Virtual Calibration for RSSI-based Indoor Localization with IEEE 802.15.4

Paolo Barsocchi[1], Stefano Lenzi[1], Stefano Chessa[1,2], Member, IEEE, Gaetano Giunta[1,3], Member IEEE
[1]ISTI-CNR, Pisa Research Area, Via G.Moruzzi 1, 56124 Pisa, Italy
[2]Computer Science Department, University of Pisa, Largo B. Pontecorvo 3, 56127 Pisa, Italy
[3]Department of Applied Electronics, University of Roma Tre, via Vasca Navale 84, 00146 Roma

Abstract— **Localization systems based on Received Signal Strength Indicator (RSSI) exploit fingerprinting (based on extensive signal strength measurements) to calibrate the system parameters. This procedure is very expensive in terms of time as it relies on human operators. In this paper we propose a virtual calibration procedure which only exploits the measurements of the RSSI between pairs of anchors. In particular we propose two heuristics for virtual calibration and we evaluate their performance with respect to an ad-hoc calibration campaign by performing measures in an indoor environment with an IEEE 802.15.4 sensor network.**

I. INTRODUCTION

Localization is an important building block of context-aware system as witnessed in [1]. The general solution based on Global Positioning System (GPS) is unfortunately available only in outdoor environments. In indoor environment a viable solution to localization of users exploits wireless sensor networks [2]. Sensor network-based solutions estimate the (unknown) location of mobile sensors (placed on the users) with respect to a set of fixed sensor (called anchors), whose position is known, by estimating the distances between the mobile node and a set of anchors. Once these distances are known a standard multilateration technique or other methods [3] can be used to determine the mobiles position. This means that the localization problem reduces to the determination of the distances between arbitrary pairs of sensor nodes. A simple and widely used way to estimate distances is based on RSSI [4-6] that does not require complex hardware. In [4] the authors suggest that algorithms that estimate distances between two wireless devices based on their reciprocal RSSI are unable to capture the myriad of effects on signal propagation in an indoor environment. Nevertheless, because of RSSI does not require a special or a sophisticated hardware, but rather it has become a standard feature in most wireless devices, RSSI-based localization techniques have received considerable research interest. As a matter of fact, in [5] the authors have shown that despite the reputation of RSSI as a coarse method to estimate range, it can achieve an accuracy of about 1.5m RMS in a test bed experiment. Fading outliers can still impair the RSSI relative location system, implying the need for a robust estimator. A method to improve the quality of localization exploiting a number of RSSI measurements averaged in a time window to counteract interference and fading has been proposed in [6]. Moreover, RSSI has been used in the RADAR [7] and in the Cricket [8] systems that can achieve a location granularity of 1.2 meters x 1.2meters.

The distance estimation techniques exploiting RSSI rely on a radio propagation model. In indoor environment these models also take into account parameters such as the wall attenuation factor (WAF) and floor attenuation factors (FAF) to model the effect of walls and floors on the radio waves. Unfortunately, RSSI is environment dependent, moreover in indoor environments, the wireless channel is very noisy and the radio frequency signal can suffer from reflection, diffraction and multipath effect, which makes the signal strength a complex function of distance. To overcome these problems, wireless location systems uses *a priori* calibration of the propagation model (called *fingerprinting*). This calibration works in two phases: the training phase and the estimation phase. In the training phase it is measured the RSSI at a grid of points in the area of interest, and in the estimation phase this information is used to estimate the propagation model parameters. Clearly, the accuracy of the calibration procedure depends on the number of points in the grid and to the number of measures taken per point. This procedure is very expensive in terms of time as it requires human intervention, which is a practical barrier to its wider adoption.

In this paper we use the same propagation model proposed in [3] which we assume to be valid, and we consider a virtual calibration procedure which only exploits the measures of the RSSI between pairs of anchors. In particular we propose two heuristics for virtual calibration and we evaluate their performance with respect to an ad-hoc calibration campaign by performing measures in an indoor environment with an IEEE 802.15.4 sensor network. We show that the performance of virtual calibration in terms of accuracy of the estimated distances is close to that achievable with more expensive, ad-hoc calibration procedures, and it is thus a viable alternative to simplify the calibration of a localization system.

