RISING

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Design and implementation of the RISING Hybrid Indoor Positioning System

RISING

Project overview: Design and implementation of the RISING Hybrid Indoor Positioning System

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Table of contents

Forward

The project will investigate the feasibility of using RFID technology combined with inertial sensors embedded in smart devices to improve the activities of first responders during emergency missions in indoor/deep indoor environments.

In this document the design and the implementation of a computing unit that provides the displacement of the user during the time of a mission are proposed.

1 Related Work

Recently, a lot of efforts have been put in developing Indoor Positioning Systems (IPSs) to provide location information of people and devices. A positioning system allows a mobile device to determine its position, and makes the position of the device available for position-based services such as navigating, tracking or monitoring, etc.

Some position-based indoor tracking systems have been used in several settings, like hospitals or museums. Inside a hospital, IPSs are used both to track expensive equipment to avoid being stolen and to guide the patients to the medical resources. IPSs are exploited in large museum to assist tourists in seeing artifacts in different places in a given sequence.

Global Navigation Satellite Systems (GNSSs), e.g. Global Positioning System (GPS) [17], are the most widely used positioning systems, since they offer maximum coverage. GNSS capability can be added to various devices enabling location-based services, such as navigation, tourism, etc. However, GNSS cannot be deployed for indoor use, because line-of-sight transmission between receivers and satellites is not possible in an indoor environment. Comparing with outdoor, indoor environments are more complex. There are various obstacles as walls, equipment, or human beings, influencing the propagation of electromagnetic waves, which lead to multi-path effects. Some interference and noise sources from other wired and wireless networks degrade the accuracy of positioning. The building geometry, the mobility of people, and the atmospheric conditions result in environmental effects [24]. Considering these issues, IPSs for indoor applications raise new challenges for the future communications systems.

Several technologies have been investigated to design IPSs. Among them, design options such as InfraRed (IR), ultrasound, Radio-Frequency IDentification (RFID), Wireless Local Area Network (WLAN), Bluetooth, Sensor Networks, Ultra-WideBand (UWB), magnetic signals, vision analysis, and audible sound seem to be the more promising. Based on these fundamental technologies, numerous IPSs have been developed by different companies, research centers and universities. Each system takes advantage of a particular positioning technology or combining some of these technologies, however, it also inherits the limitations of these technologies.

In this report, several commercially available and research-oriented IPSs will be presented and reviewed. Moreover, the advantages and disadvantages of these IPSs will be compared and discussed.

IPS definition and taxonomy

Dempsey [11] defines an IPS as a system that continuously and in real-time can determine the position of something or someone in a physical space such as in a hospital, a gymnasium, a school, etc. [41].

An IPS considers only indoor environments such as inside a building. An IPS can determine the location of users or their devices in personal networks by measuring the location of their mobile devices in an indoor environment.

A complete taxonomy for IPSs is hard to drawn, however IPSs can be classified on the basis of the location architecture, information, technologies and techniques.

General architecture for IPS

The goal of IPSs is starting to enable the location-aware computing systems in indoor situations. The general system architecture of the location-aware computing systems [15] includes 3 layers:

1. *location sensing systems:* at low level, different location sensing technologies are used to perform measurements of the location of the users and their devices;

2. *software location abstractions the software location abstractions* layer converts the data reported from the location sensing systems layer into a required presentation of the locations [5]. An example of the software location abstractions layer is the Java location Application Programming Interfaces (API) [19], that produce the location information of targets in a standard format and provide access to a database of landmarks. Thus the developers can use this Java location API to develop location-based applications for resource limited devices;

3. *location-based applications*, such as navigation and geographical advertising [44], are implemented at the highest layer, which use the location context information measured and calculated by the lower layers.

Another way of classifying IPSs is on the basis of the role of the location infrastructure. Three different approaches can be considered:

- *self-positioning architecture* calculates the positions by the targets themselves and takes advantage of the infrastructures of positioning systems, which provide high security and privacy;

- *infrastructure positioning architecture* estimates the positions of the targets using the infrastructures, which can automatically track the position of devices if they are in the coverage positioning area;

- *self-oriented infrastructure-assisted architecture* are able to track a target which have sent a request to the positioning system to start the position measurements, and then gets its location information from the system. The key point of the third architecture is that unless the device allows a positioning system to track it, no positioning activities for the device can be carried out.

Information location

The *absolute location information* is provided by IPSs when a map of the locating area such as an office, a floor, a building, etc., is available. The absolute position of a target with respect to the map can be measured and displayed. Usually, the absolute position information is offered by indoor positioning tracking systems and indoor navigation systems, because tracking and guiding services need the exact positions of the targets.

The *relative position information* is another kind of outputs offered by the IPSs, which measure the motion of different parts of a target. For example, an IPS which tracks whether the door of a car is closed or not, needs to give the relative position information of the tracked point on the door with respect to the body of the car.

The third kind of position information is *proximity location information*, which specifies only the place where a target is. The position monitoring and tracking systems in hospitals are such examples. The IPS should provide the room where a patient is. Thus location-based applications in hospital can monitor whether the patient enters in a correct room for diagnoses or operations.

Location technologies

Several wireless technologies have been developed for indoor location sensing. These technologies include IR, ultra-sound, RFID, WLAN, Bluetooth, UWB, magnetic technology, etc. Each technology has many advantages in performing location sensing for indoor use. For example, an IPS using WLAN technology does not need new infrastructures, because it can reuse the devices equipped with WLAN technology, which are widely deployed. At the same time, they have some limitations because of their properties.

Location techniques

There are four widely used techniques for indoor position estimations: triangulation, fingerprinting, proximity and vision analysis. Triangulation, fingerprinting and vision analysis positioning techniques can provide absolute, relative and proximity position information. The proximity positioning technique can only offer proximity position information.

1. *Triangulation* is based on the geometric properties of triangles. Several methods can be used to calculate the distances between the known reference points and the target:

Received Signal Strength (RSS), Angle Of Arrival (AOA) and Time Of Arrival (TOA) [41]. Each triangulation method has advantages and limitations. TOA is the most accurate technique, which can filter out multi-path effects in the indoor situations. However, it is complex to implement [16]. RSS and TOA need to know the position of at least three reference elements. AOA only requires two position-measuring elements to perform location estimation. However, when the target object to be located is far away, the AOA method may contain some errors, which will result in lower accuracy [8].

2. *Fingerprint* positioning technique is proposed to improve the accuracy of indoor position measurements by using pre measured location related data. Fingerprinting includes two phases: offline training phase and online position determination phase [20]. In the offline phase, useful location related data with respect to different places in the position estimation area is measured and collected for the position estimation. During the online position determination phase, the location related data of a target object is measured and compared with the pre-measured data collected in the offline phase to get a similar case in the database to make the location estimations.

3. The *proximity location* sensing technique examines the location of a target object with respect to a known position or an area. The proximity location technique needs to fix a number of detectors at the known positions. When a detector detects a tracked target, the position of the target is considered to be in the proximity area marked by the detector. The proximity location information provided is useful for various location-based services and applications. For example, a sensing area of a location measuring element is a room. Thus proximity sensing can accurately specify whether a tracked target is in the room or not.

4. The *vision analysis* estimates a location from the image received by one or multiple points [16]. Vision positioning [23,87] brings the comfort and efficiency to the users, since no extra tracked devices need to be carried by the tracked persons. Usually, one or multiple cameras are fixed in the tracking area of an IPS to cover the whole place and take real-time images. From the images, the tracked targets are identified. The observed images of the targets are looked up in the pre-measured database to make the position estimations. In addition, vision based positioning technique can provide useful location context for services based on the captured images.

5. In this report, we classify the IPSs based on the main medium used to determine location, which include five categories: IR signals, ultrasound waves, radio frequency, electromagnetic waves, and vision-based analysis.

IPS discussion

Many positioning systems have been developed over the years for indoor location estimations.

We introduce a variety of IPSs in this section. The location technology and technique used in each IPS are addressed to give a scientific overview of the system.

Infra red localization systems

Infrared (IR) positioning systems [7,26] are the most common positioning systems, since IR technology is available on board of various wired and wireless devices (i.e., TV, printer, mobile phones, PDAs, etc.). An IR-based positioning system, which offers absolute position estimations, needs line-of-sight communication between transmitters and receivers without interferences from the light sources [7]. Thus the coverage range per infrastructure device is limited within a room.

The IR-based systems perform positioning estimations in a very accurate way. IR emitters are small, light-weight and easy to be carried by a person. The system architecture is simple, which does not need time-consuming installation and maintenance. However, there are still some disadvantages with indoor IR positioning systems: IR signals have some limitations for sensing location, for example, interference from florescent light and sunlight [13]. This problem can be solved by using optical and electronic filters to reject the disturbance from the light sources [26], and implementing noise cancelling signal processing algorithm at the receivers [13], which raise the cost of the positioning system.

