On Optimal Tag Placement for Indoor Localization

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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 a simple radio transmitter. 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 transmitter 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. Second, we describe how multiple transmitters can be used to overcome the absorption effects of the human body. Our results indicate that four transmitters provide a reasonable trade-off between accuracy and hardware cost. We validate our findings through an extensive set of measurements gathered in a home environment. Our tests indicate that by following the guidelines proposed in this paper, the localization accuracy can improve from around 20% up to 88%.**

I. 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 an inexpensive radio transceiver which can be easily integrated into a small, lightweight, wearable tag. 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 transmitters 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

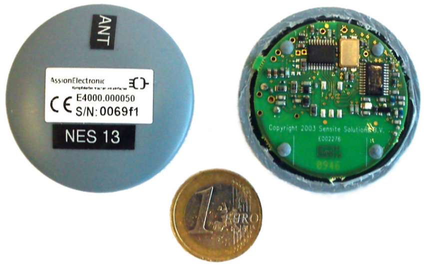


Figure 1. BN208 active RFID tags

- with four tags - two of them at the front and the other at the back.
- Following our guidelines improves the localization accuracy significantly. We performed extensive measurements in a home environment and found that accuracy improves by a factor of 4 compared to scenarios where single tags are placed carelessly.

II. Preliminaries

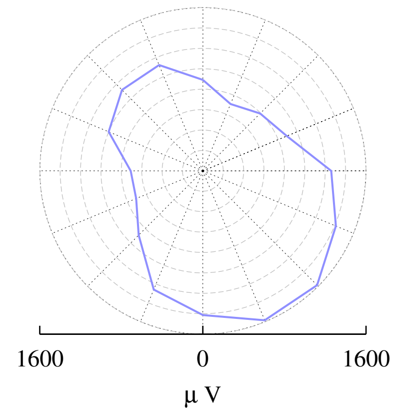
To put our work in context, we now present some preliminary information. First, we describe the hardware platform used in our experiments. Then, we provide an example that highlights the impact of signal variance on localization accuracy. Finally, we describe the methodology and metrics used in our study.

A. Hardware Platform

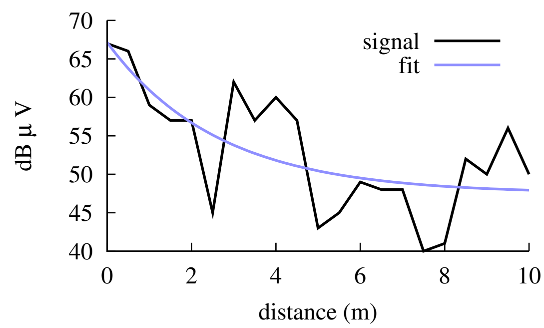
We use the LogiSphere RFID system from Sensite Solutions which operates at a frequency of 868 MHz. The system consists of readers (HBL100) and active tags (BN208). The reason for this choice is that the tags are small (Figure 1), lightweight (14 gr) and have a long lifetime. These characteristic make 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 every second. The tag has an accelerometer sensor which can detect (the lack of) movement, and hence, the tag can stop sending beacons 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.

B. 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.



(a) Antenna radiation pattern measured at 1m



(b) Signal strength vs. distance in an aisle

Figure 2. Signal strength variability example

Figure 2(a) depicts the radiation pattern of a tag, and Figure 2(b) depicts its signal strength at different distances in an aisle. As it has been reported for other hardware [14], the radiation pattern is highly anisotropic[1]. The pattern in Figure 2(a) was obtained for a distance of 1m, and we can observe that 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 2(b) 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.

[1] We measured the radiation pattern of 12 tags along their three different axis (X, Y and Z), and all the plots showed a highly anisotropic behavior.

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

C. 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.

Gathering 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.

Capturing Signal Variance. Following the proposal in [4], we use euclidean distances to capture the difference between two vectors in the feature space. Capturing this difference is important because it is a metric for the signal variance, which provides insights on the limitations of the localization system.

