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A Survey on Indoor Vehicle Localization Through RFID Technology

ANDREA MOTRONI [1], (Member, IEEE), ALICE BUFFI [2], (Member, IEEE), AND PAOLO NEPA [1,3], (Senior Member, IEEE)

[1]Department of Information Engineering, University of Pisa, 56122 Pisa, Italy
[2]Department of Energy, Systems, Territory and Constructions Engineering, University of Pisa, 56122 Pisa, Italy
[3]Italian National Research Council (CNR), Institute of Electronics, Computer and Telecommunication Engineering (IEIIT), 10129 Turin, Italy

Corresponding author: Paolo Nepa (paolo.nepa@unipi.it)

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ABSTRACT This paper presents a state-of-the-art analysis on the methods suitable for vehicle indoor localization and exploiting the RFID (Radio Frequency IDentification) technology. The survey describes three main categories of vehicle localization systems: (i) solutions exploiting only the RFID technology, (ii) sensor-fusion techniques combining data from RFID systems and proprioceptive sensors, and (iii) sensor-fusion techniques combing RFID data with those of other exteroceptive sensors in addition to the RFID system itself. For each method, implementation and methodological details are discussed, by highlighting the applied RFID technology, namely passive HF-RFID, passive UHF-RFID, or any other RFID system. Also, the employed RFID parameters, i.e., tag EPC, RSSI or backscattered phase, are discussed. The survey focuses on the achievable localization performance, also accounting for infrastructure-deployment costs together with complexity and maintenance overhead. Positioning, tracking, navigation and simultaneous localization and mapping (SLAM) issues are here considered. The analysis highlights pros and cons of each method, together with the main challenges and perspectives of RFID-based solutions for vehicle localization.

INDEX TERMS Autonomous vehicle, data fusion, exteroceptive sensors, localization, navigation, proprioceptive sensors, RFID, robot, tracking, sensor fusion, SLAM, UGV.

I. INTRODUCTION

In recent years, indoor localization has received an increasing attention as a key element to develop autonomous robots and cars, or any other unmanned vehicles [1]. Indeed, the self-localization is the first requirement to build an agent capable to guide itself through a known or unknown indoor environment [2], where the actual satellite positioning systems suffer from signal attenuation related to through-wall electromagnetic wave propagation.

In the present Industry 4.0 era, many commercial wheeled robots exist in different form factors to cover a huge variety of applications, such as retails or warehouse management, logistics, and so on. They can easily carry out sensors, cameras or grasping systems. Typically, wheeled robots are equipped with *proprioceptive sensors* to measure kinematic quantities that are helpful to retrieve the robot trajectory, e.g., Inertial Measurement Units (IMUs), encoders or optical flow sensors. In the ideal case, if the vehicle initial position is known, such sensors may enable the vehicle self-localization through a *dead-reckoning* approach [3]. However, due to the limited sensor accuracy, the measurement errors pile up, bringing to an increasing drift on the vehicle estimated trajectory.

As an alternative, *exteroceptive sensors*, such as cameras [4], sonars [5], laser range finders (LRFs) [6], or Radio-Frequency (RF) systems [7] can be adopted to circumvent the drift of the estimated trajectory, which is typical of the dead-reckoning approach. To increase the localization accuracy, widespread solutions foresee to combine data

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from both proprioceptive sensors and exteroceptive ones [8], [9] through *sensor-fusion* approaches, also known as multi-sensor data fusion, by means of several different estimation algorithms.

Undoubtedly, vehicles equipped with LRFs or cameras represent widespread commercial solutions, due to their ease of installation and high number of different implementation techniques [10], [11]. However, the presence of moving obstacles or people may degrade the localization performance of LRF-equipped vehicles, while privacy issues occur in camera-based systems, which also require for complex and time-consuming image processing. Besides, Wi-Fi, ZigBee, Bluetooth, Ultra-Wide-Band (UWB), and Radio Frequency Identification (RFID) technologies are largely employed for indoor localization purposes [12]–[17], thanks to the use of commercial-off-the-shelf (COTS) hardware. Wi-Fi, ZigBee and Bluetooth operate in the 2.4 GHz Industrial-Scientifical-Medical (ISM) band and typically guarantee a localization error of the metre order, which may not be satisfactory for vehicle localization. On the contrary, UWB and RFID systems, can allow to get centimetre order localization. In particular, UWB devices allow to cover larger areas with few reference anchors, thanks to a reading range of tens of metres, despite of a relatively high cost and the power supply need. Instead, passive RFID tags are cheap and battery free, and they can be easily installed in the scenario with almost no worries about the number of tags required for an assigned localization accuracy. In the Ultra-High-Frequency (UHF) band, tags are detectable up to 10 m with an Effective Radiated Power (ERP) of 2 W, making RFID systems classifiable as low-power consumption systems.

More recently, 5^{th} Generation of cellular networks (5G), millimetre-Waves (mmWaves) or Terahertz technologies have been also suggested [18]–[20], even if they are at an early-stage implementation. 5G and mmWave systems at 26 GHz guarantee a centimetre order localization error but require for an ad-hoc system infrastructure that is not currently easily available on the market. Terahertz technology provides dozens of GHz bandwidth which enables high spatial resolution; on the other hand, THz devices are complex and expensive, and the propagation range is limited by the relatively high atmospheric absorption. In all RF systems operating at high frequency bands, e.g., UWB, 5G and mmWaves, the multipath propagation, typical of the indoor scenario, may deeply affect the localization performance especially in presence of multiple obstacles. Such an effect can be mitigated with RFID systems working at lower frequencies.

In authors' opinion, besides all the aforesaid features of the RFID systems, their increasing presence in logistics and retails represent another advantage. In particular, commercial RFID robots are already available in the market with embedded RFID hardware to perform inventory operations [21]–[23]. Thus, the latter can be employed to develop the vehicle self-localization system by exploiting the hardware installed for inventory purpose. Such considerations lead to an increasing interest in RFID-based solutions for vehicle indoor localization, in the upcoming years.

For above reasons, in this paper we present a state-of-the-art analysis on RFID-based solutions focused on vehicle localization for indoor scenarios. In detail, we propose a classification based on solutions exploiting only the RFID technology, sensor-fusion techniques combining data from RFID systems and proprioceptive sensors, and sensor-fusion techniques combining RFID data with those of other exteroceptive sensors in addition to the RFID system itself. The pros and cons of each category are discussed together with their typical localization performance.

It is noteworthy that through the paper the term vehicle refers to a ground vehicle. Thus, the survey describes the state-of-the-art solutions addressing a 2D localization issue. Even if most of the solutions have been suggested for and tested with robots, they can be applied, or extended, to face with the localization of almost any ground vehicle, e.g., forklift, unmanned ground vehicle, and so on, once some specific requirements on vehicle size and speed are met. Aerial vehicles, e.g., drones and unmanned aerial vehicles [24], represent a different category which deserves for a separate discussion, which is outside the purpose of this paper.

Finally, we would like to highlight that chipless RFID systems could also be used for localization purposes; however, they have not been considered in the present survey since they are still at an early development stage and commercial hardware is not yet available.

The paper is organized as follows: Section II gives a brief introduction to the RFID localization fundamentals, by showing the right nomenclature needed to present the available solutions. Section III provides the main features of the above indoor vehicle localization systems, which are deeply investigated in the following sections: solutions exploiting only the RFID technology are presented in Section IV; sensor-fusion techniques combining data from RFID systems and proprioceptive sensors are described in Section V; sensor-fusion techniques combing RFID data with those of other exteroceptive sensors in addition to the RFID system itself are depicted in Section VI. Then, Section VII discusses the performance analysis and the research trends of the RFID-technology adoption for vehicle localization. Finally, concluding remarks are given in Section VIII.

II. RFID LOCALIZATION FUNDAMENTALS

A. NOMENCLATURE

When addressing RFID localization techniques, different tasks can be solved: positioning, tracking, navigation, or Simultaneous Localization and Mapping (SLAM) (Fig. 1). We refer to positioning when the method estimates the punctual position of the vehicle at a given time, being static or moving. *Tracking* is performed when the method estimates the vehicle trajectory, namely a sequence of consecutive positions assumed by the moving vehicle over the time. Such locations can be estimated independently (*memory-less*

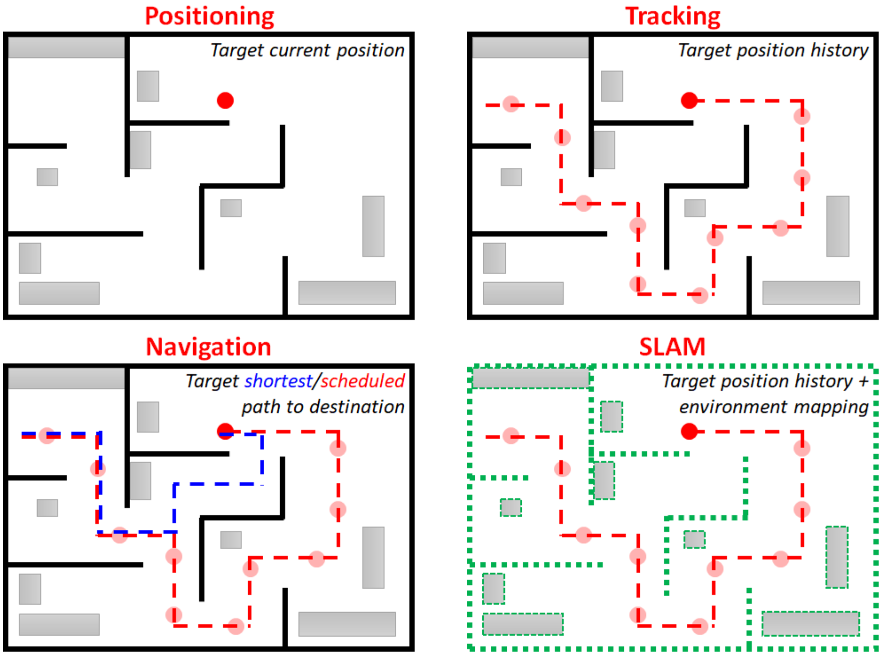


FIGURE 1. Sketch of positioning, tracking, navigation and SLAM principles.

localization), or by accounting for the previous history of the mobile unit locations, as well as of its velocity and acceleration. *Navigation* concerns the programming of the vehicle trajectory to follow a pre-determined path or to reach a target location through the shortest path. *SLAM* consists in the vehicle tracking together with the acquisition of the environment map [21]–[26]. When employing the RFID technology, SLAM solutions determine the vehicle trajectory together with the location of reference RFID tags contextually, without any a priori knowledge of the environment [27]. Through the manuscript, we will use the more general term "localization" to refer to any of the four abovementioned issues.

B. LF AND HF RFID SYSTEMS

Currently, many types of RFID systems are available on the market. The first developed solutions were the Low Frequency (LF) systems at 125 kHz and the High Frequency (HF) systems at 13.56 MHz (Fig. 2).

LF systems are usually adopted for smart cards and tickets. They exploit inductive coupling and usually require for a quasi-direct physical contact between the reader and the tag itself, so they cannot be profitably employed for localization tasks.

HF systems exploit the inductive coupling, too, but they exhibit a few-centimetres reading range which is enough to deploy localization systems based on a proximity approach. Indeed, earliest RFID-based solutions for vehicle localization were based on the *read/no-read* approach [28]. A binary detection information is derived from the reading or missed-reading information of the tag Electronic Product Code (EPC). The vehicle position is associated to the

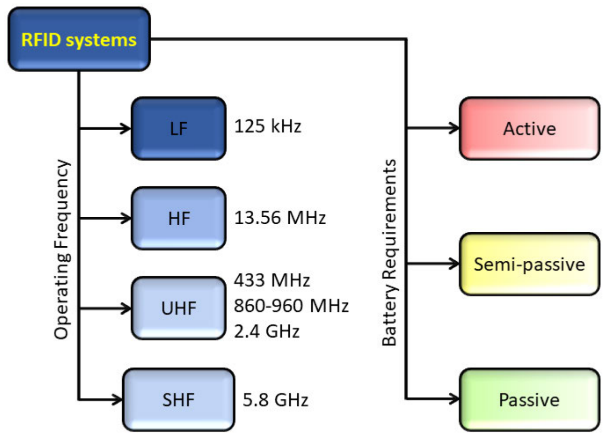


FIGURE 2. Operating frequency and battery requirements of RFID systems.

position of the detected reference tag at the reading timestamp.

C. UHF RFID SYSTEMS

More recently, Ultra High Frequency (UHF) systems at 433 MHz, 860-960 MHz, and 2.4 GHz have been implemented. Some custom RFID systems in the Super High Frequency (SHF) band working at 5.8 GHz also exist (Fig. 2).

UHF tags can be detected through a microwave signal transmission, so they rely with the electromagnetic wave propagation. The detection distance depends on several factors and mainly on the presence or absence of a tag battery. Active tags can achieve a reading range of tens of metres and they usually work at 433 MHz by reaching a reading range up to 100 m.

The first well-known solutions, such as LANDMARC [29] and SpotON [30], exploit the active RFID technology to perform tag localization. Passive RFID tags do not have any power supply, and they communicate through the *modulated backscattering* principle. So, they self-power through the impinging electromagnetic wave transmitted by the reader and reflect it back by modulating the signal to communicate their EPC, without using an internal local oscillator.

Current UHF passive tags (860-960 MHz) can reach up to 10 m of reading range [31] and they are receiving increasing attention for localization purposes, due to their low-cost, easy installation and maintenance. Semi-passive tags carry on a battery which is only used to power up the microchip or auxiliary devices such as sensors, but not to feed the transmitter. Thus, they communicate through the modulated backscattering as for passive tags.

Other than the tag identification data, COTS UHF-RFID readers usually provide a useful information about the signal amplitude, named as the Received Signal Strength Indicator (RSSI), which can be profitably employed for localization purposes [32]. In fact, it is theoretically possible to infer the reader-tag distance from RSSI measurements, so using them for ranging operations.

By referring to [33], the received signal power at the reader side can be expressed as:

$$P_{received} = P_{TX} G_{TX}^2 G_{RX}^2 M \chi^2 \left(\frac{\lambda}{4\pi d}\right)^4 |H|^4 \tag{1}$$

where λ is the signal carrier wavelength, d is the distance between the reader antenna and the tag at the reading timestamp, P_{TX} is the power transmitted by the reader, G_{TX} and G_{RX} are the gains of the reader and tag antennas, respectively, χ is the polarization matching coefficient, M is the modulation backscattering coefficient and H represents the complex factor which describes the channel response. For a line-of-sight scenario, $H = 1$.

The RSSI, measured in dBm and available in all commercial RFID readers, is a parameter proportional to the above-mentioned received signal power level (1). Consequently, it is affected by many factors such as tag model, chip sensitivity, tag orientation, tag antenna, and material properties of the tagged object. Besides, other external factors such as multipath propagation, interference and occlusion phenomena can affect the RSSI behaviour, too. It is apparent that a reliable path-loss model that may consider the effects of all above phenomena is difficult to define, and *ad hoc* modifications of (1) should be properly designed according to the application scenario. The latter represents a very difficult task especially in indoor scenarios with rich multipath propagation, by leading to an intrinsic unreliability of the RSSI-based methods, especially when localization of a moving target is pursued.

Modern readers can also provide the phase of the tag backscattered signal as an additional output information. In fact, IQ demodulators are employed in all commercial readers, and a coherent demodulation is a mandatory step for the correct signal reception (Fig. 3). Such parameter is exploitable only for passive or semi-passive RFID tags which communicate through the modulated backscattering, without employing internal local oscillators for data transmission. As demonstrated by Nikitin *et al.* in [34], phase-based localization methods allow for a better localization accuracy, since they are more robust to the multipath propagation than the RSSI-based approaches [35].

