PINSPOT: An oPen platform for INtelligent context-baSed Indoor POsiTioning

Marios Raspopoulos
University of Central Lancashire Cyprus
Larnaca, Cyprus *mraspopoulos@uclan.ac.uk*

Nearchos Paspallis
University of Central Lancashire Cyprus
Larnaca, Cyprus *npaspallis@uclan.ac.uk*

Paris Kaimakis
University of Central Lancashire Cyprus
Larnaca, Cyprus *pkaimakis@uclan.ac.uk*

Abstract

This work proposes PINSPOT; an open-access platform for collecting and sharing of context, algorithms and results in the cutting-edge area of indoor positioning. It is envisioned that this framework will become reference point for knowledge exchange which will bring the research community even closer and potentially enhance collaboration towards more effective and efficient creation of indoor positioning-related knowledge and innovation. Specifically, this platform facilitates the collection of sensor data useful for indoor positioning experimentation, the development of novel, self-learning, indoor positioning algorithms, as well as the enhancement and testing of existing ones and the dissemination and sharing of the proposed algorithms along with their configuration, the data used, and with their results.

Keywords: Positioning, Open Platform, Fingerprinting, Context-awareness, learning.

1. Introduction

The latest advances in Wireless Communication Systems and in Information Technology gave rise to various applications that require accurate information about the location of the connected devices. Especially in the context of mobile and ubiquitous computing and the Internet of Things (IoT), and for areas where satellite-based navigation systems fail to provide accurate location estimations, indoor positioning is regarded as a key-enabling technology. Although there has been much research work on different methods for indoor positioning, none of these methods has yet been officially accepted or adopted as a common unique solution by any of the wireless communication standards. This is something which is now changing as the IEEE is developing a new wireless standard which specifically proposes modifications in the MAC and PHY layers to achieve better positioning accuracy (IEEE802.11az). It is expected that the IEEE will release this standard in 2021. This is one of the reasons why the research community is actively pursuing research in this area in an attempt to come up with reliable and efficient methods and/or algorithms which offer accurate position estimation and form strong candidates for standard adoption.

Indoor positioning research during the last few decades has been typically based on the collection of extensive radio measurements (usually signal-based or time-based) which facilitate the development and testing of various positioning methods. Measurement campaigns are usually laborious and time consuming and many times this decelerates the research activities as the researchers should collect their own data. In addition to this, the information disseminated in scientific publications often does not allow the easy reproduction of the proposed algorithms and results, thus inhibiting the concept of building upon prior attempts and prior acquired knowledge.

With the above in mind we propose an open platform for intelligent context-based indoor positioning to facilitate:

- The collection of sensor data useful for indoor positioning experimentation
- The development of novel, self-learning, indoor positioning algorithms, as well as the testing and enhancement of existing ones
- The dissemination and sharing of the proposed algorithms along with their configuration, the data used, and their results.

By providing tools for the rapid improvement of the literature on indoor positioning algorithms, and by establishing an open means for their fair and consistent assessment, our platform promotes the generation of high-quality research within our community, thus serving as an excellence hub. Also, the facilities and features offered by the platform will help to research and innovate, and to develop novel, intelligent self-learning algorithms which accurately and efficiently solve the indoor positioning problem.

The main contributions of this paper are: First the definition and design of a comprehensive platform for the collection of training data, and for the evaluation of existing and newly proposed indoor positioning algorithms and techniques. Second, we present a pilot implementation of selected parts of the platform and discuss some preliminary results.

The rest of the paper is organized as follows: Section 2 outlines the motivation for proposing this platform. Section 3 presents the background knowledge and state of the art related to this work, and section 4 presents the PINSPOT architecture. Finally, section 5 describes its porotype implementation and some early reflection on its potential.

