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Research Article

On Potentials and Limitations of a Hybrid WLAN-RFID Indoor Positioning Technique

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This paper addresses the important issue of position estimation in indoor environments. Starting point of the research is positioning techniques that exploit the knowledge of power levels of RF signals from multiple 802.11 WLAN APs (Access Points). In particular, the key idea in this paper is to enhance the performance of a WLAN fingerprinting approach by coupling it to a RFID-based procedure. WLAN and RFID technologies are synergistically used to provide a platform for a more performing positioning process, in which the very strong identification capabilities of the RFID technology allow to increase the accuracy of positioning systems via WLAN fingerprinting. The algorithm performance is assessed through general and repeatable experimental campaigns, during which the main algorithm parameters are dimensioned. The results testify both to the feasibility of the solution and to its higher accuracy (attainable at very reduced costs) compared to traditional positioning techniques.

1. Introduction

Recently, the wireless telecommunications market has increased its interest towards so-called "location-based" applications, which are proposed to the end-user attention as the most promising response to their need of personalized communications in fields such as Infomobility, mobile entertainment and gaming, Intelligent Transportation Systems, assisted driving, and so forth. This phenomenon has been fostered both by the availability of mobile terminals equipped with multiple radio network interfaces, and by extensive research efforts undertaken by Industries and Research Institutions to develop platforms for efficient indoor and outdoor positioning solutions.

While the availability of low-cost GPS (Global Positioning System) [1] receivers, built in the mobile terminals, promoted the development of location-based applications in outdoor scenarios, still barriers to the spread of location-based services are present in indoor scenarios. Therein, in fact, the GPS technology (which relies on satellite signals) cannot be exploited, and no other technology has shown to be ready to play a leadership role. In order to achieve accurate position estimation inside the buildings, several solutions have been proposed, which differ from each other in the used technology, positioning accuracy, offered coverage, frequency of updates, and costs of installation and maintenance. As it will be shown in the following, several comparative studies on competing positioning systems are available from the literature; most of them are based on Radio Frequency (RF) technologies (e.g., Wi-Fi, Bluetooth) [2–7].

The technology that has gained the greatest success, thanks to its low cost, widespread diffusion, and robust communication capabilities, even in non Line of Sight (nLOS) conditions, is definitely the WLAN (Wireless Local Area Network) technology. According to WLAN-based techniques, it is possible to locate Wi-Fi card equipped devices, with an accuracy of some meters, by means of two-phase positioning algorithms. During the *offline* training phase, the Received Signal Strength Indicator (RSSI) distributions, collected from Wi-Fi Access Points (APs) situated in predefined reference positions within the interest area, are tabulated

together with their physical real-world coordinates. This originates a so-called *radio map* (or fingerprint database), in which any single dataset is called *fingerprint*. During the subsequent *online* location determination phase, RSSI samples received from a subset of APs are used to search for similar patterns in the radio map. The best match is chosen, and its physical coordinates are returned as the position estimate. Although a fingerprinting technique avoids the complicated computation of path loss, since fingerprint data are already affected by multipath and by signal attenuation phenomena, still the position estimation may not be accurate enough, thus owing to *false positives*.

On the other hand, solutions are appearing that exploit the Radio Frequency IDentification (RFID) technology, which was originally introduced as a key technology only applied to item identification in fields, such as asset tracking, manufacturing, supply chain management, retailing, electronic payment, security and access control, and so forth. RFID-based positioning solutions can be split into two main categories: *tag-oriented* and *reader-oriented*. The former aims at locating RFID tags, while the latter tries to find the position of portable RFID readers. Both approaches are likely to be employed as a basis to implement location-based services.

The idea behind the proposal in the present paper is to use both Wi-Fi and RFID technologies synergistically, to design a platform for more performing location sensing services. The very strong identification capability of RFID technology can indeed be very useful for increasing the accuracy of positioning systems based on WLAN fingerprinting techniques. The purpose of RFID components is to allow a reduction in the number of iterations when searching for the best fingerprint match in the database of the Wi-Fi positioning system. As it will become clearer in the following sections, a performing behaviour is achieved by splitting (thanks to the RFID technology) the fingerprint database into "zones" (during the *offline* phase) and, later (during the *online* phase) by introducing a "zone matching" process. The resulting technique shows the following points of strength: (a) significant reduction of false positives, (b) low additional costs compared to traditional Wi-Fi based detection systems, and (c) ability to take advantage of tags that in the future will be largely present in indoor environments (in the view of the Internet of Things). Furthermore, compared to other mechanisms, our solution is easily and quickly deployable and does not require a high tag density.

Potentials and limitations of the proposed hybrid WLAN-RFID positioning technique will be highlighted, and its effectiveness validated by a comprehensive measurement campaign. This latter will testify that the emerging synergies between a typical *communication system* (like Wi-Fi) and a typical *identification technology* (like RFID) are able to implement low complexity solutions to enhance performance of location sensing mechanism.

The rest of the paper is organised as follows. In Section 2, we survey related work in the area of location tracking in indoor environments. Section 3 reports the rationale of the proposed WLAN-RFID hybrid positioning solution and describes its operational behaviour. Section 4 focuses on experimental results obtained in different scenarios through field tests, that aim at comparing our approach with alternative location sensing solutions and at evaluating the impact of design parameters on the location accuracy. Section 5 concludes the paper.