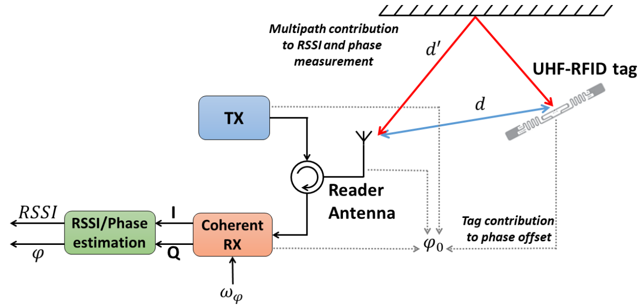


FIGURE 3. Scheme of a UHF-RFID system.

The measured phase of the tag backscattered signal can be written as:

$$\phi = mod\left(\frac{4\pi d}{\lambda} + \phi_0 + \omega_\phi, 2\pi\right) \tag{2}$$

where ω_ϕ is the phase noise and ϕ_0 is the phase offset including the effect of cables and other reader components (Fig. 3). The latter also depends on reader antenna and tag typologies, the tag chip, the tag orientation with respect to the reader antenna and the material of the tagged item, as all of them may affect the tag backscattering.

It is apparent that, for localization purposes, the first issue to be solved is the 2π phase-ambiguity. To this aim, phase unwrapping techniques can be adopted to restore the physical continuity of the phase delay. As an alternative, the phase samples can be assembled in a phasor sequence [36], [37] and then employed as an input of the localization algorithm. In both methods, multiple readings with a proper spatial sampling must be available [38]. Furthermore, the offset term ϕ_0 should be correctly measured to derive the distance information from (2), leading to time-consuming calibration procedures. To overcome above issues, alternative approaches use the Phase Difference of Arrival (PDOA) [36], [37].

An overview of the many techniques typically applied to perform localization through the UHF-RFID technology, e.g., range-based methods and range-free methods, can be found in [39], [40].

It is noteworthy that it is not possible to perform high accuracy and unambiguous ranging measurements of the reader-tag distance by using the Time of Arrival (TOA) or Time Difference of Arrival (TOA) approaches. In fact, the communication channel bandwidth of COTS UHF-RFID systems is relatively limited (around hundreds of kHz), and even the whole associated bandwidth is still not sufficient to make accurate time-of-flight measurements.

III. RFID VEHICLE LOCALIZATION

A. APPLICATION SCENARIOS

Since an RFID system represents a valuable solution to perform vehicle positioning, tracking, navigation or SLAM, the vehicle-mounted RFID infrastructure can be profitably employed for a simultaneous and accurate tagged-item inventory and localization. Thus, the RFID technology combined with ground vehicles could be promising to cover many applications typical of pervasive robotic systems [41], being a valuable alternative to other competitor technologies on the market.

In retails, lots of robots already equipped with COTS RFID-UHF hardware already exist, i.e., RFID robots [42]. Among them, AdvanRobot by Keonn [21], Tory by MetraLabs [22], and Robi by Fetch Robotics [23] are worth mentioning. Such robots are able to navigate themselves within the indoor scenario for inventory purpose.

In logistics, RFID-based vehicles such as forklifts [43], can help the implementation of smart warehouses [44], [45]. This allows not only the item inventory, but also the development of new services such as the optimization of item placement and of vehicle paths within the warehouse, the real-time interaction between the production facilities and the storage area, thus aiming to get an effective Cyber Physical System [46]. Moreover, the RFID infrastructure can help the collision avoidance or work-related injuries [47], by ensuring the operator safety.

Still in the framework of Industry 4.0, smart manufacturing can be implemented thanks to collaborative robots [48] able to interact with each other and also with human operators along the assembling line. In such case, high localization accuracy is required for robots performing the assigned task, also to guarantee the worker safety.

In healthcare, RFID robots can be also applied to implement intelligent hospitals [49] by monitoring the biomedical equipment location [50] or by guiding the patients [51].

The coexistence of humans and robots in the domestic sphere allows the deployment of smart homes where the RFID technology can be fruitfully employed. An RFID robot may *sense* the environment and interact with it. On the basis of the detected tag, the robot can accomplish specific tasks. Consequently, the RFID robot is ready to become a social robot, suitable also for elderly care [52], guidance of visual-impaired people [53] and ambient assisted living applications [54]–[55].

Again, in Smart Environment applications [56], RFID robots are employed to perform as shopping assistants [57] or tour-guide in museums or exhibitions [58]. Since such scenarios are typically multi-floor, e.g., shopping malls or museums, reference tags can be easily installed to allow the recognition of the floor/room through the association of the detected EPC with a proper database.

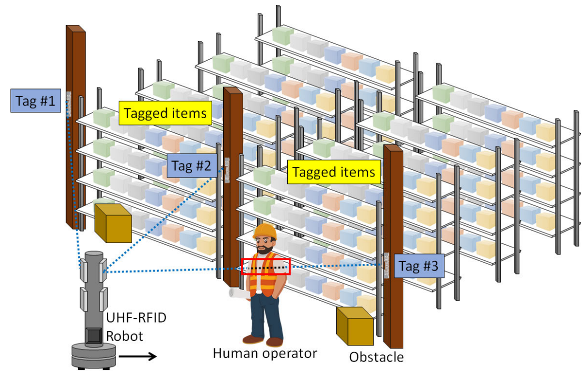


FIGURE 4. Scheme of a UHF-RFID robot equipped with multiple antennas and moving in an indoor scenario where reference tags are deployed for localization purposes.

B. RFID-BASED LOCALIZATION METHODS

A number of solutions have been presented, which are based on a mobile agent [59]–[64] or a robotic grasping system [65], [66]. We distinguish between moving-reader based systems, e.g., reader-equipped vehicles exploiting a set of reference tags, [67]–[69], and moving-tag based systems, e.g., tagged robots that self-localize by using an infrastructure of fixed reader antennas [39], [70]–[74]. The latter solution is more expensive and complex with respect to the first one, which is typically preferred.

In reader-equipped vehicles, the RFID reader, with one or more antennas, is installed on the vehicle, whereas several RFID tags are deployed in the scenario as reference markers (Fig. 4). If the tags are placed at known positions, the positioning/tracking/navigation task can be solved by properly exploiting the backscattering signal data measured from them. Alternatively, for either unknown or partially known reference tag positions, a SLAM problem [59] can be addressed.

Several factors may influence the vehicle localization when using a grid of reference tags, such as tag typology, tag density, tag orientation, and tag mutual electromagnetic coupling. A dense deployment of RFID tags may give higher localization accuracy, but it is more expensive and presents a higher influence of the electromagnetic coupling among nearby tags, together with lower number of successful readings per tag, in an assigned temporal interval. Since passive RFID tags usually do not have computational capabilities to perform any kind of data processing by themselves, the localization is performed according to a centralized scheme at the vehicle side or at the system back-end.

To reduce the number of reference tags while keeping unaltered the localization performance, widespread solutions foresee to apply a sensor-fusion approach [75], by combining data acquired by the RFID system with other sensors. In particular, we can employ proprioceptive sensors or other exteroceptive sensors in addition to the RFID system itself. Depending on the accuracy and performance of the employed sensors, this can lead to a cost enhancement which however

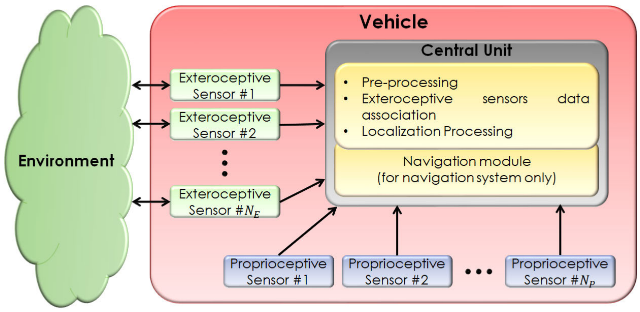


FIGURE 5. General sensor-fusion schematic combining data from several proprioceptive and exteroceptive sensors with the central unit on the vehicle.

could be tolerated according to the specific application scenario, or if high localization performance is required.

Proprioceptive sensors measure internal quantities to the mobile vehicle system. When the localization task is pursued, they are typically kinematic sensors such as encoders, optical flow sensors or IMUs equipped with accelerometers, gyroscopes and/or magnetometers. A dead-reckoning approach is typically applied to retrieve the vehicle trajectory in a local reference frame, through a single or a double integration. Since these sensors are not able to *sense* the environment, they cannot provide any information about the absolute location of the vehicle within the scenario and neither its starting location. Moreover, even if the latter is perfectly known, the only dead-reckoning is unable to track the vehicle along a long trajectory due to the low accuracy of such proprioceptive sensors. The longer the trajectory, the more the measurement error accumulates and consequently the greater the error on the estimated trajectory.

To overcome abovementioned issues, the vehicle has to be able to *sense* the external environment through exteroceptive sensors as for example Laser Range Finders, sonars, cameras, and RFID systems as well. The data collected by both the proprioceptive and the exteroceptive sensors can be combined with several approaches.

The more widespread family of sensor-fusion algorithms relies on sequential Bayesian or Monte Carlo estimators for dynamical systems, such as the Kalman Filter and its extensions (Extended Kalman Filter, EKF or Unscented Kalman Filter, UKF), or the Particle Filter (PF) and its extensions [76]. In some other cases, smoothing algorithms, or Finite Impulse Response (FIR) filters are adopted too, by resembling a vector formed by consecutive sensor-data samples [77]. All these algorithms may find application also when deploying sensor-fusion localization systems that employ proprioceptive sensors and the RFID system as an exteroceptive one.

A general representation of a sensor-fusion scheme that combines data from several proprioceptive and exteroceptive sensors is shown in Fig. 5 [78]. Typically, a centralized approach is adopted, with proprioceptive and exteroceptive data gathered by a central unit, e.g., the vehicle or the system back-end, which then performs a set of processing operations. The first one is a pre-processing step to prepare all the data for the localization procedure. The second one is the proper association of data that require for some manipulation to be correctly mapped into the environment, as for the case of the range measurements by the LRF or the images acquired by cameras [79]. The latter step can be skipped when employing the RFID system as an exteroceptive sensor, since in commercial hardware the measured parameters are automatically associated to the tag EPC within the output logfile and therefore to the tag location [80]. The third operation is the processing related to the localization algorithm itself. As far as navigation systems are concerned, the central unit is also able to send commands to the vehicle by piloting it through the environment.

In the state-of-the-art description presented in the following sections, we distinguish between three different localization schemes:

i) localization systems which only rely on RFID technology [28], [60], [67]–[72], [81]–[84] (Section IV);

ii) localization systems which fuse data from both an RFID system and proprioceptive sensors [73], [85]–[101] (Section V);

iii) localization systems which fuse data from RFID system and any additional exteroceptive sensors, possibly even together with proprioceptive sensors [52], [74], [102]–[111] (Section VI).

In each proposed solution, the operating frequency and the battery requirements of the tags can be different. The employed measured parameter, e.g., EPC, RSSI and phase may change too. For each solution, the test area description, the required system infrastructure and the achieved localization performance are reported. Moreover, each referenced solution is also classified according to the type of localization task to be performed, namely positioning, tracking, navigation, or SLAM (Fig. 1).

IV. LOCALIZATION WITH AN RFID INFRASTRUCTURE

This section is devoted to those solutions that only employ an RFID system to determine the vehicle position [28], [60], [67]–[72], [81]–[84]. This category does not rely on the sensor-fusion paradigm, as only a single source of data is available. A schematic of these systems is depicted in Fig. 6. A set of reference tags are deployed in known or unknown locations and detected by the on-board RFID reader during its motion. A summary of the state-of-the-art contributions here described is presented in Table 1, where we distinguish among solutions exploiting HF-RFID or UHF-RFID technologies.

A. HF-RFID SYSTEMS

Early solutions have exploited an HF-RFID reader on the vehicle with a grid of fixed reference tags installed in the scenario, to perform the vehicle tracking [28], [83] or navigation [81], [82], [84]. In the simpler systems, the vehicle position is associated to the position of the detected tag (Fig. 7), thus the localization performance is strictly dependent on the tag

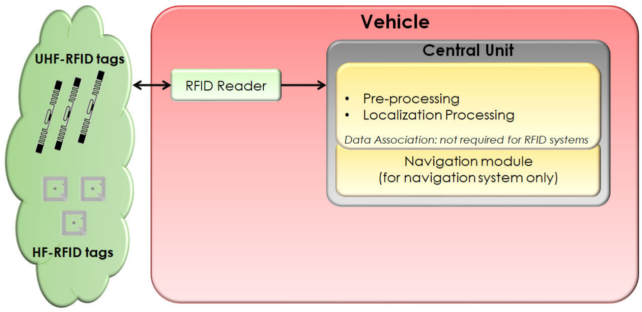


FIGURE 6. General schematic of a localization system employing only the RFID data with the central unit on the vehicle.

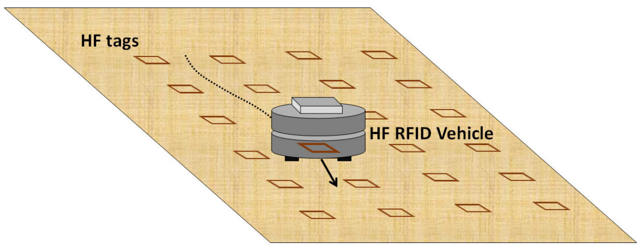


FIGURE 7. Scheme of a HF-RFID system for vehicle localization.

density. Since the reading range of HF tags is limited to a few centimetres, such a grid has to be dense if an accurate localization is required.

In [28], the authors presented a special carpet equipped with HF tags, to perform the robot tracking. The robot is equipped with an HF-RFID reader, moves upon the tagged carpet, and localizes itself by associating its position with the location of the detected RFID tag. A localization error of 9 cm was reached in a relatively small scenario (sizes are not given in the manuscript) with 19 reference tags very close to each other.

Likewise, in [81], the authors proposed a navigation method for mobile robots by using an HF-RFID system. The robot can identify tags deployed on the floor and measure its position based on the relation between previous and current location. 198 passive tags were laid on the floor in a grid-like pattern over an area of 4.2 m × 6.2 m, with 34 cm spacing. At each step, the robot orientation is updated according to the detected-tag information, to reach the assigned goal. The proposed navigation method allowed for navigation errors of 13.3 cm and 5.7 cm on the x- and y- coordinates, respectively, along a path of around 6 m.

In [82], a stigmergic approach [113] was proposed for robot navigation through an hexagonal grid of HF-RFID tags buried under a wooden floor. A robot equipped with an RFID reader can exploit the tag map to navigate to the assigned destination from any position in the environment, by simply following the tag reading information. The algorithm relies on the calculation of the shortest path and the gradient descent navigation. As an experiment, a calibration procedure run for some hours and provided a navigation RMSE error below 1 m after moving for 12 hours in a 7 m × 4 m apartment environment. 350 tags were placed underneath the floor for the tests.

In [83], the authors proposed an indoor tracking system that provides 2D position and orientation for mobile robots. A priori-knowledge of the geometry of the reader-equipped robot allows for its precise localization. The obtained average error was equal to 6.3 cm, whereas the standard deviation was 5.3 cm, in a 3.0 m × 1.8 m experimental scenario with 39 HF tags deployed on a carpet.

