RESEARCH ARTICLE

Automatic virtual calibration of range-based indoor localization systems

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ABSTRACT

The localization methods based on received signal strength indicator (RSSI) link the RSSI values to the position of the mobile to be located. In the RSSI localization techniques based on propagation models, the accuracy depends on the tuning of the propagation models parameters. In indoor wireless networks, the propagation conditions are hardly predictable due to the dynamic nature of the RSSI, and consequently the parameters of the propagation model may change. In this paper, we present an automatic virtual calibration method of the propagation model that does not require human intervention; therefore, can be periodically performed, following the wireless channel conditions. We also propose a novel RSSI-based localization algorithm that selects the RSSI values according to their strength, and uses a calibrated propagation model to transform these values into distances, in order to estimate the position of the mobile. Copyright © 2011 John Wiley & Sons, Ltd.

KEYWORDS

indoor localization; wireless sensor network; calibration parameters; indoor propagation model

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1. INTRODUCTION

Localization of devices and people has been recognized as one of the main building block of context aware systems [1–4], which have one of their main application field in ambient assisted living (AAL) applications. In indoor AAL applications, localization by means of the global positioning system is not feasible and it is solved by means of ad hoc solutions, among which one of the most promising is based on wireless sensor networks (WSN) [5]. WSN-based solutions estimate the (unknown) location of the mobile sensors (hereafter also called mobiles) with respect to a set of fixed sensors (called anchors), whose position is known. The position estimation of a mobile can be achieved by using two different approaches, either range-based or range-free. The former is defined by protocols that use absolute point-to-point distance estimates for calculating the location. The latter makes no assumption about the availability or validity of such an information. The effectiveness of these two localization approaches depends on the precision required by the applications that use the location information. Acknowledging that the range-free solutions have a coarse accuracy [6], these techniques are unsuitable in applications where the location precision is one of the main requirements. On the other hand, range-based localization exploits measurements of physical quantities related to beacon packets exchanged between the mobile and the anchors. Radio signal measurements are typically the received signal strength indicator (RSSI), the angle of arrival (AOA), the time of arrival (TOA), and the time difference of arrival (TDOA). Although AOA or TDOA can guarantee an high localization precision, they require a specific and complex hardware. This is a major drawback in particular in AAL applications, which are deeply involved with users’ monitoring and thus may suffer from complex and too invasive hardware. In this work we consider localization based on RSSI, since it does not require any special hardware and it is available in most of the standard wireless devices. Furthermore, the use of RSSI has not a significant impact on local power consumption, sensor size, and cost, and for this reason it has received considerable interest in the recent literature [7–18]. The main range-based indoor localization approaches are based on fingerprint and on signal propagation models. In both cases a mobile sensor is localized by means of a set of anchors that exchange beacon packets with the mobile in order to collect sequences of RSSIs. In particular, at a given instant of time, the system computes a tuple of RSSIs (one RSSI value obtained from each anchor),
The goal of the proposed virtual approach is to save human time developing an automatic calibration procedure. which is used to estimate the position of the mobile sensor at that time. The fingerprint schemes, also referred to as pattern matching, require a preliminary system calibration procedure (called off-line phase [11–15]). This phase is executed after the deployment of the anchors, and it consists in performing a set of RSSI measurements at a grid of points in the environment. These points correspond to possible locations of the mobile sensors that should be localized. For each point a tuple of RSSIs is produced, which is stored in a database. During the localization procedure (called online phase), every time a new RSSI tuple associated to a mobile is produced, the localization system compares such a tuple with the tuples stored in the database to find the most likely position of the mobile. Clearly, with fingerprinting there is a trade-off between the number of points in the grid (the larger this number, the more accurate the localization is) and the overhead due to the off-line phase. In practice, the main drawback of this method is the high number of extensive and accurate measurements required during the off-line phase to create the database. In fact, the creation of the database is not automatic: it is a human-based, time-consuming procedure and this is a practical barrier to its wider adoption, making it unsuitable for rapid or ad hoc deployment. For these reasons, methods alternative to fingerprint make use of signal propagation models, which are analytical models that relate RSSI measures with distances [16–19]. However, being the RSSI environment-dependent (the radio frequency signal suffers from reflection, diffraction, and multipath effects that make the signal strength rather noisy), such localization systems perform a preliminary calibration of the propagation model parameters. The calibration procedure works in two phases: the training phase and the estimation phase. In the training phase, a set of RSSIs are measured at a grid of points in the area of interest; in the estimation phase, this information is used to estimate the propagation model parameters. The relationship between RSSI and the reciprocal distance between anchors and mobile is then established by means of the calibrated propagation model. Once a number of distances estimate between the mobile and the anchors are available, the mobile position is evaluated by using a multilateration technique. As for the fingerprinting techniques, the localization based on the signal propagation model is expensive in terms of calibration time, since the calibration is not automatic. Moreover, the described calibration technique does not solve the time-dependent problem, since wireless channel variations affect the propagation model parameters, and this fact can significantly impact on the quality of the localization system. For these reasons, as highlighted in Figure 1, we propose an automatic calibration procedure (called virtual calibration) of the signal propagation model that is only based on the RSSIs measured among the anchors and that can be executed periodically and automatically (i.e., without human intervention). Based on the virtual calibration
procedure, we propose a localization algorithm that selects the anchors with higher signal strength, and it exploits the calibrated propagation model to relate RSSI measures with distances. Finally, in order to provide the mobile position, the algorithm uses a trilateration method.

