Enhancing WSN-based Indoor Positioning and Tracking through RFID Technology

Zhoubing Xiong, Zhen Yu Song
DET, Politecnico di Torino
Torino, Italy
{zhoubing.xiong, zhenyu.song}@polito.it

Andrea Scalera, Francesco Sottile,
Riccardo Tomasi, Maurizio A. Spirito
PerT Area, Istituto Superiore Mario Boella
Torino, Italy
{scalera, sottile, tomasi, spirito}@ismb.it

***Abstract*—Joint utilization of Wireless Sensor Networks (WSNs) and Radio Frequency Identification (RFID) technologies is gathering increasing attention within the Internet of Things (IoT) community due to the potential of providing pervasive context-aware applications with advantages from both worlds. While WSN system can in fact provide more sophisticated sensing, communication and processing capabilities, the possibility to passively perform detection of tags and the use of unique RFID identifiers provides IoT systems with several advantages, especially concerning maintenance; such advantages are considered especially beneficial in large-scale scenarios where thousands of nodes must be simultaneously deployed over wide areas. WSN-RFID convergence is considered especially promising in context-aware systems with indoor positioning capabilities, where data from already deployed WSN and RFID systems can be opportunistically exploited to refine and enhance collected data with position information. This paper discusses and evaluates a hybrid system where WSN and RFID technology have been integrated to support an indoor positioning service, feeding position information into a general-purpose IoT environment. Performance of the proposed system is evaluated by means of simulations and a small-scale experimental set-up. The performed analysis suggest that joint use of RFID and WSN can increase the robustness and accuracy of indoor positioning systems also in harsh propagation conditions.**

I. INTRODUCTION

Recent evolutions in electronics and wireless communication technology have significantly lowered cost of miniaturized embedded devices provided with sensing, processing and communication capabilities. Such advances have made pervasive monitoring and tracking applications cost-effective not only in small-scale deployments but also in wide-scale scenarios where data must be collected in hundreds of different locations. Thanks to such advances, new paradigms have been envisioned, where information from millions or even billions of devices can be collected, processed and exploited collaboratively within a global Internet of Things (IoT). The IoT can be defined as a pervasive extension of the current Internet where every physical object becomes part of a distributed network of heterogeneous devices which autonomously extract context information from the physical world [1].

Traditional pervasive systems are designed to monitor a predefined set of physical parameters of interest. For example, energy usage information might be relevant for an energy optimization system, while vibration information might be relevant for a structural monitoring system, etc. The IoT vision assumes instead that a single pervasive network can support seamless, interoperable, cross-application data collection from any device and for any type of data. In such a scenario, beyond data collection, it is considered very important also to establish relationship among collected data i.e. to construct "context" information [2].

In IoT environments, position information covers a primal role, because it provides useful context knowledge to be associated with other monitored parameters. For example, the meaning of a temperature reading could vary significantly in case it is close to a window, or on top of an heater, etc.

Wireless Sensor Networks (WSNs) represent a key technology for IoT scenarios such as surveillance, environmental monitoring, health, industrial manufacturing [3]. A WSN can be defined as a self-organizing network of tiny constrained nodes with sensing, processing and communication capabilities. WSN nodes usually integrate one or more low-data rate, low-power physical sensors and are expressly designed to be deployed in large-scale static or mobile environments [4]. WSN nodes leverage on a common set of protocols and algorithms to set-up autonomously an ad-hoc network which is exploited to transport data in multi-hop fashion to one or more central nodes called "sink nodes" or gateways, which in turn provide connectivity towards the Internet. WSN is a suitable technology when the range of the monitored area exceeds the radio range of a single device and when low-cost monitoring and eventually simple in-network processing of physical parameter is needed.

RFID technology also plays a key role in IoT scenarios [5], particularly where there is need to provide any physical item with a unique digital identifier. More generally, due to the low cost of single tags and the lack of batteries, passive RFID technology currently represents the de-facto reference technology for tracking objects wirelessly [6]. Within RFID deployments, normally, a device called reader is in charge of irradiating tags through a set of antennas, filtering the resulting responses from the available tags and uploading the processed information according to a standard e.g. EPCglobal [7] or proprietary data management infrastructure.