II. THE WIRELESS SYSTEM MODEL

In this paper we assume a localization system comprising a set of *anchors* $A = \{a_1, a_2 \dots a_n\}$, a set of *mobile nodes* $M = \{m_1, m_2 \dots m_p\}$ and a *localization server L*. The anchors have well known position on the map, identified by the pair (x_i, y_i). Each anchor periodically emits a beacon packet containing its identifier. The mobile nodes are those which need to be localized by the system. To this purpose a mobile node receives the beacons from the anchors, for each beacon computes the corresponding RSSI, and sends to the localization server the pair *<RSSI, anchor id>*. The

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localization server accumulates all the pairs of each mobile node and estimates the position of the mobiles exploiting a suitable propagation model.

The propagation model is used to calculate the expected RSSI map of the building. The RSSI map is evaluated only for a grid of points. For each point of the grid with coordinates (x, y), the map provides an n-dimensional vector $S(x,y) \in \Re^n$ defined as $S(x,y) = \{s_1, s_2 \dots s_n\}$ where s_i is the expected RSSI value from anchor a_i. Figure 1 shows an example of deployment of the anchors in a building.

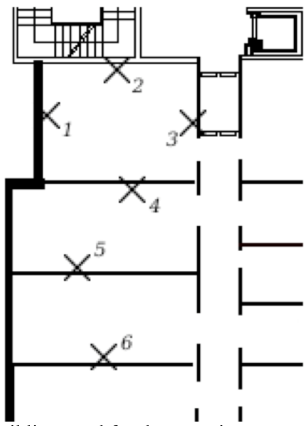

Fig. 1. Map of the building used for the experiments.

III. INDOOR PROPAGATION MODEL FOR IEEE 802.15.4

The large-scale path loss model considered in this paper is summarized in this Section. Most researchers model the indoor path loss with the one-slope model [5], which assumes a linear dependence between the path loss (dB) and the logarithm of the distance d between the transmitter and the receiver:

$$L(d)\big|_{db} = l_0 + 10\alpha \log_{10}(d) \tag{1}$$

where l_0 is the path loss at a reference distance of 1 meter (thought the paper we express distances in meters) and α is the power decay index (also called path loss exponent). A generalization of the one-slope model is the two-slope model suggested by [9] to approximate the two-ray propagation model.

The two-slope model is characterized by a *break point* that separates the various properties of propagation in near and far regions relative to the transmitter. In fact, the path loss exponent changes when the distance d is greater than the *break point*. In particular, the authors in [9] describe the existence of a transition region where the *break point b* is such that:

$$\frac{\pi h_t h_r}{\lambda} < b < \frac{4\pi h_t h_r}{\lambda} \tag{2}$$

where h_t is the transmitter antenna height, h_r is the receiver antenna height, and λ is the wavelength of the radio signal. However, in a typical sensor network scenario, the break point distance is hundreds of meters, therefore in practice the one-slope and the two-slope models are equivalent in indoor scenarios where the rooms are only a few square meters in size. Although the one-slope model is simple to use, it does not adequately account for the propagation characteristics in indoor environments. In fact, a further generalization of the one-slope model consists in adding an attenuation term due to losses introduced by walls and floors penetrated by the direct path:

$$L(d)\big|_{db} = l_0 + 10\alpha \log_{10}(d) + WAF + FAF \tag{3}$$

where FAF is the floor attenuation factor and WAF is the wall attenuation factor expressed as:

$$WAF = \sum_{i=1}^{N} k_i l_i \tag{4}$$

where k_i is the number of penetrated walls of type i, and l_i is the attenuation due to the wall of type i. Since the sensor devices were located on the same floor, the attenuation term due to the propagation among different floors was not included in (3).

A similar model was proposed in [3]. In their model they introduce a multi-wall component. This factor also includes the number of normal and fireproof doors and their status (open/closed) met by the direct paths.

We observe that these parameters are important for the IEEE 802.11 based localization, due to the lower density of the Access Points (the anchors of the system) deployed in the indoor environment. This result in a cumbersome system to handle for the end-user, since the status of the doors needs to be frequently updated. In our case we deal with a high anchor density and the anchors have a reduced radio communication range, thus the number of doors affecting direct paths is very low. For this reason we neglect the door status and we use a simplified model.