2. Motivation

The rationale behind this platform is mainly the fact that although indoor positioning has been and it continues to be a very active area of research over the last decades with various techniques, algorithms or methods being proposed, no unique or universal solution to the indoor positioning problem has been yet adopted nor standardized like it happened for outdoor positioning (see GNSS). Additionally, the various efforts in this area (projects, publications, actions, etc.) have been very dispersive with researchers, many times, falling into the trap of “reinventing the wheel” rather than constructively building on existing knowledge. This includes carrying out similar types of laborious and time-consuming measurements, doing minor improvements to existing algorithms proposed in the literature and many times failing to exactly replicate published algorithms due to either misconceptions or to inaccuracies in the algorithm descriptions in the publications. Additionally, the explosive growth of wireless communication systems with the very quick introduction and after just a few years the withdrawal or marginalization of wireless standards (see 802.11a, 802.11b, ZigBee, etc.) did not allow any of the indoor positioning efforts that have been focusing on those standards to mature enough so that they could be adopted as standardized solutions. All the aforementioned reasons (and possibly some others) have decelerated the research and scientific community on working on indoor positioning to propose a unique or universal solution to this problem. For this reason, we propose PINSPOT; an open platform which enables the easy collection and sharing (amongst the research community) of location-specific context useful for indoor positioning algorithm-testing and experimentation and through this platform perform pioneering research. We anticipate that this would form an excellence hub through which the research efforts in this area will be accelerated by facilitating advancements in various related topics such as location information extraction from various sensors and machine-learning methods which can be applied to this context to infer and acquire additional knowledge which can be fused together with computer vision and be used in Hybrid Intelligent Indoor Positioning Methods to improve the position estimation in indoor environments to the required sub-two-meter accuracy.

3. Background

3.1. Localization

Localization, or geolocation, or positioning has been a topic of research for the last half a century [6]but it became even more attractive and interesting when U.S. FCC [5] has announced that it is mandatory for all wireless service providers to be able to provide location information to public safety services in case of an emergency. While the positioning problem was solved for outdoor environments through the use of Global Navigation Satellite Systems (GNSS), Indoor Positioning Systems (IPS) still remains a big challenge and an active area of research[8]. OpusResearch in a 2014 report[21], predicted that by 2018, roughly $10 billion in consumer spending will be influenced by indoor location. The prediction was fairly accurate. This is also supported by a report by IndoorAtlas [10] which presents the results of a 2016 market research on the indoor positioning market indicating that the budget spent on IPS will be increased by 3.07% in the next five years. The reason for this is that it is estimated that today, more than 80-90% of people's time is spent indoors. Possibly the most important finding is that almost all (98%) respondents state that sub-two-meter accuracy is important for most of these indoor applications. Various approaches have been proposed in literature which include Geometric, Fingerprinting [1] and Cooperative approaches [16, 31] and techniques which fuse together various positioning methods and/or context coming from non-radio technologies (see section 3.3). Amongst the numerous techniques that were developed, the most commonly used are the geometrical ones and especially those based on the estimation of the Angle of Arrival (AoA), the Time of Arrival (ToA), the time difference of Arrival (TDoA), a combination of two or maybe three of the above or the estimation of the Received signal Strength (RSS) [11, 27]. These techniques are based on the extraction of distance and angular information of the mobile device to the various access points and then on triangulation or trilateration to estimate the position. The main difficulty in indoor positioning is the fact that the dynamism of the indoor wireless channel and the frequent Non-Line of Sight (NLoS) conditions raise specific difficulties in producing accurate position predictions therefore additional context and knowledge inferred from this context can be used to improve the accuracy.

3.2. Crowd-sourced Positioning Platforms

A platform for evaluating positioning on Android devices called Airplace was proposed by the authors of [15]. The platform is a mobile-based network-assisted architecture which includes an RSS logger, a radio-map distribution server and a "Find Me" application which facilitates the testing of various positioning algorithms and the optimization of their settings. The authors of [23] have presented Anyplace[1] ; a free open navigation service that relies on the abundance of sensory data on smartphones to deliver reliable indoor geolocation information. It implements a set of crowdsourcing-supportive mechanisms to handle the enormous amount of crowd-sensed data. A similar open platform is presented in [9], called SmartCampusAAU which facilitates the creation of indoor positioning systems. It includes an application and a backend that can be used to enable device- or infrastructure-based indoor positioning and a publicly available Open Data backend to allow researchers to share radio map and location tracking data. The platform relies on crowdsourcing techniques to construct radio-maps. Crowdsourcing [20, 32] leverages the fingerprints collected by users using their smart-devices to construct and/or update the radio-map. This obviously presents various inaccuracies that need to be considered in the position estimation phase, mainly the fact that the radio-map will not be homogeneous as it contains fingerprints from a diverse set of devices.