Measuring Accuracy. 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]. The accuracy of the system is measured as the percentage of testing samples whose classification correctly matches their location.

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(a). To capture the combined effects of placement and orientation, we perform both modifications simultaneously.

[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.

[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.

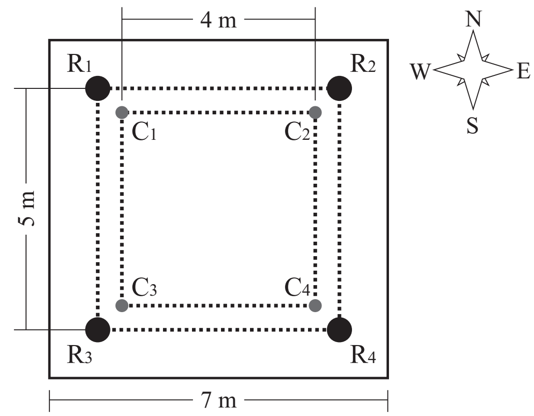


Figure 3. Laboratory layout with readers (R_i) and coordinates (C_i)

III. 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 (movement of people or objects), all experiments are conducted in a controlled setting. The next section evaluates our approach in a realistic scenario (a medium size apartment).

A. Laboratory Environment and Setup

The controlled experiments were performed in a room with the layout shown in Figure 3. We utilized four coordinates (C_i) located at the corners of a 4m×4m square. The readers (R_i) were positioned close to each corner.

Before conducting the experiments, we obtained the radiation pattern of each tag, 12 tags in total, in a similar way to Figure 2(a). 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 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

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

were controlled remotely (outside the room) to further minimize the dynamics.

B. 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 wood 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 3)
- **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.

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 II-C, 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 II-C, 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. This process is repeated for the four coordinates and 12 tags, which leads to 768 comparisons. Figure 4 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 II-C. 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 5 depicts the localization accuracy of this simple scenario. The accuracy is calculated using a nearest neighbor classifier. As explained in section II-C, we set $k = 1$ and we divide the Baseline training set into four smaller sets (each set with a 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×4 coordinates×12 tags) and, as explained earlier, each testing set is evaluated 4 times (once with each training subset). 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 5 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 calculated based on 64 unlabeled vectors (4 fingerprints×4 coordinates×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 wide misplacement performance is due to differences in the width of the main lobe. 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 orientation. On the other hand, the antenna direction with the weakest signal strength does not have a high variability among tags.

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

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 6 shows the distribution

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

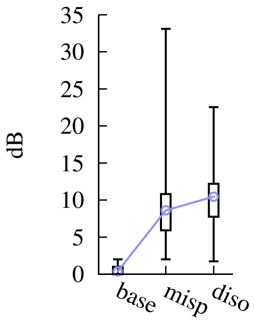


Figure 4. Signal strength variability (without human body)

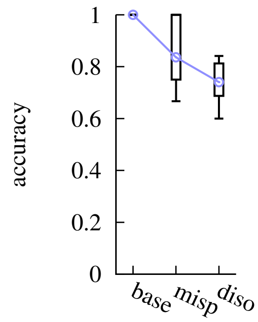


Figure 5. Impact on localization accuracy (without human body)

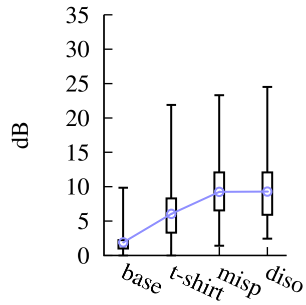


Figure 6. Signal strength variability (with human body)

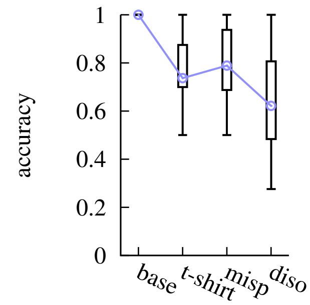


Figure 7. Impact on localization accuracy (with human body)

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 7 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.

