An open-source framework for smartphone-based indoor localization

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Abstract. In the Ambient Assisted Living (AAL) scenario, indoor localization represents one of the main pillars for the development of context-aware applications. In this context, comparing and testing indoor positioning system is a hot topic in the indoor localization research community. In fact, after several years algorithms and methods have been developed and matured, no general frameworks exist yet to reliably compare them. The scarcity of common datasets for off-line test of emerging indoor positioning systems, together with the lack of available frameworks for real-time comparison and evaluation of indoor localization solutions, is one of the main barriers to their standardization. The lack of a common usable software framework for implementing and testing new algorithms, on a fair basis, is an additional barrier.
In this work, we address this research challenge by proposing a free software framework enabling the development of indoor localization applications on the Android platform. It is composed of two applications: *PrettyIndoor* is a positioning app, *FingerFood* is a fingerprint-building app.
We show that the framework's modular architecture can be exploited to easily develop many data fusion strategies, in order to easily compare and improve indoor positioning systems.

Keywords: Indoor localization, Software framework, Software architecture, Particle filter, Kalman filter, Free software

1 Introduction

Indoor Positioning Systems (IPSs) can be used where the standard GPS technology is not available. Nevertheless, no standard solutions exist yet for the indoor scenario. A standard and efficient solution, like the GPS is for outdoor positioning, would be very useful as the base for innovative location-based service.

Possible use cases include advertising in big malls, navigating to a specific place in wide public areas, assisting users in emergency situations and many more. Among the possible target users, people with motion or cognitive impairments could perceive large crowded environments as intimidating [1]. In such situations, a wearable device able to estimate its own position autonomously could be used to guide users safely towards the desired destination. In the broader Ambient Assisted Living (AAL) scenario, indoor localization represents one of the main pillars for the development of context-aware applications [2, 3]. Most of the existing AAL applications are developed having user positioning as ground technology: elderly tele-care [4], energy expenditure monitoring [5], and safety [6] are strongly based on indoor positioning information. Knowing the position of the user is required for medical observation, prevention of mobility-related pathological conditions, and timely intervention in emergency situations.

The research community has spent big efforts in the last years to improve the current technology of indoor positioning systems. Several approaches have been proposed, including infrared light, ultrasonic sensors, WLAN, RFID, Bluetooth Low Energy, Ultra Wide Band, ZigBee and computer vision, among others [7–11]. The literature shows that researchers try to improve previous solutions using several systems, mathematical methods, and signal processing techniques. In this paper, we are specifically interested in smartphone-based methods that do not require instrumenting the environment; in other words, we consider localization systems that run on a smartphone and require no dedicated infrastructure to be deployed in the area of interest.

The main reason to avoid a dedicated infrastructure is that its deployment may be impossible for reasons of costs, security, limits on installable devices, especially in a public area, hospital, university, cultural heritage site, where regulations may be limiting the available options. As far as why we limit our interests to smartphone, the reasons are again convenience and cost. In recent years, smartphone-based solutions are emerging, as nowadays the sensors embedded in smartphones make them a solid support for positioning and navigation purposes. In practice, the state of the art in terms of on-board sensors, computation power and other hardware specifications makes smartphones mature enough for this kind of application. In this regard, the experience of the IPIN [12] [4] and IPSN [5] competitions is useful to demonstrate how, along several years, researchers are finding more and more mathematical and software solution using different technologies [13] with a specific focus on smartphone-based solutions. Winners of the smartphone-based track in the last two edition of the IPIN competition, based on the EvAAL framework, used a combination of different data fusion strategies and signal processing methods, with some commonalities. In particular, the basic data came from step detection based on compass, and inertial sensors, plus WiFi and magnetic fingerprint maps [14, 15]. Particle filters and Kalman filters were used as data fusion and state predictor algorithms.