3.3. Context-Aware Positioning and data fusion

In radio-assisted indoor positioning, the exclusive utilization and reliance on radio parameters imposes limits that are sometimes hard to overcome with current technologies implemented on smart devices. These limitations are often related to the inability of the

[1] https://anyplace.cs.ucy.ac.cy/

off-the-shelf mobile devices (usually 802.11-based) to accurately measure these parameters. To this end, the current research trend is to put forward solutions which enable data fusion of radio-context with non-radio context such as information from inertial sensors and/or any other built-in sensors on the mobile or even context which is manually added as prior knowledge (e.g. environment maps) [29] with many attempts been made towards improving the accuracy of fingerprint-based positioning techniques [30]. Other types of context collected from audio, ambient light or other sensors or from any other built-in technology (e.g. Bluetooth Low Energy - BLE) can be used to provide that extra knowledge towards a more accurate position estimation. Basically, any type of additional knowledge which would potentially give an indication about the user whereabouts can be used in conjunction with the positioning estimation process to lead to better results [3, 18, 19]. Various attempts were also reported in literature to combine context from heterogeneous radio technologies like Bluetooth, RFID etc., and demonstrated that by combining the varying capabilities of different technologies can achieve higher accuracies [2]. In a similar fashion, the author of [28]demonstrated accuracy improvements in the fingerprint–based indoor positioning, by including knowledge extracted from the architectural maps of the building. The PINSPOT platform provides the framework to collect, store and process this context and infer additional knowledge using machine learning techniques.

3.4. Machine Learning for Positioning

Machine learning has been employed in indoor positioning widely during the past years. The most widely used machine learning algorithms are based on supervised learning techniques such as Naïve Bayesian Classification. Naïve Bayes is a very efficient family of algorithms, since it is linear in the number of training examples and this is the main reason that it is used extensively in the case of indoor positioning [26] where the goal is to create a map of the indoor space while the user position in being inferred, employing the technique of Simultaneous Localization and Mapping (SLAM). On a different note, the authors of [24] collect the walking traces of several people and the exterior of the building and combine this with a grammar-based encoding of the floor-plan to identify all rooms, their size or fill the gaps in areas not visited by the pedestrians in order to produce a detailed map of the building. With the emergence of cloud computing and the high availability of processing power, the use of other machine learning algorithms is imminent. Algorithms such as Recurrent Neural Networks, Support Vector Machines (SVMs), Reinforcement learning with dynamic environment (e.g. Q-learning, SARSA) can be employed to infer the user's position, and due to their inherent characteristic of allowing recurrence during the learning process the feedback based on the variety of the sensor readings and camera readings will be used to adjust the model's training in order to reduce the error in the estimation of the user's position. To the best of our knowledge deep learning techniques have not been used in the context of the research in indoor localization and we believe that the exploration of the possibility of these techniques to offer more accurate results is incumbent, therefore a provision of machine learning algorithms is included in PINSPOT.

3.5. Computer Vision for Positioning

3D object tracking has been one of the most traditional problems in Computer Vision. A great deal of research effort has been dedicated towards tracking rigid objects such as cars [14], human heads [7, 17], deformable objects such as the human body [13, 25], and groups of them through multi-target tracking techniques [12]. A notable success story of computer vision's ability to solving tracking problems is supported by the emergence and, more recently, the immense popularization of Augmented Reality (e.g. The Pokémon Company and Ikea AR Catalog) and controller-free interfaces (Microsoft Kinect and Leap Motion).Vision has been able to meet its challenges in tracking by use of a plethora of Bayesian tracking algorithms, such as the family of variants to the Kalman filter (KF), with the extended KF (EKF) and the unscented KF (UKF) being notable examples. Although computer vision can be used on its own to facilitate positioning, combining it with radio and non-radio specific context could lead to more accurate predictions. Therefore provisions are made to collect such context in the PINSPOT platform.

4. The PINSPOT Architecture

As discussed in the previous sections, the main objectives of the PINSPOT platform are:

- The collection of sensor data to be used for indoor positioning visualization, analysis and experimentation.
- Facilitate the evaluation of existing, and the development of novel indoor positioning algorithms.
- The dissemination of implemented methods and algorithms along with their configuration, the data used, and their results.

Given these, we propose a conceptual architecture which identifies the main components of the platform, along with their main interactions. This is illustrated in Fig. 1.