IR localization systems:

• Active Badge: The Active Badge system [42];

• Firefly: Firefly designed by Cybernet System Corporation is an IR-based motion tracking system [10];

• OPTOTRAK PROseries: OPTOTRAK PROseries [32] system is one of the IPS is designed by Northern Digital Inc. for congested shops and workspaces;

• Infrared Indoor Scour Local Positioning System (IRIS LPS)[2].

Ultra-sound localization systems

Using ultrasound signal [1, 34] is another way of position measurement. Ultrasound signals are used by bats to navigate in the night, which inspire people to design a similar navigating system in the last hundreds of years.

Ultra-sound positioning systems give a kind of inexpensive positioning solutions. Usually the ultrasound signals used to locate objects need to be combined with RF signals, which perform synchronization and coordination in the system. The ultra-sound localization systems increase the system coverage area. However, they have lower measurement accuracy (several centimeters) than IR-based systems (several millimeters). The ultrasound localization systems suffer from reflected ultrasound signals and other noise sources such as jangling metal objects, crisp packets, etc.

Ultra-sound localization systems:

- Active Bat[1];
- Cricket [36], [45];
- Sonitor: The Sonitor ultrasound IPS [38].

Radio Frequency (RF) localization systems

Radio frequency (RF) technologies [27, 20] are used in IPSs, which provide some advantages as follows. Radio waves can travel through walls and human bodies easier, thus the positioning system has a larger coverage area and need less hardware comparing to other systems. RF-based positioning systems can reuse the existing RF technology systems such as access points in WLAN. Triangulation and fingerprinting techniques are widely used in RF-based positioning systems. For complicated indoor environments, location fingerprinting is an effective position estimation method, which uses location related characteristics such as RSS and location information of the transmitters to calculate the location of a user or a device.

RFID localization system

Radio Frequency IDentification (RFID) is a means of storing and retrieving data through electromagnetic transmission to an RF compatible integrated circuit [30]. The RFID positioning systems are commonly used in complex indoor environments such as office, hospital, etc. RFID as a wireless technology enables flexible and cheap identification of individual person or device [9]. There are two kinds of RFID technologies, passive RFID and active RFID [30, 14]. With passive RFID, a tracked tag is a receiver. Thus the tags with passive RFID are small and inexpensive. But the coverage range of tags is short. Active RFID tags are transceivers, which actively transmit their identification and other information. Thus the cost of tags is higher. On the other hand, the coverage area of active tags is larger. The RFID technology is not only for the indoor positioning applications, but also provides many potential services for the demands of users. The advantage of an RFID positioning system is light and small tags that can be taken by people to be tracked. The RFID system can uniquely identify equipment and persons tracked in the system. However, the proximity and absolute positioning techniques need numerous infrastructure components installed and maintained in the working area of an RFID positioning system.

• WhereNet: WhereNet positioning system [45,43].

WLAN-based positioning systems

Wireless LAN (WLAN) technology is very popular and has been implemented in public areas such as hospitals, train stations, universities, etc. WLAN-based positioning systems reuse the existing WLAN infrastructures in indoor environments, which lower the cost of indoor positioning. The accuracy of location estimations based on the signal strength of WLAN signals is affected by various elements in indoor environments such as movement and orientation of human body, the overlapping of access points, the nearby tracked mobile devices, walls, doors, etc. WLAN IPSs have the goal of increasing the location estimation performance and at the same time reducing the cost of system. WLAN technology is widely used and integrated in various wireless devices such as PDAs, laptops, mobile phones, etc. Thus the WLAN-based positioning systems can also reuse these wireless devices as tracked targets to locate persons. However, because of complex indoor environments consisting of various influenced sources [4,22], the performance of the positioning systems are not very accurate with an accuracy of several meters.

WLAN localization systems:

• RADAR [4];

• Ekahau [12];

• The COMPASS system [22].

Bluetooth localization system

Bluetooth, the IEEE 802.15.1 standard, is a specification for Wireless Personal Area Network (WPAN). Bluetooth enables a range of 100m (Bluetooth 2.0 Standards) communication to replace the IR ports mounted on mobile devices. Piconets are formed under Bluetooth specifications by using a master/slave based MAC protocol. Bluetooth technology has been implanted in various types of devices such as mobile phone, laptop, desktop, PDA, etc. In addition, Bluetooth chipsets are low cost, which results in low price tracked tags used in the positioning systems.

In Bluetooth-based positioning systems [35]- [21], various Bluetooth clusters are formed as infrastructures for positioning. The position of a Bluetooth mobile device is located by the effort of other mobile terminals in the same cluster. In this section, a Bluetooth-based IPS is introduced. A disadvantage of Bluetooth-based positioning system is that the system can only provide accuracy from 2 m to 3 m with the delay of about 20 s. The Bluetooth positioning systems suffer from the drawbacks of RF positioning technique in the complex and changing indoor situations.

• The Topaz location system [39].

Sensor based localization system

Sensor Networks: sensors are devices exposed to a physical or environmental condition including sound, pressure, temperature, light, etc., and generate proportional outputs. Sensors are typically divided into active and passive ones. Active sensors can interact with the environment (i.e., radars). Passive sensors only receive information from the outside world. The sensor-based positioning systems consist of a large number of sensors fixed in predefined locations [28]. From the measurements taken by these sensors, a person or device can be located. Positioning methods using sensor networks were discussed in [29]. This section will introduce a sensor-based IPS. Sensor-based positioning [28,3] provides a cost effective and convenient way of locating persons and devices due to the decreasing of the price and the size of sensors. At the same time, cheap and small sensors have limited processing capability and battery power comparing to other wireless devices such as mobile phone, PDA, etc. Thus using sensor technology in indoor positioning has some drawbacks: less accuracy, the limited battery power in the case of real-time tracking, lower computational ability, etc., which needs further improved to offer precise and flexible indoor positioning services.

• Online Person Tracking (OPT) System: Online Person Tracking (OPT) systems [3].

UWB localization system

Ultra Wide Band (UWB): The RF positioning systems suffer from the multi-path distortion of radio signals reflected by walls in indoor environments. The ultra- wideband (UWB) [18] pulses having a short duration (less than 1 ns) make it possible to filter the reflected signals from the original signal, which offer higher accuracy. Furthermore, the UWB sensors are cheap, which make the positioning system a cost-effective solution. In addition, the large coverage range each sensor results in that the UWB- based positioning system is scalable.

• Ubisense from AT&T [40].

Magnetic localization systems

Using magnetic signals is an old and classic way of position measuring and tracking [37]. The magnetic positioning systems offer high accuracy and do not suffer from the line-of- sight problems. The magnetic sensors are small in size, robust and cheap, which bring benefits for positioning estimations in indoor environments. The magnetic-based positioning systems can offer higher accuracy and afford multi- position tracking at the same time. However, the limited coverage range is a drawback for the performance of the magnetic IPSs. Thus increasing the coverage range of each magnetic transceiver or using various magnetic infrastructures to cover enough area for indoor use needs further study, design and development.

• MotionStar Wireless [29].

Vision-based localization systems

Vision-based positioning is a way of tracking the locations and identifying persons or devices in a complex indoor environment [23,6]. The vision-based positioning does not need the tracked person carrying or wearing any device. In vision-based positioning systems, a low price camera can cover a large area. These systems still present some drawbacks. Firstly, a vision-based localization system does not provide the privacy of people. Secondly, it is not reliable in a dynamic changing environment. The vision-based positioning is influenced by many interference sources such as weather, light, etc. In addition, tracking multiple persons moving round at the same is still a challenge for the vision-based positioning, which needs higher computational ability of the positioning system.

Vision-based localization system:

Easy Living: Microsoft [87].

Indoor Localization Strategies

Concerning to the Indoor Localization System several effort are spent in this direction. Different technologies and different strategies are studied. According with [46] the indoor localization can be divided in three categories based on the wireless sensors used.

In particular the items are divided on the distance:

• long: Frequency Modulation (FM) or GSM/CDMA;

• middle: WiFi or ZigBee.

• short: Bluetooth, Bluetooth Low Energy (BLE), Ultra-Wide Band (UWB), or Radio Frequency Identification (RFID)

In [47] the long category is used to produce CILoS. CILoS is an indoor localization system based on CDMA mobile phone signal fingerprinting. CDMA networks vary their transmission power to accommodate fluctuations in network load. This affects signal intensity and therefore limits the practicality of traditional fingerprinting approaches based on receiver signal strength (RSSI) measurements. Instead, CILoS uses fingerprints of signal delay that are robust to cell resizing. We demonstrate that CILoS achieves a median accuracy of 5 meters, and compares favorably to

RSSI fingerprinting systems. We highlight the significance of wide fingerprints, constructed through scanning multiple channels, for achieving high localization accuracy. We also show that our system can accurately differentiate between floors of a multi-floor building.