IV. CALIBRATION PROCEDURES

The objective of the calibration is to adapt the theoretical propagation model to the environment where it is actually used. Due to the dynamics of the channel, which essentially capture the spatial-temporal variations of wireless fading events, an automatic calibration procedure increases the performance of the localization systems. Virtual calibration procedure achieves this goal without human intervention, by exploiting only information obtained from the anchors. In particular, the anchors preliminary exchange beacons to compute reciprocal RSSI and the localization server uses this information to configure the parameters of the theoretical propagation model.

The parameters of the propagation model (3) are: l_0 (the path loss at distance of 1 meter), α (the air attenuation factor), and l_i (the attenuation factor for the wall of type i). Since l_0 should be estimated in a free space and it is not affected by the environment, it only depends on physical properties of the devices hardware and it can be estimated *a priori*, thus it is not object of virtual calibration.

To calibrate parameters α and l_i we propose two heuristics: *global virtual calibration* (*G-procedure*) and *per-wall virtual calibration* (*W-procedure*) comparing these with an *ad-hoc calibration* (*H-procedure*). G-procedure assigns the same parameters for every wall, based on all RSSI measures obtained from any pair of anchors. Instead, W-procedure provides an attenuation factor for the walls that directly affect the communication between specific pairs of anchors, and it uses G-procedure for all the other walls. The H-procedure, which has been used in many previous works [5, 10], exploits

TABLE I
PARAMETERS AND PERFORMANCE COMPARISON AMONG PROCEDURES

	G-procedure	W-procedure	H-procedure
α	1.45	1.45	1.46
l_1	-8.96	-8.33	-8.21
l_2	-8.96	-7.30	-6.40

the RSSI measurements on a grid of points in the environment to estimate the propagation model parameters.

Hereafter we use the following notation:

- $C = \{(a_i, a_j) \in A : a_i$ and a_j can communicate directly$\}$
- $R_i = \{a_{j1}, a_{j2}, \ldots, a_{jn}\}$ is the set containing the id of all anchors in the same room, hence $\forall(a, b) \in R_i : a \neq b$ the communication between a and b is *"wall-free"*;
- W_n is the set of all pairs (a_i, a_j) such that the communication channel between a_i and a_j crosses exactly n wall(s);

A. Global virtual calibration

The G-procedure considers a single virtual type of wall. This leads (3) to:

$$L(d)\big|_{db} = l_0 + 10\alpha \log_{10}(d) + kl_w \tag{5}$$

where k identifies the number of wall crossed by the signal and l_w is the attenuation introduced by the wall on the signal. During the virtual calibration phase we can estimate all the required parameters (l_0, α, l_w).

Substituting $d_{(i,j)}$ as actual distance between anchors a_i and a_j, and $k_{(i,j)}$ as the number of wall crossed by the direct path between anchors a_i and a_j in (5), we want to obtain an estimation $RSSI'_{(i,j)}$ of actual RSSI:

$$\begin{gathered} RSSI'_{(i,j)} = l_0 - 10\alpha \log_{10}\left(d_{(i,j)}\right) + k_{(i,j)} l_w \\ \forall i, j : \left(a_i, a_j\right) \in C \end{gathered} \tag{6}$$

The estimated $RSSI'_{(i,j)}$ differs from the measured $RSSI_{(i,j)}$ by an error component $\varepsilon_{(i,j)}$. We assume that all $\varepsilon_{(i,j)}$ are identically distributed and uncorrelated among themselves. Recalling that l_0 is estimate *a priori* (see Section IV), and according to [11], the approximation of the remaining parameters (α,l_w) that minimizes the least mean square error $\|RSSI - RSSI'\|_2$ can be achieved by direct method. The computation cost for direct method solving a linear least mean square estimator problem is polynomial [11].

B. Per-wall virtual calibration

With this technique we estimate an individual attenuation factor for each wall between any pair of anchors belonging to C. Let us assume there are q different types of wall in the map of the building and let $F = \{f_1, f_2 \ldots f_q\}$ the set of attenuation factors for each type of wall. Thus the equation (6) building the linear system becomes:

$$\begin{gathered} RSSI'_{(i,j)} = l_0 - 10\alpha \log_{10}\left(d_{(i,j)}\right) + \sum_{h=1}^{q} k_{h(i,j)} f_h \\ \forall i, j : \left(a_i, a_j\right) \in C \end{gathered} \tag{7}$$

where $k_{h(i,j)}$ is the wall number of type h crossed by signal considering the direct path anchors a_i and a_j in (5). The path loss exponent α used in this equation is previously evaluated with the G-procedure. Instead the evaluation of parameters $f_i \in F$ is achieved with the same methodology used in Subsection A, by means of the least mean square estimator.