2. Related Works

In [4, 8–10] WLAN-based location systems have been proposed, based on empirical signal strength measurements as well as on simple signal propagation models. RADAR [4] is an RF-based system for locating and tracking users inside the buildings. It uses standard IEEE 802.11 network adapters to measure signal strengths at multiple base stations, positioned to provide overlapping coverage in a given area. The system combines empirical measurements and signal propagation modeling to determine the user position. Other approaches use a Bayesian algorithm [11] or Delaunay triangulation with lines of constant signal strength [12]. The use of Delaunay triangulation and interpolation allows building a radio map with low density of calibration points and reduces the training phase delay. *WhereNet* [13] uses timing signals transmitted from tags to a network of receivers. It is based on the same 2.4 GHz band as the 802.11 and Bluetooth systems, but uses a dedicated standard protocol optimized for low power spread-spectrum position determination. The Ekahau [3] Wi-Fi positioning system computes the location of a client device by applying a probabilistic model to the signal strengths measured at the Wi-Fi client device (*Ekahau device*). The indoor environment must be calibrated a priori to provide the positioning engine with a signal strength map of the room. Ekahau devices continually send their signal strength vectors to the positioning engine, which keeps track of each device location.

In the last few years, besides *WLAN-based location*, also the *location through RFID* has been investigated from several application perspectives. Two location approaches exist: *tag-oriented* and *reader-oriented*. Earlier work on the former class of solutions is well synthesized by LANDMARC [14], which proposes to locate an active RFID tag through RF-power distances with respect to *reference* RFID tags in fixed and known locations. Power levels of the reference tags are stored in a database. Tags in unknown positions are sensed by the reader antennas and their power levels are compared to those of the reference tags. The reference tags with the most similar power readings are assumed to be the closest to the target tag and used to predict the unknown tag position by using the Nearest Neighbor Algorithm. In [15] results of a wide campaign are reported to evaluate the performance of LANDMARC under general experimental conditions, especially in indoor environments. The authors concludes that such tag-oriented algorithm may require highly expensive infrastructures, composed of many RFID tags and readers/antennas, if satisfactory position accuracy is required.

As for reader-oriented location solutions, [16] proposes a tagged environment with numerous reference tags over the area of interest, thus creating a so-called *Super-distributed*

RFID tag infrastructure. In this solution, location targets are equipped with mobile readers, thus, reversing the traditional approach in employing readers and tags. A portable reader position is discovered through either the identification of the closest reference tag surrounding it or, in case of multiple tags identification, by averaging the positions of the identified tags. Reader-oriented location solutions have also been studied in the field of assistance to blind people [17–19] and in robot localization [20], where statistical filters are exploited to enhance odometer information by means of RFID tag identification. Researches in [17, 18] are focalized on navigation rather than environment disclosure; instead, Ubibus [21] has been proposed to help blind people in public transportation scenarios.

Particle filters have also been applied in absolute location systems. Most notable works are in [22, 23], according to which the location of a user is based on measurements received from a variety of sensor systems. As already addressed, the proposal in the present paper differs from the literature in that it is an hybrid algorithm that jointly uses WLAN and RFID technologies to achieve improved location accuracy, similar to other sensor fusion approaches. The main aim is to select, by means of the RFID technology, the WLAN RSSI points that are actually close to the target WLAN device location and, then, to average their positions getting a final position estimate.

3. Proposed WLAN-RFID Hybrid Positioning Technique

In the present section the basic features of the proposed hybrid approach to positioning via a joint exploitation of WLAN fingerprinting and RFID technologies are introduced. As already addressed, the proposed location algorithm could be considered as an evolution of WLAN fingerprinting techniques; in fact, the "two phases" approach is maintained, while the RFID integration is used to overcome some inherent drawbacks of such an approach. Our proposal requires that the mobile target, whose location must be determined, is equipped with both a WLAN card and a RFID reader. Besides, a set of reference tags is associated to any given "zone" in the observation area.

Phase 1 (offline: building the fingerprinting database). Still the presence of reference points for RSSI measurements from the WLAN Access Point (APs) is required. WLAN reference points are carefully selected to populate the database and, through an accurate measurement campaign, each of them is characterized in terms of a set of RSSI values, one for each available AP. The main weakness of the described measurement phase is, undoubtedly, the possibility of measuring very similar power levels in different (and often distant) areas. This phenomenon may occur quite often in indoor environments.

In order not to stray too far from traditional WLAN fingerprinting techniques, we thought to maintain a traditional approach and merely increase the information related to each reference point. Specifically, according to the proposed approach, the observed area is split into *zones* and each reference point, besides a position (x, y), has also a "belonging zone" associated. Zones are individuated by RFID tags, positioned within the area of interest. This hopefully counters the possible ambiguity in the choice of the right area.

To take into account the variability of the propagated WLAN signal (affected by phenomena of reflection, diffraction, and scattering) measurements at one WLAN reference point need to be repeated n_o times (*number of observations*) and suitably selected. A preliminary study has shown that an acceptable number of RSSI observations, which gives a robust characterization of each reference point, is $n_o = 40$, relevant to each of the available APs. For each AP, the most frequent value of RSSI is selected among 40 available values. This might seem a too simplistic assumption, but optimization of reference point characterization is not an issue we are interested into, because the aim of the algorithm presented in this paper is to improve the positioning accuracy through the synergic action of two technologies. In the literature, more effective ways to characterize the reference points are available; whatever the choice, still the effectiveness of our approach is granted.

Phase 2 (online: positioning the mobile unit). During the online position determination phase, different from the traditional approach, our proposal exploit two kinds of measurement to identify the unknown position of a Mobile Unit (MU). Both the WLAN interface and the RFID mobile reader (plugged into the MU) measure the RSSI values from APs and RFID tags, respectively. The actual advantages of the proposal emerge during this phase. In fact, the mobile device can take its decision about its estimated position by counting on RFID RSSI measurements, in addition to the traditional WLAN RSSI values to be compared with the fingerprints in the database. More specifically, the envisaged algorithm applies a two-step approach.

First, it identifies the "zone" in the observed area where the MU is likely located, by basing its decision on RSSI values received from the RFID tags scattered across the environment and associated to each zone. During the zone identification phase, the RFID reader in the MU generates a sequence of interrogations, that is, it broadcasts *scan* messages that wake up the reachable tags and query their IDs, and associates to each identified tag an RF power level. In any position, the reader will get signals from multiple tags under its coverage and select the strongest tag signals and, consequently, the associated zone. As a results, a "rough" MU position estimation is performed.