[4] http://evaal.aaloa.org/

[5] http://ipsn.acm.org/2017/competition.html

With such a wide range of methods and sensors used, comparison of IPSs performance is a major issue. The problems are mainly the lack of a common dataset for off-line comparison of methods [16, 17] and the lack of commonly-accepted frameworks and procedures to compare and evaluate solutions in real-time. In fact, authors and scientists have presented algorithms and solutions, but usually using their own datasets and in their own different testbed locations. Considering these drawbacks, it is very difficult to compare different solutions, since experiments can seldom be reproduced. The success of the IPIN and IPSN competitions is an initial response to the comparison problem. While certainly useful, competitions have their drawbacks: they are expensive and rare, making it difficult for researchers to compare different methods on their own. A step forward towards a solution to this problem would be the widespread availability of common software frameworks for testing different algorithms on the same hardware.

The main purpose of this paper follows this line of thought: we propose an open framework to compare and evaluate IPSs. Despite the maturity of mathematical models and data-fusion algorithms, very few similar open framework solutions have been proposed. A public and common software platform allows to move towards the ambitious goal of testing the reliability and robustness of IPSs, especially when fusing different techniques. A notable related work, in terms of open source indoor localization application, is represented by AnyPlace [18]. Authors show an open, modular, scalable and extensible architecture. The goal of Anyplace is to enable entities, such as individual users, companies or organizations, to realize indoor applications using a scalable and multi-version information management approach. The major drawback is that Anyplace is server-based: it defines a big-data architecture and provides a Web 2.0 API using JSON objects for mapping, navigation and localization. The user experience is consequently limited to indoor locations covered by a reliable Internet access. In contrast, our main interest relies on methods and algorithms able to locally elaborate data on a smartphone, without relying on Internet access. To the best of our knowledge, such a solution has not yet been proposed in the literature.

In this work, we propose two free software tools running on the Android OS, for indoor localization purposes. The first tool, called *PrettyIndoor*, is the positioning application, while the second one, called *FingerFood*, is used to acquire WiFi and magnetic fingerprint maps. Both are modular, allowing to include and compose different algorithms and methods. We believe that modularity can be useful to the research community for in-depth research and service composition.

Both tools are freely distributed under the Apache Software License (ASL), version 2.0, and are publicly available on GitHub [6]. We chose to use a free software license because we consider the use of free software in research activities a definite plus, from both a practical and philosophical point of view [19].

The rest of this paper is organized as follows: Section 2 describes the design of the proposed framework in details, Section 3 presents the experiments performed

[6] https://github.com/wnlab-isti/PrettyIndoor

in order to test the framework and the obtained results, while Section 4 draws the conclusions.

2 The proposed solution

The system is composed of two applications, namely *PrettyIndoor* and *FingerFood*. The former is the position engine which implements all the algorithms and the data structures required for getting things done. It comes with a front-end, thought for researchers testing operations in many possible strategies both existing and coming in the future. The latter is a utility application that allows the user to capture WiFi and magnetic fingerprints, save them into a file, and make a textual fingerprint map that can be used by the other application.

Both applications access the phone sensors through a library which extends the Android native methods for sensor access.

2.1 Using FingerFood

The purpose of *FingerFood* is to ease the tasks related to creating fingerprint maps. The front-end is shown in Figure 1. It is composed by three Android Activities: one for survey management, one for fingerprint acquisition, and one for map completion.

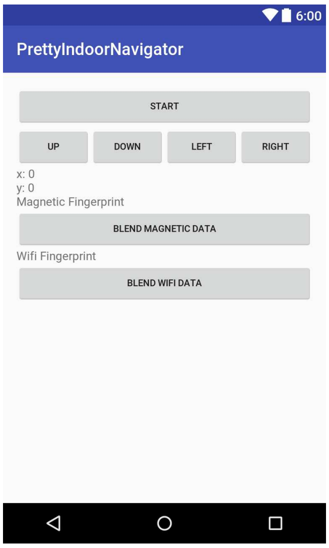

Fig. 1. the *FingerFood* activity.