Using the middle technology [48] tested a commercial Wireless Local Area Network (WLAN) based localization system in an emergency response training facility used by urban search and rescue professionals. Accuracy between 1.5 and 2 m was reported, and results were visualized on the 2D layout of the facility. Moreover different technologies can be use as in [49] in which a framework to support rescuers in emergency or during daily maintenance work proposed. The system utilized UWB in halls, WLAN in office areas, and RFID in infrastructure-free rooms such as cellar rooms or underground garages. It also integrated Building Information Modeling (BIM) technology to provide rescuers with building information of their immediate surroundings. Preliminary tests reported an accuracy of up to 3 m. Unfortunately to use middle or long technology produce an increase of the cost and also the computational cost increase.

On the short category several researches are done. This is explained because the short technology provides a low computational cost and low cost. In [50] UWB-based system was proposed. The system used a time difference of arrival (TDOA)-based algorithm for 3D location estimation. Reported accuracy in tests varied between 1 m to 2 m. The system required deployment of a large amount of sensors, and could not locate building occupants that had no access to special mobile units, which were part of the sensing network and required for localization.

[51] proposes a system to locate patients during emergencies in both outdoor and indoor environments. Radio nodes were attached to doctors and patients. Both Monte Carlo and Unscented Kalman Filter techniques were used for location estimation. The system was evaluated through simulations, and reported an accuracy that varied between 5 and 10 m.

In [52] a beacon deployment algorithm is proposed. The authors designed the algorithm to achieve to different goals: improve the room-level of the localization and reduce the effort to deploy the beacon network. The number of beacons to deploy and the location accessibility to deploy the beacons measures the deployment effort.

[53] proposes a framework for locating first responders with an RFID-based localization system. Unlike similar systems that used nodes to track occupants and placed fix readers in known locations, their proposed system used fixed nodes in known locations and attached readers to track occupants. No prototype was built or evaluated.

As [54] reviewed existing technologies for indoor localization, and proposed a system that integrated foot-mounted inertial sensors and UWB sensors to support first responders. Field tests reported accuracy between 1 and 4 m. The system suffered from heading drifts depending on the travel distance. In our approach waist mounted IMU is considered. The IMU position was choose according with the fire fighters requirements.

There are also a few commercial solutions available in the market. Stemming from research sponsored by the Department of Homeland Security, SPIE's [55] geospatial location accountability and navigation system for emergency responders (GLANSER) used a combination of various technologies including a global positioning system (GPS), an inertial measurement unit (IMU), an UWB, a Doppler radar, as well as a magnetometer, a compass, a pedometer, and an altimeter inside a wearable electronic unit. The detaIPS of the algorithm were not disclosed, but an accuracy of 3 m was claimed to be achievable in field tests. Exit Technologies [56] provided another solution that used handheld devices operating at low-frequency radios. A distressed first responder attempting reorientation or self-rescue could send out signals with a handheld device. The signals could then guide other first responders to the transmitting device. No detaIPS of the algorithm or its accuracy were disclosed.

[57] uses a backward ray-tracing algorithm to analyze angle of arrival (AOA), time of arrival (TOA) and signal power for locating first responders, who wore beacons. Using multiple receivers, they were able to cover 80% of a building and achieve an accuracy of within 10 m.

In [58] proposed an indoor localization system for emergency response operations that required no existing infrastructure or pre-characterization of the area of operation. The system relied on an ad-hoc network built on transmitters carried by both the first responders in a building and vehicles outside the building. In other studies the authors reported up to sub-meter accuracy. The system required a considerable amount of infrastructure that could require an excessive effort in on-scene deployment and maintenance.

The approach proposed in this paper combines the wireless technologies, using RFID, and inertial technologies using an Inertial Measurement Unit (IMU). A pre-deployed network is considered. RFID tags compose the network; they provide low cost and low computational cost. More over according with the firefighters requirements the inertial platform is collocated on the waist. Rescuers require that the devices are not susceptible to damage.

Conclusion

In the next generation communications networks, the telecommunications applications require various types of context information of the environments, persons and devices to offer flexible and adaptive services in personal networks. Location context is a kind of context information, which enables location-aware intelligence to improve the quality of lives. The IPSs produce absolute, relative and proximity location information for the users and their devices in indoor environments. In this deliverable, we describe the concept of IPSs and introduce the types of location data offered by IPSs.

From this literature review, we can see that each medium used in position estimations has its limitations. None of the technologies can satisfy the system requirements of performance and cost. Instead of using a single medium to estimate the locations of the targets, combining some positioning technologies can improve the quality of positioning services [33].

Another future issue concern the influence of mobility in IPS s, which includes the mobility of the located object and the mobility of people and equipment in indoor situations. The design of an IPS should ensure optimum performance for a moving target in a varying indoor situation.

Thus the position measurements, position prediction and other related context would be used together to enhance the context- aware intelligence.

This literature review provides a sketch understanding of the existing IPSs. Each IPS, which uses a certain type of technology or a combination of two or more technologies, has its design purpose, and works well under certain conditions. It is desirable that the location estimation service operates for different indoor environments and provides scalable positioning services. Thus, in future research, a combination of different existing communications technologies and location information from different sources should be considered to increase the scalability and availability of location estimation services [25].

2 System Architecture

In this section an overall of the RISING architecture is proposed. To provide the position a Bayesian algorithm is proposed. This algorithm is composed by two phases. The first one, the Prediction Phase uses the data stocked using the background service to compute the heading and to provide a rough estimate of the rescuer position. In the second one, Correction Phase, the data provided by the RFID technologies are used to improve this estimate.

The Hybrid Positioning Indoor System (HPIS) needs as input the starting point, the t_i, that represents the center of mass of the RFID tag, and the accuracy associated to the tag i. It produces as output Δx, Δy and Δz that are the rescuer displacement and Θ that is the heading of the rescuer moreover the uncertainty associated at the rescuer position is provided.

2.1 HPIS-Architecture

During the mission, the rescuer is tracked by the algorithm running on the computation unit and sketched in Fig. 1. The computation of the attitude and the position of the rescuer are addressed separately, so the *Sensory System* feeds both the *Attitude Filter* and the *Tracking System*. The *Attitude Filter* is based on data retrieved from the inertial platform and computes the attitude of the rescuer with respect to a Cartesian global reference frame. The output of this filter is used by the *Tracking System* to produce the pose (i.e., the position and the heading) of the rescuer exploiting also data collected from both the inertial platform and PILDs. To this end, the *Tracking System* is further decomposed into a prediction-correction Bayesian filter, according with the approach used in robotics localization, where both proprioceptive and exteroceptive sensors are jointly used.

It is worth noticing that all the filters run in a on-line fashion, however the loops have different frequencies: the attitude computation depends on the availability of data from the gyroscope, the inertial prediction is based on the step-event detection, and the RFID refinement is based on the

PILD detection event, as it will be explained in the following section.

In Fig. 1 the HIPS-Architecture is shown.

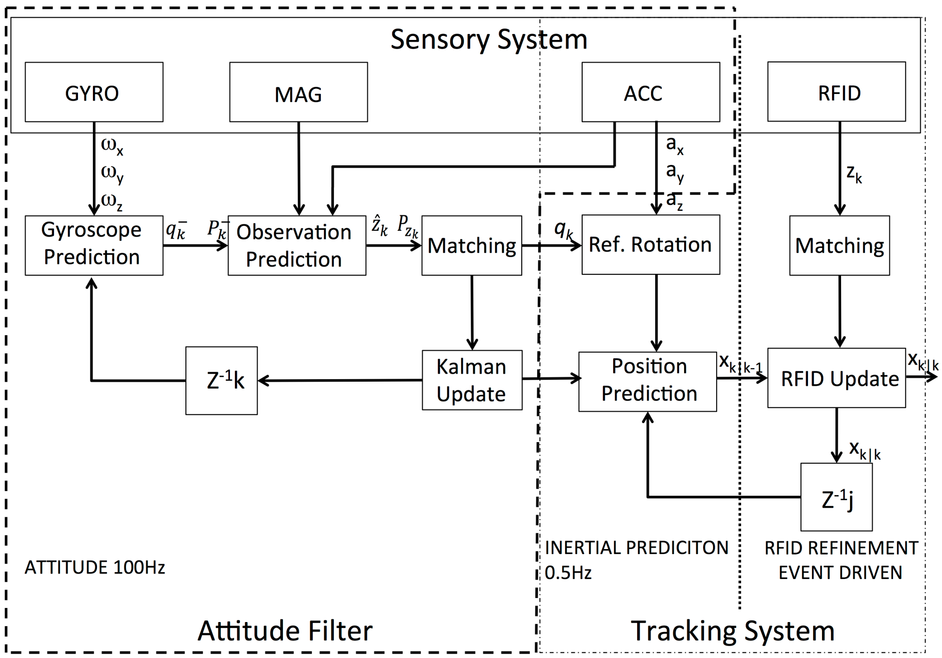


Figure 1 HIPS-Architecture

The HIPS is composed by three phases:

- **Attitude Estimation (AE)** that computes the attitude of the IMU using data coming from accelerometer, gyroscopes, and magnetometer;
- **Pattern Recognition (PR)** that classifies two patterns: flat walking and stay still;
- **Position Estimation (PE)** that updates user pose according to the walking feature and the heading.