The solution presented in [84] showed a navigation algorithm where a set of HF tags placed on the floor provide information to guide the robot through a desired path. The adopted navigation strategy is the Circular Navigation Guidance (CNG). A mean navigation error of 6.5 cm was achieved, when 81 tags were deployed on a 25 cm spacing grid to cover a 2 m × 2 m area.

B. UHF-RFID SYSTEMS

Most recent solutions exploit a UHF-RFID reader on the vehicle with a grid of fixed reference tags installed in the scenario [67]–[69]. As for HF-RFID based systems, localization performance depends on the tag density, even if the larger reading range allows for a coarser tag deployment. Both range-based [67] and range-free methods [68], [69] were proposed.

In [67], a set of reference passive tags is placed close to the known robot path in such a way that at least two reference tags are detected at each reader interrogation. The proposed algorithm is a Kalman-Filter variant based on two steps. Firstly, a rough location of the reader is estimated through an RSSI model which neglects the angle-dependence of the path loss due to the non-isotropic antenna radiation-pattern. Then, an iterative procedure is implemented to determine the angle path-loss and therefore to modify the RSSI model by aiming to improve the ranging accuracy. Finally, the position is refined by accounting for some geometrical constraints. Experiments were conducted by considering a robot path of around 4.75 m in a 6 m × 6 m area, by employing 8 reference tags, which were located 1.2 m apart each other and 2 m far from the robot path. The average absolute position error was 10 cm, and the average of the absolute tag-reader distance errors was about 6 cm. In [68], the authors suggested a tracking system adopting passive UHF-RFID tags attached either on the floor or at the ceiling. Based on the tag EPC, the algorithm extracts the portions of space where a tag is detectable. Then, the algorithm assumes that the vehicle motion follows a 3D B-spline surface function and leverages the RFID detection data to estimate the robot trajectory. The method also considers when the reader is close to the room corners and some difficulties to detect the tags may be faced. The obtained average localization error was 3.7 cm, when 81 tags were deployed in a 7 m × 7 m area. In [69], the authors proposed a navigation scheme with passive UHF-RFID tags to guide robots through large environments. Basically, the tag EPC is associated to an instruction for the robot motion. A robot moves autonomously through a hallway and knows

TABLE 1. Vehicle localization solutions employing an RFID infrastructure.

Ref.	*Year*	*Application*	*Input Parameter*	*2D performance*	*Experimental scenario*	*Infrastructure*
Localization with HF-RFID Systems						
[28]	2009	Tracking	EPC	Localization error of 9 cm	Sizes not available	19 tags
[81]	2009	Navigation	EPC	Localization error of 13.3 cm in the *x*- coordinate and 5.7 cm on the *y*- coordinate	4.2 m × 6.2 m area	198 tags with 34 cm spacing
[82]	2009	Navigation	EPC	Navigation RMSE below 1 m after running for a 12-hours calibration step	7 m × 4 m apartment environment	350 tags underneath the floor
[83]	2012	Tracking	EPC	Average error of 6.3 cm, and standard deviation of 5.3 cm	3.0 m × 1.8 m area	39 tags
[84]	2012	Navigation	EPC	Mean error of 6.5 cm	2 m × 2 m area	81 tags with 25 cm spacing
Localization with UHF-RFID Systems						
[67]	2011	Positioning	RSSI	Average absolute error of 10 cm, and the average absolute tag-reader-distance error of around 6 cm	Robot path of around 4.75 m, in a 6 m × 6 m area	8 tags with 1.2 m spacing and 2 m far from the robot path
[68]	2013	Tracking	EPC	Average localization error of 3.7 cm	7 m × 7 m room	81 tags
[69]	2014	Navigation	EPC	Robot correctly recognizes the steering direction	University building (not specified size)	4 tags
[70]	2012	Tracking	Phase	RMSE of centimetre order	3 m × 3 m area	4 fixed antennas (moving tag)
[71]	2017	Tracking	Phase, RSSI	Localization error below 10 cm	3 m × 3 m area	3-4 fixed antennas (moving tag)
[60]	2014	Tag Following (navigate to tag)	RSSI	Mean tracking error of around 30 cm	Sizes not available	Hallway: 400 tags (both UHF and HF) Library: 700 tags (both UHF and HF)
[72]	2020	Navigation	RSSI	Steady state error of 28 cm	7 m × 7 m area	One single tag

if it has to turn left or right based on the detected tag, to reach the assigned destination. Experiments were conducted with four tags in a university building of not specified sizes.

By considering the above-mentioned solutions, we can state that the localization error can be of centimetre order, for an average tag density of roughly 1 tag per square metre.

Generally speaking, when performing vehicle localization with a grid of UHF-RFID reference tags, their installation and the knowledge of their exact position are key issues. Typically, during the setup stage, the reference tag database is created, by associating the tag EPC to its position within the scenario. Obviously, the uncertainty in the position measurements reflects on the uncertainty in the vehicle localization. In RSSI-based methods, this issue is less critical, since the amplitude of the tag backscattering signal exhibits a relatively small variation with respect to the positions. On the contrary, in phase-based methods the phase value is more sensitive to the position variations, as the wavelength is nearby 34 cm at the UHF operating frequency band. Consequently, when phase-based methods are applied, small errors in the knowledge of the reference tag positions may have a significant impact on the accuracy of the vehicle localization.

As an alternative to the employment of reader-equipped vehicles, it is possible to install the tag on the vehicle, by using an infrastructure of fixed reader antennas all around the scenario. In such framework, we want to mention the existing solutions to locate moving tags [70], [71]. Both are range-based approaches exploiting an infrastructure of four reader antennas. In [70], a phase-based tracking method for moving tags and an infrastructure of fixed antennas was presented. The phase measurement ambiguity is solved by using the EKF and the Rauch-Tung-Striebel smoother, where the dynamic state includes position, velocity and phase offset term, for each antenna. The RSSI allows to estimate the initial position of the tag. Such a solution achieved a localization root mean square error (RMSE) of centimetre order when employing four reader antennas at the corners of a 3 m × 3 m room. In [71], the authors proposed another phase-based method to track the position of a moving UHF-RFID tag. An Extreme Learning Machine processes the RSSI data to determine the tag position, while phase data are used to estimate the tag velocity. Then, both position and velocity allow for applying the linear Kalman Filter. More than 90% of measurement results showed a localization error lower than 10 cm, when employing four antennas in a 3 m × 3 m area.

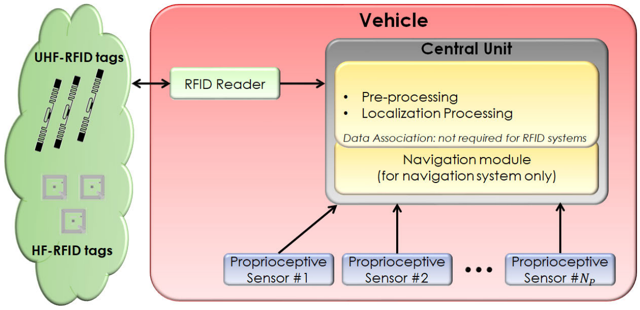


FIGURE 8. General schematic of a localization system employing a sensor fusion approach that combines RFID system and proprioceptive sensors. The central unit is on the vehicle.

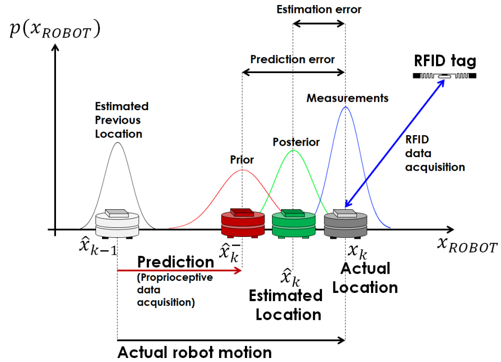


FIGURE 9. Graphical representation of a localization sequential estimator that fuses RFID and proprioceptive data.

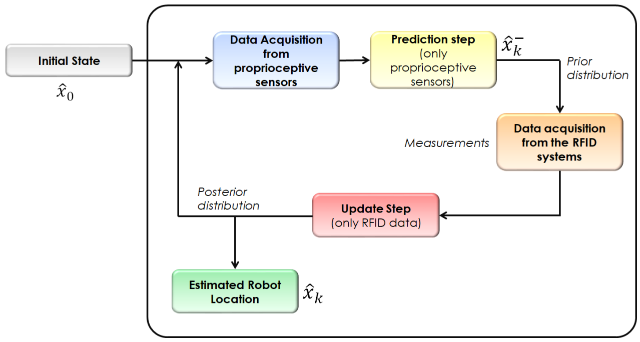


FIGURE 10. Block schematics of a localization sequential estimator that fuses RFID and proprioceptive data.

In such framework, it is worth mentioning the tag-following system presented in [60], which represents a kind of navigation solution in which a robot is guided by following a moving UHF-RFID tag. The algorithm relies on a combination of a two-stage dynamic motion model with a dual particle filter, to capture the dynamic motion of the object and to quickly recover it from failures in tracking. To work properly, the robot needs to measure RSSI data. Tests were performed in a hallway and in a library environment of not specified sizes, by deploying 400 and 7000 tags, respectively. The robot travelled for a path of about 418 m in 1503 s in the hallway, and for a 102 m long path in 465 s in the library. The algorithm showed a mean navigation error of about 30 cm.

Another navigation solution for robots equipped with UHF RFID commercial systems was proposed in [72]. The goal is to make the robot reaching a static RFID tag. At each step, the robot stops and turns to different directions on the basis of the RSSI measurements. A set of experiments have been carried out by including different initial heading-angles of the robot with respect to the goal. The experimental results showed an average steady-state error less than 28 cm within a navigation area of approximately of 7 m × 7 m, with a time interval between 176 s and 236 s to reach the goal.

V. RFID SENSOR-FUSION WITH PROPRIOCEPTIVE SENSORS

Typically, vehicles are equipped with IMUs or rotary encoders able to measure the wheel motion. In this section, we address the fusion of the data gathered by the RFID system with those measured by the proprioceptive sensors to perform vehicle localization. Such kind of system is the most representative and widespread category.

When proprioceptive sensors concur to the vehicle position estimation, the reference tag density can be reduced, thanks to the *a-priori* information about the vehicle motion given by on-board sensors, so reducing the installation cost and complexity. A simple schematic of such systems is depicted in Fig. 8. A common approach to fuse proprioceptive sensors and RFID data employs sequential estimators. Typically, two main steps can be recognized: a *prediction* step and an *update* step [9]. To better understand, we can imagine tracking a vehicle moving on a straight line (x-axis), as shown in Fig. 9. The prediction step uses the kinematic proprioceptive sensors data (e.g., odometry data) to compute the *prior* probability density function, namely prior distribution, of the vehicle location on the straight direction, so it consists of a first hypothesis on the vehicle motion. Then, the prediction step computes the predicted location at the k-th timestamp $\hat{x}_k^-$ starting from the location estimated at the previous step $\hat{x}_{k-1}$. After that, the update step consists in using the measured RFID data (EPC, RSSI, or phase) to compute a likelihood function and use it to update the prior distribution, in order to find the posterior distribution of the vehicle location. From the posterior distribution, it is possible to infer the vehicle estimated location $\hat{x}_k$, which should be closer to the actual location x_k than the predicted location $\hat{x}_k^-$. This process is repeated for each time instant k, as the prediction and update steps are enclosed in a loop. Fig. 10 shows a block diagram of a general localization sequential (or recursive) estimator that fuses RFID and proprioceptive data.

A summary of the state-of-the-art on RFID sensor-fusion with proprioceptive sensors is presented in Table 2. Performance is relative to the 2D localization issues, unless otherwise specified. For a better understanding, the main solutions have been split into four categories, according to the operating frequency and measured parameter:

- solutions with HF-RFID systems exploiting the EPC [85], [86];
- solutions with UHF-RFID systems exploiting the EPC [87], [88].
- RSSI-based solutions with UHF-RFID systems [89]–[92].
- phase-based solutions with UHF-RFID systems [73], [93]–[98], [100], [101].

A. HF-RFID SYSTEM AND EPC PARAMETER

HF systems only allow for EPC data gathering. In this case, localization performance is strictly dependent on the tag density, but the presence of other sensors allows to reduce the infrastructure complexity with respect to HF-based solutions that do not rely on additional sensors. In [85], the authors proposed a triangular geometry of the tag grid as it reduces the estimation error with respect to the regular squared grid. Basically, the new configuration is formed by a regular squared grid where the tags location on the even rows are shifted with respect to the tag location on the odd rows. The experimental analysis showed a localization error of around 1 cm, in a 1 m × 1 m area with tags deployed on a grid with a 5-cm step. In [86], a SLAM solution was presented. The prediction step is done with odometry, then a delayed-state EKF provides the position estimation and mapping by employing the tag detection data. The HF-RFID reader is carried by the robot, and some HF tags are placed on the walls. Through an experimental campaign, the authors showed a mean mapping error of 2.43 m, with 25 tags in a 20 m × 50 m environment. In the same scenario, the mapping error could be reduced down to 1.44 m by resorting to 66 tags.

B. UHF-RFID SYSTEM AND EPC PARAMETER

The detection information of UHF-RFID tags has a different meaning with respect to that of HF-RFID tags. Indeed, the detection information of UHF-RFID tags cannot be univocally associated with a specific location within the scenario, due to the detection range of few metres and to the wide beam of the conventional UHF reader antennas. To get a satisfactory localization accuracy, probabilistic tag detection models are usually inferred from tag detection.

A SLAM system based on odometry data and UHF-RFID measurements was proposed in [87]. The reference tags are arbitrarily placed in the scenario and their positions are unknown. Thanks to a graph-based close-loop algorithm, the RFID data allow to correct the odometry errors. Fingerprinting maps are built based on the reference-tag detection at a given reference time. Different features are extracted from the combination of close maps and far maps and are employed on a k-Nearest Neighbour (k-NN) classifier able to recognize previously visited locations (close-loop approach). A mean residual localization error of around 40 cm was reached by employing 400 reference tags in a 195 m^2 area, when considering trajectories with arbitrary shapes and of lengths from 68 m to 295 m. In [88], the authors proposed a tracking system for UHF-RFID robot by exploiting a probabilistic sensing model of the reference tag detection. The algorithm estimates the speed of the moving agent by exploiting the reader antenna reading range and the maximum time duration of the tag staying within such reading range. Based on this value, different algorithms can be applied: a PF algorithm, a Weighted Centroid Localization (WCL) algorithm or a hybrid algorithm. WCL algorithms allows to reduce the computational cost. The experimental results showed a localization error lower than 20 cm for a robot moving at a speed between 0.1 m/s and 0.6 m/s, in a 4 m × 6 m area, with 120 reference tags deployed on a square grid with 50-cm spacing.

C. UHF-RFID SYSTEM AND RSSI PARAMETER

In this subsection, sensor-fusion approaches combining RSSI data by a set of reference tags with data by proprioceptive sensors [89]–[92] are investigated.