WSN and RFID are historically born to cover different needs, although they can be considered substitutive technologies in some use cases. A number of research works have been recently considering joint utilization of these technologies to exploit the advantages of both systems [8]–[10].

This work evaluates how the joint use of RFID and WSN technologies can be effectively exploited within IoT positioning and tracking systems. The motivating goal of this research is to

978-0-7695-4813-5/12 $26.00 © 2012 IEEE
DOI 10.1109/RFID.2012.26

enable enrichment of data collected by WSN nodes with more precise position information, which can be further exploited by context-aware systems. Starting from previous work which assessed the feasibility of joint use of WSN and RFID in indoor positioning applications through simulations [11], this paper outlines the reference design of a hybrid indoor positioning system leveraging both WSN radio information and RFID detection events. Performance of the proposed systems are evaluated by means of simulations and a small-scale experimental set-up.

The remainder of the paper is organized as follows: Sec. II provides a brief overview of the state of the art of indoor positioning systems; Sec. III provides details about the reference architecture of the proposed system and its main components, namely the WSN segment, the RFID segment and the employed positioning algorithm; Sec. IV provides simulation and experimental results which have been used to validate the system in controlled conditions; finally, Sec. V draws conclusions.

II. Related Work

Positioning and tracking are crucial features in many ubiquitous computing and robotics applications where knowledge about the location of the objects is needed [12], [13]. In outdoor scenarios, GNSS (Global Navigation Satellite Systems) such as the Global Positioning System (GPS) are considered mature technologies and are widely adopted. However, GNSS are normally not suitable for indoor scenarios because walls or other fixed structures obstruct GNSS signals. In order to overcome such disadvantage and achieve positioning of people or devices in indoor environments, significant research has been conducted and different Indoor Positioning Systems (IPSs) have been proposed over the years [14]–[16].

Dempsey [17] defines an IPS as a system which can infer the position of a target inside the physical space where the detection system is installed, in real-time or within a maximum time delay. IPS are generally based on some prior knowledge about position of special nodes, namely the *anchor* nodes, and aim at estimating position of one ore more *mobile* nodes, whose position is unknown, by processing ranging data collected and exchanged by both mobile and anchor nodes.

According to Liu [18] there are four different system topologies for IPS. In remote positioning system *(i)*, a mobile node acts as main signal transmitter and several anchor measuring units receive and measure its broadcasted signal. The results from all measuring units are collected, and the location of the transmitter is computed in a central master station. In self-positioning systems *(ii)* the mobile acts instead as measuring unit. This unit receives the signals of several transmitters in known locations and computes its location locally, based on the measured signals. Two middle-way approaches are also possible: in indirect remote positioning systems *(iii)* measurements collected by the mobile node are transmitted via a wireless data link for remote position computation; in indirect self-positioning systems *(iv)* measurements collected locally by fixed stations are transmitted to the mobile through a wireless data link.

According to Hightower [19], IPS can also be classified based on the employed position stimation technique (e.g. triangulation, fingerprinting, proximity, vision analysis, etc.) and the output type (e.g. absolute or relative position information, proximity, etc). Position stimation techniques can be combined to compensate for the limitations of single techniques.

Finally, IPS can be ultimately be classified based on the different underlying technologies adopted for ranging e.g. infrared (IR), ultra-sound (US), RFID, WLAN, Bluetooth, Ultra-Wide Band (UWB), etc. Each technology brings unique advantages in the indoor position inference. IPS can use a single location technology or combine multiple technologies together to increase both accuracy and robustness. A non-comprehensive list of IPS available in literature is reported in the follwing.

Active Badge [14] is one of the earliest optical IR-based IPS: thanks to a transmitter with parallel optical beam and a receiver with an amplified photo diode, it can estimate distance range between target node and the base station with an average accuracy of 2%, and thus extract room proximity information. The main disadvantage of similar techniques are the short range, the line of sight (LOS) propagation path requirement and inaccuracy due to multipath effects.

