Indoor Location for Smart Environments with Wireless Sensor and Actuator Networks

ZHAO, Zhongliang, et al.

Abstract

Smart environments interconnect indoor building environments, indoor wireless sensor and actuator networks, smartphones, and human together to provide smart infrastructure management and intelligent user experiences. To enable the “smart” operations, a complete set of hardware and software components are required. In this work, we present Smart Syndesi, a system for creating indoor location-aware smart building environments using wireless sensor and actuator networks (WSANs). Smart Syndesi includes an indoor tracking system, a WSAN for indoor environmental monitoring and activation automation, and a gateway interconnecting WSAN, tracking system with mobile users. The indoor positioning system tracks the real-time location of occupants with high accuracy, which works as a basis for indoor location-based sensor actuation automation. To show how the multiple software/hardware components are integrated, we implemented the system prototype and performed intensive experiments in indoor office environments to automate the indoor location-driven environmental sensor monitoring and activation process. The tracked indoor location [...]
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Keywords: Artificial Intelligence, Indoor Positioning, Environment Automation, Wireless Sensor and Actuator Networks.

I. INTRODUCTION

Smart environments, for instance smart home or smart office, are expected to be intelligent and human-aware. Google's recent acquisition of Nest Labs [1], whose products include smart sensor-driven and programmable thermostats, certainly shows the huge market potential of smart environment applications. In the meanwhile, Human-Centric Computing (HCC) focuses on improving application experiences by enhancing application usability. Research activities on HCC have been advancing in past years due to the rapid development of mobile devices such as smartphones, wearable devices, as well as distributed environmental sensors. Understanding human beings and their contexts certainly helps to facilitate the development of smart environment applications.

Home automation or office automation, targets to provide convenient, comfortable, and energy efficient home or working environments to the residents or occupants via the automation of home or office appliances. In particular, office automation could improve the office working experiences. For instance, when a man enters the office room, the lighting system should be switched on and be configured to a luminance level that is of his favorites, and the window curtains should also be opened automatically.

Recent advances in Artificial Intelligence (AI) technology have enabled computer machines to perform better than human being in certain tasks related to intelligence, such as aspects of image recognition. The combination of artificial intelligence and automation will automate entire task-handling process. For instance, the latest machine learning algorithms enable us to design efficient and scalable indoor positioning system without calibration process, which makes the system much more stable. The user's indoor behaviors and preferences can also be analyzed to find out patterns that can be used to trigger the automation operations.

Given the previous examples, intelligent automation is the key target in smart environment applications. However, most of the existing products on the home/office automation markets do not exhibit sufficient intelligence. To achieve the real intelligent automation, both software intelligence and hardware automation procedure are needed. This means the "smart environments" are really "smart" only if they are aware of human status such as their locations, preferences, intentions, etc. The software intelligent algorithms should detect human status first, which then trigger the hardware automation procedure.

To provide software intelligence and being the human status aware, such as indoor locations, an efficient and accurate indoor positioning system is required. The system should be able to track user's indoor locations without asking people to carry additional devices. Moreover, an infrastructure management platform, such as a wireless sensor and actuator network, should be established to connect the software intelligence with hardware appliances such that intelligent decisions could be transferred to trigger the electrical appliances.

In this work, we have built an indoor location-aware smart office environment, by combining an indoor localization system with an infrastructure management system using existing office WiFi networks and wireless sensor and actuator networks. The system is able to track people's indoor location and automate the operations of office building appliances properly. The main contributions could be summarized as follows.

- We implement and deploy the indoor positioning system in a smart office testbed, the Syndesi framework, and integrate the indoor localization functions.
- We implement the Syndesi automation feature by enabling the indoor location-aware automation process.
We conduct a set of extensive experiments to validate the system in complex indoor environments with long tracking paths. Results show that the indoor location-driven smart environment appliances automation is working fine in real-time fashion.

The structure of the paper is as follows: Section II discusses existing solutions and background related to this work; Section III details the proposed system architecture and describes the integration challenges, and Section IV presents the system deployment and evaluation details to validate the proposed integrated system. Finally, Section V concludes the paper and discusses the main achievements of this research.