Second, the information relevant to the estimated zone is used to filter the WLAN RSSI entries in the database, over which the best matching algorithm must be executed. This drastically reduces ambiguities in associating measured RSSI values to fingerprinting values, thus enhancing the accuracy and effectiveness of the overall method. This second step is thus a sort of "refinement" of the localization estimation process. Figure 1 illustrates the whole process foreseen by the proposed approach.

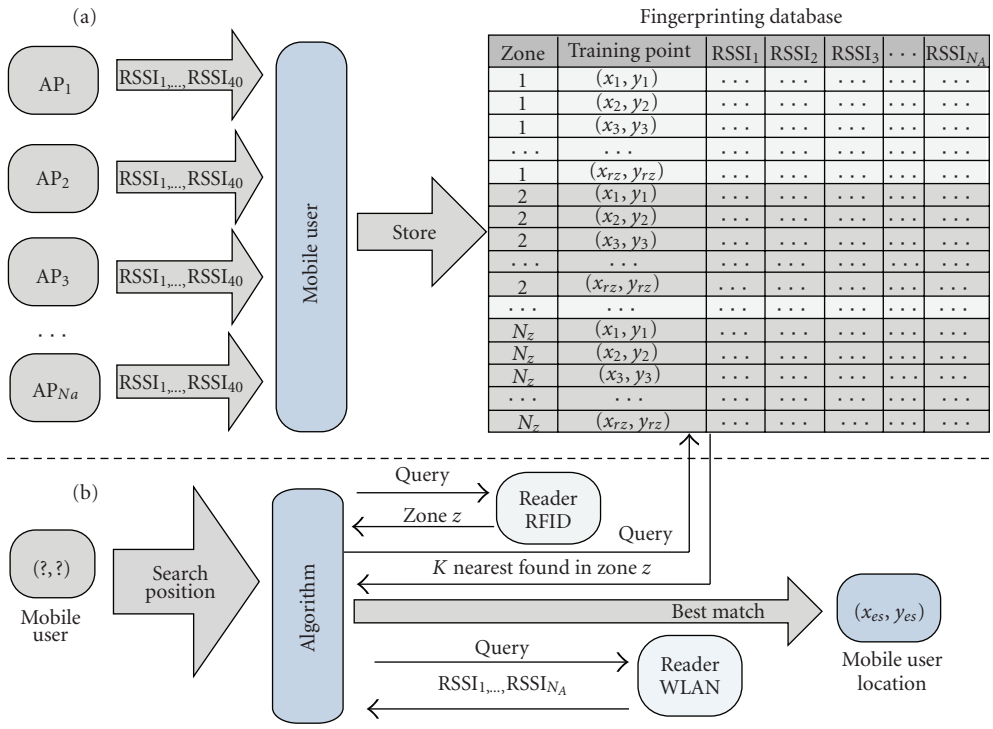


Figure 1: Online (a) and offline (b) phases of the proposed algorithm.

```
//zone determination: get the zone with the strongest RSSI value
for each zone in numZone
    for each tag in numTag
        maxTagRSSI [zone] = ValueRSSI (tag, zone);

selectedZone = zone with highest maxTagRSSI;

//for each AP, the most frequent value of RSSI is selected among the
numObservations available
for each ap in numAP
    for each obs in numObservations
        vectorRSSI [ap] = mostFrequentRSSI (ap, obs);

//search the k nearest reference points to vectorRSSI in zone subset of
database
selectedReferencePoints = searchDB (selectedZone, vectorRSSI, k);

userPosition = weightedFunction (selectedReferencePoints)
```

Algorithm 1: *Maximum RSSI mode:* pseudocode description.

During the zone determination phase, the RFID reader in the MU can act in two alternative ways. According to the first mode, named *maximum RSSI*, the reader generates a sequence of interrogations with increased transmission power. The Reader starts interrogating at the lowest admitted transmission power and stops when the first tag (likely the nearest) is reached. If more than one tag is detected, then only the one with the highest transmission power is considered as an indicator of the location zone. Algorithm 1 shows the pseudocode description of this approach. According to the alternative policy, named *average RSSI* instead, the Reader directly starts interrogating tags at the highest allowed transmission power, in order to detect the largest number of RFID tags is possible, and calculates an average RSSI value per zone, according to the pseudo-code in Algorithm 2. The higher computational load of the average RSSI approach when compared to the maximum RSSI approach, is counterbalanced by the lower cost of the former method in terms of positioning time; it, in fact, avoids the progressive augmentation of the transmitted power in 1dbm steps, until a RFID tag is detected.

```
//zone determination: get the zone with the strongest average RSSI value
for each zone in numZone
    for each tag in numTag
      averageTagRSSI [zone] = valueRSSI (tag, zone);

selectedZone = zone with max averageTagRSSI;

//for each AP, the most frequent value of RSSI is selected among the
numObservations available
for each ap in numAP
    for each obs in numObservations
      vectorRSSI [ap] = mostFrequentRSSI (ap, obs);

//search the k nearest reference points to vectorRSSI in zone subset of
database
selectedReferencePoints = searchDB (selectedZone, vectorRSSI, k);

userPosition = weightedFunction (selectedReferencePoints);
```

Algorithm 2: *Average RSSI mode:* pseudocode description.

4. Performance Analysis

In this section, a comprehensive performance evaluation campaign, which aims at assessing the behaviour of the proposed hybrid WLAN-RFID solution, is illustrated.