US solutions such as the MIT Cricket [20] are based on the time of arrival of the sound signal between the target and the anchor nodes. They usually provide good accuracy, in the order of few centimeters. The main disadvantages of this technology are that propagation velocity of the ultrasound signal is deeply affected by the temperature and humidity changes in the environment and typical maximum range is around 10 meters [21].

RF-based solutions are considered cost-effective in WSN environment because they avoid the need to install extra equipment on nodes, unlike IR or US methods. Techniques using this technology can be roughly classified into three categories: angle-of-arrival (AOA), propagation time based measurements and received signal strength indicator (RSSI) based distance measurements.

AOA methods are based on the receiver antenna amplitude or phase response. The accuracy of this method depends on the antenna directivity, multipath reflection and signal shadowing; overall they can achieve 2-4 meters accuracy [22] . It presents two main problems: nodes require a directional antenna with beam forming and LOS propagation path is needed between the transmitter and the receiver. Time of arrival (TOA) and time difference of arrival (TDOA) techniques are both based on measurement of the propagation time. These methods are hard to implement in WSN using RF signals because very accurate timers are needed to reach an acceptable accuracy. However, some systems use UWB technology for an accurate TOA estimation. UWB systems achieve a high range accuracy as the transmitted signals are composed of pulses of very short time duration which provide very good time resolution features. For instance, Ubisense devices [23] achieve an accuracy of about 30 cm.

RSSI methods are instead based on the measurement of the radio power at the receiver. Despite RSSI measurement is time varying and unstable under most circumstances, RSSI-based solutions are widely used as localization technique in WSN systems. RSSI measurements are in fact adopted in many WSN communication standards and are thus made available at no cost by normal radio transceivers installed onboard WSN nodes, withouth need for additional hardware affecting power consumption, size or cost of WSN nodes.

Two common techniques to exploit RSSI for localization are based on fingerprinting signal strengths and conversion of signal strength to distance.

In fingerprinting techniques, a map of the signal strength behavior in the coverage area is constructed. In a first phase, a set of a offline measurements is performed to build a database; then, during the real-time location phase, the algorithm searches for the best matches between the RSSI samples and the stored values. Precision of such methods is normally limited: MoteTrack [24] can achieve an 80% location-tracking accuracy of 1.6 meters and Ekahau Positioning Engine [25] achieves an accuracy of 1-2 meters. The disadvantage of this method is the tiresome calibration phase, i.e. the measurements collection to construct the database. Furthermore, if a prior measurements are used, when an environmental change occurs a new calibration phase is needed.

Another family of techniques involves conversion RSSI to distance using Friis equation [26]. This equation establishes the strength of a signal sent by a radio transmitter in free space at one particular distance, following an exponential relation. In this kind of algorithms transmitting nodes (either anchors or mobiles) broadcast their last known position along with any RSSI information previously collected from other nodes. Using the exponential relation, the receiver can convert the RSSI measurements into distances and, by means of triangulation, estimate its location in relation to the anchors. Localization errors in these methods are in average slightly higher than in fingerprinting for two main reasons: the way that the empirical RSSI-distance relation differs from the theoretical model assumed in the algorithm and the environmental changes affecting RSSI stability. Although this kind of algorithms provide lower accuracy than other techniques, its simplicity make it more suitable to be employed in low-power systems.

IPS based on RFID systems have been widely explored and discussed in scientific literature [27]–[32]; they can be roughly classified according to the same taxonomy used for WSN-based IPS, except for a major difference. In WSN-based IPS anchor and mobile nodes are normally realized using the same hardware and exchange ranging information in a peer-to-peer fashion. In RFID-based IPS, two distinct schemes are instead generally possible [30]: in the "active" scheme the mobile node is implemented by a portable RFID reader, while tags are used as anchors; in the "passive" scheme RFID tags are instead objects to be located while RFID readers are in known position.