In [89], a navigation problem was presented where the robot must follow an UHF-RFID-guided path. The current robot position is estimated through a Particle Swarm Optimization (PSO) algorithm applied to the RSSI data. A Fuzzy Logic Controller (FLC) controls the robot actuators to let it follow the provided mission. To validate the method, a 36 m^2 room with two reference tags was built through a simulator. Numerical simulations predicted a navigation RMSE of 6 cm. In [90], the authors presented a self-recognition method for vehicle tracking, which exploits a modification of a classical particle filter. A calibration process is executed to a map of points where the two readers, placed on the vehicle in a symmetrical position, measure the same RSSI values. After that, the odometer is used to predict the hypothetical position of the moving vehicle. Then, the RSSI values gathered by the reference tags are employed for the vehicle position estimations. As a further step, the actual tag location is corrected by comparing the observations of the two readers and using the tag position of the unique observation with identical RSSI or the smallest RSSI difference. Finally, the vehicle location is corrected on the basis of the tag location. The method allowed for a centimetre order localization error for a vehicle moving at different speeds in a real indoor scenario of 5 m × 10 m, by employing a dense grid with 578 tags. In [91], the authors proposed an extended unbiased finite impulse response (EFIR) filter for robot self-localization (tracking). The robot is equipped with a UHF-RFID reader and it can measure the distance from at least two tags at once, by employing an RSSI model. The prediction step is done with odometry data provided by the encoders on the wheels. The update step is done with the EFIR filter that performs the smoothing by exploiting the RSSI-based distance data retrieved through a path-loss model. Such filter is more robust with respect to the Kalman filter under unbounded disturbances. Simulated results showed a centimetre order localization error in a 16 m × 12 m area with 35 reference tags.

In [92], a tracking method which adopts an active UHF-RFID system was presented. The target device is a mobile

TABLE 2. Vehicle localization solutions exploiting a sensor-fusion approach between RFID and proprioceptive sensors.

Ref.	*Year*	*Application*	*Proprioceptive sensors*	*2D performance*	*Experimental scenario*	*Infrastructure*
Localization with HF-RFID Systems. Input parameter: EPC						
[85]	2007	Tracking	Encoders	Localization error of around 1 cm	1 m × 1 m area	Tags with 5 cm spacing
[86]	2010	SLAM	Encoders	Test 1: Average mapping error of 2.43 m Test 2: Average mapping error of 1.44 m	20 m × 50 m area	Test 1: 25 tags Test 2: 66 tags
Localization with UHF-RFID Systems. Input parameter: EPC						
[87]	2010	SLAM	Encoders	Mean residual cartesian error of around 40 cm	Trajectories of length between 68 m to 295 m with arbitrary shapes in a 195 m^2 area	400 tags
[88]	2015	Tracking	Encoders (not mandatory)	Localization error below 20 cm for a robot moving at speed between 0.1 m/s to 0.6 m/s	4 m × 6 m area	120 tags with 50 cm spacing
Localization with UHF-RFID Systems. Input parameter: RSSI						
[89]	2008	Navigation	Encoders (for drive commands)	RMSE of 6 cm (simulated analysis)	36 m^2 room (simulated scenario)	2 tags
[90]	2013	Tracking	Encoders	Centimetre order localization error	5 m × 10 m area	578 tags
[91]	2014	Tracking	Encoders	Centimetre order localization error (simulated analysis)	16 m × 12 m area	35 tags
[92]	2015	Tracking	Active RFID tags and Bluetooth	Localization error below 1 m	Room sizes varying from 18 m^2 to 50 m^2	10 active tags with 5 m spacing placed at the room walls
Localization with UHF-RFID Systems. Input parameter: Phase						
[93]	2014	Tracking	Encoders and custom tags	Average position error of about 4 cm	6 m^2 area	2 tags
[94]	2015	Tracking	Encoders and custom tags	Localization error of 4 cm	4 m × 3 m room	2 tags
[95]	2019	Tracking	Encoders	Localization error of centimetre order with 99% probability (simulated analysis)	100 m × 10 m area	Tags spacing varying from 1 m to 5 m
[96] [97]	2019	Tracking	IMU	Localization error below 20 cm, (simulated analysis)	10 m × 10 m area	2 tags
[98]	2020	Tracking	Encoders	Average localization error of 11.4 cm	2.5 m × 2.5 m area	2 tags
[100]	2020	Tracking	Encoders	RMSE of 40 cm (simulated analysis)	60 m × 60 m area	4 tags
[101]	2020	Tracking	Encoders	Test 1: median error of 5.4 cm Test 2: median error of 5.9 cm	Test 1: 3.5 m × 2.6 m office environment Test 2: 5 m × 5 m office-like cluttered environment	Test 1: 30 tags with 60 cm spacing Test 2: 42 tags with 60 cm spacing
[73]	2019	Tracking	(IMU) – custom 5.8 GHz tag	(1D) RMSE of 5 mm	A 0.64 m long rectilinear path	1 fixed antenna (moving tag)

phone connected to an RFID reader via Bluetooth, and two active tags are deployed in the scenario. At first, a Kalman filter is used to remove the fluctuations of the measured RSSI values due to multipath. Once RSSI values are stabilized, they are transformed into distance measurements through a path-loss model. Hence, thanks to the Heron's formula, a bi-lateration estimation technique is performed. The method was tested in rooms with different sizes, from 18 m^2 to 50 m^2, with 10 active tags placed on the room walls every 5 m. The localization error never exceeded 1 m in all the analysed scenarios.

D. UHF-RFID SYSTEM AND PHASE PARAMETER

More recently, sensor-fusion approaches combine the phase parameter available in modern UHF-RFID readers with data gathered by the proprioceptive sensors [73], [93]–[101].

In [93], the robot tracking was achieved through a multi-hypothesis EKF which combines the data from odometry sensors and the phase of the signal backscattered by the reference tags. The latter are custom tags placed at the ceiling, which were designed to have a proper radiation pattern. A calibration procedure for each reference tag is required to estimate the phase-offset term (2). The average position error was 4 cm in a 6 m^2 room with two reference tags. An extended version was presented in [94], which exploits both RSSI and phase data. The new algorithm shows higher robustness with respect to the errors on the knowledge of the reference tag positions. Moreover, the phase offset calibration procedure is avoided. Experimental results showed that a robot can be localized with an error of around 4 cm in a 4 m × 3 m room by employing two reference tags in the whole area. The author concludes that the method can be employed in scenarios of arbitrary sizes if deploying one reference tag every 2 m^2.

In [95], the authors investigated the local and global non-linear observabilities of the tracking system composed by a unicycle robot which measures the PDOA data from multiple UHF-RFID reference tags deployed in the environment. It has been demonstrated that a dynamic position estimator based only on the phase measurement is possible. The prediction step is performed with the encoder data, while phase data are employed to estimate the radial speed of the vehicle with respect to the detected tags. Then, the latter are used as input for the update step of a UKF algorithm. Preliminary results in a realistic 100 m × 10 m simulated scenario showed that the estimation error is of centimetre order with 99% probability. The tag grid spacing ranges from 1 m to 5 m.

More recently, a novel phase-based tracking method for moving agents was presented in [96] after the patent application in 2019 [97]. The robot localization is achieved through a particle smoothing-like approach, by combining the kinematic data with the phase of the signal backscattered by a few reference tags. By acquiring data during the relative motion of the mobile reader with respect to the reference tags, it is possible to collect several phase samples resembling a synthetic array, by notably reducing the reference tag density. The phase variation of the tag backscattered signal varies according to the distance variation between the reader antenna and the tag, thus representing a peculiar parameter to estimate the mobile-node trajectory. The algorithm can work with COTS devices, and no calibration is required. The simulated analysis showed a localization error below 20 cm, for robot arbitrary paths in an area of 10 m × 10 m, by employing two reference tags only. In [98], the method was tested in a real scenario, when two rotary encoders are used as proprioceptive sensors [99]. Two reference tags were deployed on the ceiling of a 2.5 m × 2.5 m office environment. The obtained average error was 11.4 cm on a robot path of around 4 m.

In [100], an EKF with a Rauch-Tung-Striebel (RTS) smoother was designed to perform the robot tracking when rotary encoders are equipped. To properly meet the observability requirements, at least three tags are required to be within the reader detection area at each observation time. The authors tested the performance and the computational burden of the algorithm for different sizes of the RTS smoother, through a numerical analysis. A 40 cm RMSE can be achieved with a smoother size of 55 samples, when running a complex trajectory in a simulated 60 m × 60 m warehouse environment, with four reference tags with an assumed unlimited reading range.

In [101] a sensor-fusion algorithm was developed to track a mobile robot equipped with two rotary encoders and two RFID antennas pointed towards the floor. Sensor fusion is performed through a particle filter that uses the data gathered by the encoders in the prediction step, and PDoA together with detection data acquired from a set of reference tags placed at the floor in the update step. Thanks to the PDoA, the method releases from the calibration of the phase offset of each reference tag. Two tests have been conducted. In the first one, the robot moved in a 3.5 m × 2.6 m office environment with 30 tags spaced by 60 cm. The obtained median position error was 5.4 cm for a 10 m path. The second test has been conducted in a 5 m × 5 m office-like cluttered environment with the presence of metallic objects, and 42 tags were deployed with a grid spacing of 60 cm. A median error of 5.9 cm was achieved on a 9-m long path.

In [73], the Hybrid Inertial Microwave Reflectometry (HIMR) method combined RSSI, phase and acceleration data to track a 5.8 GHz custom semi-passive RFID tag in a 1-D space, with one static reader. Here, the goal is to develop a motion capture system which could be also applicable to the mobile robot localization. The estimation algorithm is derived using a continuous-time model of the system. The accelerometer is embedded in the RFID tag, and acceleration data are directly backscattered by the tag itself. Results from measured data showed that the new approach results in a 5-mm tracking RMSE during the tag motion on a 0.64 m long rectilinear path. Moreover, authors showed that RSSI and phase data at the working frequency of 5.8 GHz, can be enough to achieve mm-order localization even without inertial sensors.

VI. RFID SENSOR-FUSION WITH ADDITIONAL EXTEROCEPTIVE SENSORS

When vehicles are equipped with additional exteroceptive sensors other than the RFID system, it is possible to include them in the data fusion process. This category of systems has a higher cost with respect to solutions where RFID data are fused with proprioceptive-sensor data and may present a slightly higher power consumption.

Exteroceptive sensors can have different natures: cameras, i.e., computer vision systems, [55], [74], [102]–[104], Laser Range Finders [58], [105], [106], Wi-Fi and other RF systems [107]–[108], ultrasounds [109], [110], or hybrid solutions [52], [111]. The introduction of a second exteroceptive system in addition to the RFID system does not imply that proprioceptive sensors must be removed. A schematic of a sensor fusion architecture for this category of systems is shown in Fig. 11.

A summary of methods based on RFID sensor-fusion with other exteroceptive sensors in addition to the RFID system itself is presented in Table 3.

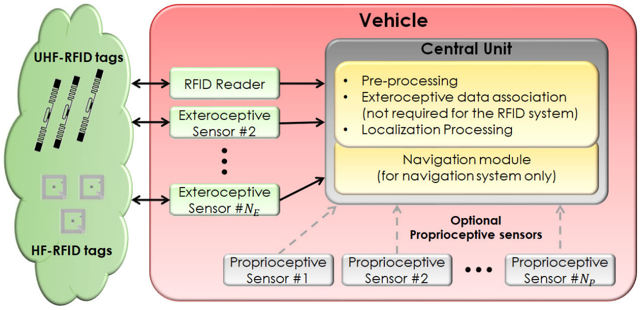


FIGURE 11. General schematic of a localization system employing a sensor fusion approach between RFID system and other exteroceptive sensors in addition to the RFID system itself. The central unit is on the vehicle.

A. RFID SENSOR-FUSION WITH COMPUTER VISION

Computer Vision (CV) and RFID are usually employed together for static object detection and localization [112]. Dynamic vehicle tracking can also be performed [55], [74], [102]–[104]. The combination of such two technologies can lead to several advantages. At first, the RFID system can act when the room light conditions are inadequate, and the CV system fails. Moreover, RFID tags can provide some *a-priori* information about the scenario that can be profitably used by the CV algorithms. By tagging objects and vision markers put in the area of interest, they can be easily recognized by the RFID reader at the robot side. Thus, the information gathered by the reader can help the CV system by reducing the recognition complexity and consequently the computational cost. In [102], a combined method employing computer vision and UHF-RFID system was proposed to solve the kidnapped robot problem. The latter consists of a situation where an autonomous robot in operation is carried to an arbitrary unknown location and must reinitialize correctly its position [114]. This process is mandatory if the system was meant for robot tracking, navigation, or SLAM. Few tags are deployed in the environment. When the robot is placed close to one of them, the recovery procedure starts. At first, the tag bearing with respect to the on-board RFID antenna is determined with a Fuzzy Logic scheme. Then, a monocular camera implements the Speeded Up Robust Feature (SURF) algorithm to find the location of some control points, which could be represented by QR codes. A tag was placed in a 6 m $\times$ 7 m laboratory area, and localization after kidnapping had a mean error of 8.3 cm. The localization error never exceeded 6.4 cm in a 6 m $\times$ 9 m hallway with three RFID tags.

The authors of [103] proposed a sensor-fusion tracking system that combines an HF-RFID system and CV to localize a robot. The HF tags are deployed on the floor, the reader is mounted on the robot and the camera is placed on the ceiling. The sensor fusion strategy accounts for illumination conditions. In good light conditions, localization is performed by using the camera; when the uncertainty of the camera-based localization algorithm overpasses a certain threshold due to bad illumination conditions, the system switches to RFID-based localization only. When this happens, the robot position is associated to the detected tag position as common for localization systems in the HF band. The obtained localization error was below 10 cm in a test area of 6.5 m $\times$ 2.5 m, with two cameras on the ceiling and a tag grid spacing of 0.4 m.

A system that tracks and identifies trolleys in the entry area of a distribution center was presented in [104]. The area is monitored by an UHF-RFID system, consisting of a fixed reader with four antennas, and a pair of webcams. The trolleys are equipped with a passive RFID tag and an optical marker. The system uses a Particle Filter to combine RSSI data from the RFID system and image data from the webcams. The resulting system achieved an RMSE of less than 30 cm in static and dynamic scenarios in a laboratory environment (room size is not specified).

In [55], a multi-sensor fusion process was proposed to track a robotic wheeled walker designed to support people with psychomotor problems. The walker is equipped with two encoders, a HF RFID reader, a gyroscope, and a front camera. HF tags and QR codes are placed on the room floor in overlapped locations according to a regular grid. The prediction step is done through the on-board proprioceptive sensors. During the update step, the tag detection information is used to correct the walker location, while the camera detecting the QR codes concurs to the orientation update. Experiments were conducted in a 150 m^2 indoor environment with obstacles, where 30 tags and 30 QR were placed with 2 m spacing. In the 95% of the case, the obtained position RMSE and orientation RMSE were below 50 cm, and 0.15 rad, respectively.

CV-based object tracking systems may find difficulties to track objects moving simultaneously, and sometimes they cannot recognize the object by looking at the shape and colour. In [74], the authors proposed to combine RFID and CV technologies for object tracking. A CV algorithm determines the moving object trajectories. Meanwhile, a COTS RFID reader measures phase data from RFID tags. Then, starting from hypothetical phase histories of moving objects and measured RFID data, it is possible to associate object and tag with a likelihood approach. Experiments were conducted in a 4 m $\times$ 8 m room, with only one RFID antenna and a camera. The measured tracking error was around 1 cm.

B. RFID SENSOR-FUSION WITH LASER RANGE FINDER

RFID systems are not able to retrieve geometrical information about the environment, or to detect obstacles unless they are equipped with tags. On the other hand, Laser Range Finders can perform those tasks, so resulting appealing for combined approaches, especially if vehicle navigation in complex scenarios is required. In some cases, LRF simply concurs to vehicle localization.