The first steps are the definition of a metric to quantify location errors, that is, the distance between estimated position and actual position, and the setting up of a test-bed to perform our evaluation campaign. With reference to a given zone of interest $z \in [1, N_Z]$ in which the best matching algorithm has to be run, and to a number n of APs, let's define $S_{pz} = \{\mathrm{RSSI}_{pzn}\}_{n=1,\ldots,N_A}$, a generic power vector for any pth reference point (with $p \in [1, r_z]$) belonging to the zone z. As addressed above, during the online position determination phase, the zone z is individuated by scanning the closest RFID tags.

As a subsequent step, the algorithm scans and collects the RSSI values received from different APs. Let's define $\theta = \{\mathrm{RSSI}_n\}_{n=1,\ldots,N_A}$ the *n-uple* of power values measured by the mobile device's WLAN card in the unknown position. Thus, a set of distances can be defined in the RSSI space, between the set of collected measures from the unknown position and each reference point of the generic zone z, $e_{pz} = d(\theta, S_{pz})$, $E = \{e_{pz}\}_{p=1,\ldots,r_z}$. The vector E of distances is used to apply the *k-nearest neighbours* algorithm.

As regards the definition of distance d in the space of RSSI measures and relevant weights w, we utilize the *Euclidean distance in signal strengths*, defined as

$$d_{pz} = \sqrt{\sum_{n=1}^{N_A} \left(\theta - S_{pz}\right)^2}, \tag{1}$$

and a *weight function,* referred to as *received power,* defined as

$$w_m = \frac{1/e_{pz_m}}{\sum_{m=1}^{k} 1/e_{pz_m}}. \tag{2}$$

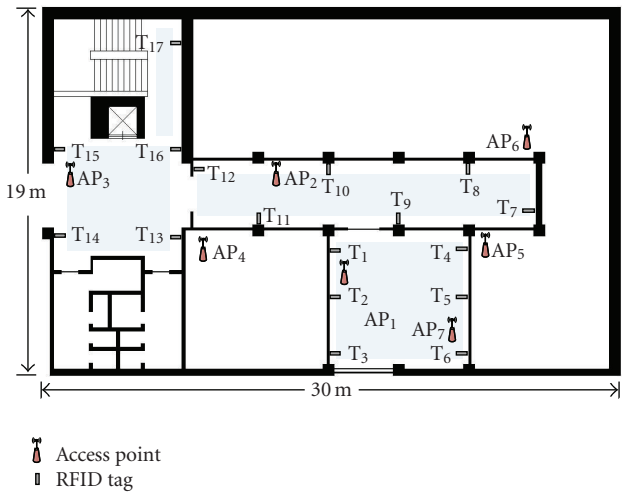
To quantify the performance levels of our approach, the error distance is used as a metric of the accuracy of the system.

4.1. Indoor Test-Bed Definition. An indoor test-bed is deployed in an office floor of the University of Reggio Calabria, Italy, and measurements are taken in "non ideal" conditions, that is, usual environmental conditions during working hours (please refer to Figures 2(a) and 2(b) for the scenario layout—AP and Tag positions, as well as zone splitting, are *only for illustration purposes*). Experiments are carried out by using i-Q RFID tags produced by Identec Solutions and operating in the UHF range [24], capable of up to 100 m identification range; WLAN Access Point model is WL-537 produced by 3Com [25] while the portable RFID reader, is a low-cost Identec i-Card3 PCMCIA reader, mounted on a Acer laptop PC with wireless card Intel(R) PRO/Wireless 2200BG programmed to run the proposed algorithms. The i-Card3 reader generates interrogations at different RF transmission power values, ranging between −60 dbm and 10 dbm.

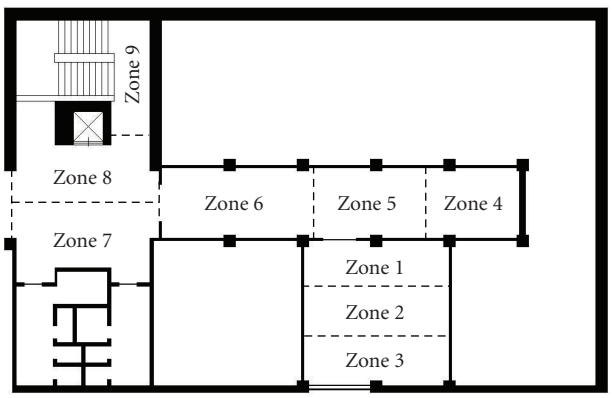
Design parameters considered during the evaluation campaign are: (i) *number of zones* (N_Z) discriminated by means of active RFID tags in the area of interest, (ii) *gap* (Δ) in centimetres between reference points belonging to the WLAN RSSI grid, (iii) *number of access points* (N_A).

In the remaining part of the paper four different evaluation campaigns are illustrated to give the reader an accurate view of the algorithm potentials. Being the last set of experiments performed outdoor, an outdoor test-area, which will be better described later, has been exploited.

4.2. First Campaign: "Max RSSI Values" Hybrid versus WLAN Fingerprinting. The first set of measurement aims at comparing the performance of the Hybrid WLAN-RFID algorithm and of the well-know RADAR [4] technique, used as a reference in our test-bed. In the specific sample scenario



(a)



(b)

Figure 2: (a) Indoor area chosen for the experiments; (b) example of splitting into zones.

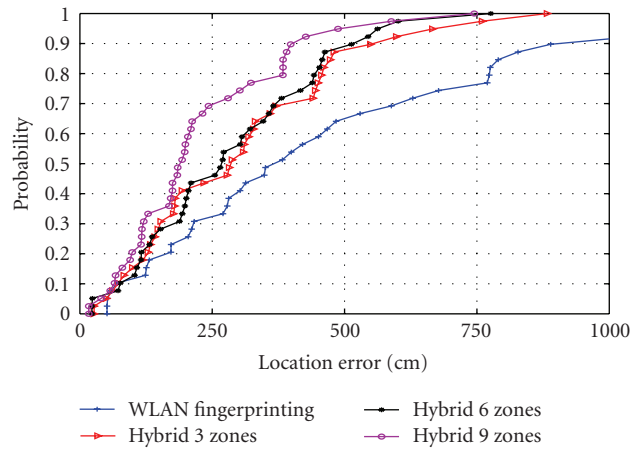


Figure 3: WLAN Fingerprinting versus Hybrid WLAN-RFID: location error; $N_Z = [3, 6, 9]$, $\Delta = 240$ cm, $N_A = 4$; "maximum RSSI" mode.