3 Inertial Positioning System

3.1 Pattern Recognition

During the *PR* the data provided by the accelerometer, in particular, are used to compute the activities of the rescuer during the mission. Here only two activities are considered:

{stay still; walking}.

To do this the signals properties as the covariance or the number of the peaks in the time window are studied to understand the activities.

Since the proposed application considers only a planar environments, the User Activity detects only 2 activities, i.e., stay still and walking, The pattern recognition is approached as a sequential decision problem under uncertainty and it is implemented by a decision tree. To this end, an adaptive time window is applied to select and analyze b_k samples from the accelerometer measurements along the vertical axes of the body frame (i.e., $a_{k,V}$). During staying still the noise covariance of the accelerometer measurements is considerably reduced, thus this pattern is identified by comparing the covariance of the vertical acceleration signal (i.e., P_a) with an experimentally set threshold α:

$$P_a = cov(a_{k-b_k,V}, \dots ,a_{k,V}) \leq \alpha.$$

3.2 Attitude Estimate

The Attitude Filter estimates the attitude of the IMU wore by the rescuer with respect to a global reference frame. It is based on an Extended Kalman Filter (EKF) that merges data collected from gyroscopes, accelerometers and magnetometers. The vector state is represented by means of quaternions: these mathematical entities, indeed, need less computational effort in recursive updating and avoid the singularity issues that affect angular descriptors, like Euler angles. Quaternions can be defined as:

$$q = [\eta, \varepsilon]^T$$

where $\eta = cos\frac{\theta}{2}$ is the scalar part of the quaternion, $\varepsilon = sin\frac{\theta}{2} r$ is the vector part of the quaternion, θ is the pitch angle, and r is the unit vector of a rotation axis with respect to a Cartesian reference frame $O-xyz$. In the prediction step, the following differential equations is used to evaluate the angular motion of a rigid body:

$$\frac{d}{dt} q = \Omega q$$

where:

$$\Omega = \begin{bmatrix} 0 & -\omega_z & \omega_y & -\omega_x \\ \omega_z & 0 & -\omega_x & -\omega_y \\ -\omega_y & \omega_x & 0 & -\omega_z \\ \omega_z & \omega_y & \omega_x & 0 \end{bmatrix}^T$$

in which $\omega(t) = [\omega_x(t), \omega_y(t), \omega_z(t)]$ represents the angular velocity measured by the IMU.

The corresponding discrete-time model is as follows:

$$\begin{cases} \hat{q}_k = e^{\Omega_k \Delta t_k} \hat{q}_{k-1} = \Phi_k \hat{q}_{k-1} \\ \hat{q}_0 = \hat{q}(0) \end{cases}$$

where $\Delta t_k = [t_{k-1}, t_k]$ is the sampling time interval. The quaternion q_k is computed at each sampling time k, starting from the initial condition q_0.

The initial condition q_0 is obtained from the acceleration considering the rescuer standing still at the beginning of the mission:

$$q_{0,1} = cos\left(\frac{\phi}{2}\right)$$

$$q_{0,2} = \bar{a}_x sin\left(\frac{\phi}{2}\right)$$

$$q_{0,2} = \bar{a}_y sin\left(\frac{\phi}{2}\right)$$

$$q_{0,3} = \bar{a}_z sin\left(\frac{\phi}{2}\right)$$

where $\bar{a} = [\bar{a}_x, \bar{a}_y\ \bar{a}_z]$ is the IMU acceleration vector reprojected according to the initial reference frame and ϕ is the inner product between the acceleration vector and the reference. The *z-axis* of the initial frame represents the vertical axis of the rescuer while the *y-axis* and the *x-axis* are the medio-lateral and the antero-posterior components, respectively. In this way, the gravity component is only along the *z-axis* and can be easily compensated. Knowing the attitude of the initial reference frame with respect to the global reference frame, it is easy to compute the IMU attitude by simple rotation. Concerning the global reference frame, the *z-axis* of represents the vertical axis of the environment, while the rescuer moves on the $(x - y)$ plane.

The covariance matrix of the prediction step can be expressed as:

$$P^q_{k|k-1} = \Phi_k P^q_{k-1|k-1} \Phi_k^T + Q_k$$

where Q_k is the accuracy of the gyroscopes.

The measurement model is built by stacking the accelerometer and magnetometer measurement vectors as shown in the following equation:

$$z_k = \begin{bmatrix} a_k \\ m_k \end{bmatrix}$$

The expected measurement from accelerometers can be computed according to:

$$\hat{a}_k = h_a(\hat{q}_{k|k-1}) = K_a R(\hat{q}_{k|k-1}) g$$

where $\hat{a} = [\hat{a}_x \quad \hat{a}_y \quad \hat{a}_z]^T$ represents the acceleration in the body frame, K_a is the scale factor matrix, g is the gravity vector, and $R(\hat{q}_{k|k-1})$ is the rotation matrix from the body frame to the global reference frame:

$$R(\hat{q}_{k|k-1}) = \begin{bmatrix} 2(\eta^2 + \epsilon_x^2) - 1 & 2(\epsilon_x \epsilon_y - \eta \epsilon_z) & 2(\epsilon_x \epsilon_z - \eta \epsilon_y) \\ 2(\epsilon_x \epsilon_y - \eta \epsilon_z) & 2(\eta^2 + \epsilon_y^2) - 1 & 2(\epsilon_y \epsilon_z - \eta \epsilon_x) \\ 2(\epsilon_x \epsilon_z - \eta \epsilon_y) & 2(\epsilon_y \epsilon_z - \eta \epsilon_x) & 2(\eta^2 + \epsilon_z^2) - 1 \end{bmatrix}$$

It is worth underlying that data from accelerometers can be used only when the rescuer is still, otherwise the gravity cannot be compensated, so a validation gate is set up and the acceleration correction is performed only when $//a_k// - g < \varepsilon_a$, where $// \cdot //$ is the Euclidean norm and a_k is the vector of the accelerometer measurements.

The expected measurement from magnetometers can be computed according to the following equations:

$$\hat{m}_k = h_m(\hat{q}_{k|k-1}) = K_m R(\hat{q}_{k|k-1}) d$$

where $\hat{m} = [\hat{m}_x \quad \hat{m}_y \quad \hat{m}_z]^T$ represents the magnetic field in the body frame, Km is the scale factor matrix and d is the Earths magnetic field. To prevent the use of magnetometer measures affected by large magnetic disturbances a matching test is set up, so the update is performed only when $||m_k|| - d < \varepsilon m$ and $||m_k - m_{k-1}|| < \varepsilon_{\Delta m}$, where m_k is the vector of the magnetometer measurements.

When the measurements are available, i.e. they have passed the test, the estimate is updated according to the EKF equations The correspondent covariance matrix is given by:

$$S_k = H_k P^q_{k|k-1} H_k^T + V_k$$

$$K_k = P^q_{k|k-1} H_k^T S_k^{-1}$$

$$\hat{q}_{k|k} = \hat{q}_{k|k-1} + K_k [z_k - h](\hat{q}_{k|k-1})$$

$$P^q_{k|k} = (I - K_k H_k) P^q_{k|k-1}$$

where H_k is the Jacobian of the observation vector $h(\cdot) = [h_a^T(\cdot),\ h_m^T(\cdot)]^T$, V_k is the covariance matrix of the measurements, and K_k is the Kalman gain matrix.

3.3 Step Estimate

During *PE*, the position of the rescuer $x_k = [p_{x,k}, p_{y,k}, p_{z,k}]^T$ with respect to the absolute reference framework and its accuracy (i.e., the covariance matrix $P_{k|k-1}$) is updated according to the following equations:

$$x_{k|k-1} = x_{k-1|k-1} + l_k$$

$$P^x{}_{k|k-1} = P^x{}_{k-1|k-1} + Q^x{}_k$$

In which $l_k = [l_{x,k}, l_{y,k}, l_{z,k}]^T$ is the displacement of the rescuer during the sampling interval $[k-1, ..., k]$ and $Q^x{}_k$ is the associated uncertainty. Both l_k and $Q^x{}_k$ are computed according to c that identify the activities.