To use *FingerFood*, the user has to select the survey he wants to work on or create a new one. During fingerprint acquisition, coordinates can be chosen by either directly writing them or moving step by step using the arrows. Step length can be customized. When pressing the buttons "Start WiFi acquisition" and "Start magnetic field acquisition" the application locally registers the coordinates and the received data for the specified duration. Once the user has finished the survey on a given floor, data is merged directly on the device by averaging the registered measurements and so the map is created. It can be exported into a text file, but there is no need to do it when using *PrettyIndoor*, which communicates directly with the *FingerFood*'s Content Provider.

2.2 Using PrettyIndoor

The positioning application is composed of an Android service implementing the back-end and an essential graphical user interface shown in Figure 2. These two

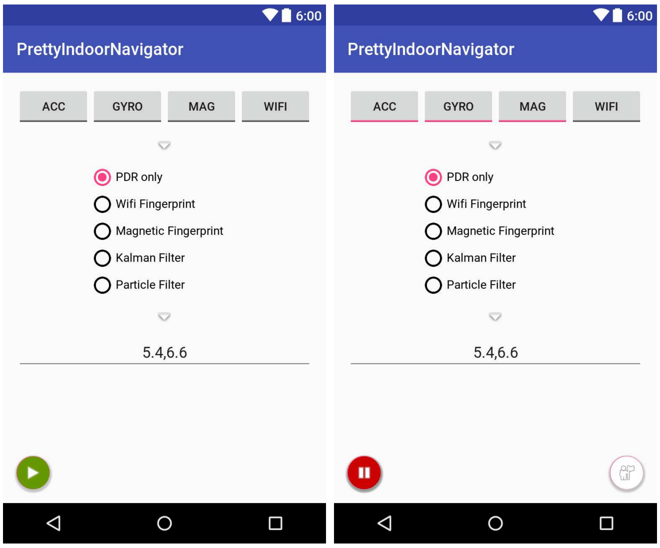

Fig. 2. Left: the screen during positioning hasn't started. Right: screen while positioning is active.

main components provide all the utilities for testing indoor navigation solutions. Currently, the user can choose among PDR-driven, fingerprint-driven or mixed strategies but more techniques are planned to be implemented.

PrettyIndoor requires a starting position, to be specified in the text box. After doing this, the localization service can be started by pressing the green *Play* button. This action switches the front-end to the *online* mode: the bottom floating action buttons change and the toggle buttons corresponding to sensors used by the chosen strategy are switched on. These buttons allow to enable and disable any data source during run-time, which is a useful function for doing a deeper testing. The indoor positioning service runs in the background updating its saved *current position* in real-time, using the user-selected method. The current position can be saved into a log file, which is automatically created by the application, by pressing the bottom-right button in online-mode GUI. The format of the position log is simple: `timestamp`,x, y, z, where `timestamp` is the time when the button is pressed, x, y is the 2D position on a floor, the position moves on the z-axis by using an integer value representing the floor, where 0 is the ground floor. Lines are newline-terminated, so the log is a standard a CSV text file where every row contains a different time-position relation. To save the current position the *flag* button must be pressed, but the separation of the back-end logic into an Android service allows to easily expose this function to a future extension of the application and even to third-party applications.

2.3 Navigator internals

Figure 3 shows the architectural concept of *PrettyIndoor*. The main goal was to develop an three-tier architecture with a logical separation between native raw data, data abstraction layer and core logic layer. The strength of this model is the easy implementation of further modules and strategies into the core logic layer and more specifically, inside the localization strategy sub-layer. In fact, handlers which manage the native raw data, coming from the physical sensors on the smartphone board, are offered using an adapter. It allows to implement new algorithm, or to enhance the previous one, with no any a priori knowledge of how the operating system manages sensor data. The final output is a local coordinates triple x, y, z useful for rendering, navigation, and mapping.