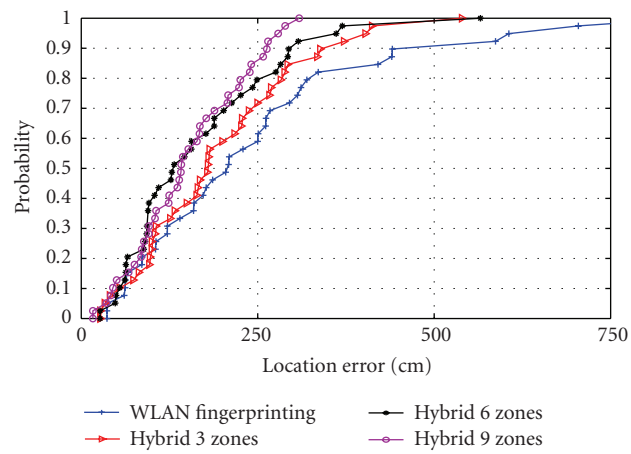


Figure 4: WLAN Fingerprinting versus Hybrid WLAN-RFID: location error; $N_Z = [3, 6, 9]$, $\Delta = 120$ cm, $N_A = 7$; "maximum RSSI" mode.

presented in this initial campaign, we set $N_Z = [0, 3, 6, 9]$, $\Delta = [240, 120]$, and $N_A = [4, 7]$. $N_Z = 0$ is the special case of WLAN fingerprinting approach only, without the presence of RFID tags; obviously, this corresponds to the standard RADAR algorithm.

Initial studies focuses on the *maximum RSSI approach*, with a RFID Reader transmission power progressively increasing in steps of 1 dbm at a time, until one (or more) RFID tag is detected. The main objective is the evaluation of the influence that system parameters have on the proposed approach. To this purpose, the performance of the positioning algorithm is evaluated by varying number of zones N_Z, gap between reference points Δ, and number of access points N_A.

What is expected is a significant decrease in location errors consequent to denser grids of reference WLAN points (i.e., reduction of the Δ value). Also, an increase in the number of WLAN APs would favour a performance increase, due to the beneficial effect of the greater number of RSSI samples taken into consideration. Lastly, by increasing the number of zones identified through the RFID technology, the positioning errors are likely reduced, due to the more accurate matching among measures and entries in the fingerprinting database.

In Figure 3, a comparison between the *WLAN only* and the *hybrid WLAN-RFID* fingerprinting technique, for a variable number of zones, is shown. Curves illustrate the experimental cumulative distributions of the location errors of both fingerprinting algorithms, when $k = 3$ reference WLAN points are selected as *near WLAN points* and *received power* is used as the weight function among near WLAN points. The choice of the number of near WLAN points is the result of a tuning campaign that considered a trade-off between attainable location accuracy and computational load. In this sample configuration, the hybrid solution attains a lower location error when increasing the number of zones; this witnessing to the beneficial effects of the introduction of RFID technologies into WLAN positioning methods.

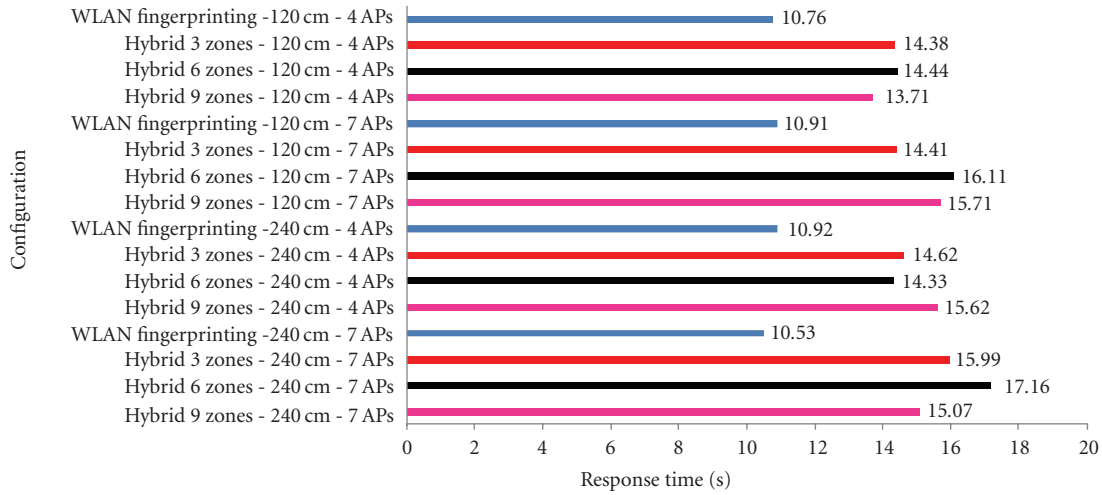


Figure 5: Response time in different configurations ("maximum RSSI" mode).