The remainder of this paper is organized as follows: Section 2 recalls the main range-based indoor localization approaches, Section 3 describes the indoor propagation model used by the localization algorithm, Section 4 performs a channel analysis in order to improve the localization system; details of the localization algorithm are explained in Section 5, while Section 6 shows the experimental results. Finally, conclusions and future work are offered in Section 7.

2. RELATED WORK

The estimation of link distance on unknown indoor environments has been a topic of research in recent years since it is a foundation for many different applications. As a result, many studies have explored new algorithms that exploit the RSSIs collected in ad hoc measurement campaigns to calibrate the localization system. In particular, authors in [12] evaluate the performance of their localization system based on fingerprinting technique, deploying 20 anchors in about 1700 m². They show that their system can reach the 50th and 80th percentile of the localization error with 0.9 and 1.6 m, respectively. Another work based on fingerprinting is the COMPASS system [13] that exploits the user orientation to improve the quality of the localization information. The major drawback of these two works is that they both need a database of RSSIs, whose creation requires an extensive and accurate measurement campaign.

In [19] the authors use an idealized propagation model and propose a simple connectivity-based localization method for both outdoor and indoor environments. RADAR [16] exploits the existing wireless LAN (rather than an ad hoc installation of sensors) and achieves an accuracy of about 4 m with about 50% probability. The online person tracking (OPT) system [17] (designed to provide location information to context-aware applications based on WSN) achieves an accuracy that varies from 1.5 to 3.8 m by using a trilateration technique combined with a weighted minimum mean square error (W-MMSE) localization algorithm. A similar triangulation approach is also used in [20], which first constructs the set of circles centered in the anchors with radius equal to the distances between the anchors and the mobile. Then, it computes the points of intersection among such circles, it finds all possible triangles that have the intersection points as vertices, and, finally, it estimates the mobile position as the centroid of the smaller triangle.

In our work we use a similar algorithm based on triangulation and intersection points, but, as we will explain later (and differently than in [20]), we estimate the mobile position as the centroid of all the intersection points selected from the three anchors with greatest RSSI. In any case, the main drawback of all these methods is the calibration of the propagation model, which is executed off-line and requires an extensive RSSI measurement campaign. Furthermore, changes in the environment may invalidate the calibration executed in the off-line phase [20,21]. In [22] the authors exploit the estimated distance between the anchors and the mobile to evaluate and update the propagation model parameters. This automatic calibration technique estimates the right model parameter only if the estimated mobile position is the real one. In fact, when a localization error occurs, it also results in an error of the propagation model parameters. Differently than all these approaches, in this work we exploit the RSSI exchanged among the anchors to estimate the propagation model parameters. This enables a completely automatic calibration procedure (i.e., it does not require human intervention) that can be repeated at any environmental condition change.