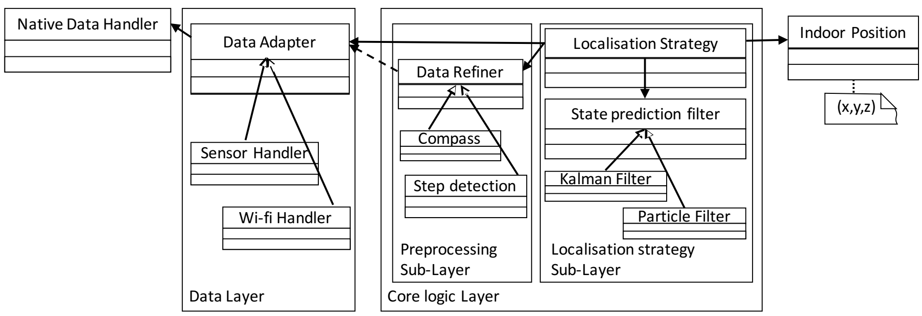

Fig. 3. Architecture of *PrettyIndoor* application.

As shown in Figure 4, the current version of the *PrettyIndoor*'s service implements five different strategies for solving the indoor location problem: Pedestrian Dead Reckoning (PDR), k-Nearest Neighbours (K-NN) WiFi based fingerprinting, k-Nearest Neighbours (K-NN) geomagnetic based fingerprinting, Kalman filter PDR-fingerprinting fusion, and particle filtering fusion.

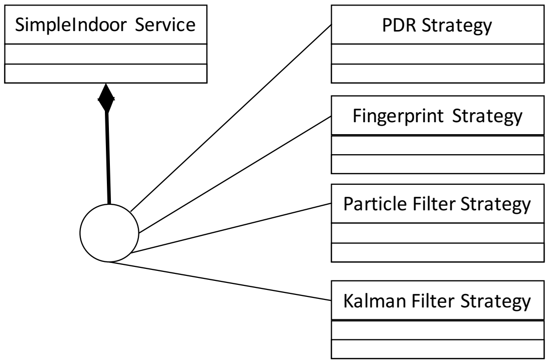

Fig. 4. Scheme of the implemented strategies.

The first strategy is based on PDR techniques. It relies only on accelerometer, gyroscope and magnetometer using sensors for determining orientation and step events. The conceptual work-flow is shown in Figure 5. This implementation of the technique consider an average step length of 0.6 m and simply elaborates the variation on the x, y coordinates and adds it to the previous saved position.

Strategies that use a fingerprint map compare either the measured WiFi RSSI or magnetic field with the values in the database. The position is then found by operating on the results of the k-Nearest Neighbours (k-NN). A lot of solutions in literature don't limit themselves to the usage of a single technique, instead they usually combine more of them. In order to do this, one of the location strategies contained in the application uses a Kalman filter. It always keep the positions found by both PDR and fingerprint, whose difference is then corrected combining it with a predefined covariance. This refined variation is then added to the position and this output is assumed as the new coordinates.

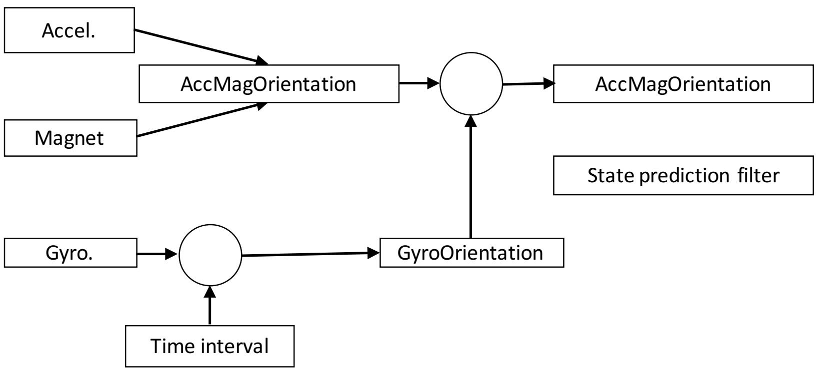

Fig. 5. The work-flow of the orientation algorithm.

