for a study which showed that fingerprinting is a viable method for localization. Over time, this idea has been tested successfully with a broad spectrum of technologies. Examples include Bluetooth [5], GSM [6], 802.15.4 [7], [10], FM [22], DECT [8], and passive [11] as well as active RFID [12]. Together, these studies provide a clear indication for the broad applicability of fingerprinting in indoor environments. *Typically these studies focus on evaluating the technology without a systematic analysis of the impacts caused by a human body. Providing such an analysis is a primary goal of our work.*

For the study in this paper, we build upon the existing work in several ways. To gather robust fingerprints, we borrow the concept of fingerprinting the highest value [4] to filter deep fades, and we combine this with trimmer filters [15] to remove high peaks. To compute accuracies, we use nearest neighbor methods similar to [4, 5, 6, 7, 8] while using the euclidean distance. We are aware that there are more elaborate metrics [23] and filtering techniques [24] which are designed to improve the accuracy, but the focus of our study is to create a clear link among the relative performance of different effects.

Our study is related to other studies on signal variability. In [9], for example, the authors study the low level temporal effects of indoor signal propagation to optimize network technology. [25] studies the variability of signal strength at stationary transceivers caused by human bodies to enable device-free localization. In contrast, we are focusing on the variability effects caused by mobile transceivers placed on a human body to quantify the impact on localization accuracy.

We point out that the individual effects have been previously noted by other researchers. For example, RADAR proposes to take measurements in which the user faces a different direction (e.g. north, south, east and west) to overcome the absorption effect of bodies. This has turned out to become a common approach that is also used to calibrate commercial 802.11 systems such as Ekahau [26] and we also apply this technique but we propose to replace complex processing with using multiple tags. Most other works, however, do not systematically analyze this effect [5, 6, 22, 8] or evaluate their systems in more controlled settings, e.g. [12].

Our proposal to use multiple tags is related to [27] which analyzes the effects of using multiple antennas to improve signal strength fingerprinting. Similarly to our finding the study concludes that it is possible to achieve significant improvements by introducing additional antennas. In contrast to our proposal, however, [27] studies 802.11 and introduces the antennas at the access points. Conceptually, our proposal is therefore more closely related to [16] which uses multiple sensor nodes on a body to enable localization. However, [16] attaches nodes loosely to the person (i.e. by hanging them around the neck or putting them into the pockets of the trousers). Based on our results, this is likely to cause inaccuracies due to node misplacement and disorientation.

Regarding the effects of antenna disorientation there have been a few studies already. Interestingly, [27] indicates that the rotation of the external antenna of an off-the-shelf 802.11 access points does not cause significant effects on the received signal strength. We hypothesize that this is due to the more complex antenna arrays found in today's access points. Similar to our finding, the study in [13] shows that the localization capabilities of current 802.15.4 hardware is significantly impacted by antenna disorientations. However, in contrast to our work [13] does not analyze other body effects such as misplacement or absorption.

Indoor localization is a dense research area and several issues evolving around the effects of the human body on localization have been noted. To our knowledge, our work is the first to perform a comprehensive analysis that quantifies the effects and derives a set of simple, practicable guidelines to minimize them. As our validation shows, following these guidelines can improve the accuracy by a factor of 4.

6. Conclusions

Motivated by the limitations of current RSS-fingerprinting techniques, we quantified three negative effects on localization accuracy resulting from placing tags on persons. We build on top of the existing state of the art by analyzing these effects systematically in the context of indoor localization. Based on the analysis, we propose PMMS, a set of simple guidelines that effectively counteract the effects. To minimize the signal variance caused by tag misplacement and disorientation, it is necessary to steadily attach tags to the torso of people. To overcome body absorption effects, it is recommended to use multiple tags covering the front and back of the body. The validation of PMMS in a realistic scenario shows that following these guidelines can consistently improve the performance of indoor localization. Compared to a single tag that is loosely attached to the body, using four tags tightly attached to a belt on the waist, increases the localization accuracy by a factor of 4 (from around 20% to up to 88%) and reduces the average error by aproximately 40% (from around 7 meters to 4 meters).

In the light of new pervasive computing technologies such as body area networks (BAN), we hope that a systematic study of placement issues will help other researchers to achieve a high localization accuracy in their applications.

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