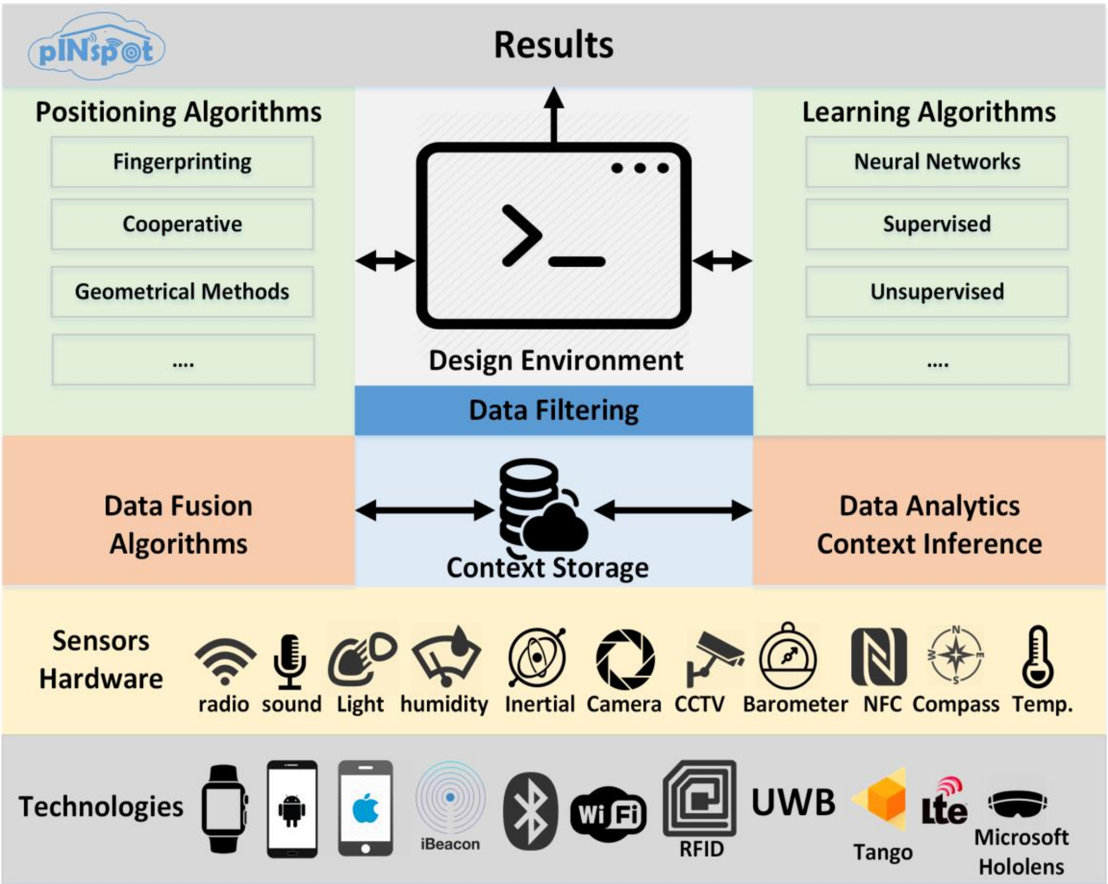

Fig. 1. PINSPOT's platform conceptual Architecture

The PINSPOT platform architecture consists of the Technology and Hardware layer suite which comprises of the various sensors which could provide location-specific information to a cloud repository. Data can be extracted from each hardware component or sensor through specific APIs which are provisioned by the underlying technology and stored on the cloud so as to be made available for data processing and filtering. Data fusion algorithms and data analysis and inference methods are then applied onto this context to generate or infer new knowledge which is useful for the various positioning and machine learning methods. This context/knowledge is fed back to the cloud, is filtered and delivered into the design environment where it forms the input to the positioning and learning algorithms to estimate the position. The user has the option, through the Design Environment to use and/or combine existing positioning and learning algorithms and modify/enhance them or to create new ones from scratch and also upload them on the platform. The availability of a plethora of datasets collected in various environments under various conditions makes it possible to more thoroughly test new algorithms but also to perform a more realistic comparison against methods reported in literature since the datasets through which they have been test are already available in the repository. A presentation layer is also provisioned to present the results.

5. The PINSPOT Platform

PINSPOT envisions to be a comprehensive platform for studying and evaluating indoor positioning systems. As such, Fig. 2 shows a system level view of the PINSPOT architecture. At the core of this architecture is a repository for collected data. Data is normally collected via the developed mobile app, running on a suitable smartphone or tablet device. The mobile app interacts with the cloud-based system via the Data Collection API. Non-standard data, including pictures, video and simulated data are also supported, and uploaded through a web-based interface via the Data Upload API. The Offline Uploading web interface allows the uploader to include additional tags to the uploaded data (e.g. relevant timestamps in a video, or custom data which could be inferred from a video such as the position of humans). All uploaded data (via the mobile app or the offline interface) requires authentication and is associated with the authenticated user.