While the choice of the scheme to be applied depend on application requirements (e.g. the number of objects to locate, etc.), both schemes can be used with different types of tags (e.g. HF/UHF tags, active/passive tags, etc.) providing different performance in terms of maximum range (from a few centimeters to 10 meters), propagation model and costs [31].

The main advantages of RFID-based IPS include the low cost of tags, the ease of maintenance due to the lack of batteries and the widespread deployment already available in many application scenarios e.g. for inventory or access control purposes.

III. Reference Architecture and Design

This article presents a hybrid positioning system which combines WSN and RFID technologies to compensate the limitations of each technique. On one hand the WSN provides a good coverage but a low positioning accuracy due to the high variance of RSSI measurements. On the other hand, the RFID technology provides a very precise positioning information but a limited coverage. Thus, the right combination of the two technologies represents a good strategy to building an IPS with increased positioning accuracy and availability.

The reference architecture of the proposed solution is described in Fig. 1. The discussed implementation exploits three different segments to collect field data, namely an UHF RFID system, a HF RFID system and a WSN.

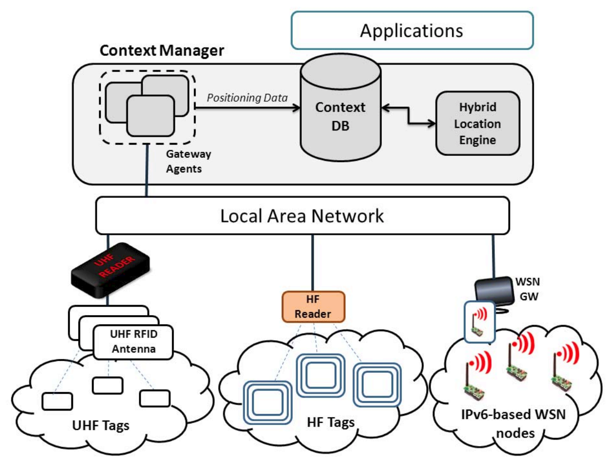

Figure 1. The proposed reference architecture.

The WSN segment support a self-configuring, IPv6-based network of Telos rev.B [33] or STM32W [34] nodes running the Contiki operating system [35]. Within the WSN, mobile nodes periodically broadcast a UDP ranging request, which is used by anchor nodes to measure uplink RSSI. Anchor nodes reply in turn with a ranging response, including the measured uplink RSSI. Finally, the mobile node measures all downlink RSSI, aggregates all ranging responses and forwards all the uplink-downlink tuples (one for each anchor) to the WSN gateway. The WSN gateway is a simple COTS (Commercial Off-The-Shelf) low-power PC running Linux.

The RFID segments are instead based on a set of COTS HF and UHF RFID readers which irradiate periodically and issue an event when a new tag is detected.

Data collected by the three different segments is pre-processed by technology-specific gateways and transferred via an IP-based local area network to a central entity named Context Manager i.e. a virtual distributed entity which is used to handle generalized context information extracted from the underlying platform-specific components. Within the Context Manager a virtual delegate named Gateway Agent is configured to filter all the (large) amount of data from its respective platform-specific gateway and feed it into any subscribing entities i.e. any feature of the system which is interested of receiving the specific data type. Based on such data and from configuration data also hosted inside the Context Manager the Hybrid Location Engine (described in Sec. III-A) is in charge of extracting the physical location of objects associated with the sources of the physical-world events, namely RFID tags and WSN nodes.

Based on the analysis presented in Sec. II, the proposed system can be classified as an hybrid scheme exploiting both indirect remote positioning systems and indirect self-positioning. The WSN segment uses RSSI with conversion to distance, while both RFID segments adopts a passive positioning scheme with passive tags. The overall position estimation technique is a particular triangulation technique, namely the hybrid cooperative extended Kalman filter (hcEKF), which provides absolute positions as output.