II. RELATED WORK

The first problem in smart environment application is to detect or identify the number and identification of the residents or occupants in home or office building environments. Such knowledge can be very useful to various home/office automation applications, such as energy management, lighting control, and security. Ebadat et al. [13] proposed to estimate the number of people in an indoor environment using information available in standard HVAC (heating, ventilating, and air conditioning) systems. Their approach avoids the installation of extra hard sensors in the environment and offers a new solution to this problem. He et al. [14] offers a different solution to this problem by using the Google Glass, which combines data from both visual and inertial sensors. Mao et al. [15] investigated the issue of building occupancy estimation by using a wireless CO₂ sensor network.

Determining people’s indoor locations is another essential requirement for building smart office or smart home applications. GPS technology, which provides accurate positioning for outdoor environments, cannot deliver satisfied indoor positioning because of the signal propagation losses. Therefore, many solutions have been proposed to provide accurate indoor positioning service. In [16], authors proposed a fingerprinting-based solution by combining digital compass and WiFi information. The authors of [17] proposed a tracking system by exploiting particle filter features. This work adopted a particle filter to combine PDR (pedestrian dead reckoning), and floor plans together. A WiFi component records RSSI values periodically from all available access points on a floor. WiFi information is used to perform room recognition and turn verifying. The PDR component outputs a human motion vector model, which is used as input for the particle filter component. The authors of [18] implemented a Radial Basis Function Network to estimate the location of occupants using RFID (Radio-Frequency Identification) and IR (Infra-Red) sensor data. Leveraging the fact that almost all the indoor occupants carry smartphones, Carrera et al. [12] designed a terminal-based positioning system, which uses an enhanced particle filter to fuse PDR, WiFi ranging, and floor plan, to further improve indoor positioning accuracy. Chen et al. [19] designed a smart home application, which focuses on indoor greeneries for improving indoor living environments.

To build an infrastructure platform that controls the electrical appliances in smart environments, wireless sensor and actuator networks are the dominant technology [20], [21], [22], [23], [24]. WSN, rather than WiFi based networks, have been popularly employed for remote control and monitoring applications, mainly because of their low cost and reduced power consumption [25], [26], [27], [28]. The deployment of such a system is not easy due to the existences of different communication standards. Tudose et al. [29] proposed a wireless sensor networking using 6LoWPAN to connect sensors and actuators in a home automation application. The authors of [11] presented Syndesi, a framework for creating personalized smart environments using WSANs. It combines WSANs with different communication technologies, such as Near Field Communication (NFC), Bluetooth, ZigBee, and 6LoWPAN along with an electrical interface to control office appliances.

III. INDOOR LOCATION FOR SMART ENVIRONMENTS

This section details the design of the proposed indoor location-aware smart environment architecture. We first present the architecture of the proposed system and its components. Then, we describe some implementation details and mathematical algorithms that support our application. Moreover, we discuss the challenges when integrating all the components.

A. Overall Architecture

The Smart Syndesi framework, as shown in Figure 1, is a system comprised of heterogeneous hardware devices together with intelligent software engines. It has three main components, namely the Syndesi wireless sensor and actuator network management testbed, an indoor localization and navigation engine, and a human-centric actuation automation module. The Syndesi testbed is responsible for creating and managing personalized smart environments using WSANs. It can also control electronic appliances via an electrical interface. The indoor localization and navigation engine estimates the indoor location of users in real-time fashion. The human-centric actuation automation module is responsible for activating the correlated actuators automatically based on the estimated user locations. In the following, we describe the functions of each module in detail.