The web-based interface also allows authenticated users to perform experiments online and view the results in the form of reports and graphs. Before an experiment, the end users are able to target specific datasets (e.g. all data collected as part of a specific collection session), and filter the data even further (e.g. identify that only data from a specific brand of device should be used). Additionally, specific algorithms can be selected from a set of existing or custom (user uploaded) algorithms (e.g. the KNN algorithm etc.). Further tuning of the algorithm will be allowed in terms of adjusting certain parameters (e.g. set the K to a value such as 3 or 4). Finally, the user can specify general simulation settings, such as the method with which the dataset will be split, the number of rounds to repeat the simulation, and ratio of training/testing data, etc.

The simulation itself takes place asynchronously (potentially over a long period of time) and the user is notified (by email) when the results are ready for collection. The results include standard, text-based reports as well as graph-based visualization (e.g. comparing the results with those from other experiments on similar data).

Finally, the simulation engine allows for the utilization of intermediate Context Inferring, which can be used to feed the positioning algorithms. For example, a context-inferring algorithm could be used to compute step counting using a stream of accelerometer readings, and the result (i.e. the step counts) can be used further on by a positioning algorithm which needs these inertial measurements to optimize its results.

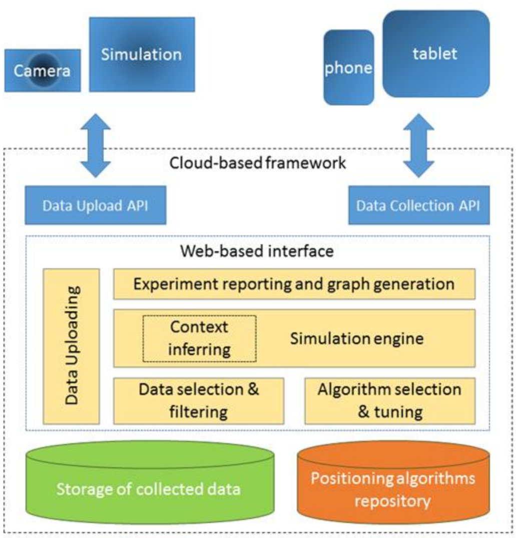

Fig. 2. PINSPOT's platform system architecture

5.1. Prototype Implementation

We implemented a prototype of the PINSPOT platform with the purpose of assessing the feasibility of its objectives. The implementation consists of a cloud-based data repository (based on Google's AppEngine platform[2] and the Datastore NoSQL database system[3]) and an Android-based client. The client builds on our previous work[22]which provided a rich-client platform for collecting context-annotated measurements of WiFi radiomaps. In that work though, the data is collected on the mobile device and then exported. Then, using a script-like system the data is further processed and evaluated over different algorithms . In this, evolved version of the client, we have added the following functionalities:

1. Browse online datasets (i.e. on the cloud-based repository).
2. Create new datasets and upload them to the cloud repository.
3. Perform evaluation of different algorithms directly on the mobile device, using any of the available datasets.

Additional functionality—not yet implemented but—planned are:

4. Dataset manipulation API for *splitting*, *merging* and *anonymizing* existing datasets.
5. An open API for defining or uploading algorithms for testing and evaluation of newly developed location inference algorithms.

The following subsection describe in more detail the main components of the prototyped implementation.

Cloud-based data repository

The cloud-based data repository serves as a transparent, open repository of datasets, which aims to facilitate the evaluation of various indoor-positioning algorithms. From a technical perspective, it is based on Google's AppEngine platform, and provides a REST-ful [4] API for *accessing*, *creating*, and *deleting* datasets of indoor positioning measurements. Using open standards and protocols such as the REST-ful architecture and the JavaScript Object Notation (JSON) for storing and exchanging the datasets allows for easy development and deployment across more platforms (e.g. beyond the Android-based client described later in this section). The source code of this cloud-based implementation is available on GitHub and a live system is accessible at http://caips-server.appspot.com.