A. Location Engine

As it can be observed from Fig. 1, the positioning algorithm is implemented in a centralized way in the hybrid location engine which periodically estimates the positions of all unknown mobile nodes. Note that a mobile node can be equipped with a combination of the following three radio frequency (RF) devices: a WSN node, an UHF-RFID tag and a HF badge. For instance, a mobile node may be equipped with either all the three different elements or with only two of them (e.g., with a WSN node and a HF badge) or just with single device (e.g., a WSN node or an UHF-RFID tag).

As depicted in Fig. 1, the location engine reads from a Context DB (e.g. every $\Delta \mathrm{T}_p$ seconds) the following data: RSSI measurements derived from WSN nodes, detection events from UHF-RFID tags and HF badges. After that, according to the positions of WSN anchors, UHF-RFID antennas and HF badge readers, the hybrid location engine estimates the positions of all mobile nodes by combining different measurements. Since the UHF-RFID and HF-RFID detection events are available at the corresponding readers, these data are not forwarded to the corresponding unknown mobile nodes, for instance, through the WSN technologies, to implement a distributed positioning algorithm. On the contrary, in order to reduce communication latency, all data, including also RSSI measurements from WSN devices, are collected in the context DB, then the location engine estimates the position of the mobile nodes in a centralized manner.

The hybrid position estimation process is detailed more precisely in the following.

1) **Location Information Reading**

First of all, the location engine reads from the DB the location information of all devices. In particular, this information includes the device ID and the corresponding type (i.e. WSN, UHF-RFID or HF badge). Additionally, for each device there is flag which specifies if it is '*fixed*' or '*mobile*'. A '*fixed*' device may be either a WSN anchor, a UHF-RFID antenna or a HF badge reader whose positions are *a priori* known, while a '*mobile*' device is a node with unknown position and, as mentioned above, it may be equipped with different RF devices. Finally, the location engine reads from the DB information about how the different RF devices are binded with each other.

2) **Measurements Reading**

In this step, the location engine reads from the DB all the available observations, i.e. RSSI, UHF-RFID tag and HF badge detection events, in the time interval $[t_k - \Delta T_{\mathrm{DB}},\ t_k]$, where t_k is the current time and ΔT_{DB} is the width of the temporal window. It worth observing that the larger ΔT_{DB} the larger number of measurements (i.e. higher connectivity). However, in a mobility scenario a larger ΔT_{DB} value may lead to a worse tracking performance as the algorithm use old range measurements that refer to past mobile nodes' positions far from the current ones. Therefore, a suitable choice of this parameter is a trade off between number of measurements and freshness of the measurements which in turns depends on the mobility degree of the unknown nodes. In fact, it may happen that more than one measurement is available, for instance, between a specific couple of WSN nodes. In this case, a weighted average is applied. In particular, the weight associated to a measurement is calculated according to an exponential function which uses as input the time difference between the current time t_k and the time stamp at which the measurement is stored into the DB. For example, a low weight is assigned to an old measurement while a larger weight is given to a more recent one.

3) **Positioning Estimation**

In this step the location engine estimates the positions of all mobile nodes. Since two mobile WSN nodes are able to perform RSSI measurements between each other, a cooperative scheme can be applied where the location engine, apart from range measurements from anchors, uses also range measurements performed among mobile nodes. The adoption of this approach improves both the positioning accuracy and system robustness (i.e. position availability) as more measurements are available to localize the mobile nodes. It is worth noting that the cooperation scheme can only be applied to mobile nodes equipped with a WSN device. In fact, when a mobile node is equipped with only either a UHF-RFID tag or a HF badge device, the cooperation cannot be applied as the device itself is passive and it cannot perform measurements with respect to other passive devices.

Since the HF badge can be detected by the reader only when the distance from it is very short (e.g., a few centimeters), the location engine uses the badge detection event as a very accurate position and time information. In fact, when a HF badge is detected, the location engine sets the estimated position of the associated mobile node to the HF reader's position and ignores the other observations (i.e. RSSI or UHF-RFID detection). However, since the HF badge readers are only available at the door, mainly for control access purposes, the

HF badge readers provide sporadic events. In fact, most of the time, the hybrid location engine uses RSSI measurements from WSN devices and UHF-RFID events.