V. SIMULATION AND RESULTS

As observed in [3] the measured RSSI is function of the path loss and of the wall attenuation factor, which can be estimated with the above calibration technique. Furthermore, transmit powers will vary as batteries become depleted. This implies that the parameters change during the sensors' lifetime.

In this section we present the results of a measurement campaign aimed at comparing the performance of the three heuristics proposed in the previous section.

We performed a two phases of measurements, each aimed at (1) performing the calibration of the propagation model using the three different procedure, namely: H-procedure, G-procedure, and W-procedure, and (2) measuring the RSSI on a grid of points in the environment, to compare the localization error performance of the procedures.

We use the H-procedure as reference technique, and we evaluate the performance of the two virtual calibration techniques in terms of the following formula:

$$\phi_G = \left\| stdclb(RSSI) - slfclb_G(RSSI) \right\|_2 \tag{8}$$

$$\phi_W = \left\| stdclb(RSSI) - slfclb_W(RSSI) \right\|_2 \tag{9}$$

Where *stdclb* is the function computing the distance based on the propagation model calibrated with H-procedure, $slfclb_G$ provides the distance by means of the propagation model calibrated with G-procedure and $slfclb_W$ provides the distance by means of the propagation model calibrated with W-procedure.

In order to gather a better view of the comparison we studied the Probability Density Function (PDF) of ϕ_G and ϕ_W the errors. Based on the set of all the RSSI measured between the communications from anchors to mobile, produced during the second phase of the measuring campaign, we estimated the PDF error as the frequency of the error affecting the estimated distance. In the next subsection we present the setup of our experiment and the results of the comparison between our techniques.

A. Experimental setup

We performed the experiments in our laboratory. It is a typical office environment with an area of approximately $7m$ by $11m$. It has desks, chairs, cabinets, computers, monitors, etc. This environment is harsh for wireless communication due to multi-path reflections from walls and the possibility of interference from electronic devices. Figure 1 shows the layout of the laboratory and the deployment of the anchors in the rooms.

For the experiments we used a Sensor Network of 7 MicaZ [12] which uses the Chipcom CC2420 radio subsystem implementing the IEEE 802.15.4 standard. The experiments consist in a set of measures between a pair of anchors or between an anchor and a point of the grid (in case of ad-hoc calibration). Each measure collects 300 RSSIs, where every RSSI is averaged over a set of 100 samples. Each sample is obtained exchanging a beacon packet between two sensors every 1/32 second, using the highest transmission power of the MicaZ.

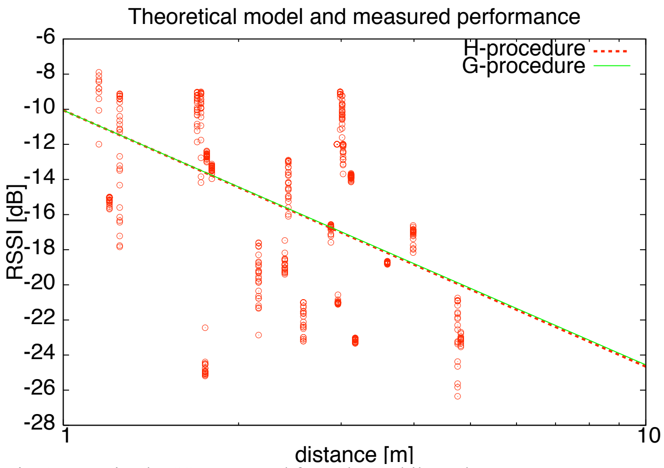

Fig. 2. Received RSSI measured from the mobile node.

As mentioned in Section IV the l_0 parameter can be estimated *a priori* as the path loss at a reference distance. To this purpose we preliminary evaluated l_0 measuring the RSSI between two anchors deployed at 1 meter distance, obtaining $l_0 = -10.06$.

We preliminary executed the H-procedure to obtain the reference parameters of the propagation model to be used for the comparison with G-procedure and W-procedure techniques. In particular we estimated $\alpha = 1.46$, $l_1 = -8.21$dB, $l_2 = -6.4$dB. The parameters obtained with all the calibration methods are shown in Table I.