B. Syndesi Testbed

Syndesi [11] is focused on providing personalized services for smart environments combining sensor networks, electrical appliances, actuators and gateways, utilizing communication protocols and technologies such as Near-Field Communication (NFC), Bluetooth, ZigBee, 802.15.4, 6LoWPAN etc. The whole system is built following a RESTful architectural approach, providing interoperability between its resources, devices, services and the Internet. Benefiting from Syndesi’s REST-enabled services, many additional updates have been implemented. One of the most important updates is an interactive Android application for mobile devices, which allows
smartphone users equipped with the Syndesi Android application to directly interact with the system’s actuators, as well as contribute with data collected from the smartphone sensors. Moreover, the mobile app integrates indoor localization mechanisms, which are discussed in detail in the next sections, in order to provide live location-stamped data and allow for operation automation based on user location.

The Syndesi components are deployed in 4 office rooms in the University of Geneva premises where 7 people currently work. The core WSAN is comprised by 28 TelosB [7] and Zolertia Z1 [8] sensor motes which are connected with the existing electrical and electronic office devices, such as lights, fans, electric curtains etc., via solid state relays. The core of the Syndesi testbed is implemented on a Linux based machine where the gateway server is deployed. It serves as a connection point for all the elements and components as the WSAN, the mobile crowdsensing smartphone application, the web etc. Every service or resource is provided as a web service, in the form of a RESTful API deployed also in the gateway server, and linked to the web through a proxy service. In addition, an SQL database is hosted on the server where sensor data can be pushed via corresponding APIs. As REST architecture implies, the API calls have the simple form of a URI utilizing GET or POST methods.

In figure 2 we present a 3D-model of one of the offices. The red marks indicate the electrical devices that are connected to Syndesi and thus capable of being triggered via the designated APIs. Most of devices such as the fans, lights and coffee machine support switching on/off while the electric curtain motor is actuated up/down. Some sensor motes (green marks) are placed on the wall for purely monitoring purposes. Using those motes, an automated polling scheme is set-up since September 2016 which collects environmental data, such as temperature and illuminance, and stores it on the server database following a predefined temporal pattern.

C. Indoor Localization and Navigation Engine

To track people in indoor environments, we have designed an indoor positioning system to support real-time indoor localization and navigation. Our approach [12] is able to provide high accuracy by fusing smartphone’s on-board sensor readings, such as Inertial Measurement Unit (IMU), WiFi received signal strength (RSS), and floor plan information in a particle filter. All the tracking algorithms run on the smart-phone itself, which requires no additional hardware deployment. Figure 3 depicts the system architecture of the indoor positioning system, which contains four components as follows:

1) Inertial Measurement Unit: In order to estimate the pedestrian displacement, we use two sensors, the accelerometer, and the geomagnetic field sensor. The displacement of the pedestrian at time $t$ is defined by the motion vector $M_{vt} = [\theta_t, \ell_t]$, where $\theta_t$ is heading orientation and $\ell_t$ is stride length at time $t$. Time $t$ is the instant that the pedestrian executes a new step. Therefore, step recognition and heading orientation methods are implemented in this component. The step recognition method is developed by parsing acceleration readings, whereas the heading orientation is determined by a digital compass developed from the geomagnetic field and accelerometer sensors. Despite the stride length value can vary along the trajectory, in this work we assume that $\ell$ is a constant value in order to focus on the tracking algorithm.

2) Floor Plan Component: Information about the area of interest is used to further improve the tracking accuracy. This
component defines the constraints by the area of interest. Thus, zones in the floor plan, where the pedestrian is not allowed to walk, e.g., walls, furniture, are defined as not allowed zones.

3) **Radio Information Component:** Radio information needs to be converted to range values. In order to achieve high ranging accuracy we adopt the Non-Linear Regression (NLR) model presented in [10]. The NLR model is defined as follows:

\[ d_{j,t} = \alpha_j \cdot e^{RSS_{j,t} \cdot \beta_j}. \]  

\[ d_{j,t} \] is the distance between the target object and the \( j \)th AN at the instant \( t \). Both \( \alpha_j \) and \( \beta_j \) are environmental variables defined for the \( j \)th AN. \( RSS_{j,t} \) is the signal power measured from the \( j \)th AN at time \( t \).