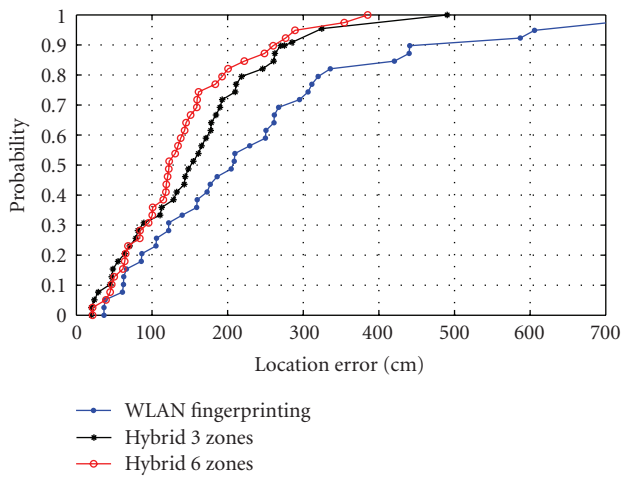


Figure 6: WLAN Fingerprinting versus Hybrid WLAN-RFID: location error; $N_Z = [3, 6]$, $\Delta = 120$ cm, $N_A = 7$; "average RSSI" mode.

The good level of performance significantly improves when thickening the grid of reference points and increasing the number of WLAN APs, as Figure 4 shows.

Results are highly valuable, compared to what is available in the literature, if we consider the good trade-off among achieved performance, amount of used equipment, and low cost of the solution. Each probability value plotted in Figure 4 is computed with a 95% confidence interval.

In Table 1 location estimation errors obtained during different measurement campaign are reported. In the last column figures relevant to the location estimation error when considering 90% of the measurements, $\text{Error}_{90\%}$, are reported.

Parameter values considered are those that show a better trade-off between positioning accuracy, equipment costs, and processing time. This last aspect shall be better investigated if we recall that, differently from a RADAR-like fingerprinting approach, in a hybrid WLAN-RFID solution the number of iterations in the fingerprint database to search the best match is smaller, due to a reduced localization area. Notwithstanding, one might think that this advantage is invalidated by the lengthening of the computational time, due to the additional phase of zone identification.

In Figure 5, an increase in the average response time of the hybrid solution compared to traditional WLAN fingerprinting is confirmed. Fortunately, a small increase, ranging from 3 seconds to 4 seconds only, is observed; this demonstrates that the advantages in terms of achievable location accuracy overcome the disadvantages caused by the additional processing delay.

Table 1: Location estimation error.

Δ	N_A	Algorithm	Average Error (cm)	$\text{Error}_{90\%}$ (cm)
240 cm	4	*WLAN Fingerprinting*	504	904
		Hybrid - 3 zones	308	554
		Hybrid - 6 zones	291	516
		Hybrid - 9 zones	237	401
	7	*WLAN Fingerprinting*	350	732
		Hybrid - 3 zones	270	509
		Hybrid - 6 zones	221	416
		Hybrid - 9 zones	180	295
120 cm	4	*WLAN Fingerprinting*	441	952
		Hybrid - 3 zones	250	461
		Hybrid - 6 zones	198	380
		Hybrid - 9 zones	171	289
	7	*WLAN Fingerprinting*	249	455
		Hybrid - 3 zones	198	342
		Hybrid - 6 zones	168	295
		Hybrid - 9 zones	152	263

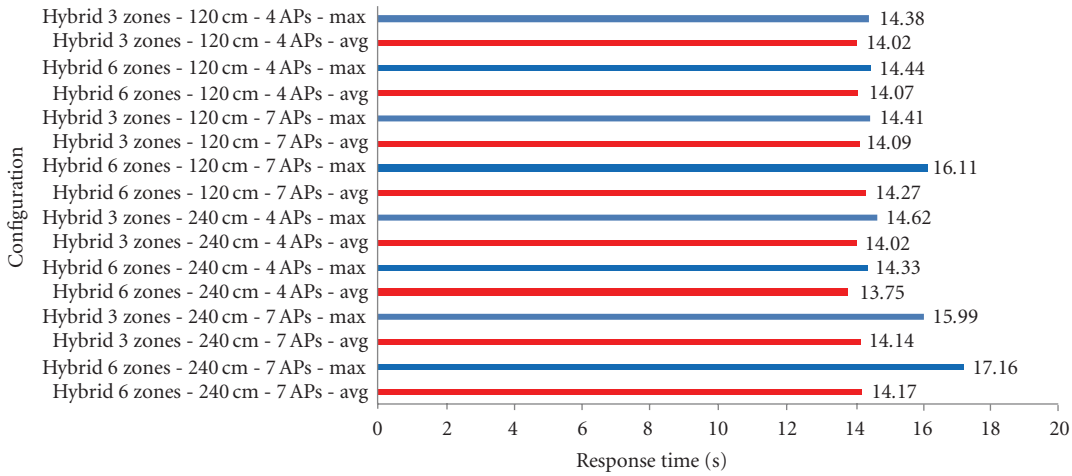


Figure 7: Response time: comparison of "average RSSI" (Avg) mode and "maximum RSSI" (Max) mode.

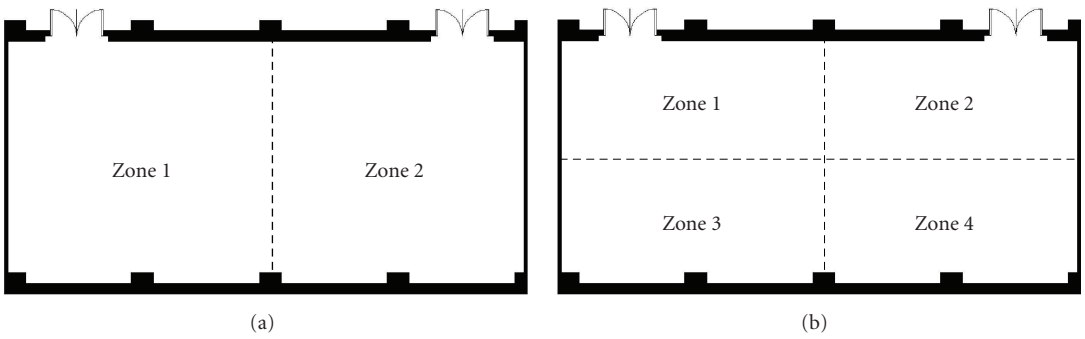


Figure 8: Area of localization split into (a) 2 and (b) 4 zones.