During our experiments we observed the typical features of radio channels [13]: *Asymmetrical links* (the connectivity from node A to node B might be different than that from node B to node A), *Non-isotropic connectivity* (the connectivity is not necessarily the same in all the directions from the source), and *Non-monotonic distance decay* (nodes that are far away from the source may have better connectivity than nodes that are closer). Note that non-monotonic distance decay is the main cause of localization error.

B. Global virtual calibration performance

With Global virtual calibration (G-procedure) the estimated parameters are $\alpha = 1.45$ and $l_1 = l_2 = l_w = -8.96$dB. Figure 2 shows the results obtained in a single room, without the attenuation introduced by the walls ($WAF = 0$). In particular, Figure 2 shows the received power measured from the mobile. The dotted line is the H-procedure, and the solid line is G-procedure. As we can see from the figure, the two lines are practically overlapped due to the optimal fit of both lines, with the real path loss exponent. Consequently, the error of G-procedure with respect to the H-procedure ϕ_G is negligible.

Figure 3 shows the PDF of ϕ_G for measures obtained in the whole environment ($WAF \neq 0$). In this case the error is less then 1.5m in the 90% of the cases. This result is due to the fact that the attenuation factor of both walls has been forced to be the same.

Consider that, from the measures in our environment, the H-procedure is affected by an error of about 1.5m. Thus, the error of 1.5m of the G-procedure with respect to the H-procedure can be considered acceptable since it fits the highest precision achievable in our environment.

TABLE II
CDF OF THE ERRORS

Error [m]	CDF of ϕ_G	CDF of ϕ_W
0.25	0.604	0.896
0.5	0.732	0.919
1	0.868	0.973
1.5	0.901	0.984

C. Per-wall virtual calibration performance

With W-procedure the estimated parameters are $\alpha = 1.45$, $l_1 = -8.33$dB, and $l_2 = -7.3$dB. The main difficulty for this calibration method is due to the different number of sample used to estimate the single wall attenuation. In our case we have 5 anchors to estimate the first wall and other 3 anchors for the second one. Therefore, in order to resolve the Equation (7) with the least mean square estimator, we weigh the WAF parameters with a number directly proportional to the number of established links between pairs of anchors and inversely proportional to the number of anchors.

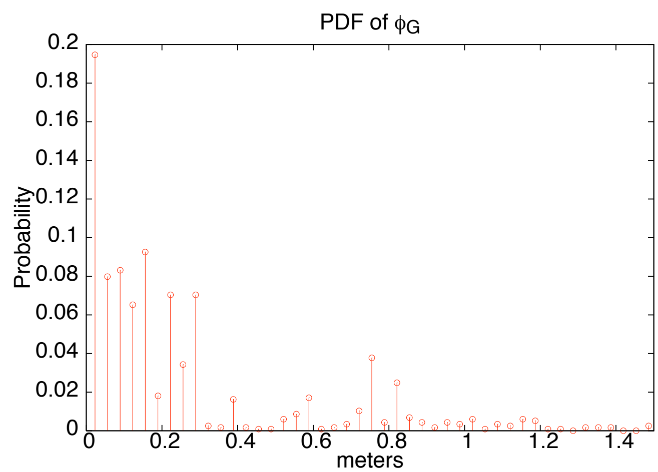

Fig. 3. PDF of ϕ_G considering all the measured data.

Figure 4 shows the PDF of ϕ_W. It is seen that virtual calibration of individual walls improves the performance of virtual calibration; in particular comparing the W-procedure with the H-procedure we observed an error less than 1.5m in the 98% of the cases. This is a significant improvement over G-procedure. Table II summarize the results obtained showing the Cumulative Distribution Function (CDF) of ϕ_G and ϕ_W. This table highlight that the W-procedure increase the performance with respect to the G-procedure. Not surprisingly, the W-procedure outperforms the G-procedure, due to the better accuracy in the walls modeling.

To measure the performance of the two virtual calibration procedure (G-procedure and W-procedure) with respect to the H-procedure we evaluated the localization error. The metric chosen to measure the performance considers the localization error between our novel calibration procedure and the conventional H-procedure with a fixed localization algorithm.