WiFi measurements storage and exchange format

To allow for interoperability across the various mobile platforms and the cloud-based system, a JSON-based format was defined for storing and accessing the datasets. This format, at its current version, defines the following properties:

- A unique id of the dataset (used as the primary key in the Datastore).
- The id (typically the email) of the creator of the dataset.
- A version indicating the format properties (to be used to allow transformation in future variations of this format).
- A text-based description of the dataset.
- A collection (array) of the measurements.

At the same time, each measurement has details about the floor of the building and the coordinates where the measurement was taken, as well as the id of the person who recorded the measurement. Notably, it also has a collection of radio entries, each with the unique mac address of the corresponding WiFi router, the signal strength (in decibel) and the frequency use by this particular channel. And finally, it includes a list of context values describing the context of the device taking the measurement, as recorded by its own hardware and software sensors.

[2] https://cloud.google.com/appengine
[3] https://cloud.google.com/datastore

Listing 1: Anonymized sample of a dataset

```
{
  "id":5682617542246400,
  "createdBy":" anonymous@mail.com",
  "timestamp":1484039886891,
  "formatVersion":1,
  "description":"/document/primary:Download/fingerprint-2017-01-12T115041-
example.json",
  "measurementEntries": [
    {
      "uuid":"d08dc0ba-ede8-4187-bdac-dd1a0bd0ed64",
      "floorUUID":"19dabed9-52e5-483f-ab7d-d014c6b966e4",
      "createdBy":"anonymous@mail.com",
      "timestamp":1484039866891,
      "coordinates": {
        "lat":35.008038222789764, "lng":33.69705834776846 },
      "radioDataEntries": [
       { "macAddress":"34:...:fe", "ssid":-44, "frequency":5200 },
       { "macAddress":"34:...:ff", "ssid":-44, "frequency":5200 },
        ...,
       { "macAddress":"00:...:17", "ssid":-88, "frequency":2417 }
      ]
    }
  ],
  "context": [
    { "acceleration": [ -0.33, -1.86, 9.76 ] },
    { "battery-charging-state": [ "charging  via ac charge" ] },
    { "model": [ "LG-P710" ] },
    { "battery-level": [ "91.0%" ] },
    { "magnetic-field": [ -221.75, 36.25, 538.50 ] },
    { "make": [ "LGE" ] }
}
```

The datasets are stored on the Datastore in their original JSON-based format, allowing for easier and quicker access by clients. In the case where datasets are required to be processed on the server side, such as to be anonymized or merged, these are first converted to their usual, object-based representation using the GSON library[4].

Android-based client

To facilitate quick collection of experimental-grade WiFi radiomap measurements, we developed the Context-Aware Indoor Positioning System [22]. However, that platform was limited to the collection of data and required to export it and process it offline.
Taking advantage of the new platform architecture, it is now possible to also:

1. Browse existing datasets from the cloud-based system.
2. Create new datasets, either from the local database or from an existing JSON-formatted file.
3. Set up a simulation-based experiment on a selected dataset by choosing the preferred algorithm and by splitting the measurements to training/test subsets accordingly.

For instance, this functionality is illustrated in the following figures.

[4] https://github.com/google/gson

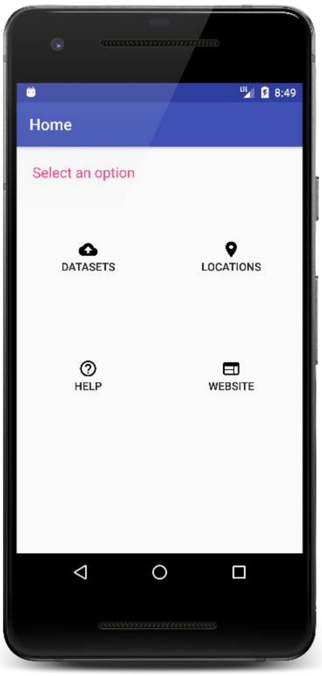

Fig. 3 Main menu of the app—allowing the user to browse the cloud-based datasets or collect more data