3. INDOOR PROPAGATION MODEL FOR IEEE802.15.4

Most researchers model the indoor path loss with the one-slope model [8], which assumes a linear dependence between the path loss (dB) and the logarithm of the distance \( d \) between the transmitter and the receiver:

\[
L(d)_{dB} = l_0 + 10\alpha \log_{10}(d)
\]

where \( l_0 \) is the path loss at a reference distance of 1 m and \( \alpha \) is the power decay index (also called path loss exponent). A generalization of the one-slope model is the two-slope model suggested by [23] 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, authors in [23] describe the existence of a transition region where the break point \( b \) is such that:

\[
\frac{\pi h_t h_r}{\lambda} < b < \frac{4\pi h_t h_r}{\lambda}
\]

where \( h_t \) is the transmitter antenna height, \( h_r \) the receiver antenna height, and \( \lambda \) is the wavelength of the radio signal. However, in a typical sensor network scenario, the break point distance is in order of hundreds of meters; therefore, in practice, the one-slope and the two-slope models are equivalent in indoor scenarios where the rooms only are 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:

\[
L(d)_{dB} = l_0 + 10\alpha \log_{10}(d) + \text{WAF} + \text{FAF}
\]
Automatic calibration of indoor localization

P. Barsocchi et al.

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

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

(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 $i$. Without loss in generality, in this paper we assume that sensors are all located on the same floor; hence, the attenuation term due to the propagation among different floors is not included in Equation 3. A similar model was proposed in [24], where a multi-wall component is introduced, which 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 low density of the WiFi access points (that act as 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 an high anchor density; 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. The received power RSSI is obtained as the difference between the transmitted power $P_t$ and $L(d)$, i.e.,

$$\text{RSSI} = P_t - L(d)_{\text{dB}} = P_t - l_0 - 10\alpha \log_{10}(d) - \sum_{i=1}^{N} k_i l_i.$$  

(5)

Letting $r_0 = P_t - l_0$ be the RSSI at the reference distance of 1 m, Equation 5 can be expressed as:

$$\text{RSSI} = r_0 - 10\alpha \log_{10}(d) - \sum_{i=1}^{N} k_i l_i.$$  

(6)

Equation 6 will be used during the calibration procedure to estimate the propagation model parameters ($r_0$, $\alpha$, $l_i$). Our calibration procedure is independent of the propagation model. In fact, we show that we are able to estimate the parameters of the chosen propagation model by exploiting the communications among anchors, without performing a preliminary measurement campaign. In order to verify this method we have chosen a propagation model widely accepted in the literature; however, our solution can be adopted even selecting a different propagation model.

4. CHANNEL ANALYSIS

The wireless channel is affected by multipath fading that causes fluctuations in the receiver signals amplitude and phase. The sum of the signals can be constructive or destruc-

tive. This phenomenon, together with the shadowing effect, may strongly limit the performance of wireless communication systems and makes the RSSI values unstable. For this reason, we first address the inherent impairments of an indoor environment that prevents a localization system from being accurate; then we propose a methodology for mitigating such impairments (Section 5). In other words, our aim in this section, is to answer the question: what is essential to know about a wireless channel from a localization point of view? Specifically, we investigate the impact of the RSSI channel variations on the localization performance in WSN. The RSSI values used for this analysis have been collected during a whole working day from a set of six anchors (IRIS [25] equipped with AT86RF230 radio) and a mobile deployed in a common office room. The anchors emit 16 beacons per second and the mobile sensor, that is placed in a fixed position in the room, receives the beacons and measures the RSSI values. The experiment was conducted in about 11 h during which we collected about 6 55 000 RSSI samples.

Figure 2 shows the box-and-whisker diagram of the RSSIs that depicts, for the different distances between the anchors and the mobile, five statistics are depicted: the smallest observed value, the lower quantile (0.05), the median, the upper quantile (0.95), and the largest observed value. As we can observe from Figure 2, the RSSI dynamically changes during the day of about 3 dB depending on the distance between sensors. Therefore, fixing static propagation parameters is, in general, not sufficient in order to take into account the RSSI time-variations, whereas an automatic (and periodic) calibration procedure can follow the wireless channel variations. Figure 2 also shows that when distances are greater than about 2 m, the RSSI variations increase up to 6 dB with respect to the median, hence the RSSI fluctuations are also dependent on the distance (they are larger with larger distances). This suggests that the highest measured values of RSSI are, in general, more reliable,
and this fact can be taken into account in the localization algorithm to improve its accuracy.