In [105], the authors proposed a SLAM system exploiting a laser ranging sensor, an RFID system and an odometer. Firstly, the laser scanner learns the geometric structure of the environment. Then, the reference tag positions are estimated based on the robot path, by exploiting the posterior

TABLE 3. Vehicle localization solutions exploiting a sensor-fusion approach with RFID and other exteroceptive sensors.

Ref.	*Year*	*Application*	*RFID system*	*Input parameter*	*Other exteroceptive sensors*	*2D performance*	*Experimental scenario*	*Infrastructure*
RFID + Computer Vision								
[102]	2009	Positioning	Passive UHF	EPC	Computer Vision	Test 1: mean localization error of 8.3 cm Test 2: maximum localization error of 6.4 cm.	Test 1: 6 m × 7 m laboratory area Test 2: 6 m × 9 m hallway	Test 1: 1 tag Test 2: 3 tags
[103]	2010	Tracking	Passive HF	EPC	Computer Vision	Localization error below 10 cm	6.5 m × 2.5 m area	Two cameras on the ceiling and tags with 0.4 m spacing
[104]	2013	Tracking	Passive UHF	RSSI	Computer Vision	Localization error below 30 cm	Not specified	One RFID antenna and two cameras
[55]	2015	Tracking	Passive HF	EPC	Computer Vision	Position RMSE below 50 cm, and orientation RMSE below 0.15 rad in the 95% of the cases	150 m^2 area with obstacles	30 tags with 2 m spacing
[74]	2017	Tracking	Passive UHF	Phase	Computer Vision	Tracking error of around 1 cm (camera-based localization)	4 m × 8 m room	One RFID antenna and one camera
RFID + Laser Range Finder								
[105]	2004	SLAM	Passive UHF	EPC	Laser range scanner and encoders	Localization error of few metres	28 m × 28 m area	100 tags
[106]	2007	Tracking	Passive HF	EPC	Two laser range sensors	Localization error below 50 cm	1.77 m × 2.05 m area	Tags deployed with grid spacing of 20 cm
[58]	2007	Tracking	Active UHF	RSSI	Laser and encoders	Test 1: position error below 20 cm and orientation error below 25° Test 2: a steady-state localization error of 0.2 cm (laser-based)	6 m × 7 m room	Four tags on the ceiling of the room
RFID + Wi-Fi and/or other Radio Frequency technologies								
[107]	2016	Tracking	Passive UHF	RSSI	Wi-Fi 802.11	Not specified	120 m × 60 m area	7 Wi-Fi Access Points (APs) and 27 RFID reference tags
[108]	2019	Positioning	Not specified	Not specified	Wi-Fi 802.11 and Bluetooth (iBeacon)	Localization error below 2 m in more than 90% of cases	1500 m^2 multi-office environment	12 wireless AP, 36 RFID tags and 20 iBeacons
RFID + Ultrasounds								
[109]	2011	Tracking	Passive HF	EPC	Array of nine sonars	Test 1: average position error of 1.6 cm (no obstacles) Test 2: average position error of 2.4 cm (no obstacles) and of 2.7 cm (with obstacles)	6 m × 2.4 m area	Test 1: 91 tags with 30 cm spacing Test 2: 66 tags with 50 cm spacing
[110]	2016	Navigation	Passive LF	EPC	Ultrasounds	Navigation error below 58 cm	4 m × 3 m area	18 tags
RFID + Multi-sensor solutions								
[52]	2007	Navigation	Active UHF	EPC	Laser and ultrasounds	Navigation task correctly accomplished	30 m long hallway	Not specified
[111]	2007	Tracking	Custom laser-activated UHF tags	EPC	Laser and cameras	Localization error below 20 mm (camera-based)	Room office with maximum reader-tag distance of 7 m	4 tags

distribution over potential positions of an RFID tag, which is built through a preliminary calibration procedure on the tag detection frequency. The detection probabilistic model is then combined with odometer data through a PF algorithm to locate the reference tags. The obtained estimated positions were then employed to further improve the robot localization up to a few metres of localization error, as shown in a 28 m $\times$ 28 m environment with 100 tags.

In [106], the authors proposed a tracking method based on a Support Vector Machine (SVM) combined to a least square method to determine the position of an RFID reader mounted on a robot. The measured features are read/no read data of HF tags placed in the environment. Tag position can be known or unknown as in the SLAM algorithms where a long training procedure is required for the calibration. The robot must be also equipped with two laser ranging sensors to measure the distance from the walls. An experimental setup was realized in a 1.77 m $\times$ 2.05 m scenario with a grid spacing of 20 cm. The obtained localization error was less than 50 cm.

In [58], a sensor-fusion tracking system comprising an active RFID system, an odometer and a laser scanner was proposed. By employing the odometer data from the driving wheels and the laser scanning measurements of the robot surroundings, a localization algorithm based on Extended Information Filter (EIR) is proposed to continuously keep track of the robot poses at slow speeds. The RSSI data acquired by the RFID reader were used to estimate both the unknown start-up position and orientation of the tour-guide robot at any circumstance, with a least square method. A first experiment using only the RFID system was conducted to measure the accuracy of the proposed method for the robot static position estimate, with one reader on the head and four tags on the ceiling of a 6 m $\times$ 7 m room. A position error of less than 20 cm and an orientation error of less than 25° were observed. A second experiment validated the EIR performance and showed a steady-state robot localization error of 0.2 cm for a robot performing straight-line movements.

C. RFID SENSOR-FUSION WITH WI-FI AND/OR OTHER RF TECHNOLOGIES

Since IEEE 802.11 Wi-Fi coverage in indoor buildings is widespread, it might be reasonable to investigate how to combine an RFID system and a pre-existing Wi-Fi infrastructure to locate a moving agent. Wi-Fi systems operate in the ISM band, so they can provide RSSI measurements at a different operating frequency with respect to RFID systems. Since Wi-Fi devices are active and need for a local internal oscillator to communicate, the phase information is not exploitable. Moreover, the single communication channel bandwidth is not enough to perform TOA measurements, so only the RSSI information can be used. The same reasoning is valid for BLE, ZigBee, or other narrowband RF technologies.

In [107], the authors proposed a novel indoor tracking mechanism, which realizes an effective data fusion of Wi-Fi and UHF-RFID signal parameters. Two variants of the Kalman Filter localization algorithm are proposed. RSSI values acquired from the Access Points (APs) can be processed to measure the distances between them and the moving object, and then a multilateration algorithm is performed. The experimental setup was deployed in a museum hall of 120 m $\times$ 60 m, with 7 Wi-Fi APs and 27 RFID reference tags (results of the experimental campaign are not given).

In [108], an indoor positioning system, fusing Bluetooth, Wi-Fi and RFID systems data was presented. The typology of the RFID system is not specified. Variants of Kalman filter algorithm are investigated to provide multiple fusion positioning schemes. Wi-Fi technology is used to estimate the position of the moving device through a fingerprinting and a Weighted k-NN method. Apple iBeacons and RFID systems are used to refine the position estimation. To validate the performance of the proposed approach, experiments were conducted in a 1500 m^2 multi-office environment. 12 wireless APs, 36 RFID tags and 20 iBeacons were installed for Wi-Fi fingerprinting, iBeacon correction and RFID positioning, respectively. Localization error lied under 2 m in more than 90% of test cases.

D. RFID SENSOR-FUSION WITH ULTRASOUNDS

Similarly, to LRF, ultrasounds can be used to provide the vehicle with information about the geometrical constraints of the scenario and the presence of obstacles. With respect to LRF however, sound waves suffer from acoustic noise and are not supposed to be used in noisy environments such as crowded shops or warehouses.

In [109], a system for robot tracking combined HF-RFID technology and an array of nine sonars. HF tags are placed on the floor to form a regular grid, and the reader antenna was installed on the robot facing downward. The sonars are used to estimate the distance from obstacles and walls. Information about the scenario are fused together to RFID EPC to estimate the robot position over time. Two experiments were conducted in a 6.0 m $\times$ 2.4 m area. In the first one, no obstacles were placed in the area. The average position estimation error was 1.6 cm with a grid of 91 reference tags with a 30 cm spacing, and 2.4 cm with 66 tags placed with a grid step of 50 cm. When the test area was filled with obstacles, the average position estimation error was 2.7 cm with 66 tags placed with a grid step of 50 cm. In [110], a LF-RFID system was combined with sonars to design a navigation scheme for mobile robots. A fuzzy cognitive map allows for generating the drive commands to guide the robot through an optimized path. 18 tags were deployed in a 4 m $\times$ 3 m area. According to conducted experiments, the average deviation from the optimal trajectory never exceeded 58 cm.

E. MULTI-SENSOR SOLUTIONS

Some solutions exist which combine RFID data with more than one exteroceptive sensor. The cost of the system is higher, but better performance and reliability are expected.

The authors of [52] presented a multisensory-hybrid navigation method for an active mobile robot assistant, with the combination of several ultrasonic ranging sensors, one laser scanner and a UHF-RFID system. First, a global optimal path is determined by the Dijkstra's programming approach. Second, a fuzzy adaptive speed control method is proposed to adapt the robot to users' speed and to keep a desired distance from them. Third, the UHF-RFID system is used to reduce the hypothesis estimation error by adding one more environment

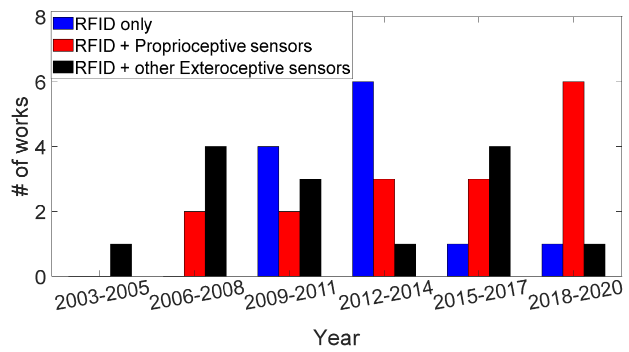


FIGURE 12. Timeline of number of papers analysed in this survey, with respect to the publishing year, according to the proposed categorization.

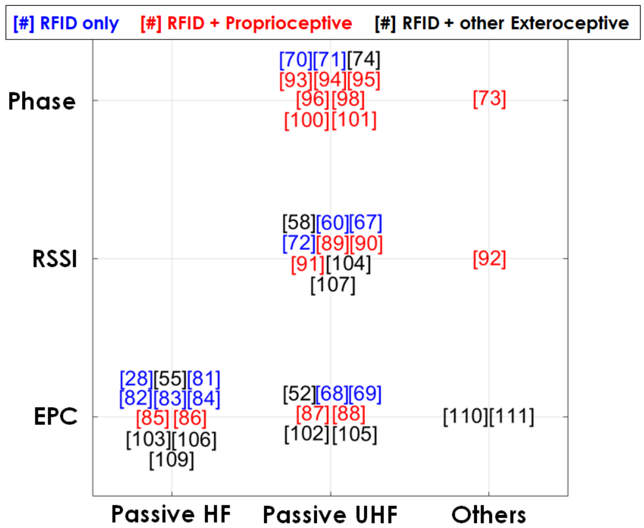


FIGURE 13. Classification indicating the type of adopted RFID system (abscissa), the employed RFID parameter and adopted sensors (ordinate): RFID only (blue), RFID system and proprioceptive sensors (red), and RFID system with other exteroceptive sensors (black).

feature for similar environment identification. Thus, this is combined with the laser scanning data to achieve global localization. Finally, the fuzzy hybrid navigation is achieved by merging three useful fuzzy behaviours, which are constructed by fusing the laser scanner and the ultrasonic range finder. Experiments were made in a 30 m long hallway showing that the robot was able to correctly accomplish the navigation task.

In [111], a new artificial landmark-based tracking system for mobile robots in indoor environments was introduced. The system combines custom active UHF-RFID tags, a laser and a camera stereovision localization system mounted on the robot. The RFID tags are modified to include a Light Emitting Diode (LED) and are used to store the LEDs location data. The on-robot laser impinges one RFID tag at a time and turns on the LED. Then, the RFID reader collects the data stored in tags and the cameras measure the distance between the robot and the LED. The localization scheme is a multi-lateration approach resorting to a set of reference laser-activated RFID tags. Since tag location is directly sent in the RFID message, no central database is needed to register the reference tag locations. Tests conducted by the authors showed a localization error below 20 mm in a room office of not-specified sizes with four reference tags. The maximum reader-tag distance is 7 m. A reduced localization accuracy is expected in larger scenarios since camera resolution decreases with distance.

VII. DISCUSSION

A. ANALYSIS AND RESEARCH TRENDS

On the basis of the state-of-the-art analysis here carried out, it is apparent that the RFID technology has been recently investigated as an effective enabling technology for mobile vehicle localization. Both HF and UHF systems have been employing, with several configurations which typically exploit a grid of reference tags. To investigate the trends in the adoption of such radio systems, Fig. 12 shows a timeline of the presence of RFID-based methods for vehicle localization, grouped according to the classification adopted in this paper: localization with only RFID systems, [28], [60], [67]–[72], [81]–[84], RFID systems combined with proprioceptive sensors [73], [85]–[101] and RFID systems combined with other exteroceptive sensors in addition to the RFID system itself [52], [74], [102]–[111] through sensor-fusion approaches. In particular, the timeline investigates the trend from 2003 to 2020.

The most representative category is the RFID sensor-fusion localization system with proprioceptive sensors (red bars), which represents 40% of the analysed references, with an increasing interest over the time. The reason could be that such a system represents a good compromise between installation cost and performance, as we better show later in this section.

By considering the localization tasks, i.e., positioning, tracking, navigation, or SLAM, the most representative category is the "tracking" one, with more than 60% of the total papers analysed in this survey. This is reasonable, since the vehicle tracking issue is the enabler for navigation and SLAM tasks.

Fig. 13 shows the details of the RFID data employed in the localization method, as well as the typology of the RFID system. On the x-axis there is the adopted RFID technology divided into three categories: *Passive HF, Passive UHF*, and *Others*, the latter comprising active RFID tags and custom RFID tags operating at different frequencies, e.g., the SHF band, and the custom tags with other embedded sensors as IMUs or embedded devices as LEDs. On the y-axis there is the employed localization parameter: *EPC*, *RSSI*, and *Phase*. Each paper is identified in the grid through its bibliographic reference number used in this manuscript. The text colour refers to one of the three categories of the localization scheme. The most represented RFID system for the analysed vehicle localization scheme is the passive UHF one, which is employed in more than 60% of the proposed methods. The reason is that the higher reading range of UHF systems,

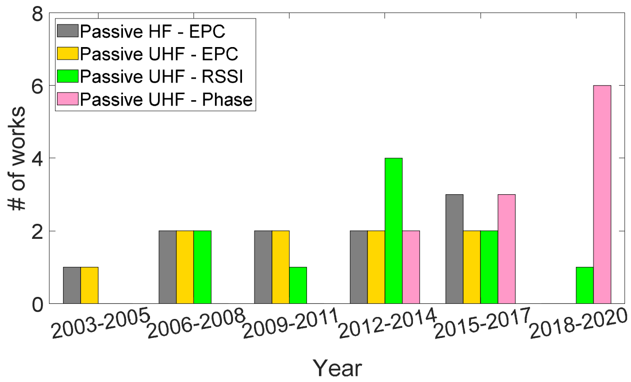


FIGURE 14. Timeline of number of papers analyzed in this survey with respect to the publishing year and categorized with respect to the employed RFID parameter.

with respect to the HF ones, allows for an infrastructure of reference tags with lower density, with a consequent cost reduction and lower deployment overhead.