The RSSI measurements performed among WSN nodes are related to the distance according to the *log-normal shadowing path loss model* [36], where the received power $\tilde{P}$ (expressed in dBm) is a function of the distance between the transmitter and receiver d:

$$\tilde{P}(d) = P_0 - 10\alpha \log_{10}(d/d_0) + X_\sigma, \quad (1)$$

where P_0 (expressed in dBm) is the mean power received at the reference distance d_0 (typically 1 meter), α is the path loss exponent, and X_σ is an additive measurement noise (Gaussian distributed) which models the shadowing effect.

Concerning the UHF-RFID measurements, as in [37], each detection event is translated to a distance measurement equal to half of the interrogation range, r. Thus, the RFID-based range measurements can be modeled as:

$$\tilde{d} = r/2 + n, \quad (2)$$

where n is the measurement noise, which is assumed Gaussian distributed with zero mean and a variance depending on r [37].

The location engine is based on the hybrid cooperative extended Kalman filter (hcEKF) algorithm proposed in [37] adapted to integrate also HF badge events.

In order to estimate the positions of mobile nodes, the hcEKF takes into account all the available RSSI measurements performed between WSN mobile nodes and WSN anchors as well as among WSN mobiles. Moreover, the hcEKF uses also UHF-RFID detection from RFID antennas (please refer to [37] for more details about the hcEKF algorithm). The whole procedure of the hybrid location engine is summarized in Alg. 1.

Algorithm 1 Hybrid Location Engine

```
Read location information from DB
for k =1 to K do {time slot index}
  read measurements from DB in the interval [t_k − ΔT_p, t_k]
  for m = 1 to M do {mobile nodes}
    if HF-badge event for m then
      set position estimate equal to the HF reader's location
      initialize the hcEKF according to the new location
    else
      extract all measurements related to mobile m
      if there are measurements for m then
        estimate the mobile position using hcEKF [37]
      else
        position estimation not available
        set current estimation to the previous one
      end if
    end if
    upload position estimate to DB and plot it on the map
  end for
end for
```

IV. Simulation and Experimental Results

The performance of the hybrid location engine is evaluated first through Matlab simulations and then by means of real measurements.

The selected validation scenario is based on the Pervasive Technologies (PerT) laboratories at Istituto Superiore Mario Boella (ISMB) composed of two adjacent open spaces, namely room 1 and room 2, connected by a corridor (see in Fig. 2). This scenario of size about 25 m ×10 m is typical office environment, although the building structure is mainly composed of metal.

A. Simulation Results

Concerning the simulation scenario, the RF devices are deployed as follows: a wireless sensor network composed of 11 anchor nodes are placed around the two open spaces to optimize the location accuracy; 4 UHF-RFID antennas are deployed only in the room 2; 5 badge readers are installed at the doors to provide access control; 3 hybrid mobile nodes are considered, all of them equipped with a WSN device, an UHF-RFID tag and a HF badge.

The three mobile nodes move along three different trajectories as showed in Figure 2: mobile M1 moves in room 1 (exact positions represented by red dots), mobile M2 moves in room 2 (green dots), and mobile M3 moves from room 1 to room 2 through the corridor (blue dots).

RSSI measurements are generated by using the log-normal model reported in (1). The sensitivity of the WSN receiver was set to -90 dBm which determines the connectivity information. The badge reader generates a badge event when the mobile crosses a door. The UHF-RFID antennas provide a detection event when a passive UHF-RFID tag is within the interrogation area with radius $r = 2$ m.

In order to provide steady statistics, 100 Monte Carlo runs were performed. Two different algorithms were tested: the hcEKF and a EKF (non cooperative and non hybrid) based only on RSSI measurements performed with WSN devices. Figure 2 shows just one realization where only the estimated positions related to mobile node M3 are plotted to avoid an overcrowded figure. Thanks to the HF-badge device, the hybrid location engine initializes the three mobiles to the corresponding HF-badge reader positions, while the EKF is initialized to the coordinates of the scenario's center.