In order to further investigate this aspect, we evaluate the localization error produced by a localization system based on the signal propagation model. The propagation model parameters used in this study are estimated by using a preliminary calibration procedure. Figure 3 shows the error between the actual and the estimated distance between the mobile and the anchors. The estimated distance is computed leveraging the RSSI and the calibrated propagation model. From Figure 3 we observe that higher RSSI values produce small errors in the estimated distance. This fact is due to two independent effects. Since the propagation model has an exponential law, a fluctuation in the RSSI at short distance has a smaller effect on the estimated distance than the same fluctuation at a larger distance. Secondly, the estimation of \( r_0 \) (the RSSI at 1 m distance) is very accurate since at this distance the effects of multipath fading and shadowing on the measured RSSI are negligible. Figure 4 further motivates our assumption of using the higher RSSI value to estimate the distance between the mobile and the anchors. Figure 4 shows the maximum, the mean, and the minimum of the distance error when the RSSIs are categorized in five intervals. It can be observed that higher RSSI values produce a smaller distance error estimation. In fact, when the RSSIs are between 41 and 45, the maximum, the mean, and the minimum error distance are 1.97, 0.94, and 0.07 m, respectively, which are lower than when the RSSIs are between 31 and 35.

5. THE LOCALIZATION ALGORITHM

In this paper we assume a localization system comprising a set of anchors \( A = \{a_1, a_2, \ldots, a_n\} \) and a mobile \( m \). Each anchor \( a_i \) has a well-known position on the map, identified by the pair \((x_i, y_i)\). The localization system exploits two procedures: the calibration and the localization procedures. During the calibration procedure, the anchors preliminary exchange beacons to compute reciprocal RSSIs and the localization system uses this information and the distance between them to estimate the parameters of the analytical propagation model. In the localization phase, the anchors receive the beacons emitted from the mobile, and for each beacon they compute the corresponding RSSI. All the pairs \((\text{RSSI}, \text{anchor}_{id})\) are then transmitted to a localization server that estimates the mobile position by exploiting a calibrated propagation model. We choose this network-based approach in order to reduce the power consumption of the mobile, since in this way it has not to perform any computation. Furthermore, the mobile only has to send a beacon periodically, but it can remain in idle mode between any two consecutive beacons (which means that, between any two beacons, it can turn off the radio and the processing subsystems). Figure 5 shows the lifetime of the mobile as a function of the sampling rate of the wireless channel, assuming that the sensor is a micaZ mote [25] equipped a IEEE 802.15.4 radio subsystem and a battery of 2000 mAh. It is worth to note that, if the localization system is deployed on a network where other applications exist, the system can exploits the communications required by the applications themselves to sample the channel, thus reducing the actual number of beacons sent by the mobile node.

5.1. Calibration procedures

The objective of the calibration is to adapt the propagation model to the environment where it is actually used. Due to the dynamics of the channel, which result in the spatial–temporal variations of wireless fading events, an automatic calibration procedure that can be periodically performed without human intervention may increase the performance
of the localization system, since it continuously adapts the propagation model to the changed environmental conditions. The proposed virtual calibration procedure achieves this goal without human intervention, by only exploiting information obtained from the anchors. In the virtual calibration, the anchors preliminary exchange beacons to compute reciprocal RSSIs that are used to configure the parameters of the propagation model. The parameters of the propagation model (that appear in Equation 3) are: \( r_0 \) (the RSSI at distance of 1 m), \( \alpha \) (the path loss exponent), and \( l_i \) (the attenuation factor for the wall of type \( i \)). The \( r_0 \) parameter should be estimated in a free space. However, some tests performed on our localization hardware showed that it is not affected by the battery power of mobile or anchors. Therefore, in our approach it is estimated a priori, and it is not object of the proposed virtual calibration. On the other hand, if this is not the case (hence it varies with the battery level of the devices), \( r_0 \) can be calibrated a priori for different battery levels of the devices (this result in a list of values for different battery levels), and the localization system may use the appropriate value according to the actual battery power level of the mobile. In any case, this issue is out of the scope of the paper, and we assume that \( r_0 \) is estimated a priori. Moreover, we assume that the transmit power level for the calibration and for the localization procedure is the same. Otherwise a list of the estimated \( r_0 \) for different transmit power levels must be a priori evaluated and the localization system may use the appropriate value according to the transmit power level of the mobile. Since the automatic calibration procedure exploits the communications among anchors to estimate the propagation model parameters, a network overhead is produced. This overhead depends on the frequency and the duration of the calibration phase. In our experiment, we calibrated the system by collecting the RSSIs (at 32 Hz) for 60 s and we performed the calibration immediately before the localization phase. Therefore, during the calibration phase, about 1/20 of the WSN capacity was exploited by the localization system.