Another strategy that uses a state estimation filter is based on a particle filter. In contrast with the previous one, this filter directly operates on the position. In fact, during the initialization a number of particles representing the possible positions are generated on the start point. When a step is detected, they are moved by the variation detected by the PDR plus a random error. This error comes from a model represented by a zero-mean Gaussian distribution with σ set to 0.15 m. For each particle, the algorithm then calculates a distance $d_{particle} = \sum_{i=1}^{n} \frac{d_i}{r_{i,particle}}$ and constraints the particles to lie inside the map. Picking a random number from 0 to an experimentally tunable maximum, if it lies between zero and $d_{particle}$, the particle is removed. Eventually, a number of particles is resampled in order to restore their original number. All these strategies take account the map topology in order to assure the correctness of the found positions.

2.4 Portability through data encapsulation

Since portability is a ubiquitous requirement in recent software production, *PrettyIndoor*, *FingerFood* and their libraries accomplish this by encapsulating data in a proper type for each kind of source.

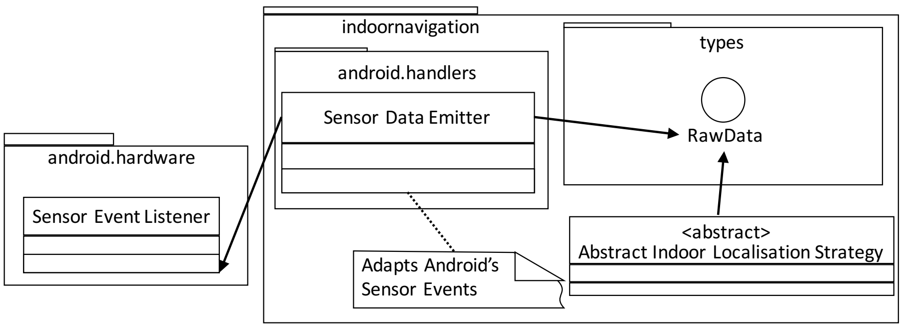

Fig. 6. The work-flow of the adapter pattern.

Figure 6 represents how the listener and the adapter are organized and work. For example, when an Android *SensorEvent* is sent to its listener, the array containing its floating point values is read by the adapter for making an *Acceleration* object which is then sent to the classes that are waiting for it.

The actual data type hierarchy is represented in Figure 7. For this, the Android service that implements navigation makes a new data object when an Android sensor event arrives through an adapter class.

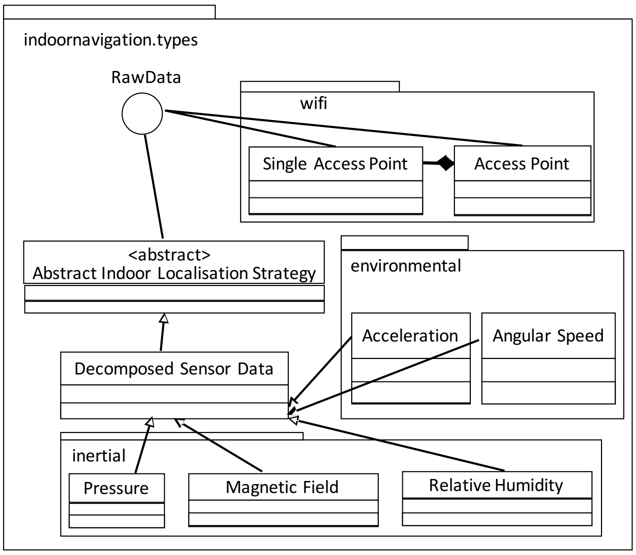

Fig. 7. Data encapsulation layer.

3 Experimental Evaluation

In order to test the capabilities offered by the proposed open framework, different experimental campaigns have been performed at the Italian National Council of Research (CNR), located in Pisa. The map of the experimental region is characterized by a straight corridor with offices located on both sides, a small hall between the two corridor and two offices of 10 m^2, as shown in Figure 8.