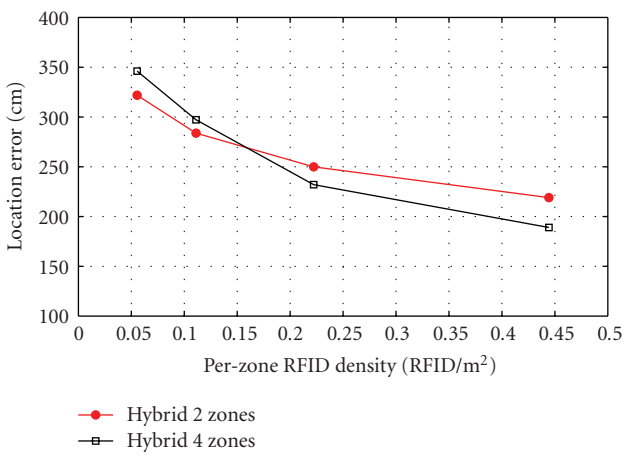


Figure 9: Comparison of location error: Hybrid with 2 zones versus Hybrid with 4 zones when varying per-zone RFID density.

4.3. Second Campaign: "Maximum RSSI" versus "Average RSSI" Modes. The test campaign illustrated in the present section aims at comparing two possible approaches to the zone selection: "maximum RSSI" and "average RSSI" modes. In Figure 6, sample curves of location error probability are reported, which show how the latter approach overcomes the former in terms of performance.

For a thorough comparison of the two approaches, the reader can refer to the output of sample test campaigns reported in Table 2. It is manifest that the "average RSSI" approach allows for an additional location accuracy with respect to the "maximum RSSI" mode.

The average performance increase is about 22,5% when considering the 90% measurement error (about 1 additional meter of accuracy achievable) and 17,3% (about 40 cm) when considering the average localization error. The response time also decreases (please refer to Figure 7). Specifically, under the same test conditions an average reduction of the response time equal to 7% (more that 1 second less) is observed.

The main reason of a better location accuracy is that the choice of considering average RSSI values of RFID tags better fits the radio propagation characteristics in indoor environments (such as, severe multipath, rare LOS path, absorption, diffraction, and reflection [26]). This reduces the number of zone errors and false positives. The variant based on the maximum RSSI values would, in fact, be deceived by the likely presence of spurious peaks of power in the RFID responses. In the average RSSI variant, during the estimation of the reference zone, any power peak in the zone is offset.

Table 2: Location estimation error for maximum RSSI and average RSSI techniques.

Δ	N_A	Algorithm		Average Error (cm)	$\text{Error}_{90\%}$ (cm)
240 cm	4	*WLAN Fingerprinting*		504	904
		Hybrid 3 zones	Max	308	554
			Average	264	526
		Hybrid 6 zones	Max	291	516
			Average	212	326
	7	*WLAN Fingerprinting*		350	732
		Hybrid 3 zones	Max	270	509
			Average	215	366
		Hybrid 6 zones	Max	221	416
			Average	194	311
120 cm	4	*WLAN Fingerprinting*		441	952
		Hybrid 3 zones	Max	250	461
			Average	213	337
		Hybrid 6 zones	Max	198	380
			Average	168	284
	7	*WLAN Fingerprinting*		249	455
		Hybrid 3 zones	Max	198	342
			Average	158	270
		Hybrid 6 zones	Max	168	295
			Average	143	260

Figure 10: Outdoor localization area.

Please notice that, besides the advantage in terms of accuracy, response time decreases: this situation is justified by the type of interrogation carried out by the RFID reader. In case of "maximum RSSI", the Reader runs a series of tag interrogations at increasing power, awaiting for tag response (with the consequent waste of time in case of unanswered questions); differently, in case of "average RSSI," the Reader interrogates tags only at its maximum power.

4.4. Third Campaign: Dependence on the Density of RFID Tags. So far, we have shown that the estimated location error of the Hybrid approach depends on the number of zones in the area of interest, the number of APs used, the gap among WLAN training points, and, finally, by the algorithm by which a zone is identified. Now we want to demonstrate that a further parameter to be considered, to a full discussion, is the density of RFID tags. The expected behaviour is that the location estimate accuracy increases by increasing the tag density because, once again, false positives are reduced. With the introduction of our hybrid approach we are able to distinguish two types of false positives: *intra-zone* and *inter-zone* false positives. Intra-zone false positives are typical of WLAN fingerprinting techniques. Inter-zone false positives are a peculiarity of our algorithm. Parameters N_Z, N_A, and Δ affect intra-zone false positives; while the area identification algorithm and the density of RFID tags are responsible for inter-zone false positives. The latter type of false positives affects tracking errors more than the previous one because, if the zone is wrongly identified, the portion of database considered by the usual fingerprinting technique does not include any combination $[\text{RSSI}_1,\ldots,\text{RSSI}_{N_A}]$ associated with the test point (or its surroundings); therefore, localization error certainly occurs.

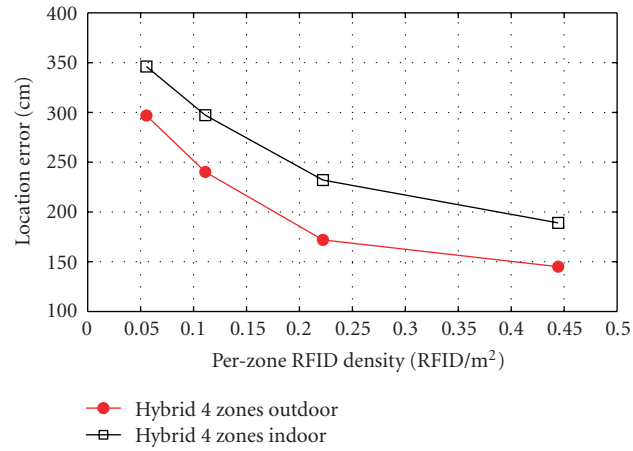


Figure 11: Comparison of location error between Hybrid 4 zones indoor and Hybrid 4 zones outdoor while varying the per-zone RFID density.