To calibrate \( \alpha \) and \( l_i \) parameters we propose two heuristics: global virtual calibration (G-procedure) and virtual calibration (W-procedure). By means of comparison we also consider the common, manually operated, ad hoc calibration (H-procedure) that exploits the RSSI measured on a grid of points in the environment to estimate the propagation model parameters. The G-procedure assigns the same parameters to every wall, based on all RSSI measures obtained from any pair of anchors. This procedure is best suited when a limited number of anchors is deployed in the localization environment. In fact, in this case only a few walls are crossed by the links connecting the anchors, while many walls are not crossed at all. For this reason, the G-procedure assumes that all the walls are the same (i.e., all the signals that cross the walls undergo the same attenuation), and it computes a single \( l_i \) parameter for all the walls. Differently than the G-procedure, the W-procedure provides an attenuation factor for each wall that directly affects the communication between any pairs of anchors. This method is clearly more precise than the G-procedure, and it is best suited when many different walls are crossed by different communication links among anchors (in general this occurs when the system makes use of many anchors). In this case the calibration procedure estimates each \( l_i \) parameter exploiting all the communications among the pairs of anchors that cross the wall of type \( i \). In any case, the attenuation factor of the walls that do not cross any communication link is estimated according to the G-procedure. The H-procedure, which has been used in many previous work [8,26], exploiting the RSSIs measured on a grid of points in the environment, estimates the propagation model parameters. Hereafter we define \( C = \{(a_i, a_j) \in A\} \) to indicate a direct communication between the anchors \( a_i \) and \( a_j \).

5.1.1. Global virtual calibration.
During the virtual calibration procedure we estimate all the required parameters (\( r_0, \alpha, l_i \)), using the Equation 6. The G-procedure considers a single virtual type of wall, \( l_w \); therefore, substituting in Equation 6 \( d(i, j) \) as actual distance between anchors \( a_i \) and \( a_j \), and \( k(i, j) \) as the number of walls crossed by the direct path between anchors \( a_i \) and \( a_j \), we obtain an estimation RSSI(i, j) of actual RSSI:

\[
\text{RSSI}(i,j) = r_0 - 10 \alpha \log_{10}(d_{i,j}) \cdot k(i,j) \quad \forall (i,j) \in C
\]

(7)

The estimated RSSI(i, j) differs from the measured RSSI(i, j) by an error component \( \epsilon(i,j) \). We assume that all \( \epsilon(i,j) \) are identically distributed and uncorrelated among themselves. Recalling that \( r_0 \) is estimated a priori, and according to [27], the approximation of the remaining parameters (\( \alpha, l_w \)) that minimizes the least mean square (LMS) error \( \| \text{RSSI} - \text{RSSI} \|_2 \) can be achieved by a direct method. The computation cost for direct method solving a linear LMS estimator problem is polynomial [27].
5.1.2. Per-wall virtual calibration.

We use this technique to estimate an individual attenuation factor for each wall between any pair of anchors belonging to \( C \). Let us assume that there are \( q \) different types of walls in the map of the building, and let \( L = \{ l_1, l_2, \ldots, l_q \} \) be the set of attenuation factors for each type of wall. Thus, Equation 7 becomes:

\[
\text{RSSI}_{i,j} = r_0 - 10 \alpha \log_{10}(d_{i,j}^2) - \sum_{h=1}^{q} k_{h(i,j)} l_h
\]

\[\forall i, j : (a_i, a_j) \in C \tag{8}\]

where \( k_{h(i,j)} \) is the number of wall of type \( h \) crossed by the signal considering the direct path anchors \( a_i \) and \( a_j \) in Equation 7. The path loss exponent \( \alpha \) used in this equation is previously evaluated with the G-procedure. Instead, the evaluation of parameters \( l_h \in L \) is achieved with the same methodology used in Section 5.1.1, by means of the LMS estimator.