C. *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 as depicted in Figure 3. 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 lobe of the tags is 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 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 8. We observed 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 6).

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 wide fingerprints of multiple tags, we attach 12 tags steadily to a belt in the waist line of a person (main lobe facing up). For the training and testing 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 $<$coordinate, location$>$ tuple. The overall and per-tag accuracy is calculated analogous to the previous experiments.

Figure 9 shows the resulting accuracy distribution of the different tag combinations. For example, the value 2 in the x-axis represent all the potential combinations of 2 tags (out of 12). This figure provides two important trends. First, more tags provides better accuracy, but it has diminishing returns.

[7]The human body consists of 65 percent of water which is well-known to have a high absorption. To mitigate this, [4] proposes to capture fingerprints at different orientations when creating a signal propagation map.

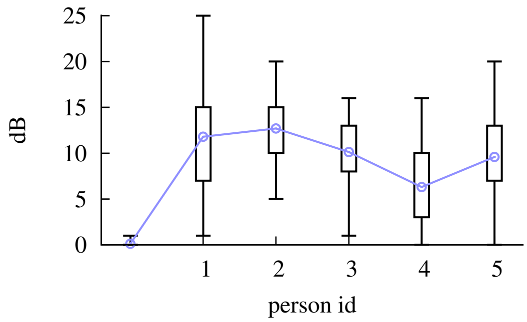


Figure 8. Absorption and signal strength variability of human body

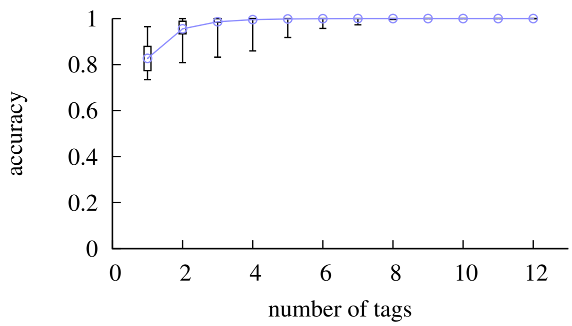


Figure 9. Localization accuracy of multiple tags on human body

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.

D. 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.**

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.

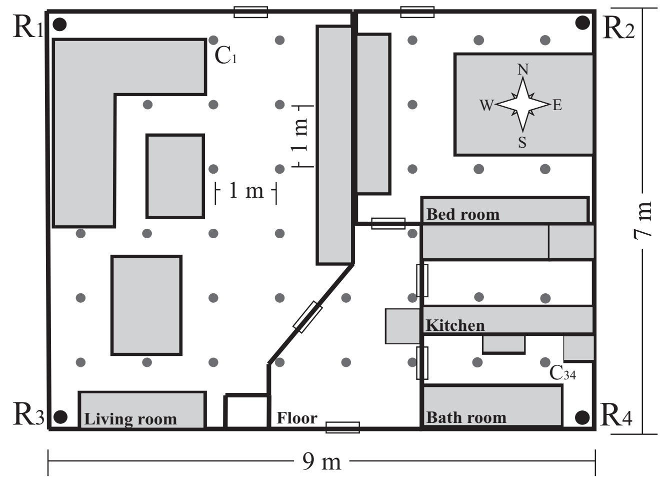


Figure 10. Apartment layout with readers (R_i) and coordinates (C_i)

Figure 11. Tag placement on t-shirt (loose) and with belts (tight)

IV. 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 shown in Figure 10. 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 10).