Using *FingerFoood*, WiFi and magnetic fingerprints were acquired by standing still for 5 s in each reference point, in order to create two fingerprint maps. The points are equally spaced by 60 cm in both directions in order to uniformly cover the interested area.

Figure 9 shows the two different paths used in the experimental campaign, represented as green lines. Paths are composed by 13 and 8 points, respectively. Points were placed on the floor, using circle markers, used as ground truth. An actor, who held the smartphone in his right hand, used the *PrettyIndoor* application as explained in Section 2.2. We tested the application using two different smartphones: a Xiaomi Mi3w with Android 4.3, and an Lg G3 with Android 6.4. Finally, for each path and for each smartphone, different runs were performed using the different algorithms and strategies currently implemented on *PrettyIndoor*.

In order to test the proposed framework, we evaluate the results on different paths calculating min error, max error, mean error, and third quartile error, the latter according to the EvAAL competition metric. The overall localization performance is measured on two paths for five different strategies:

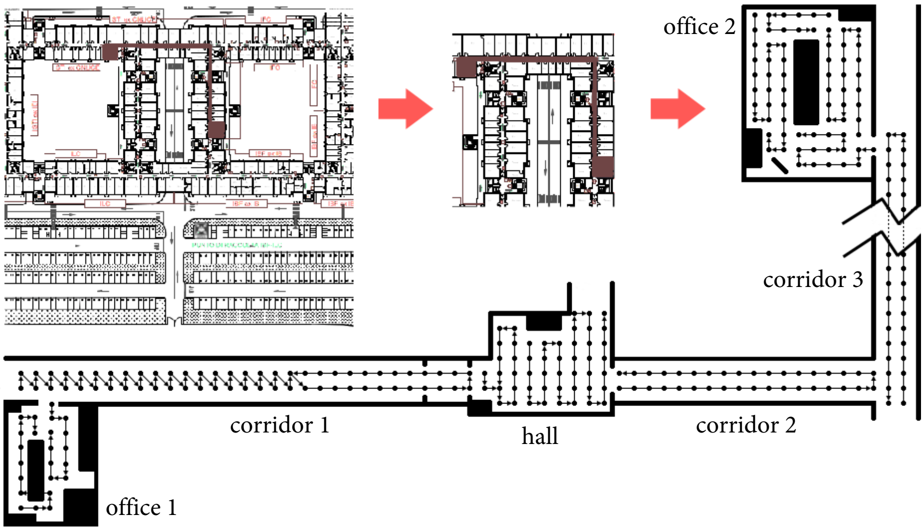

Fig. 8. The map of the environment used in the experimental campaigns. Dots in the map represent the reference points.

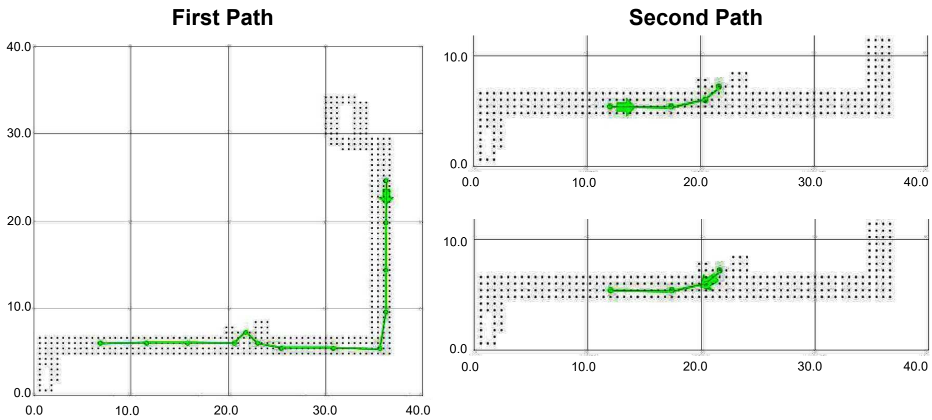

Fig. 9. The two evaluation paths.