Specifically, during *stay still*, c=*stand* so $l_k = 03$ and $Q^x{}_k = 0_{3\times3}$ and the accelerometer and gyroscope bias are updated. The step detection is obtained using the human body dynamic associated at the human gait cycle. The gait-cycle can be divided in two phases:

- double limb support period;
- single limb support period;

In *walking*, c = *walk* and $l_k = [s_k cos\theta_k, s_k sin\theta k, 0]$ where s_k is the step length. These periods are identified by start and stop events. There are two different events that represent a step. The first one begins when the first foot strikes and ends when the other foots toe-off. On the other hand, the second one starts with the opposite foot toe-off and ends with opposite foot strikes. These events can be identifying using the accelerations. In fact, using the local minimum and the local maximum of the vertical acceleration it is possible identify a step. After the local minimum and local maximum identification, the step length is computed by using the following equation: computer as:

$$s_k \beta \sqrt[4]{a_{V,M} - a_{V,m}}$$

We denote respectively as $a_{V,Mk}$ and $a_{V,mk}$ as the maximum and the minimum vertical accelerations during the step batch for time interval $(k - b, k]$ and β is the user stride length.

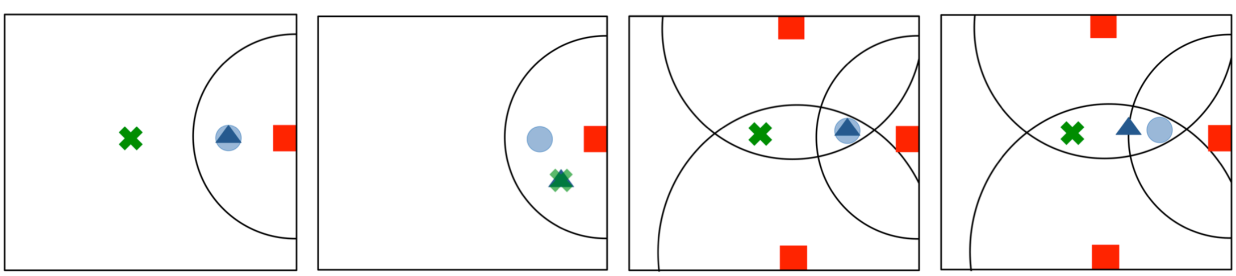
The corresponding covariance is

$$Q^x{}_k = [s_k cos\theta_k,\ s_k sin\theta_k,\ 0]^T\ P_s[s_k cos\theta_k,\ s_k sin\theta_k,\ 0],$$

where P_S is a diagonal matrix.

4 HIPS RFID Correction

The correction step refines the position estimate upon tag detection. According to the REFIRE protocol, the tag provides its own Geographical Coordinates, its Orientation, and its Accuracy wi. The Geographical Coordinates and the Orientation are used to compute the center of the radiation lobe Ti that is exploited to update the position of the rescuer. It is worth noticing that the Geographical Coordinates need to be expressed with respect to the Cartesian global reference frame. Since no ranging technique is adopted in this work, only the position of the rescuer is corrected, due to observability issues. When a rescuer is in the main radiation lobe of the tag, the reader receives information from the tag and the rescuer's position is updated according with four strategies as shown in Fig. 2.



(a) Single tag reset. **(b) Single tag update.** **(c) Multiple tags reset.** **(d) Multiple tags update.**

Figure 2 Correction strategies: rescuer position in prediction step (green cross), rescuer position after correction (blue triangle), perceived tags (red squares), radiation lobe center (blue dot), and radiation lobe (black circles).

The first two strategies consider a single tag detection, specifically in the first one (see Fig. 2(a)), the inertial prediction estimates the rescuers outside the radiation lobe of the perceived tag i. In this case, the position and the accuracy are reset according with the following equations:

$$\hat{p}_{j|j} = T^i$$

$$\hat{P}^{p}_{j|j} = \omega_i I_{2\times 2}$$

where $\hat{p}_{j|j-1}$ represents a new initial position and the covariance $\hat{P}_{j|j-1}$ is set according with the accuracy ω_i provided by the tag. In the second one (see Fig. 2(b)), the rescuer position is estimated inside the main radiation lobe of the perceived tag i, in this case the pose is not updated but the accuracy is eventually bounded according to the following equations:

$$\hat{p}_{j|j} = \hat{p}_{j|j-1}$$

$$\hat{P}_{j|j} = \begin{cases} \hat{P}^{p}_{j|j-1} & tr\left[\hat{P}^{p}_{j|j-1}\right] < \omega_i^2 \\ \omega_i I_{2\times 2} & otherwise \end{cases}$$

where $tr\left[\hat{P}^{p}_{j|j-1}\right]$ represents the uncertainty measurement.

In the last two cases, the rescuer is inside the main radiation lobe of r tags. If the inertial prediction locates the rescuer outside the radiation lobes (see Fig. 2(c)), the position $\hat{p}_{j|j}$ is updated according to the following equations:

$$\hat{p}_{j|j} = T^i$$

$$\hat{P}^{p}_{j|j} = \sum_{i=1}^{r} \omega_i \left(T^i - \bar{T}^j\right)\left(T^i - \bar{T}^j\right)^T$$

where $\bar{T}^j$ is the average center of gravity of the r tag radiation lobes.

Finally, when the inertial prediction locates the rescuer inside the radiation lobe of a subset of the r perceived tags, the position $\hat{p}_{j|j}$ is updated according to the following equations:

$$\hat{p}_{j|j} = \hat{p}_{j|j-1} + L_j\left(T^j - \left[\hat{p}_{j|j-1}\right]r\right)$$

$$\hat{P}_{j|j} = \begin{cases} \hat{P}^{p}_{j|j-1} & tr\left[\hat{P}^{p}_{j|j-1}\right] < tr\left[S_j\right] \\ \hat{P}^{p}_{j|j-1} - L_j S_j L_j^T & otherwise \end{cases}$$

where T_j is the block vector of the coordinates retrieved from the r tags, $\left[\hat{p}_{j|j-1}\right]r$ is a block vector stacking r times the coordinates of the position of the rescuer, $tr\left[S_j\right]$ is the tags combined uncertainty, and L_j represents a gain. This gain is computed as:

$$L_j = P_{pz,j} S_j^{-1}$$

where:

$$P_{pz,j} = \sum_{i=1}^{r} \omega_i \left(T^i - \hat{p}_{j|j-1}\right)\left(T^i - \bar{T}^j\right)^T$$

and S_j is:

$$S_j = \sum_{i=1}^{r} \omega_i \left(T^i - \hat{p}_{j|j-1}\right)\left(T^i - \hat{p}_{j|j-1}\right)^T$$

It is worth noticing that the correction step is performed only on the perceived tags. Thus, when the rescuer is inside the radiation lobe of q tags, but the reader perceives only r tags, the remaining $q-r$ tags are not used to correct the position estimate, since no information is retrieved.

5 Implementation

In this section the implementation of the devices according to the structure proposed in Fig. 3 is proposed.

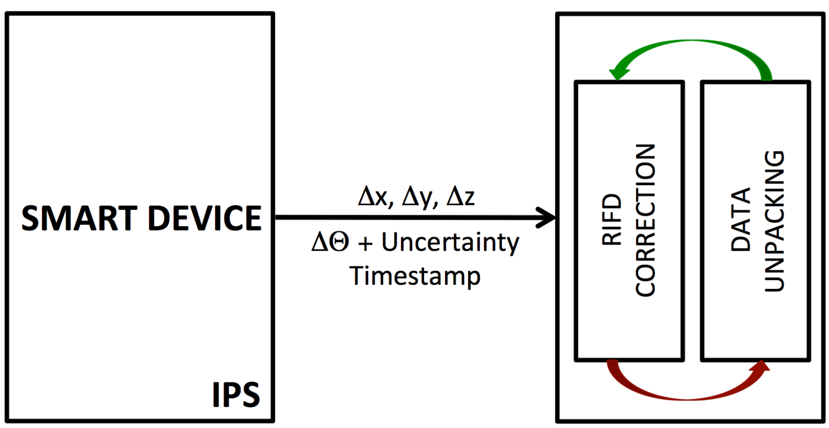


Figure 3 Application functional diagram

5.1 Android Component

In this section, the fundamental component in the Android software architecture are reported.

Background Service

A Background Service is a component that allows to execute operations in background even if the application that states them is not in action. In other cases an other component of the application can starts the Background Service and it can continue to work in background even if an another application is used. It is also possible that another component can interact whit it. Usually are useful in background operation as: file download, music execution, and geo-localization.

The Background Service doesn't have a graphic interface which the user can interact but at the same time they should not be confused with processes or threads, intact a Background Service is mange in a different way and has a particular life cycle. Moreover, they can use the interfaces provided by Android integrating them self with the system.

The Background Service are useful every time that we want to do something in background without occupy the screen.