5.2. Localization procedure

The localization algorithm estimates the position of the mobile. To this purpose it accumulates a set of pairs \((\text{RSSI}, \text{anchor}_{a_i})\) received by the mobile and it computes the mobile position by estimating its distance from each anchor. The distance between the mobile and an anchor is estimated by using the propagation model and the values of RSSI that are measured by the anchors when receiving the beacons from the mobile. Among all the received RSSI measurements, our localization algorithm selects only those measures coming from the three anchors with the greatest RSSI (let \( a_1, a_2, \) and \( a_3 \) be such anchors). This because, as observed in Section 4, the anchors that have a smaller RSSI are farther from the mobile, thus the RSSI values they produce are noisier and less reliable. Using the RSSIs obtained from \( a_1, a_2, \) and \( a_3 \), the localization algorithm estimates their distance from the mobile, and it uses these distances as the radii of three circles (centered, respectively, in \( a_1, a_2, \) and \( a_3 \)). Then it estimates the position of the mobile as a function of the intersection points among the circles (see Figure 6). If there are no intersection points (never happened in the experiments we carried out) the localization algorithm may adopt different solutions; to hold the previous position can be one possible solution. Summarizing, the algorithm uses a trilateration method by using the three anchors with higher RSSI in order to decrease the bias introduced by the other anchors.

The main idea is to treat the intersection points, estimated at \((X, Y)\), as point masses \( m_i \) and to find the center of gravity (centroid) of all these masses. In the most general form, the coordinates of the centroid of \( n \) point masses \( m_i \) are given by:

\[
(X_G, Y_G) = \left( \frac{\sum_{i=1}^{n} m_i X_i}{\sum_{i=1}^{n} m_i}, \frac{\sum_{i=1}^{n} m_i Y_i}{\sum_{i=1}^{n} m_i} \right) \tag{9}
\]

which, for equal masses \( m_i \) simplifies to:

\[
(X_G, Y_G) = \left( \frac{\sum_{i=1}^{n} X_i}{n}, \frac{\sum_{i=1}^{n} Y_i}{n} \right) \tag{10}
\]

An example of how the localization algorithm works is shown in Figure 6, where a mobile sensor \( M \) is within the communication range of four anchors. The three anchors \( a_1, a_2, \) and \( a_3 \) with a greater RSSI are selected, and the six intersection points \( \{I_1, \ldots, I_6\} \) are evaluated. The mobile position \( M \) is then estimated by using the Equation 10. In practice, the localization algorithm is based on the combination of two different techniques: the trilateration and the centroid. The trilateration is a range-based localization technique, while the centroid is a range-free method. Next section will show that the use of these two methods contributes to reduce the localization error. In fact, the range-based method has an intrinsic error due to the wireless channel variability, which is mitigated by the range-free method.

6. EXPERIMENTAL RESULTS

In this section, we present the performance of the proposed automatic calibration procedure, of our localization algorithm (calibration procedure and localization procedure), and finally the performance of our localization system exploiting the context information provided by smart devices deployed in the environment.
6.1. Experimental setup

We performed the experiments in our laboratory, which is a typical office environment with an area of approximately 7 m by 11 m. In the room desks, chairs, cabinets, computers, monitors are present. This environment is harsh for wireless communications due to multi-path reflections from walls and the possibility of interference by electronic devices. Figure 7 shows the layout of the laboratory and the deployment of the anchors in the experimental area. For the experiments we used a WSN composed of 8 MicaZ [25] equipped with the Chipcon CC2420 radio subsystem implementing the IEEE 802.15.4 standard. The experiments consisted in a set of measures between a pair of anchors or between an anchor and 12 points of the grid (in the case of H-procedure). Each measure collects 300 RSSIs, where every RSSI is averaged over a set of 50 samples. Each sample is obtained exchanging a beacon packet between two sensors every 1/32 second, using the highest transmission power of the MicaZ. As mentioned in Section 5, the $r_0$ parameter is estimated a priori, as the RSSI at a reference distance. To this purpose we preliminary evaluated $r_0$ measuring the RSSI between two anchors deployed at 1 m distance, obtaining $r_0 = -10.06$. We also performed the H-procedure to obtain the reference parameters of the propagation model to be used for comparison with the G-procedure and the W-procedure. The parameters obtained by using the LMS estimator for all the calibration methods are shown in Table I. Although the estimated values of $\alpha$ are below the usual values assumed for open spaces, they are realistic for indoor environments with the features of the rooms used in our experiments, since similar values have been obtained in [22,28,29]. In fact, in [28] the author estimates in a grocery a path loss exponent of 1.81, while in [22] the authors estimate an $\alpha$ value of 1.3 and 1.79 for two different rooms of their laboratory. In [29], the author conducts a measurement campaign in several rooms having different shape and width. The $\alpha$ value estimated in the larger room (above 10 m in width) was 2.18, in the medium room (above 6 m in width) was 1.99, and in the hallway (2.4 m in width) it was 1.72.