We equipped a person with 10 tags as shown in Figure 11. 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,

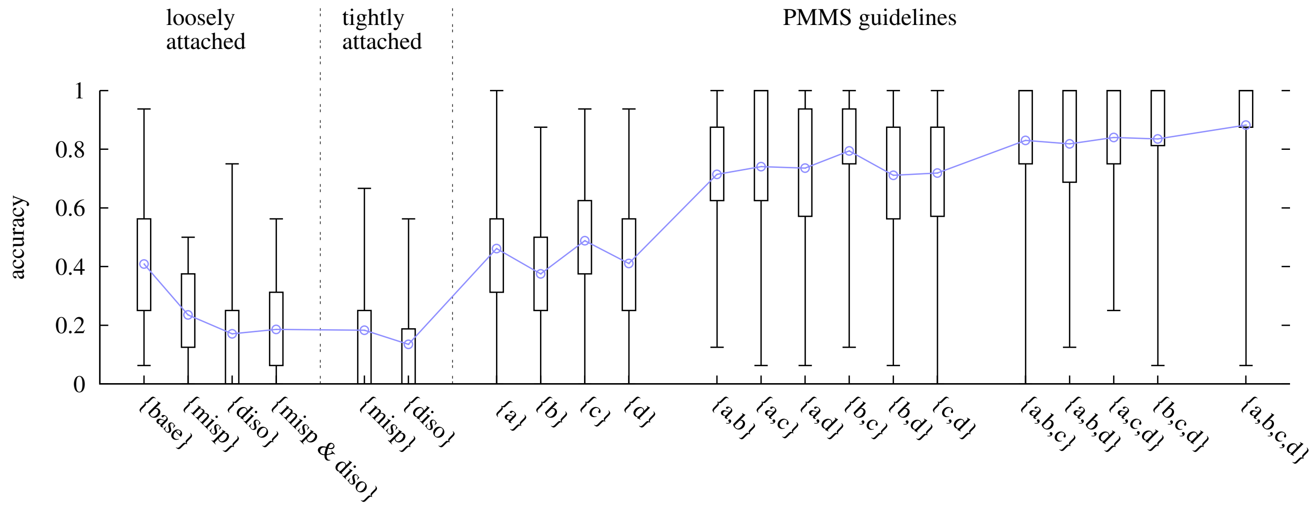


Figure 12. Localization accuracy evaluation when applying guidelines on four tags (a, b, c, d) in realistic scenario

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 of the system in two ways, in a per-location basis and in an overall basis. In the per-location evaluation, we measure the number of times that a particular coordinate was guessed correctly out of 16 attempts (2 training sets $\times$ 4 directions $\times$ 2 fingerprints). The overall accuracy reflects the fraction of correct guesses out of 544 attempts (272 fingerprints $\times$ 2 training sets).

The resulting accuracy distribution is shown in the candlestick plot in Figure 12. The plot shows the minimal and maximal accuracy for all coordinates, as well as, the interval between the 25th and the 75th percentile (box). The connecting line represents the overall accuracy. 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} seem to capture a lower bound behavior when compared to the loosely attached tags {misp},{diso},{misp+diso}. 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 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. Consider two sets of tags placed in a body: the first set contains {base},{misp},{diso},{misp+diso} and the second {a},{b},{c},{d}. In the first set, only the *base* tag provides an accuracy similar to the second set (which follows our method)[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 performance by up to 50%. Following our guidelines guarantees a fairly constant and good performance.

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. For a fine grain scenario like ours (1$\times$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). The figure shows that utilizing 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.

[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 11).

V. 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 let 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] and we combine this with [15] to filter 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 the 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. 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 improves the accuracy by a factor of 4.

VI. Conclusions

Motivated by the limitations of current RSS-fingerprinting techniques, we quantified three negative effects on localization accuracy resulting from placing tags on persons. Some of these effects have been reported in the literature. We build on top of the existing state of the art by analyzing them systematically in the context of indoor localization. Based on the analysis, we propose PMMS – three simple guidelines to effectively counter the effects. To minimize the signal variance caused by tag misplacement and disorientation, it is necessary to steadily attach tags to the torso. To overcome body effects, it is necessary to use wide fingerprints constructed from multiple tags. The validation of PMMS in a realistic scenario shows that following the guidelines can consistently improve localization accuracy. Using four tags tightly attached we achieve an improvement by a factor of 4 (from around 20% to up to 88%).

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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