It is important now to stress what a background service is not: it is not a separated process. If it is not specified it is executed in the same process in which is integrated, As previously said is not a thread but that does not mean that it works outside the main thread, in fact it is executed in the main thread of the host process, A SB provides two main characteristics:

- A structure for the application to tell the system what you want to do in the background (even when the user does not interact directly with the application);
- A structure for the application to expose some function- ality to other applications.

In Fig.4 the life cycle of a Background Service is sketched:

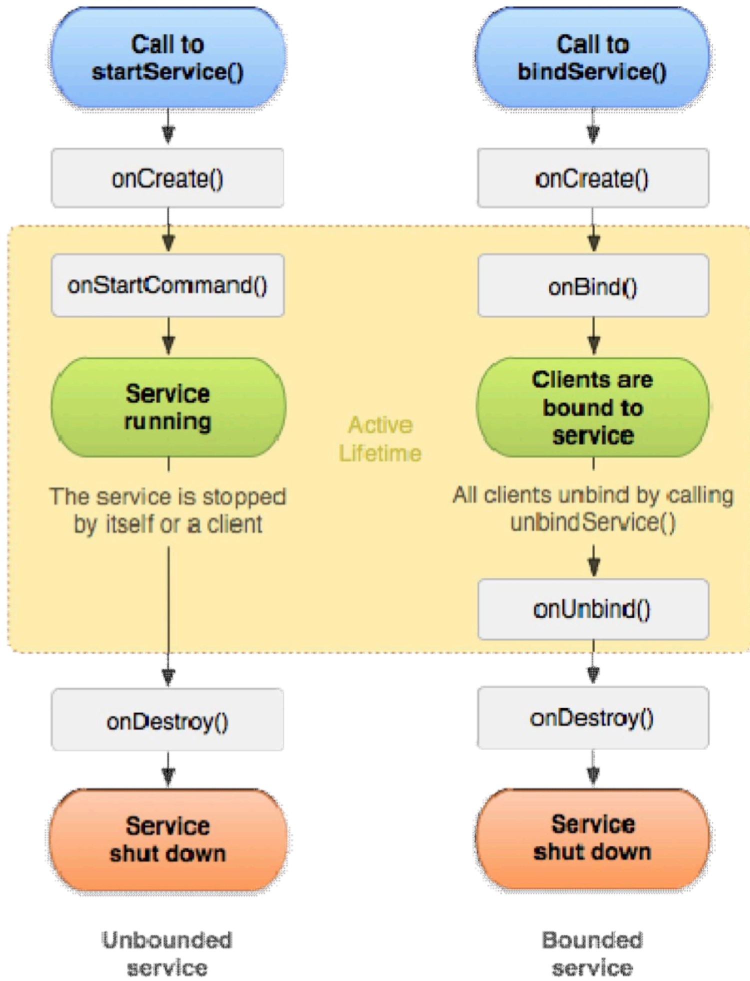


Figure 4 Life cycle of a Background Service

Activity

In each application, it is possible to find one or more fundamental elements, but it is not sure that it has it all. However, in most cases, the applications include al least an Activity. According with the Android documentation an Activity is defined as: “a single and precise thing that the user can do”. Obviously, that assumes that the user to do something has to interact with the device. Exists a similarity between the concept of window, in a desktop system and the concept of Activity in Android. We can say that the Activity is the component in an application that uses the display and interacts with the user, Usually the Activities are presented to the user as full screen window but they can be used also ad mobile window incorporated one in another Activity. The Activity of Android have exclusivity. That means that is possible to execute more Activity concurrently, but only one can occupies the display.

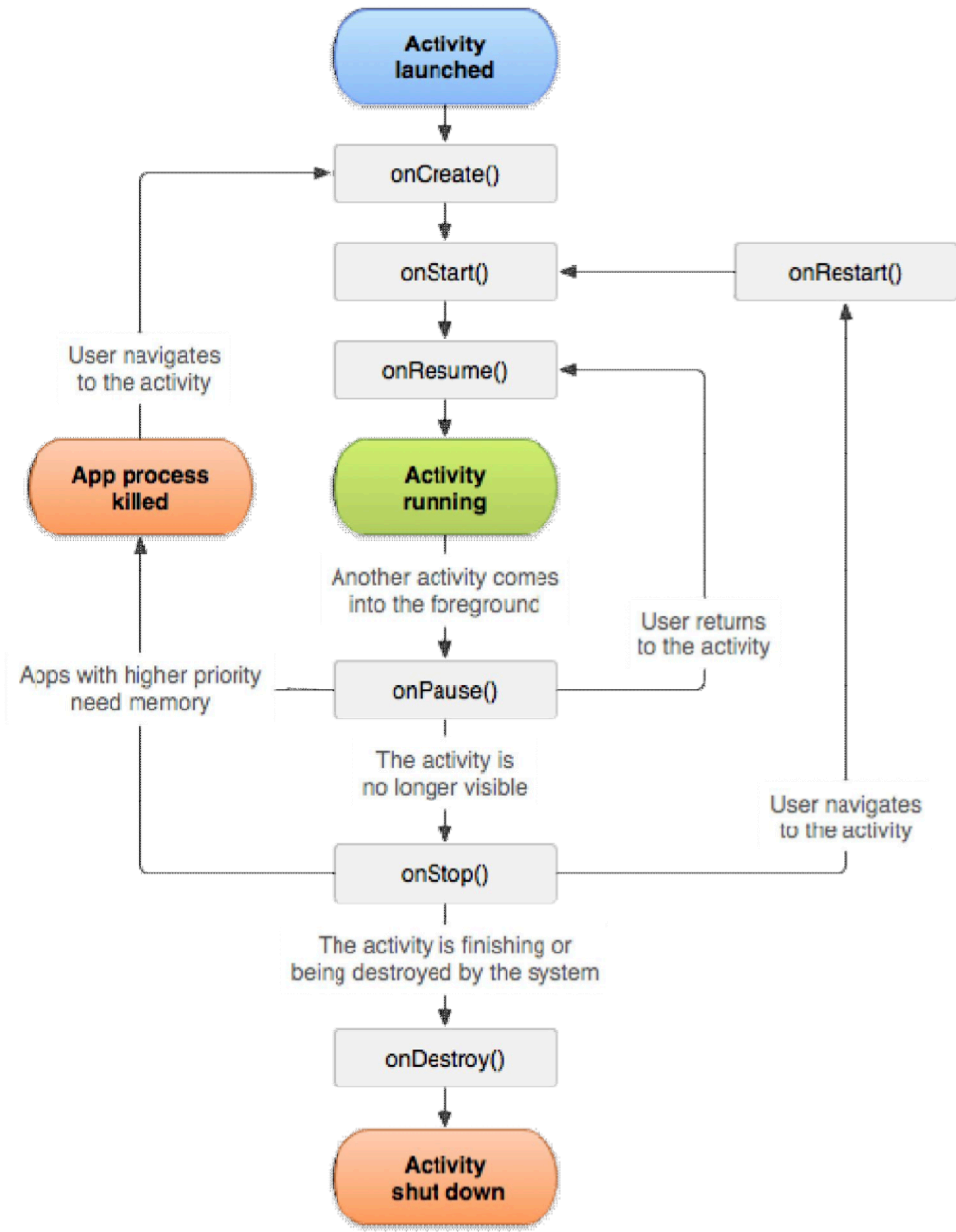


Figure 5 Life cycle of an Acitvity

The Activity can be close spontaneously if they have finished their tasks. The cases in which an Activity can arrested can be two:

• The Activity is hibernated and the system arbitrarily decide it is no longer useful and therefore destroys it.

• The system is out of memory, he needs to reclaim space and kills Activity in the background.

The Fig. 5 illustrates the sequence of calls to methods Activity performed during the changes in status of the Activity. The rectangles represent the callback methods you can implement to perform operations when the Activity you move between states, while the ovals represent the states in which an Activity can be.

5.2 Smart Device

The Smart Device has been implemented exploiting components of the Android architecture. Specifically, an Android app has been developed using two components: the Activity and the Background Service.

Activity is the visual representation of an Android application. It is a pre-defined class in Android architecture: every application having a user interface must inherit it for creating windows.

On the contrary, an Android Background Service has been conceived as a background thread: it is used to accomplish repetitive and potentially long running tasks (e.g., checking for new data, data processing, etc.). To this end, no user interface is foreseen for a Background Service, even if it can be started and ended by an Activity. A Background Service has a higher priority than inactive or invisible activities, therefore, it is less likely that the Android system terminates them. It is used to do something in background without overload the user interface. A Background Service provides two main features:

• A structure for the application to tell the system what do in the background;

• A structure for the application to export some functionalities to other applications.