Now, we focus on the RFID parameter, i.e., EPC, RSSI, or phase, mostly employed. Even though the phase is the most promising localization parameter available in RFID systems, it only represents less than 30% of the case studies. On the contrary, the methods exploiting the tag EPC are almost 50% of the total. There are many reasons to justify this phenomenon. The first one is that the phase parameter is available only for passive UHF systems or custom systems that allow coherent demodulation, so not all RFID systems can use it. Secondly, even though any UHF-RFID reader must estimate the phase to correctly retrieve the tag EPC from the backscattering signal, the phase is not always available as an output parameter in COTS readers. The third reason can be retrieved from research trends over the time. In particular, Fig. 14 shows the timeline of the RFID-based methods for vehicle localization, using passive RFID systems and exploiting the EPC, the RSSI or the phase parameter, from 2003 to 2020. As apparent, the phase-based methods have been investigated only in the recent years, since only modern readers give such output data. On the contrary, localization methods based on tag EPC were more popular in the past but have been discarded in the last years, e.g., 2018-2020. Finally, at the authors' best knowledge, RSSI-based vehicle-localization methods have received a very limited attention in the last three years.

B. PERFORMANCE ANALYSIS

Localization performance in RFID-based localization must be evaluated by also considering the system architecture, the spatial density of the reference tags and the installation complexity.

Fig. 15 shows the localization error of the solutions investigated in this survey, with respect to the infrastructure complexity expressed in terms of tag spatial density (number of tags per square metre). Different types of markers indicate the category of the localization system. The reference number is added within the corresponding marker. The marker colour indicates the adopted RFID system with the employed parameter. We can observe that most of the contributions in the category "Passive HF Systems with EPC" (grey markers) have on average the highest infrastructure complexity, with the highest number of reference tags per square metre, as expected. The category of "Passive UHF Systems with RSSI" (green markers) is the more heterogeneous as the performance is strictly dependent on the RSSI model, on the sensor-fusion method and on the adopted sensors. Finally, the category "Passive UHF Systems with Phase" (pink markers) provides on average a localization error below 10 cm and requires a number of tags per square metre lower than one, without the use of other exteroceptive technologies apart of the RFID system.

TABLE 4. Features of each category of RFID-based solutions for vehicle indoor localization.

	RFID only	*RFID + proprioceptive*	*RFID + other exteroceptive*
Cost	Medium-Low	Medium	Medium-High
Energy consumption	Low	Medium-Low	Medium-High
Complexity	Low	Medium	Medium-High

For a fair comparison, we excluded from this diagram all the solutions here investigated where only a simulated analysis was presented or where some parameters are missing in the experiment description, as for example the number of reference tags or the size of the test area. Moreover, solutions where the RFID system is not employed as the main localization technology and only operates as a support to other localization schemes exploiting exteroceptive sensors, e.g., CV-based approaches, are excluded too.

It is noteworthy that not all the analysed methods presented the performance with the same criteria. Some of them show the RMSE result, others the mean localization error, and still others the median error.

Table 4 summarizes the features of the analysed works in terms of cost, complexity, energy consumption and scalability.

The cost of a solution is estimated based on the required hardware to build the infrastructure. The energy consumption is determined on the basis of the employment of active/passive devices and the power supply.

The complexity is evaluated by considering the hardware infrastructure, depending on the scenario size, the reference-tag density, the need of a calibration procedure and the integration requirements for hardware components. The table is not meant to be exhaustive, but it could be useful for an immediate comparison between the proposed solution categories.

Eventually, it is underlined that the present survey focused on indoor vehicle localization which necessarily includes the exploitation of the RFID technology, either alone or com-

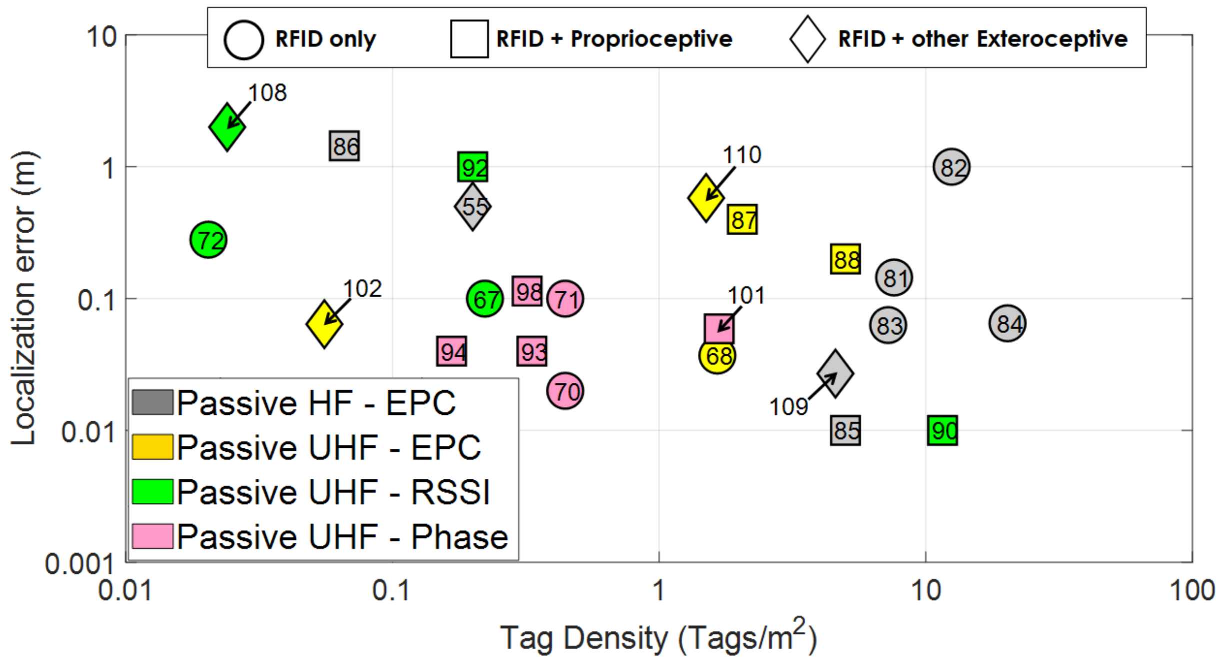


FIGURE 15. Localization error vs tag density by considering the analysed papers.

bined with other localization technologies. For a detailed review on the many other methods and technologies, the interested reader can refer to [25], [116].

VIII. CONCLUSION

This paper presented a survey of the methods exploiting the RFID technology for vehicle positioning, tracking, navigation or simultaneous localization and mapping. Three main categories of vehicle localization systems have been identified, namely, solutions exploiting only the RFID technology, sensor-fusion techniques combining data from RFID systems and proprioceptive sensors, and sensor-fusion techniques combing RFID data from those of other exteroceptive sensors in addition to the RFID system itself. Together with the implementation and methodological details, the applied RFID technology (passive HF system, passive UHF system, or other RFID systems) and the employed RFID parameter (EPC, RSSI, phase, or any their combination) have been discussed.

By generally speaking, the selection of the vehicle localization scheme is strictly related to the application scenario together with the tolerated implementation cost and complexity. As a result of the present survey, the authors believe that the category of the phase-based passive UHF-RFID systems combined with proprioceptive sensors seems to be the most investigated and relevant solution in the recent years. Even if it is at an early stage, the authors consider that further research efforts should be carried out in this direction, aiming to improve the robustness and the reliability of such promising solutions. Indeed, such systems could represent valuable competitors to classical indoor positioning systems for real-world applications, thanks to their low cost, extreme flexibility and ease of implementation.

REFERENCES

[1] G. Bresson, Z. Alsayed, L. Yu, and S. Glaser, "Simultaneous localization and mapping: A survey of current trends in autonomous driving," *IEEE Trans. Intell. Vehicles*, vol. 2, no. 3, pp. 194–220, Sep. 2017, doi: 10.1109/TIV.2017.2749181.

[2] B. Paden, M. Cap, S. Z. Yong, D. Yershov, and E. Frazzoli, "A survey of motion planning and control techniques for self-driving urban vehicles," *IEEE Trans. Intell. Vehicles*, vol. 1, no. 1, pp. 33–55, Mar. 2016, doi: 10.1109/TIV.2016.2578706.

[3] J.-X. Yu, Z.-X. Cai, and Z.-H. Duan, "Dead reckoning of mobile robot in complex terrain based on proprioceptive sensors," in *Proc. Int. Conf. Mach. Learn. Cybern.*, Kunming, China, Jul. 2008, pp. 1930–1935, doi: 10.1109/ICMLC.2008.4620722.

[4] N. V. Jankovic, S. V. Ciric, and N. S. Jovicic, "System for indoor localization of mobile robots by using machine vision," in *Proc. 23rd Telecommun. Forum Telfor (TELFOR)*, Belgrade, Serbia, Nov. 2015, pp. 619–622, doi: 10.1109/TELFOR.2015.7377543.

[5] L. Jetto, S. Longhi, and G. Venturini, "Development and experimental validation of an adaptive extended Kalman filter for the localization of mobile robots," *IEEE Trans. Robot. Autom.*, vol. 15, no. 2, pp. 219–229, Apr. 1999, doi: 10.1109/70.760343.

[6] L. Garrote, T. Barros, R. Pereira, and U. J. Nunes, "Absolute indoor positioning-aided laser-based particle filter localization with a refinement stage," in *Proc. IECON-45th Annu. Conf. IEEE Ind. Electron. Soc.*, Lisbon, Portugal, Oct. 2019, pp. 597–603, doi: 10.1109/IECON.2019.8927475.

[7] Z. Fang, Z. Zhao, X. Cui, D. Geng, Y. Xuan, L. Du, J. Xu, and S. Wu, "Multi-odor sources localization and tracking with wireless sensor network and mobile robots," in *Proc. IET Int. Conf. Wireless Sensor Netw. (IET-WSN)*, Beijing, China, 2010, pp. 60–65, doi: 10.1049/cp.2010.1028.

[8] M. Yin and F. Lian, "Robot localization and mapping by matching the environmental features from proprioceptive and exteroceptive sensors," in *Proc. SICE Annu. Conf.*, Taipei, Taiwan, 2010, pp. 191–196.

[9] S. Jain, S. Nandy, R. Ray, and S. N. Shome, "Application of particle filtering technique for sensor fusion in mobile robotics," in *Proc. IEEE Int. Conf. Mechatronics Autom.*, Beijing, China, Aug. 2011, pp. 2285–2290, doi: 10.1109/ICMA.2011.5986341.

[10] A. Li, X. Ruan, J. Huang, X. Zhu, and F. Wang, "Review of vision-based simultaneous localization and mapping," in *Proc. IEEE 3rd Inf. Technol., Netw., Electron. Autom. Control Conf. (ITNEC)*, Chengdu, China, Mar. 2019, pp. 117–123, doi: 10.1109/ITNEC.2019.8729285.

[11] G. Anousaki and K. Kyriakopoulos, "Simultaneous localization and map building of skid-steered robots," *IEEE Robot. Autom. Mag.*, vol. 14, no. 1, pp. 79–89, Mar. 2007, doi: 10.1109/MRA.2007.339625.

[12] C. Yang and H.-R. Shao, "WiFi-based indoor positioning," *IEEE Commun. Mag.*, vol. 53, no. 3, pp. 150–157, Mar. 2015, doi: 10.1109/MCOM.2015.7060497.

[13] V. Bianchi, P. Ciampolini, and I. De Munari, "RSSI-based indoor localization and identification for ZigBee wireless sensor networks in smart homes," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 2, pp. 566–575, Feb. 2019, doi: 10.1109/TIM.2018.2851675.

[14] G. Michau, A. Nantes, A. Bhaskar, E. Chung, P. Abry, and P. Borgnat, "Bluetooth data in an urban context: Retrieving vehicle trajectories," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 9, pp. 2377–2386, Sep. 2017, doi: 10.1109/TITS.2016.2642304.

[15] S. Gezici, Z. Tian, G. B. Giannakis, H. Kobayashi, A. F. Molisch, H. V. Poor, and Z. Sahinoglu, "Localization via ultra-wideband radios: A look at positioning aspects for future sensor networks," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 70–84, Jul. 2005, doi: 10.1109/MSP.2005.1458289.

[16] J. Zhang, X. Wang, Z. Yu, Y. Lyu, S. Mao, S. C. Periaswamy, J. Patton, and X. Wang, "Robust RFID based 6-DoF localization for unmanned aerial vehicles," *IEEE Access*, vol. 7, pp. 77348–77361, 2019, doi: 10.1109/ACCESS.2019.2922211.

[17] F. Bernardini, A. Buffi, D. Fontanelli, D. Macii, V. Magnago, M. Marracci, A. Motroni, P. Nepa, and B. Tellini, "Robot-based indoor positioning of UHF-RFID tags: The SAR method with multiple trajectories," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–15, 2021, doi: 10.1109/TIM.2020.3033728.

[18] C. B. Barneto, T. Riihonen, M. Turunen, M. Koivisto, J. Talvitie, and M. Valkama, "Radio-based sensing and indoor mapping with millimeter-wave 5G NR signals," in *Proc. Int. Conf. Localization GNSS (ICL-GNSS)*, Jun. 2020, pp. 1–5, doi: 10.1109/ICL-GNSS49876.2020.9115568.

[19] P. Gertzell, J. Landelius, H. Nyqvist, A. Fascista, A. Coluccia, G. Seco-Granados, N. Garcia, and H. Wymeersch, "5G multi-BS positioning with a single-antenna receiver," in *Proc. IEEE 31st Annu. Int. Symp. Pers., Indoor Mobile Radio Commun.*, Aug. 2020, pp. 1–5, doi: 10.1109/PIMRC48278.2020.9217124.

[20] C. Laoudias, A. Moreira, S. Kim, S. Lee, L. Wirola, and C. Fischione, "A survey of enabling technologies for network localization, tracking, and navigation," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 4, pp. 3607–3644, 4th Quart., 2018, doi: 10.1109/COMST.2018.2855063.

[21] *RFID Robot for Automatic Inventory: AdvanRobotTM*. Accessed: Dec. 1, 2020. [Online]. Available: https://www.keonn.com/systems/view-all-2/inventory-robots.html

[22] *TORY: Efficient Automated RFID Inventory*. Accessed: Dec. 1, 2020. [Online]. Available: https://www.metralabs.com/en/rfid-robot-tory/

[23] *Tag Surveyor: Autonomous RFID Tag Tracking*. Accessed: Dec. 1, 2020. [Online]. Available: https://fetchrobotics.com/products-technology/datasurvey/tagsurveyor/

[24] A. Tzitzis, A. G. Dimitriou, A. Filotheou, S. Siachalou, E. Tsardoulias, S. Megalou, A. Bletsas, K. Panayiotou, A. Symeonidis, and T. Yioultsis, "Real-time 3D localization of RFID-tagged products by ground robots and drones with commercial off-the-shelf RFID equipment: Challenges and solutions," in *Proc. IEEE Int. Conf. RFID (RFID)*, Orlando, FL, USA, Sep. 2020, pp. 1–8, doi: 10.1109/RFID49298.2020.9244904.

[25] D. Dardari, P. Closas, and P. M. Djuric, "Indoor tracking: Theory, methods, and technologies," *IEEE Trans. Veh. Technol.*, vol. 64, no. 4, pp. 1263–1278, Apr. 2015, doi: 10.1109/TVT.2015.2403868.

[26] H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping: Part I," *IEEE Robot. Autom. Mag.*, vol. 13, no. 2, pp. 99–110, Jun. 2006, doi: 10.1109/MRA.2006.1638022.