When M3 is in the corridor, the EKF diverges due to the bad geometry of the WSN anchors deployment while the hcEKF is able to estimate its trajectory close to the the true one thanks to the cooperation with the other mobile nodes. When M3 approaches room 2, the non cooperative EKF starts diverging again while the hcEKF is able to track the mobile by using also measurements from UHF-RFID.

Figure 3 shows the tracking performance in term of cumulative distribution function (CDF) of the positioning errors. In addition, it reports also the Root Mean Square (RMS) of the positioning error, expressed in meters.

It can be observed that the hcEKF, which combines RSSI and detection events from RFID, outperforms the standard EKF,

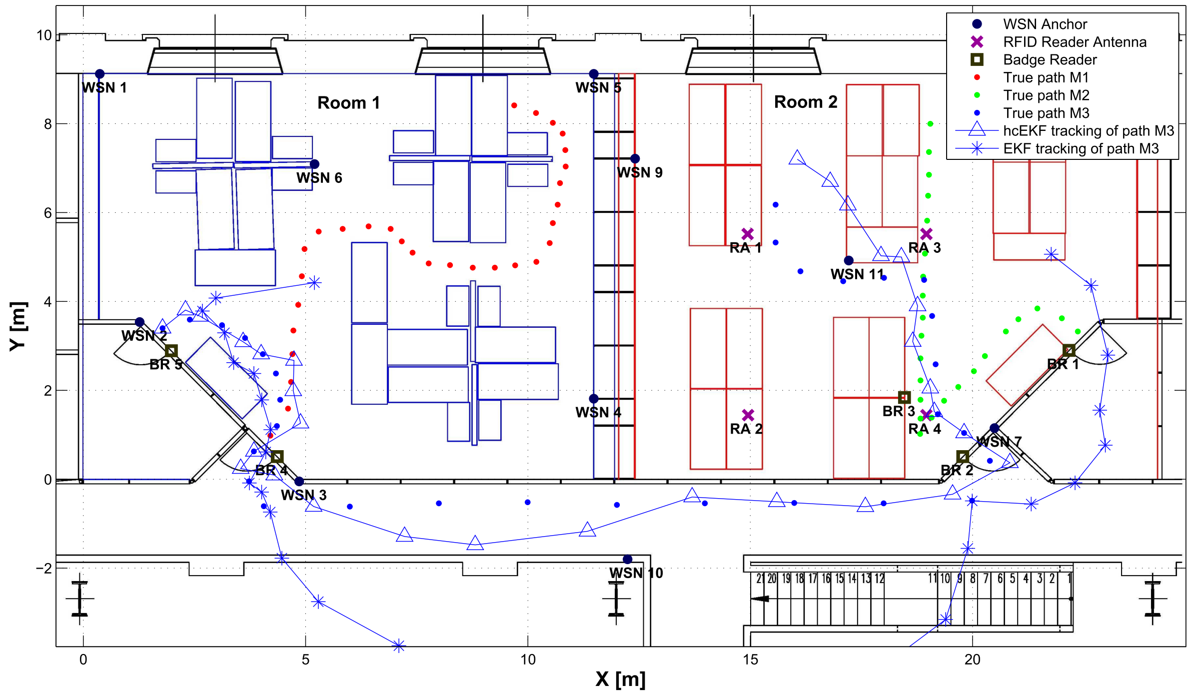

Figure 2. Simulation Scenario and mobile nodes' trajectories.

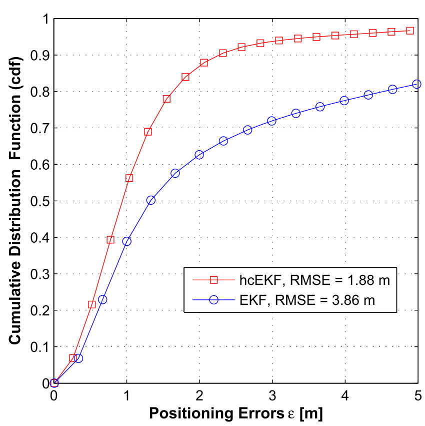

Figure 3. Tracking performance.

which uses only RSSI measurements.