In Smart Device, Activity allows to start/end computation and display the user position on a map. Consequently, the user interface of Smart Device switches on the Background Service and presents to the user the path in indoor environment. It is composed by two buttons and a map, preloaded in the smartphone. When Smart Device is activated, the user fixes the initial position by tapping on the map. When a user clicks the start button of the Smart Device, the Background Service is activated and computes the user position. This result is shown on the map until the app is on.

The Background Service also logs data: it continuously collects data from IMU and magnetometer while computing the user position. All information gathered from the Background Service are stored in four files, containing data from accelerometer, gyroscope, magnetometer, user position, and a timestamp.

The Android architecture allows the handling of sensor data by using predefined type. Specifically, in Smart Device the following types are considered:

• Type Accelerometer;

• Type Gyroscope;

• Type MagneticField.

Android architecture does not allow to set a sampling period; however, the priority of a Background Service can be set. By selecting the highest priority (i.e., Real Time - Fastest), data from IMU can be collected at sampling frequency 100 Hz and data from magnetometer at 50 Hz.

5.3 Correction

The correction is implemented inside the RISING interface in the smart unit. The smart IMU forward information about the activity, the step length and the orientation over a Bluetooth channel. Inside the RISING interface, the data are fused with the information from the RFID tags according to the rules above introduced.

5.4 Inertial Platform Calibration

All those sensors have been involved during the experiments, estimating the random walk component following the IEEE Std 952–1997 procedures [1]. For both accelerometers and gyroscopes, the largest errors are usually bias instabilities (measured in *deg/s* for the gyro bias drift, or mg for the accelerometer bias), and scale factors. Bias and scale factors can be estimated by the well-known six-position static test method [1]. This method requires the inertial system to be mounted on a leveled table with each sensitive axis pointing alternately up and down. For a triad of orthogonal sensors this results in a total of six positions. The bias b^j_i can be computed as:

$$b_i^j = \frac{\hat{m}_{i\uparrow}^j - \hat{m}_{i\downarrow}^j}{2}$$

where $\hat{m}$ is the mean value of the measurements retrieved from sensor $j \in \{a, w\}$ along the *i-th* axis ($i \in \{x, y, z\}$), upward (↑) downward (↓). Scale (S) factors can then be calculated according to the following equations:

$$S_i^j = \frac{\hat{m}_{i\uparrow}^j - \hat{m}_{i\downarrow}^j - 2K}{2K}$$

where the value K is a known reference signal. For accelerometers, K is the local gravity constant and for gyroscopes it is the magnitude of the earth rotation rate at the given latitude. It is worth mentioning that the earth rotation rate can only be used for navigation and tactical grade gyroscopes, since low grade gyroscopes such as MEMS suffer from bias instability and noise levels that can completely mask the earth reference signal.

To further improve the estimation of scale factors for gyroscopes, also the angle rate test has been performed using a professional record player as turntable. The scale factor can be retrieved by rotating the table through a defined angle rate ω in both the clockwise $\widehat{\omega}_{i,cl}^{w}$ and counter clockwise $\widehat{\omega}_{i,ccl}^{w}$

$$S_i^{\omega} = \frac{\widehat{\omega}_{i,cl}^{w} - \widehat{\omega}_{i,ccl}^{w}}{2\omega}$$

The six-position calibration accuracy depends on how well the axes are aligned with the vertical axes of the local level frame: this standard calibration method can be used to determine the bias and scale factors of the sensors, but cannot estimate the axes misalignments (non-orthogonalities). To estimate the non-orthogonalities, not considered here, an improved six-position test can be performed which takes into account all three types of errors.

The main sources of magnetic distortion are scaling and bias, wide-band noise, hard/soft iron bias. As shown in [24], a calibration procedure is able to alleviate the effects of these disturbances. The magnetometer calibration problem can be recast into a unified transformation parameterized by a rotation R, a scaling S, and an offset b. Consequently, it can be shown [24] that, for all linear transformations of the magnetic field, the magnetometer readings will always lie on an ellipsoid manifold. A maximum likelihood estimator can be used to find the optimal calibration parameters, which maximize the likelihood of the sensor readings. The calibration algorithm is derived in the sensor frame and does not require any specific information about the magnetic fields magnitude and body frame coordinates. This allows for magnetometer calibration without external aiding references.

5.5 IPS

Pattern Recognition Threshold

A time window is applied for selecting W samples from the tri-axial accelerometer data.

During staying still the noise covariance of the accelerometer measurements is considerably reduced, thus this pattern is identified by comparing the covariance of the vertical acceleration signal with an experimentally set threshold α.

Considering the flat walking: it is taken by evaluating the dynamics of the V to this end, a threshold is determined: α. That corresponds to the mean value of V acceleration calibrated on the user by experimental trials.

Heading

To Estimate the orientation in the application the Complementary filter is used. According to the theory of complementary filter, this algorithm combines two different set of data, the static and the dynamic one. Static data contain the information generated by accelerometer and magnetometer, while dynamic data is obtained by gyroscope. Using static data the static quaternion q_σ is obtained, while dynamic data provide dynamic quaternion q_δ. Static quaternion q_σ is computed by using the Factored Quaternion Algorithm (FQA). FQA is a geometrically intuitive algorithm for determining orientation of a static or slow- moving body from measured acceleration and local magnetic field vectors. FQA provides the static quaternion $q_{\sigma,k}$ using the acceleration from IMU and local magnetic field measurements from magnetometer, as in [11], when new measurement are available.

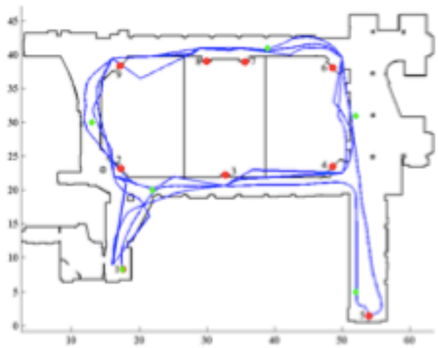
The static quaternion $q_{\sigma,k}$ is useful when sensor module is stationary or slowly moving. In this case, indeed, accelerometer and magnetometer can provide absolute body orientation. However, when the angular rate measurement is high, the accelerometer and magnetometer measurements are no longer accurate and gyroscope measures need to be used. The output of the C-AE filter is the yaw angle, that represents the pedestrian heading.

```
import android.content.Intent;
import android.hardware.Sensor;
import android.hardware.SensorEvent;
import android.hardware.SensorManager;

public class OrientationLogger extends SensorLogger {
        float[] gravity, geomagnetic;
        public OrientationLogger(String name, Intent intent) { super(name, intent);}

private boolean sameType(Sensor sensor, int type) { return sensor.getType() == type;}

@Override   public void onSensorChanged(SensorEvent event) {
        if (sameType(event.sensor, Sensor.TYPE_ACCELEROMETER)) gravity = event.values;
        if (sameType(event.sensor, Sensor.TYPE_MAGNETIC_FIELD)) geomagnetic = event.values;
        if (gravity != null && geomagnetic != null) {float R[] = new float[9];   float R2[]=new
float[9];
        if (SensorManager.getRotationMatrix(R, null, gravity, geomagnetic))
        {gravity = geomagnetic = null;
        float orientation[] = new float[3];
        SensorManager.getOrientation(R, orientation);
        writeLog(orientation); }}}}
```

Step Detection

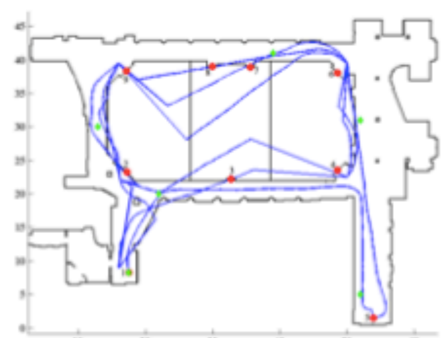
The step detection is obtained according to the paratmeter k. This parameter k is a parameter depending on the user characteristhics and needs to be estimated by the calibration procedure.

6 Results



(a) Estimated path using 9 tags: HIPS estimate (blue line).

(b) Estimated path using 8 tags: HIPS estimate (blue line).



(c) Estimated path using 5 tags: HIPS estimate (blue line).

Figure 6 Indoor results in office like environment: HIPS estimate (blue line), check points position (green stars), and tags position (red dots).

In the experimental trial, the passive OMNI-ID Dura 3000 UHF tags are used. The user is equipped with wearable Bluetooth UHF RFID reader on the shoulder. The reader is connected to the RISING interface by Bluetooth. The reader is able to process 6 queries to the tag during a navigation. The user travels at 0.7m/s. To test the performance of the application several check points are deployed in the experiments environment. The error is computed as the distance between the check point position and the estimated one. In the following section experiments in which position correction and computation correction are discussed.

The testing environment is composed by a long ring-shaped corridor bounds by rooms. This environment has been selected for its closed-loop layout, that allows a better assessment of the performance of the localization algorithm.