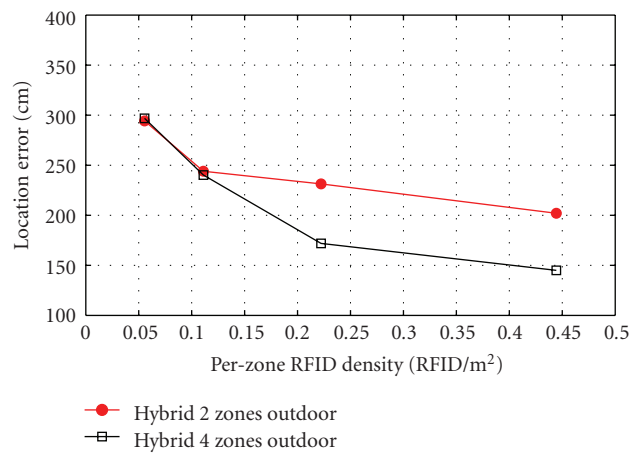


Figure 12: Comparison of location error between Hybrid 2 zones and Hybrid 4 zones while varying the per-zone RFID density.

A different test area is set up (due to the need for symmetrical conditions) to perform the analysis of the effects of tag density, as in Figures 8(a) and 8(b). In this scenario we consider constant parameters $N_A = 4$ and $\Delta = 150$, whereas the best algorithm of zone selection, that is, *average RSSI*, is used. Therefore, let us introduce a new parameter, the *per-zone RFID density* ($\mathrm{Pz_{Rd}}$), which defines the RFID tag density used in each zone. The location accuracy performance will be evaluated in terms of per-zone RFID tag density (RFID/m^2), when considering the sample cases $N_Z = 2$ and $N_Z = 4$.

Figure 9 shows the location error vs. the density of RFID tags, both for the hybrid algorithm with 2 zones and for the hybrid algorithm with 4 zones. The figure shows that curves intersect for $\mathrm{Pz_{Rd}} = 0.15$ RFID tags/m^2. In general, as shown in the first test campaign, the benefits in terms of location accuracy improve when increasing the number of zones. Actually, this rule is valid above a given RFID tag density $\mathrm{Pz_{Rd}}$ threshold, here $\mathrm{Thr_{density}}$. Below the threshold, in fact, the phenomenon of indoor interference (multipath fading) makes the Tag-to-Reader power response unstable and unreliable. Then, the zone selection algorithm, although working on average values, still shows a higher failure probability when the number of zones increases (for the same number of RFID tags), and commits a greater number of inter-zone mistakes. Specifically,

(i) when $\mathrm{Pz_{Rd}} < \mathrm{Thr_{density}}$, the inter-zone error is more frequent and, therefore, a limited zoning should be considered;

(ii) when $\mathrm{Pz_{Rd}} \geq \mathrm{Thr_{density}}$, the inter-zone error is uncommon, the intra-area error (due to WLAN) dominates, and then a more extensive zoning can be considered.

4.5. Fourth Campaign: Outdoor Scenario. Now let us consider an outdoor scenario (Figure 10), in order to highlight how the performance of the proposed algorithm changes. We consider an area in which barriers and electromagnetic phenomena are less manifest than in typical indoor environments.

It is expected that inter-zone errors, due to the RFID technology, and intra-zone errors, due to the WLAN technology, are less than in the indoor case. Furthermore, it is also important to analyze how the value of $\mathrm{Thr_{density}}$ varies in certain conditions.

In order to compare indoor and outdoor scenarios, let us consider again $N_A = 4$, $\Delta = 150$, and the "*average RSSI*" algorithm for zone selection. Figure 11 shows the performance, in terms of location error, of the hybrid algorithm with 4 zones both indoor and outdoor, when varying the RFID tag density. It is also interesting to understand if the proposed positioning method can be exploited *with continuity* when passing from the inside out. As expected, the best performance is achieved outdoor, as less inter- and intra-zone errors are experienced. This is due to the fact that undesired interfering phenomena are contained, or at least reduced, compared to the indoor case. Similar behaviour can be demonstrated with any value of N_Z.

In the outdoor environment, errors of localization with varying density of RFID tags are illustrated in Figure 12, both for the case Hybrid 2 zones and for the case Hybrid 4 zones. It is observed that the value $\mathrm{Thr_{density}}$ is now lower than indoor, about 0.08 RFID tags/m^2. This feature is a direct consequence of the lower interference conditions in which the Hybrid algorithm is operating. We can, therefore, state that, in outdoor environments, the proposed algorithm works well even for low RFID tag densities.

5. Conclusions

In this paper we investigated the feasibility of a new approach to positioning, which exploits *WLAN and RFID Integration* to enhance the performance of a localization algorithm in indoor scenarios. We started from the well-know fingerprinting approach, based on the evaluation of RF power levels from various WLAN 802.11 APs (Access Points). Besides, RFID technology has been introduced to split into zones the whole localization area. A first positive effect has been the severe reduction of the number of search iterations in the fingerprints database (by forcing the algorithm to search the best match only within the actual area of interest). A further effect of the joint use of the two technologies has been the more accurate estimates of the client device position and a manifest reduction in the localization error. A thorough measurement campaign is conducted in indoor and outdoor environments to study the impact of main project parameters affecting the final location accuracy, in order to determine the best operational conditions. The results testified both to the feasibility of the proposed solution and to its higher accuracy when compared to a traditional WLAN-based reference positioning technique.

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