[27] F. Martinelli, "Simultaneous localization and mapping using the phase of passive UHF-RFID signals," *J. Intell. Robot. Syst.*, vol. 94, nos. 3–4, pp. 711–725, Jul. 2018, doi: 10.1007/s10846-018-0903-8.

[28] R. Tesoriero, J. Gallud, M. Lozano, and V. R. Penichet, "Tracking autonomous entities using RFID technology," *IEEE Trans. Consum. Electron.*, vol. 55, no. 2, pp. 650–655, May 2009, doi: 10.1109/TCE.2009.5174435.

[29] L. M. Ni, Y. Liu, Y. Cho Lau, and A. P. Patil, "LANDMARC: Indoor location sensing using active RFID," in *Proc. 1st IEEE Int. Conf. Pervasive Comput. Commun. (PerCom)*, Fort Worth, TX, USA, Mar. 2003, pp. 407–415, doi: 10.1109/PERCOM.2003.1192765.

[30] J. Hightower, G. Borriello, and R. Want, "SpotOn: An indoor 3D location sensing technology based on RF signal strength," Dept. Comput. Sci. Eng., Univ. Washington, Seattle, WA, USA, Tech. Rep. #2000-02-02, 2000.

[31] K. Finkenzeller, *RFID Handbook: Radio-Frequency Identification Fundamentals and Applications*. Hoboken, NJ, USA, Wiley, 2004.

[32] A. Koch and A. Zell, "RFID-enabled location fingerprinting based on similarity models from probabilistic similarity measures," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Stockholm, Sweden, May 2016, pp. 4557–4563, doi: 10.1109/ICRA.2016.7487656.

[33] P. V. Nikitin and K. V. S. Rao, "Antennas and propagation in UHF RFID systems," in *Proc. IEEE Int. Conf. RFID*, Las Vegas, NV, USA, Apr. 2008, pp. 277–288, doi: 10.1109/RFID.2008.4519368.

[34] P. V. Nikitin, R. Martinez, S. Ramamurthy, H. Leland, G. Spiess, and K. V. S. Rao, "Phase based spatial identification of UHF RFID tags," in *Proc. IEEE Int. Conf. RFID (IEEE RFID)*, Orlando, FL, USA, Apr. 2010, pp. 102–109, doi: 10.1109/RFID.2010.5467253.

[35] M. B. Akbar, D. G. Taylor, and G. D. Durgin, "Amplitude and phase difference estimation bounds for multisensor based tracking of RFID tags," in *Proc. IEEE Int. Conf. RFID (RFID)*, San Diego, CA, USA, Apr. 2015, pp. 105–112, doi: 10.1109/RFID.2015.7113080.

[36] A. Motroni, P. Nepa, V. Magnago, A. Buffi, B. Tellini, D. Fontanelli, and D. Macii, "SAR-based indoor localization of UHF-RFID tags via mobile robot," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Nantes, France, Sep. 2018, pp. 1–8, doi: 10.1109/IPIN.2018.8533847.

[37] A. Buffi, A. Motroni, P. Nepa, B. Tellini, and R. Cioni, "A SAR-based measurement method for passive-tag positioning with a flying UHF-RFID reader," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 3, pp. 845–853, Mar. 2019, doi: 10.1109/TIM.2018.2857045.

[38] A. Tzitzis, S. Megalou, S. Siachalou, T. G. Emmanouil, A. Kehagias, T. V. Yioultsis, and A. G. Dimitriou, "Localization of RFID tags by a moving robot, via phase unwrapping and non-linear optimization," *IEEE J. Radio Freq. Identificat.*, vol. 3, no. 4, pp. 216–226, Dec. 2019, doi: 10.1109/JRFID.2019.2936969.

[39] T. Sanpechuda and L. Kovavisaruch, "A review of RFID localization: Applications and techniques," in *Proc. 5th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol.*, Krabi, Thailand, May 2008, pp. 769–772, doi: 10.1109/ECTICON.2008.4600544.

[40] C. Li, L. Mo, and D. Zhang, "Review on UHF RFID localization methods," *IEEE J. Radio Freq. Identificat.*, vol. 3, no. 4, pp. 205–215, Dec. 2019, doi: 10.1109/JRFID.2019.2924346.

[41] T. Deyle, H. Nguyen, M. S. Reynolds, and C. C. Kemp, "RFID-guided robots for pervasive automation," *IEEE Pervas. Comput.*, vol. 9, no. 2, pp. 37–45, Apr. 2010, doi: 10.1109/MPRV.2010.17.

[42] A. Milella, D. D. Paola, and G. Cicirelli, "RFID technology for mobile robot surveillance," in *Mechatronic Systems Applications*. IntechOpen, 2010, doi: 10.5772/8920.

[43] P. Nepa A. Motroni, A. Congi, E. M. Ferro, M. Pesi, G. Giorgi, A. Buffi, M. Lazzarotti, J. Bellucci, S. Galigani, M. Frosolini, M. Braglia, A. Bigongiari, G. Isola, F. Bertuccelli, M. G. Scutellà, M. Pappalardo, M. Passacantando, D. Loschiavo, A. Rubichi, C. Salvador, F. Bonifacio, F. Zani, "I-READ 4.0: Internet-of-READers for an efficient asset management in large warehouses with high stock rotation index," in *Proc. IEEE 5th Int. Forum Res. Technol. Soc. Ind. (RTSI)*, Florence, Italy, Sep. 2019, pp. 67–72, doi: 10.1109/RTSI.2019.8895574.

[44] D. M. S. Velandia, N. Kaur, W. G. Whittow, P. P. Conway, and A. A. West, "Towards industrial Internet of Things: Crankshaft monitoring, traceability and tracking using RFID," *Robot. Comput.-Integr. Manuf.*, vol. 41, pp. 66–77, Oct. 2016, doi: 10.1016/j.rcim.2016.02.004.

[45] K. Zhao, M. Zhu, B. Xiao, X. Yang, C. Gong, and J. Wu, "Joint RFID and UWB technologies in intelligent warehousing management system," *IEEE Internet Things J.*, vol. 7, no. 12, pp. 11640–11655, Dec. 2020, doi: 10.1109/JIOT.2020.2998484.

[46] H. Xu, W. Yu, D. Griffith, and N. Golmie, "A survey on industrial Internet of Things: A cyber-physical systems perspective," *IEEE Access*, vol. 6, pp. 78238–78259, 2018, doi: 10.1109/ACCESS.2018.2884906.

[47] J. Teizer, "Wearable, wireless identification sensing platform: Self-monitoring alert and reporting technology for hazard avoidance and training (smarthat)," *J. Inf. Technol. Construct.*, vol. 20, no. 19, pp. 295–312, May 2015.

[48] S. Krishna, E. S. Rahul, and R. R. Bhavani, "RFID based-human localization in robot-cells for a better shared workspace interaction," *CSI Trans. ICT*, vol. 4, no. 1, pp. 37–43, Mar. 2016, doi: 10.1007/s40012-016-0084-1.

[49] E. Sopensky, "The RFID-enabled intelligent hospital," *IEEE Potentials*, vol. 34, no. 5, pp. 27–31, Sep. 2015, doi: 10.1109/MPOT.2015.2410393.

[50] F. S. Gómez, N. E. Suárez Escobar, and J. Vázquez, "RFID + Wi-Fi system to control the location of biomedical equipment within hospital areas and linked to an intelligent inventory," *Health Technol.*, vol. 10, no. 2, pp. 479–483, Mar. 2020, doi: 10.1007/s12553-019-00393-6.

[51] W. Yao, C.-H. Chu, and Z. Li, "The use of RFID in healthcare: Benefits and barriers," in *Proc. IEEE Int. Conf. RFID-Technol. Appl.*, Guangzhou, China, Jun. 2010, pp. 128–134, doi: 10.1109/RFID-TA.2010.5529874.

[52] C.-C. Tsai, S.-M. Hu, H.-C. Huang, and S.-M. Hsieh, "Fuzzy hybrid navigation of an active mobile robotic assistant: A multisensory fusion approach," in *Proc. IEEE Workshop Adv. Robot. Social Impacts*, Hsinchu, Taiwan, Dec. 2007, pp. 1–6, doi: 10.1109/ARSO.2007.4531423.

[53] V. Kulyukin, C. Gharpure, J. Nicholson, and S. Pavithran, "RFID in robot-assisted indoor navigation for the visually impaired," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Sendai, Japan, vol. 2, Sep./Oct. 2004, pp. 1979–1984, doi: 10.1109/IROS.2004.1389688.

[54] R. Parada, J. Melia-Segui, M. Morenza-Cinos, A. Carreras, and R. Pous, "Using RFID to detect interactions in ambient assisted living environments," *IEEE Intell. Syst.*, vol. 30, no. 4, pp. 16–22, Jul. 2015, doi: 10.1109/MIS.2015.43.

[55] P. Nazemzadeh, D. Fontanelli, and D. Macii, "An indoor position tracking technique based on data fusion for ambient assisted living," in *Proc. IEEE Int. Conf. Comput. Intell. Virtual Environ. Meas. Syst. Appl. (CIVEMSA)*, Milan, Italy, Jul. 2013, pp. 7–12, doi: 10.1109/CIVEMSA.2013.6617387.

[56] C. Ramos, G. Marreiros, R. Santos, and C. F. Freitas, "Smart offices and intelligent decision rooms," in *Handbook of Ambient Intelligence and Smart Environments*, H. Nakashima, H. Aghajan, and J. C. Augusto, Eds. Boston, MA, USA: Springer, 2010, pp. 851–880.

[57] J. Sales, J. V. Martí, R. Marín, E. Cervera, and P. J. Sanz, "CompaRob: The shopping cart assistance robot," *Int. J. Distrib. Sensor Netw.*, vol. 12, no. 2, Feb. 2016, Art. no. 4781280, doi: 10.1155/2016/4781280.

[58] H.-H. Lin, C.-C. Tsai, and H.-Y. Chang, "Global posture estimation of a tour-guide robot using RFID and laser scanning measurements," in *Proc. IECON-33rd Annu. Conf. IEEE Ind. Electron. Soc.*, Taipei, Taiwan, 2007, pp. 483–488, doi: 10.1109/IECON.2007.4460081.

[59] C. Forster, D. Sabatta, R. Siegwart, and D. Scaramuzza, "RFID-based hybrid metric-topological SLAM for GPS-denied environments," in *Proc. IEEE Int. Conf. Robot. Autom.*, Karlsruhe, Germany, May 2013, pp. 5228–5234, doi: 10.1109/ICRA.2013.6631324.

[60] R. Liu, G. Huskic, and A. Zell, "Dynamic objects tracking with a mobile robot using passive UHF RFID tags," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Chicago, IL, USA, Sep. 2014, pp. 4247–4252, doi: 10.1109/IROS.2014.6943161.

[61] E. DiGiampaolo and F. Martinelli, "A robotic system for localization of passive UHF-RFID tagged objects on shelves," *IEEE Sensors J.*, vol. 18, no. 20, pp. 8558–8568, Oct. 2018, doi: 10.1109/JSEN.2018.2865339.

[62] A. Motroni, P. Nepa, A. Buffi, P. Tripicchio, and M. Unetti, "RFID tag localization with UGV in retail applications," in *Proc. 3rd Int. Conf. Smart Sustain. Technol. (SpliTech)*, Split, Croatia, Jun. 2018, pp. 1–5.

[63] A. Motroni, P. Nepa, P. Tripicchio, and M. Unetti, "A multi-antenna SAR-based method for UHF RFID tag localization via UGV," in *Proc. IEEE Int. Conf. RFID Technol. Appl. (RFID-TA)*, Macau, China, Sep. 2018, pp. 1–6, doi: 10.1109/RFID-TA.2018.8552780.

[64] F. Bernardini, A. Buffi, A. Motroni, P. Nepa, B. Tellini, P. Tripicchio, and M. Unetti, "Particle swarm optimization in SAR-based method enabling real-time 3D positioning of UHF-RFID tags," *IEEE J. Radio Freq. Identificat.*, vol. 4, no. 4, pp. 300–313, Dec. 2020, doi: 10.1109/JRFID.2020.3005351.

[65] J. Wang, F. Adib, R. Knepper, D. Katabi, and D. Rus, "RF-compass: Robot object manipulation using RFIDs," in *Proc. 19th Annu. Int. Conf. Mobile Comput. Netw. (MobiCom)*, 2013, pp. 3–14, doi: 10.1145/2500423.2500451.

[66] C. Thormann and A. Winkler, "Localization of workpieces by robot manipulators using RFID technology," in *Proc. 24th Int. Conf. Methods Models Autom. Robot. (MMAR)*, Międzyzdroje, Poland, Aug. 2019, pp. 52–57, doi: 10.1109/MMAR.2019.8864714.

[67] S. S. Saab and Z. S. Nakad, "A standalone RFID indoor positioning system using passive tags," *IEEE Trans. Ind. Electron.*, vol. 58, no. 5, pp. 1961–1970, May 2011, doi: 10.1109/TIE.2010.2055774.

[68] J. H. Cho and M.-W. Cho, "Effective position tracking using B-Spline surface equation based on wireless sensor networks and passive UHF-RFID," *IEEE Trans. Instrum. Meas.*, vol. 62, no. 9, pp. 2456–2464, Sep. 2013, doi: 10.1109/TIM.2013.2259099.

[69] A. Corrales Paredes, M. Malfaz, and M. A. Salichs, "Signage system for the navigation of autonomous robots in indoor environments," *IEEE Trans. Ind. Informat.*, vol. 10, no. 1, pp. 680–688, Feb. 2014, doi: 10.1109/TII.2013.2246173.

[70] S. Sarkka, V. V. Viikari, M. Huusko, and K. Jaakkola, "Phase-based UHF RFID tracking with nonlinear Kalman filtering and smoothing," *IEEE Sensors J.*, vol. 12, no. 5, pp. 904–910, May 2012, doi: 10.1109/JSEN.2011.2164062.

[71] H. Ma and K. Wang, "Fusion of RSS and phase shift using the Kalman filter for RFID tracking," *IEEE Sensors J.*, vol. 17, no. 11, pp. 3551–3558, Jun. 2017, doi: 10.1109/JSEN.2017.2696054.

[72] J. H. Teo, A. Loganathan, P. Goh, and N. S. Ahmad, "Autonomous mobile robot navigation via RFID signal strength sensing," *Int. J. Mech. Eng. Robot. Res.*, vol. 9, no. 8, pp. 1140–1144, 2020.

[73] Q. Yang, D. G. Taylor, M. B. Akbar, and G. D. Durgin, "Analysis of Kalman filter-based localization for HIMR RFID systems," *IEEE J. Radio Freq. Identificat.*, vol. 3, no. 3, pp. 164–172, Sep. 2019, doi: 10.1109/JRFID.2019.2921001.

[74] C. Duan, X. Rao, L. Yang, and Y. Liu, "Fusing RFID and computer vision for fine-grained object tracking," in *Proc. IEEE INFOCOM-IEEE Conf. Comput. Commun.*, Atlanta, GA, USA, May 2017, pp. 1–9, doi: 10.1109/INFOCOM.2017.8057161.

[75] D. Smith and S. Singh, "Approaches to multisensor data fusion in target tracking: A survey," *IEEE Trans. Knowl. Data Eng.*, vol. 18, no. 12, pp. 1696–1710, Dec. 2006, doi: 10.1109/TKDE.2006.183.

[76] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Feb. 2002, doi: 10.1109/78.978374.