The localization algorithm selected is based on the RF map of the area. The RF map is a database containing the estimated receiver power from each anchors for each point (x, y) positioned over a regular grid. The RF map covers the entire area and it has been generated using the estimated parameters for each virtual calibration procedure. The RSSIs measured by

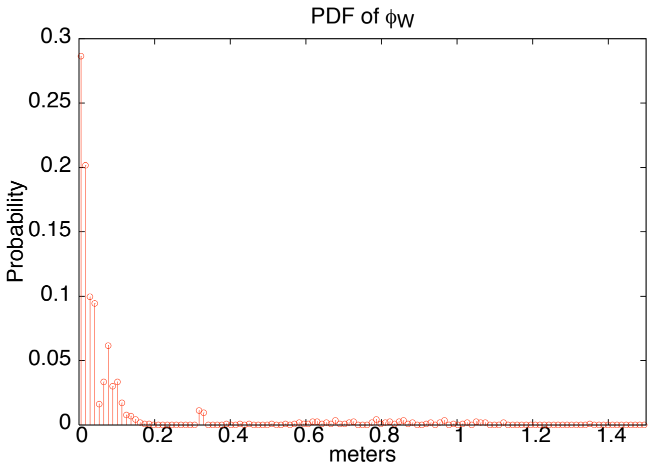

Fig. 4. PDF of ϕ_W considering all the measured data.

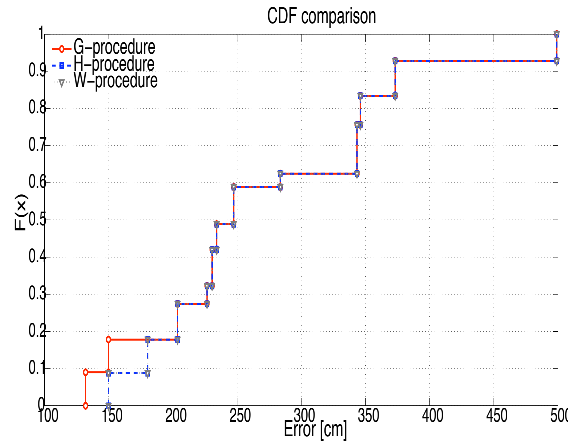

Fig. 5. Localization error using the Euclidean metric with the H, G, and W-procedures.

the mobile (received by the anchors) is compared to the data stored in an RF map of the area to discriminate the position of the mobile.

Indicating with $\mathbf{w} = (w_1, w_2 \ldots w_n)$ the vector of the measured power, it is compared to the stored power vectors $\mathbf{W}(i,j) = (W(i,j)1, W(i,j)2 \ldots W(i,j)n)$, for each (i,j) contained in the RF map. The vector $\mathbf{W}(i,j)$ contains the estimated powers we aspect to received (in respect to the signal propagation model chosen) on the (x_i, y_j) point from the anchors.

The point on the RF map resulting in the minimum distance from $\mathbf{w}$ is selected as the position of the mobile. From the work in [7], the Euclidean metric gives better results with respect to the other methods. Considering that the mobile is positioned in the (x_i, y_j) point of the RF map, the definition of our localization results in $(i,j)=\arg\{\min_{(h,k)\in N\mathrm{x}M} \| w - W_{(h,k)} \|^2\}$, where N is the set $\{1,2 \ldots n\}$ with n the number of rows, and M is the set $\{1,2 \ldots m\}$ with m the number of columns.

Figure 5 shows the Cumulative Distribution Function obtained by using the above mentioned localization algorithm for each calibration procedure.

Other localization algorithms based on RF map can be used to localize the mobile node. We fixed a simple localization algorithm to demonstrate that our virtual calibration procedure performs mostly like other ad-hoc calibration procedures which requires a measurement campaigns that are time consuming and in general expensive.

As depicted in Figure 5 the G-procedure performs like the commonly used H-procedure, in terms of localization error. In fact, it is worth to note that, the CFD of the W-procedure is identical to the H-procedure one, thus it is mostly hidden in the graph. This means that virtual calibration procedure results in the same localization error like the expensive ad-hoc calibration procedure.

VI. Conclusions

We proposed a virtual calibration procedure for localization that only exploits RSSI measurements between pairs of anchors. In particular, we propose two heuristics for virtual calibration and evaluate their performance with respect to fingerprinting in indoor environments with IEEE 802.15.4 sensor network. We showed that the performance of virtual calibration, in terms of accuracy of the estimated distances, is close to that achievable with more expensive fingerprinting. The proposed method is thus a viable alternative to simplify the calibration of a localization system.

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