6.2. Calibration performance

In this subsection we present the results of the measurement campaign aimed at comparing the performance of the three heuristics proposed in the previous section. As observed in [24], the measured RSSI is a function of the path loss and of the wall attenuation factor, which can be estimated with the above calibration technique. Furthermore, the values of the model parameters strongly depend on the specific and time-dependent wireless channel environment where the mobile and the anchors are. This fact also affects the values of the propagation model parameters during the localization procedure. We performed two phases of measurements. The first phase aimed at performing the calibration of the propagation model by using the three different procedures, namely H-procedure, G-procedure, and W-procedure. The second phase aimed at measuring the RSSI on a grid of points in the environment, and to compare the distance error of the procedures. We used the H-procedure as the reference technique, and we evaluated the performance of the two virtual calibration techniques according to the following formula:

$$\phi_G = \|\Psi_G(RSSI) - \Psi_G(RSSI)\|_2$$

(11)

$$\phi_W = \|\Psi(RSSI) - \Psi_W(RSSI)\|_2$$

(12)

where $\Psi$ is the function that computes the distance based on the propagation model calibrated with the H-procedure, $\Psi_G$ provides the distance by means of the propagation model calibrated with the G-procedure, and $\Psi_W$ provides the distance by means of the propagation model calibrated with the W-procedure. In order to gather a better view of the comparison, we studied the cumulative density function (CDF) of $\phi_G$ and $\phi_W$. Based on the set of all the RSSIs measured between the anchors and the mobile produced during the second phase of the measuring campaign, we evaluated the CDF of the error affecting the estimated distance. Table II summarizes the results obtained showing the CDF of $\phi_G$ and $\phi_W$. This table highlights that the W-procedure performs better than the G-procedure. Not surprisingly, the W-procedure outperforms the G-procedure, due to the better accuracy in the walls modeling. Figure 8 shows the CDF obtained by using our localization algorithm (solid line) for each calibration procedure. As shown in this figure, the

![Figure 7](image79x545to289x712)

Figure 7. Map of the building used for the experiments.

**Table I.** Parameters and performance comparison among procedures.

<table>
<thead>
<tr>
<th>Procedure</th>
<th>$\alpha$</th>
<th>$h_1$</th>
<th>$h_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>G-procedure</td>
<td>1.45</td>
<td>8.96</td>
<td>8.96</td>
</tr>
<tr>
<td>W-procedure</td>
<td>1.45</td>
<td>8.33</td>
<td>7.30</td>
</tr>
<tr>
<td>H-procedure</td>
<td>1.46</td>
<td>8.21</td>
<td>6.40</td>
</tr>
</tbody>
</table>
Table II. CDF of the errors.

<table>
<thead>
<tr>
<th>Error (m)</th>
<th>CDF of $\phi_u$</th>
<th>CDF of $\phi_d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>0.604</td>
<td>0.896</td>
</tr>
<tr>
<td>0.5</td>
<td>0.732</td>
<td>0.919</td>
</tr>
<tr>
<td>1</td>
<td>0.868</td>
<td>0.973</td>
</tr>
<tr>
<td>1.5</td>
<td>0.901</td>
<td>0.984</td>
</tr>
</tbody>
</table>

G-procedure performs like the commonly used H-procedure in terms of localization error, and the W-procedure is practically identical to the H-procedure. This means that virtual calibration procedure results in the same localization error as the more expensive H-procedure.