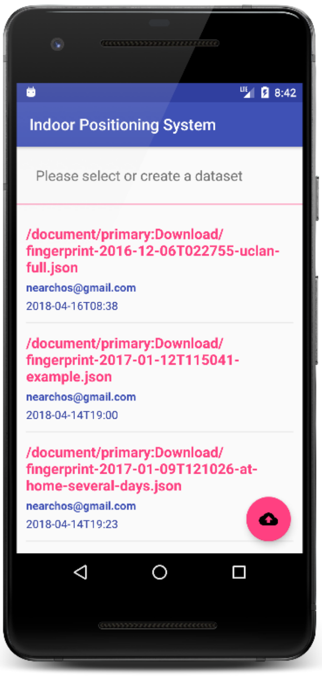

Fig. 4 Browse the datasets stored on the cloud-based system

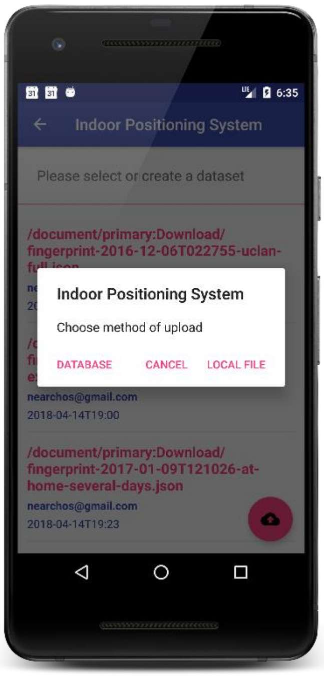

Fig. 5 Create a new dataset by uploading data from the local DB or by uploading a file

The main menu (see Fig. 3) allows to choose between browsing and processing existing sets or alternatively view or configure locations for further measurements. The datasets option initially displays a list of the available, cloud-stored datasets, allowing the user to either choose a datastore or create a new one (see Fig. 4). When the user selects to create a new datastore, two main options are available: choose to upload the measurements currently stored in the database or, choose to upload the data stored on a local (previously exported) JSON-formatted file.

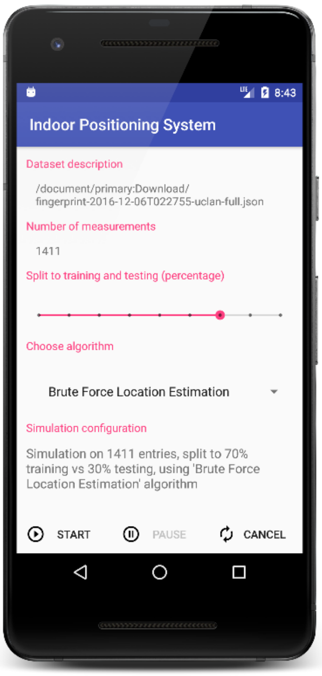

Fig. 6 Viewing a selected dataset (in this case with 1411 measurements)

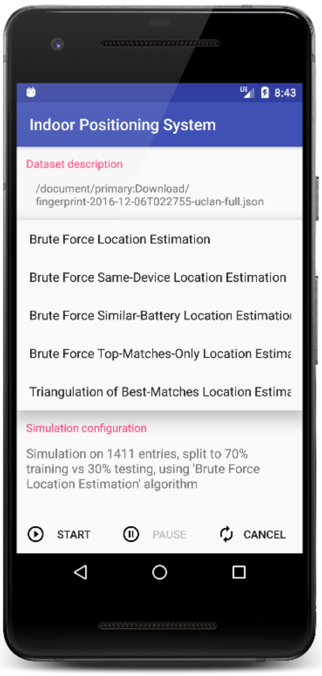

Fig. 7 Choosing among a set of algorithms to perform an experiment

Fig. 8 Starting the experiment (splitting the dataset to 50/50 training and test measurements)

Once a dataset is collected, the user can view its main attributes (see previous description of the exchange format). Furthermore, the user can customize two properties which dictate the experiment: The split of the dataset measurements to training and testing subsets (e.g. to a 70/30 ration), and the selection of the algorithm to be evaluated. Finally, the processing (experiment) can be started, paused and cancelled by the user. If the user navigates away from the application, the processing is cancelled automatically.
While the developed platform is still in its early, prototype phase, it has shown good potential in becoming a convenient and practical tool for the evaluation of existing and newly proposed algorithms for inferring indoor locations from existing measurements.

6. Conclusion

This paper has presented PINSPOT; an open platform which provides tools for the rapid improvement of the literature on indoor positioning algorithms, and by establishing an open means for their fair and consistent assessment, it promotes the generation of high-quality research within our community, thus serving as an excellence hub and a point of reference or interaction of researchers working in this field around the globe. Researchers can use the facilities offered by this platform, in order to research and innovate, and to develop novel, intelligent algorithms which accurately and efficiently solve the indoor positioning problem. Even in its early prototype version the PINSPOT platform implementation presented in this paper demonstrated a strong potential to achieve this.

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