[77] A. S. Paul and E. A. Wan, "RSSI-based indoor localization and tracking using sigma-point Kalman smoothers," *IEEE J. Sel. Topics Signal Process.*, vol. 3, no. 5, pp. 860–873, Oct. 2009, doi: 10.1109/JSTSP.2009.2032309.

[78] D. Macii, A. Boni, M. D. Cecco, and D. Petri, "Tutorial 14: Multisensor data fusion," *IEEE Instrum. Meas. Mag.*, vol. 11, no. 3, pp. 24–33, Jun. 2008, doi: 10.1109/MIM.2008.4534375.

[79] C. Rasmussen and G. D. Hager, "Probabilistic data association methods for tracking complex visual objects," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 6, pp. 560–576, Jun. 2001, doi: 10.1109/34.927458.

[80] A. Kleiner, C. Dornhege, and S. Dali, "Mapping disaster areas jointly: RFID-coordinated SLAM by Hurnans and robots," in *Proc. IEEE Int. Workshop Saf., Secur. Rescue Robot.*, Rome, Italy, Sep. 2007, pp. 1–6, doi: 10.1109/SSRR.2007.4381263.

[81] S. Park and S. Hashimoto, "Autonomous mobile robot navigation using passive RFID in indoor environment," *IEEE Trans. Ind. Electron.*, vol. 56, no. 7, pp. 2366–2373, Jul. 2009, doi: 10.1109/TIE.2009.2013690.

[82] R. Johansson and A. Saffiotti, "Navigating by stigmergy: A realization on an RFID floor for minimalistic robots," in *Proc. IEEE Int. Conf. Robot. Autom.*, Kobe, Japan, May 2009, pp. 245–252, doi: 10.1109/ROBOT.2009.5152737.

[83] A. A. N. Shirehjini, A. Yassine, and S. Shirmohammadi, "An RFID-based position and orientation measurement system for mobile objects in intelligent environments," *IEEE Trans. Instrum. Meas.*, vol. 61, no. 6, pp. 1664–1675, Jun. 2012, doi: 10.1109/TIM.2011.2181912.

[84] Y. Guo, X. Guo, and G. Wang, "Using RFID in localization for indoor navigation of mobile robots," in *Proc. IEEE Int. Conf. Mechatronics Autom.*, Chengdu, China, Aug. 2012, pp. 1892–1897, doi: 10.1109/ICMA.2012.6285110.

[85] S. Han, D. Kim, and J. Lee, "A new tag arrangement pattern for a differential driving mobile robot based on RFID system," in *Proc. Int. Conf. Control, Autom. Syst.*, Seoul, South Korea, 2007, pp. 1228–1233, doi: 10.1109/ICCAS.2007.4406522.

[86] J.-F. Chen and C.-C. Wang, "Simultaneous localization and mapping using a short-range passive RFID reader with sparse tags in large environments," in *Proc. IEEE Workshop Adv. Robot. Social Impacts*, Seoul, South Korea, Oct. 2010, pp. 136–141, doi: 10.1109/ARSO.2010.5680012.

[87] P. Vorst and A. Zell, "Fully autonomous trajectory estimation with long-range passive RFID," in *Proc. IEEE Int. Conf. Robot. Autom.*, Anchorage, AK, USA, May 2010, pp. 1867–1872, doi: 10.1109/ROBOT.2010.5509810.

[88] L. Yang, J. Cao, W. Zhu, and S. Tang, "Accurate and efficient object tracking based on passive RFID," *IEEE Trans. Mobile Comput.*, vol. 14, no. 11, pp. 2188–2200, Nov. 2015, doi: 10.1109/TMC.2014.2381232.

[89] W. Gueaieb and M. S. Miah, "Mobile robot navigation using particle swarm optimization and noisy RFID communication," in *Proc. IEEE Int. Conf. Comput. Intell. Meas. Syst. Appl.*, Istanbul, Turkey, Jul. 2008, pp. 111–116, doi: 10.1109/CIMSA.2008.4595843.

[90] S. Park and H. Lee, "Self-recognition of vehicle position using UHF passive RFID tags," *IEEE Trans. Ind. Electron.*, vol. 60, no. 1, pp. 226–234, Jan. 2013, doi: 10.1109/TIE.2012.2185018.

[91] J. J. Pomarico-Franquiz and Y. S. Shmaliy, "Accurate self-localization in RFID tag information grids using FIR filtering," *IEEE Trans. Ind. Informat.*, vol. 10, no. 2, pp. 1317–1326, May 2014, doi: 10.1109/TII.2014.2310952.

[92] C.-H. Huang, L.-H. Lee, C. C. Ho, L.-L. Wu, and Z.-H. Lai, "Real-time RFID indoor positioning system based on Kalman-filter drift removal and Heron-bilateration location estimation," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 3, pp. 728–739, Mar. 2015, doi: 10.1109/TIM.2014.2347691.

[93] E. DiGiampaolo and F. Martinelli, "Mobile robot localization using the phase of passive UHF RFID signals," *IEEE Trans. Ind. Electron.*, vol. 61, no. 1, pp. 365–376, Jan. 2014, doi: 10.1109/TIE.2013.2248333.

[94] F. Martinelli, "A robot localization system combining RSSI and phase shift in UHF-RFID signals," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 5, pp. 1782–1796, Sep. 2015, doi: 10.1109/TCST.2014.2386777.

[95] V. Magnago, L. Palopoli, A. Buffi, B. Tellini, A. Motroni, P. Nepa, D. Macii, and D. Fontanelli, "Ranging-free UHF-RFID robot positioning through phase measurements of passive tags," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 5, pp. 2408–2418, May 2020, doi: 10.1109/TIM.2019.2960900.

[96] A. Motroni, P. Nepa, A. Buffi, and B. Tellini, "A phase-based method for mobile node localization through UHF-RFID passive tags," in *Proc. IEEE Int. Conf. RFID Technol. Appl. (RFID-TA)*, Pisa, Italy, Sep. 2019, pp. 470–475.

[97] A. Buffi, P. Nepa, A. Motroni, and B. Tellini, "Mobile device self-location method using at least one passive radio-frequency device," EU Patent Appl. 20 197 281.7, Sep. 21, 2020.

[98] A. Motroni, A. Buffi, P. Nepa, and B. Tellini, "Sensor-fusion and tracking method for indoor vehicles with low-density UHF-RFID tags," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–14, 2021, doi: 10.1109/TIM.2020.3027926.

[99] A. Motroni, P. Nepa, A. Buffi, and B. Tellini, "Robot localization via passive UHF-RFID technology: State-of-the-art and challenges," in *Proc. IEEE Int. Conf. RFID (RFID)*, Orlando, FL, USA, Sep. 2020, pp. 1–8, doi: 10.1109/RFID49298.2020.9244884.

[100] F. Shamsfakhr, L. Palopoli, D. Fontanelli, A. Motroni, and A. Buffi, "Robot localisation using UHF-RFID tags for industrial IoT applications," in *Proc. IEEE Int. Workshop Metrol. Ind. 4.0 IoT*, Roma, Italy, Jun. 2020, pp. 659–664, doi: 10.1109/MetroInd4.0IoT48571.2020.9138210.

[101] B. Tao, H. Wu, Z. Gong, Z. Yin, and H. Ding, "An RFID-based mobile robot localization method combining phase difference and readability," *IEEE Trans. Autom. Sci. Eng.*, early access, Jul. 17, 2020, doi: 10.1109/TASE.2020.3006724.

[102] A. Milella, D. D. Paola, G. Cicirelli, and T. D'Orazio, "RFID tag bearing estimation for mobile robot localization," in *Proc. Int. Conf. Adv. Robot.*, Munich, Germany, 2009, pp. 1–6.

[103] B.-S. Choi and J.-J. Lee, "Sensor network based localization algorithm using fusion sensor-agent for indoor service robot," *IEEE Trans. Consum. Electron.*, vol. 56, no. 3, pp. 1457–1465, Aug. 2010, doi: 10.1109/TCE.2010.5606283.

[104] F. Schwiegelshohn, T. Nick, and J. Gotze, "Localization based on fusion of RFID and stereo image data," in *Proc. 10th Workshop Positioning, Navigat. Commun. (WPNC)*, Dresden, Germany, Mar. 2013, pp. 1–6, doi: 10.1109/WPNC.2013.6533297.

[105] D. Hahnel, W. Burgard, D. Fox, K. Fishkin, and M. Philipose, "Mapping and localization with RFID technology," in *Proc. IEEE Int. Conf. Robot. Autom.*, New Orleans, LA, USA, vol. 1, Dec. 2004, pp. 1015–1020, doi: 10.1109/ROBOT.2004.1307283.

[106] Y. Senta, Y. Kimuro, S. Takarabe, and T. Hasegawa, "Machine learning approach to self-localization of mobile robots using RFID tag," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatronics*, Zürich, Switzerland, Sep. 2007, pp. 1–6, doi: 10.1109/AIM.2007.4412485.

[107] Y. Wang and X. Xu, "Indoor localization service based on the data fusion of Wi-Fi and RFID," in *Proc. IEEE Int. Conf. Web Services (ICWS)*, San Francisco, CA, USA, Jun. 2016, pp. 180–187, doi: 10.1109/ICWS.2016.31.

[108] T. Gu, Y. Tang, R. Wang, L. Lu, Z. Wang, and L. Chang, "Indoor localization fusion algorithm based on signal filtering optimization of multi-sensor," in *Proc. 11th Int. Conf. Adv. Comput. Intell. (ICACI)*, Guilin, China, Jun. 2019, pp. 250–255, doi: 10.1109/ICACI.2019.8778463.

[109] B.-S. Choi, J.-W. Lee, J.-J. Lee, and K.-T. Park, "A hierarchical algorithm for indoor mobile robot localization using RFID sensor fusion," *IEEE Trans. Ind. Electron.*, vol. 58, no. 6, pp. 2226–2235, Jun. 2011, doi: 10.1109/TIE.2011.2109330.

[110] J. Vascak and J. Hvizdos, "Vehicle navigation by fuzzy cognitive maps using sonar and RFID technologies," in *Proc. IEEE 14th Int. Symp. Appl. Mach. Intell. Informat. (SAMI)*, Herlany, Slovakia, Jan. 2016, pp. 75–80, doi: 10.1109/SAMI.2016.7422985.

[111] Y. Zhou, W. Liu, and P. Huang, "Laser-activated RFID-based indoor localization system for mobile robots," in *Proc. IEEE Int. Conf. Robot. Autom.*, Roma, Italy, Apr. 2007, pp. 4600–4605, doi: 10.1109/ROBOT.2007.364188.

[112] M. Goller, C. Feichtenhofer, and A. Pinz, "Fusing RFID and computer vision for probabilistic tag localization," in *Proc. IEEE Int. Conf. RFID (IEEE RFID)*, Orlando, FL, USA, Apr. 2014, pp. 89–96, doi: 10.1109/RFID.2014.6810717.

[113] J. Werfel and R. Nagpal, "Extended stigmergy in collective construction," *IEEE Intell. Syst.*, vol. 21, no. 2, pp. 20–28, Mar. 2006, doi: 10.1109/MIS.2006.25.

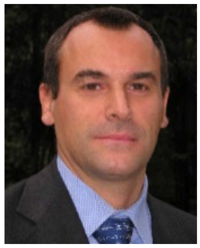
[114] I. Bukhori and Z. H. Ismail, "Detection of kidnapped robot problem in Monte Carlo localization based on the natural displacement of the robot," *Int. J. Adv. Robot. Syst.*, vol. 14, no. 4, pp. 1–6, Jul. 2017, doi: 10.1177/1729881417717469.

[115] F. Potorti, A. Crivello, P. Barsocchi, and F. Palumbo, "Evaluation of indoor localisation systems: Comments on the ISO/IEC 18305 standard," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Nantes, France, Sep. 2018, pp. 1–7, doi: 10.1109/IPIN.2018.8533710.

[116] A. Yassin, Y. Nasser, M. Awad, A. Al-Dubai, R. Liu, C. Yuen, R. Raulefs, and E. Aboutanios, "Recent advances in indoor localization: A survey on theoretical approaches and applications," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 1327–1346, 2nd Quart., 2017, doi: 10.1109/COMST.2016.2632427.

ANDREA MOTRONI (Member, IEEE) received the B.E. and M.E. *(summa cum laude)* degrees in telecommunications engineering from the University of Pisa, Pisa, Italy, in 2015 and 2017, respectively, where he is currently pursuing the Ph.D. degree in information engineering. In 2020, he was a Visiting Ph.D. Student with the Graz University of Technology, Graz, Austria. He has coauthored one European patent application. His current research interest includes indoor radiolocalization systems, with specific focus on UHF-RFID phase-based algorithms for vehicle tracking and UHF-RFID smart gates and applications for Internet of Things and Industry 4.0. In 2019, he was the President of the IEEE Student Branch of the University of Pisa.

ALICE BUFFI (Member, IEEE) received the B.S. and M.S. *(summa cum laude)* degrees in telecommunications engineering and the Ph.D. (Doctor Europaeus) degree in applied electromagnetism in electrical and biomedical engineering, electronics, smart sensors, nanotechnologies from the University of Pisa, Pisa, Italy, in 2006, 2008 and 2012, respectively. In 2011, she was a Visiting Ph.D. Student with the Queen Mary University of London, London, U.K. Since 2012, she has been with the University of Pisa, where she is currently an Associate Professor with the Department of Energy, Systems, Territory and Construction Engineering. She has coauthored several international journal papers and international conferences contributions, one European patent, and one European patent application. Her current research topics include measurement methods to locate static or moving items through radio frequency identification (RFID) systems operating at the ultra-high-frequency (UHF) band in Industry 4.0 scenarios. Besides, she has interests in classification methods for smart gates and smart storage systems and aging process in battery cells. She is a member of the IEEE Instrumentation and Measurement Society and the Antennas and Propagation Society. She was a recipient of the Best Paper Award at the IEEE RFID-TA 2019 International Conference and the Young Scientist Award from the International Union of Radio Science, Commission B, in 2013 and 2016, respectively. She serves as an Associate Editor for the IEEE Journal of Radio Frequency Identification.



PAOLO NEPA (Senior Member, IEEE) received the Laurea (Doctor) degree *(summa cum laude)* in electronics engineering from the University of Pisa, Pisa, Italy, in 1990. Since 1990, he has been with the Department of Information Engineering, University of Pisa, where he is currently a Full Professor. In 1998, he was with the Electro Science Laboratory (ESL), The Ohio State University (OSU), Columbus, OH, USA, as a Visiting Scholar supported by a Grant of the Italian National Research Council. At ESL, he was involved in research on efficient hybrid techniques for the analysis of large antenna arrays. In the context of UHF-RFID systems, he is working on techniques for radiolocalization of either tagged objects or readers. He has coauthored more than 300 international journal articles and conference contributions. He is also involved in the design of wideband and multiband antennas, mainly for base stations and mobile terminals of communication systems, as well as in the design of antennas optimized for near-field coupling and focusing. He was working on channel characterization, wearable antenna design, and diversity scheme implementation for body-centric communication systems. His research interests include the extension of high-frequency techniques to electromagnetic scattering from material structures and its application to the development of radio propagation models for indoor and outdoor scenarios of wireless communication systems. He is a member of the Technical Advisory Board of URSI Commission B—Fields and Waves and served as the General Chair for the IEEE RFID-TA 2019 International Conference. He was a recipient of the Young Scientist Award from the International Union of Radio Science, Commission B, in 1998. Since 2016, he has been serving as an Associate Editor for the IEEE Antennas and Wireless Propagation Letters.