– PDR - only using the inertial sensors;
– WiFi - only using the WiFi fingerprint database;
– GeoMag - only using the magnetic database;
– PF - using the first three fused in a particle filter;
– KF - using the first three fused in a Kalman filter.

Table 1 shows the results obtained using two different devices: the Xiaomi Mi3w smartphone (left table) and the LG G3 smartphone (right table).

Table 1. Performance obtained with two different devices. Left: Xiaomi Mi3w (Android 4.3). Right: LG G3 (Android 6.4)

	PF	KF	PDR	$WiFi$	$GeoMag$
First Path					
ϵ_{min}	3.7	6.7	4.8	0.9	1.1
ϵ_{max}	31.9	41.0	36.5	24.1	21.0
ϵ_{mean}	20.4	26.4	23.2	11.8	10.4
ϵ_{thq}	22.9	36.0	27.1	20.5	16.1
Second Path					
ϵ_{min}	0.4	16.6	0.6	1.4	5.3
ϵ_{max}	7.3	34.3	9.8	7.9	13.9
ϵ_{mean}	5.0	21.7	6.9	4.0	7.8
ϵ_{thq}	6.6	23.6	9.4	5.0	9.0

	PF	KF	PDR	$WiFi$	$GeoMag$
First Path					
ϵ_{min}	2.0	11.2	4.2	0.5	2.1
ϵ_{max}	24.5	38.9	32.8	20.8	17.1
ϵ_{mean}	13.6	27.0	23.0	11.1	8.3
ϵ_{thq}	16.1	35.1	25.8	19.4	13.1
Second Path					
ϵ_{min}	0.6	17.4	0.9	1.6	6.2
ϵ_{max}	6.3	31.1	8.7	7.7	11.9
ϵ_{mean}	6.0	19.4	8.0	4.3	7.5
ϵ_{thq}	4.6	20.1	8.2	4.5	8.7

Performance is generally better for the second path. By looking at the results, for the first three simple strategies, we can observe that a significant part of path 1 has bad WiFi performance in a specific area, which probably means that the fingerprint database should be improved in that area. Similar observations can be done for the magnetic fingerprint database. Additionally, one can observe that the step detection implementation is far from perfect, and works reasonably well only if there are bends in the path. In contrast, steps are lost in long rectilinear paths. These problems are all concentrated in the second path, which explains why particle filter performance is much better for the first path.

It is worth noting that the above analysis is much eased by the modular nature of the tools, which allow to enable, disable and fuse modules together.

All in all, the results obtained in the second path suggest that the framework can produce good results once the algorithms are optimized, and its purpose is fulfilled, that is, creating a flexible, extensible and modular indoor localization suite for Android that can be useful for researcher thanks to the free software license used for distribution.

4 Conclusion

In this work, we propose a free software framework to develop indoor localization applications. We show that its modular architecture can be exploited to easily develop diverse data fusion strategies and to analyze their relative strengths and weaknesses.

The *PrettyIndoor* application is currently available and usable on Android smartphones and can easily be used to generate logs in order to validate algorithms and enhancement. It is a modular development environment for implementing existing and future IPS solutions, algorithm and fusion strategy implementations, and testing them on different paths into different indoor environments in a fair way.

FingerFood can currently be used to collect and store fingerprint maps for WiFi and magnetic field. The modular and expendable architecture of both tools makes them a basis for the research community working on indoor localization.

Both applications are still under active development. Future work includes refining the already implemented methods, introducing an adaptive motion module for a better understanding of the human walking pace and more.

The free software Apache software license used for distribution allows anyone to use, modify and redistribute the software, whether modified or not. It also avoids the risk that developers include algorithms on which they own a patent, with the future purpose of asking royalties on them.

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