4) **Data Fusion Component:** We propose a particle filter approach by fusing PDR, WiFi, and floor plan information to support real-time tracking in indoor environments. In our approach, an additional re-sampling method is incorporated in order to further mitigate the errors caused by off-the-shelf WiFi sensors embedded on commodity smartphones. Thus, the state vector at time \( t \) is defined as follows:

\[ X_t = [x_t, y_t, \theta_t, \ell_t], \]

\( (x_t, y_t) \) are the Cartesian coordinates of the target object, \( \theta_t \) is the heading orientation and \( \ell_t \) is the stride length at time \( t \). The prediction function can be written as:

\[ X_t = F \cdot X_{t-1} + \eta, \]

where

\[ F = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \eta = \begin{bmatrix} \ell \cos(\theta) \\ 0 \\ \ell \sin(\theta) \\ 0 \end{bmatrix}, \theta = \theta' + \varepsilon' \]

\[ \ell = \ell' + \varepsilon'' \]

Heading orientation and stride length are assumed to interfere by zero-mean Gaussian random noises. Therefore, \( \varepsilon' \) and \( \varepsilon'' \) are the errors introduced in the calculation process.

All the components and algorithms are running on the smartphones, which continuously explore the existing WiFi network and on-board sensors.

D. **Machine learning for Room Recognition**

Location plays an essential role in context-aware smart environment applications. Information about the location of users or their identities could be needed to develop customized services. Therefore, different localization approaches should be implemented based on the required accuracy. Some applications might need sub-meter level accuracy, while meter level accuracy could be sufficient for some applications. In smart environment applications, room level accuracy could already enable automate activations of actuators based on estimated user locations, such as turn on/off lights and open/close curtains when a user is coming/leaving into a room. Before the integration of the localization mechanisms, Syndesi application users had an assigned office room corresponding to their working location, which was used as location on their sensed data. Therefore, in this work, we regard a room level localization accuracy is enough and propose an indoor localization approach, which is able to provide user localization information in a room level accuracy.

The rapid development of WiFi capable mobile devices, and the wide availability of WiFi network infrastructure have promoted several research on provide indoor localization by using WiFi technology. However, instability of the WiFi signal propagation in indoor environments introduces errors in the localization process. Therefore, a simple WiFi localization approach like triangulation cannot cover the demands of practical applications. Nevertheless, WiFi signal propagation instability can be used as fingerprinting identifier for locations in indoor environments. Thus, we consider the room recognition as a classification problem and we propose a simple WiFi fingerprint room recognition approach. The key idea is to combine the signal strength from multiple access points in order to build WiFi fingerprints for supervised learning. In this work we propose a fingerprinting room recognition based on the WiFi RSS transmitted by nearby WiFi access points. This approach does not require additional specialized hardware or special infrastructure support, thus making it feasible for implementation even in mobile devices limited in power and resources. The proposed approach consists of two phases: the off-line training phase and the on-line localization phase. The training phase is intended to build the fingerprint database, which consists of vectors of WiFi RSS collected from the nearby WiFi access points. During the training phase, each survey room is characterized by a set of vectors of WiFi RSS readings. During the on-line localization phase, the predicted room likelihood is calculated based on the previously collected information and the current WiFi RSS vector. Thus, room recognition can be handled by searching for the closest match of the test data in feature space. We implement two simple yet proven to be efficient classification algorithms for this purpose: the k-Nearest Neighbor (KNN) algorithm and the Support Vector Machine classifier. KNN ans SVN are some of the simplest classification algorithms available for supervised learning [2]. Therefore, when a localization task is launched in the mobile app, both classifiers are employed and in case of
a classification mismatch the process is repeated with a newly collected WiFi RSS vector.

E. Mobile Application

The mobile application has been developed in Android Studio and IntelliJ IDEA [4] using the Android SDK with API level 21. It supports devices from API level 15 and above, which now encompasses over 99.1% of Android smartphone users [6]. Figure 4 depicts the main components of the app, the sensing unit, which is responsible for querying the smartphone sensors for values, the localization unit, where the smartphone location is being estimated and the control unit, which handles the various actuation/automation tasks as well as the resource and power management. The application is constructed around the Model-View-Controller (MVC) pattern [30]. Users, sensor data and nodes are models, views are handled by Android activities and controllers are using services to run in the background and the broadcast method to communicate and update the user interface. The application follows the Separation of Concerns (SoC) design principles [31] to facilitate the maintenance and development. All the data transmitted to the server are formatted in JSON format.