B. Experimental Results

Since the current availability of WSN devices was not sufficient to allow a full deployment in the selected scenario, the experimental results were carried out only in room 2, where five WSN anchors, four UHF-RFID antennas and three HF readers were deployed as showed in in Fig. 2. Starting from the badge reader BR2, a mobile node, equipped with a WSN node, an UHF-RFID tag and a HF badge, moved with pedestrian mobility along a zig zag trajectory within the mentioned area. Fig. 4 shows the tracking performance when the WSN-only tracking algorithm and the hybrid one were applied, respectively. The average positioning errors, expressed in meters, are reported in the upper part of the two figures.

It can be observed that experimental results are consistent with simulations: the WSN-only tracking algorithm shows larger errors due to the large noisy that affects the RSSI measurements while the hybrid tracking algorithm is able to track better the movement of mobile thanks to the additional information from RFID.

V. Conclusions

This paper discussed performance of a hybrid RFID-WSN system for tracking people and objects in indoor scenarios. Experimental and simulation results suggested that the joint use of RFID and WSN can increase the robustness and accuracy of indoor positioning systems also in harsh propagation conditions, though increasing the complexity of the system. More specifically, both simulation and experimental results showed that the RFID-WSN hybrid configuration outperforms set-ups employing single technologies. Based on the performed analysis it is possible to conclude that indoor positioning systems can effectively benefit from both RFID and WSN technology and the proposed configuration can be cost-effective

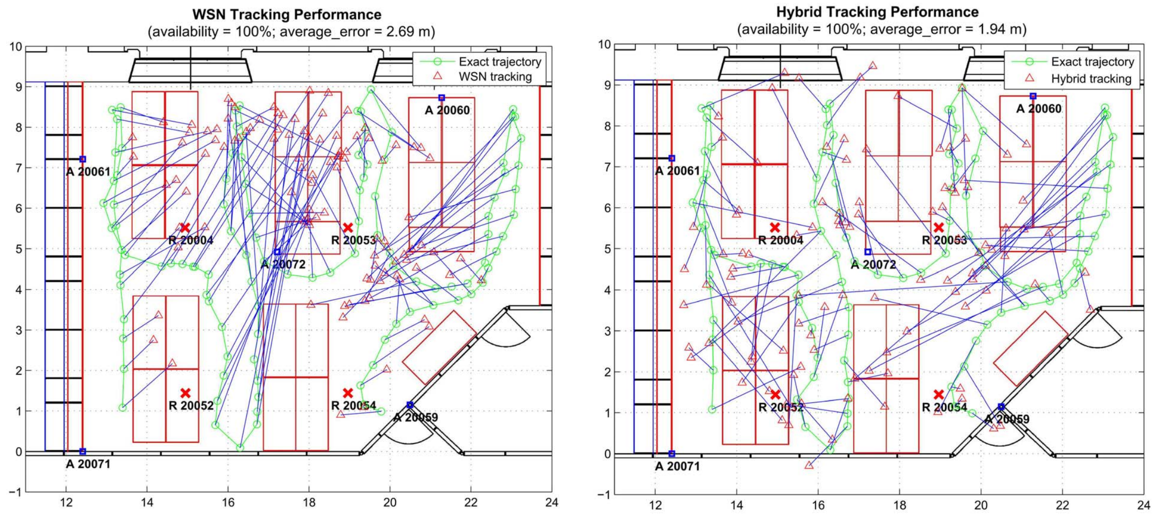

Figure 4. Experimental tracking results.

in situations where RFID and WSN are already in place for other purposes such as equipment monitoring or access control.

Acknowledgment

This paper has been partially supported by regional project "GA-RF-WSN" and by the European FP7 project BUTLER, under contract no: 287901.

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