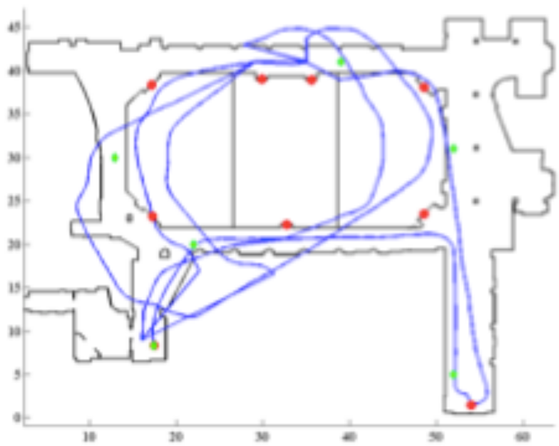


Figure 7 Estimated path using tags placed on the corridor (sub–optimal deployment): estimate path (blue line), check points position (green stars), and tags position (red dots).

The sampling frequency of the smart IMU (i.e., a ASUS Zenphone 2), the one of RFID reader is 5 Hz, and a step is detected at ~1 Hz. To this end, a synchronization procedure has been performed for data alignment. In these trials, the RFID system detection area has a range of r = 250 cm.

The trial represents a penetrating mission along the corridor. The rescuer executes about 500 m. The objective of this trial is to analyze the improvement that the RFID technology combined with the inertial one can provide. Several configurations have been examined for assessing the impact of the RFID correction: according to this approach, a tradeoff between accuracy and the deployment overhead needs to be found. To this end, in the environment were deployed 9 tags according to Fig. 6. Depending on the specific test performed, only a selected number of tags were used for the position correction. The results of the experiments are depicted in Fig. 6a shows the system outcome by using tags for position correction: in this configuration, 9 tags are located in optimal positions and the PDR estimate is remarkably improved after the correction. Even if tag labeled as Tag 5 (see Fig. 6b) is not considered the results obtained with the correction is almost near to the one obtained with the best tag deployment. In the last one result (see Fig. 6c) is reported the path improved using only the tags at the corners (total 5 tags) and even if the result obtained is deteriorated compared to the one with the optimal tags positions, the target performance (i.e. room- level localization accuracy) are reached.

To better understand the impact of the tags RFID position, a sub-optimal deployment of the tags in the experiment shown in Fig. 6 is reported in Fig. 7: the performance of the approach is downgraded. The tags considered are only the one placed along the corridor, and according to this tags deployment the RFID-based estimate is not able to locate the rescuer with a room-level localization accuracy.

	1°	2°	3°	4°	5°	6°	1°	3°	4°	5°	6°	3°	4°	5°	6°	1°
CORRECTION ALL TAGS	0	0.56	0.28	0.72	0.38	1.96	1.65	2.11	2.62	0.18	2.4	0.41	2.06	1.60	1.34	1.65
CORRECTION ALL TAGS NOT $N5$	0	0.56	0.28	0.72	0.38	1.96	1.65	2.11	2.62	0.18	2.4	0.41	2.06	1.60	1.34	1.65
CORRECTION CORNER TAGS	0	0.56	0.28	0.72	0.47	2.82	1.65	2.53	2.62	0.18	3.58	0.95	1.72	3.35	4.28	1.65
CORRECTION CORRIDOR TAGS	0	0.56	0.28	0.72	2.05	4.8	1.65	3.30	13.34	11.12	11.19	7.84	10.7	4.54	9.43	1.65

Table 1 Prediction and correction Euclidean errors [m]

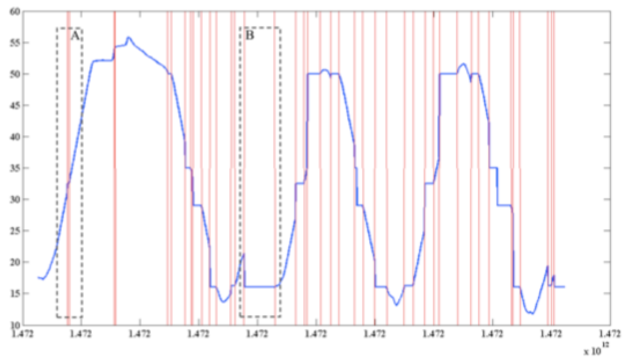
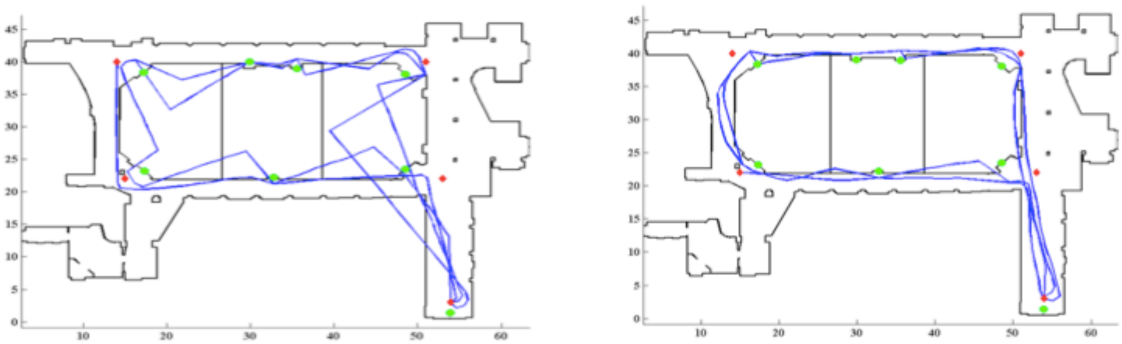


Figure 8 Position estimate along x-axis m (blue) and tag activation pattern (red, ON = 60 – OFF = 10) vs time ms.

Concerning the trial in Fig. 6, six check points deployed in the environment and are considered to determine the performance of the IPS. The Euclidean distance between the check points and the estimated ones (i.e., the positioning error) has been used as performance index.

In Tab. 1 the results obtained with the different tags configuration are summarized. It is possible to see how the error is related to the tags deployment. If the optimal tags configuration is considered the error is 2.62 m that is the same error obtained do not considering the Tag 5. On the other hand it is possible to see how the results obtained using a not optimal configuration of the tags do not improve in a relevance fashion the result obtained using only the prediction, in fact the maximum error is 13.34 m. The results is improve because even if the tags positions are not the optimal one the presence of a tag, if detected, applies a correction on the path estimated. The maximum error in the correction step using the tags on the corner is around 4.28s m computed according with the performance index still fits the rescuer requirements of the room-level accuracy (~5 m error). Moreover, in this trial the impact of the correction step can be appreciated in the output, where some discontinuities arise in the estimated path. To better appreciate this effect, in Fig. 8 the output along the x-axis and the tag activation pattern is depicted. Specifically, it highlights two different corrections occurred during the experiment. The correction step inside the A area does not change the estimate along the x−axis, since the output of the prediction step is accurate. On the contrary, a discontinuity can be appreciated in the correction inside the B area, since the estimate accumulated error.

It is worth noticing that in the trials the errors source depends on the heading error: the heading is not corrected by tags and a residual bias affects the estimate downgrading the overall results.



(a) Corrected path using Inertial Platform data and position information from exteroceptive sensors – User A. Axis unit: [m]

(b) Corrected Path using Inertial Platform data and position information from exteroceptive sensors – User B. Axis unit: [m]

Figure 9 Results of the experiments with different users: the path estimated by the algorithm (blue line) using RFID tags (green circles) and the checkpoints (red diamonds)

In these tests, the goal is the tracking of two different users in the environment equipped with the same smart device, waist mounted, with an embedded inertial platform and the improvement of this estimate using RFID technology. The error is computed for both the experiment (User A and User B) considering correction on position only.

The position computed by the algorithm is obtained by analyzing a stream of data provided by the IMU. Data from accelerometer and gyroscope are available at sampling frequency 100 Hz, and data from magnetometer at 50 Hz. The data computed to produce the path of the user are corrected using the information provided by the external infrastructure composed by exteroceptive sensors (i.e., RFID tags).

In Fig. 9 results of the comparative experiment is reported. Users move along a complex path (about 305 m) characterized by straight lines and curves in order to stress the heading estimation process.

Several check points have been considered and the errors are reported in Tab. 2 and Tab. 3. In the correction using only position update the average error for the user.

Euclidean Error - User A	1	2	3	4	5	1	2	3	4	5	1
Position Correction	0	1.61	1.91	0.1	2.26	1.15	1.31	3.97	0.1	2.76	2.22

Table 2 Euclidean Error User A [m] at check points

Euclidean Error - User B	1	2	3	4	5	1	2	3	4	5	1
Position Correction	0	2.62	0.32	0.8	1.42	1.37	2.00	0.1	1.25	1.5	1.23

Table 3 Euclidean Error User B [m] at check points

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