6.3. Localization performance

In this subsection we analyze the accuracy of our localization algorithm in the environment showed in Figure 7.

Figure 8 shows the CDF obtained by using our localization algorithm with the propagation model calibrated by using the virtual calibration method (solid line) compared with a commonly used LMS algorithm [24,30,31] (dotted line). As depicted in this figure, our localization algorithm outperforms the LMS algorithm. In fact, the median is 1.7 and 2.5 m, respectively. It worth to note the relationship between the anchor density and the accuracy of the localization algorithm. In fact, Figure 9 shows how the location error performs when the number of anchors changes. As expected, the localization error decreases as the density of the anchors increases (the density in the figures is measured in terms of square meters covered by an anchor). For example, if we want to achieve the 90th percentile location error within 2.5 m, we must deploy an anchor every $11^2$, which in our experimental testbed means three anchors per room.

6.4. Localization using context information

This subsection investigates the advantages of integrating our localization algorithm with the context information provided by smart devices deployed in the environment. The idea is that at a given instant, the knowledge of which of the room the user is found can be used by the localization algorithm in order to increase the overall localization performance. In fact, in AAL applications the precise user position can be occasionally estimated by using the context information coming from the devices deployed in a room and activated by the user itself. An example is when the user turns on the light in a room by pressing a switch: this action allows the AAL system to infer that the user position is in the room.

To take into account possible context information, we propose a modified version of the localization procedure described in Section 5.2. The modified algorithm uses the context information in order to choose the room where the user is located (this information is inferred by the AAL system); then it uses only the intersection points within the selected room to compute the user position. An example of how the localization algorithm works is shown in Figure 10 (for the sake of simplicity, this figure is depicted disregarding the effect of the walls attenuation). The three anchors $a_1$, $a_2$, and $a_3$ with a greater RSSI are selected and only two out of the five intersection points ($I_1$ and $I_2$) are assessed. The mobile position $M$ is then estimated by using the Equation 10. Of course there exists a remote chance that all the intersection points are outside the room (however, this never happened in all our experiments). In this case, clearly the information is not consistent and, depending on the requirements of the localization system, there are different possible alternatives; for example, the system may return an inconsistency, or it may return the last known position, etc.

The results shown in Figure 11 underline that by using the context information the performance considerably
increases (in the 90% of cases the localization error is lower than 2 m). It is also important to note that the performance of the LMS algorithm is only marginally increased compared with Figure 8. Therefore, in a typical localization application, where the AAL information is taken for granted, the proposed localization system better exploits this information than the LMS algorithm.

7. CONCLUSIONS

In this paper, the authors considered the problem of the indoor localization based on RSSI with standard IEEE 802.15.4 radio interfaces. Specifically, the paper presents a novel localization algorithm based on trilateration through real-time RSSI values obtained by exchanging beacon packets between the mobile and the anchors. The algorithm selects and weights the RSSI measurements according to their strength, and it uses a propagation model to transform RSSI measurements into distances. The path loss exponent, as well as the wall attenuation factors, which characterize the propagation model channel between the mobile and the anchors, are dynamically calibrated by using the RSSI exchanged among the anchors. This calibration method avoids the ad hoc and time-consuming calibration phases needed with other calibration methods, and it is suitable in dynamic environments where the propagation model needs to be periodically calibrated. The experimental results show that the performance of the virtual calibration, in terms of accuracy of the estimated distances, is close to that achievable with more expensive ad hoc methods, and that the localization algorithm increases the performance with respect to the commonly used LMS algorithm. Finally, the paper shows that the availability of context information from which the position of the mobile can be inferred, also contributes to improve the localization performance. There are a number of important aspects related to localization that are out of the scope of this paper and deserve more attention in the future. We believe that the study on how the localization precision affects the network load and the network lifetime, and a comparison of localization systems under these aspects are definitively, aspects that need to be investigated. Tracking is also another topic that is strongly related to localization, and a deeper integration of tracking and localization may be helpful to reduce the localization error. With respect to this work, the concept of automatic calibration could be extended to other localization methods (for example to fingerprinting or other methods), which constitutes a further step in our studies.

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