1) Sensing unit: When a user gives permission to access his/her device sensors in the settings, the application first discovers the available sensors in the device and then establishes a monitoring scheme. The polling rate is set manually in the settings, the default value being one measurement per minute. After each new sensing event, the raw data is converted to JSON, after being stamped with the user’s id and location provided by the localization unit. Then, a network controller communicates with the RESTful service provided by the Syndesi server and transmits the data via HTTP calls. This controller can easily be derived to create subclasses to connect to other types of servers, making the app easily adaptable to different environments. The HTTP requests are made using Volley [9], an HTTP library made for Android that permits more efficient and faster networking by using caching, multiple concurrent connections and an automatic scheduling for network requests. All tasks performed by the sensing unit are run as services that can run also in the background, therefore allowing for continuous data collection even during the smartphone’s idle periods.

2) Localization unit: The localization unit is where the localization tasks are implemented. As mentioned in section III-D the full tracking mechanism was evaluated as too power-consuming to be used in a mobile app, so we adopted a lightweight version of the same algorithm to achieve accurate room-level localization. The lightweight version uses only the radio information component to derive the user room, in a temporal interval defined by the user. When a localization task is launched, the app scans for surrounding WiFi signals and forms a new WiFi RSS vector which is then fed on the SVN and KNN classifiers. The classifiers are trained every time the app is initially launched, providing that way the possibility of training on different data without the need of re-installation of the whole application. Just as in the sensing unit, the localization tasks are run as services that can be run on the background. The classifiers used for the localization come from OpenCV [3], an open source computer vision and machine learning library.
3) **Control unit:** The control unit communicates with the gateway server via a network controller who sends HTTP requests in order to receive the list of sensor nodes registered in the WSAN. The nodes are parsed from the JSON response and displayed on the app screen. The user can toggle a node by clicking on it, which enables the network controller to send a mediate (HTTP GET) request to the server, using the node’s id and the desired status as parameters. Besides the manual triggering of the actuators, the control unit includes an automated environment control module which uses the tracked indoor location to activate smart management within the Syndesi framework. If a user enables that option on the settings, When a change of location is detected it will trigger a process that switches on the appropriate appliances, such as lights, that are in the same room as the device, switching off the ones in the previous room if no one else is currently located inside. The user can also set in the environment control configuration a desired ambient temperature and illuminance, which when compared to the live measured values will actuate an office fan, turn off some lights or pull up/down a curtain in corresponding cases. Figure 5 shows a screenshot of the application home screen, where the latest sensor values are displayed as well as the current location and the server status. Figure 6 shows the various settings of the application.

**F. Integration challenges**

1) **Machine learning library:** The first challenge when integrating the indoor localization algorithm in the mobile application was the inclusion of the different classification algorithms such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). Presently, there does not exist separate pure machine learning libraries developed for Android, so we decided to utilize the OpenCV even though OpenCV was initially designed for image processing tasks. This library is open source and already exists in Android but the downside is that the user has to install it separately, something our app prompts him/her to do if it is not already installed. We are currently in the process of moving the localization computations on the server side for future versions of the app to deal with this issue.

2) **Android permissions:** The initial app was built and tested on phones running Android OS version 5.x. Most of the OS updates since then have modified the permission policy for the application, which led to a constant refactoring of the app in order to be in line with the newest changes and the advanced Android policy. Right now the app is fully compatible with the latest version of Android 7.1.2.

3) **Battery consumption:** The initial version of the app was configured to collect data every 3 minutes and in a full working day (8 hours) we measured an average of 3% battery consumption. Although, as new features continued to be added to the app, e.g. faster polling rates, expensive localization processing, node management etc., it became significantly more power demanding. To deal with this issue, we introduced a new power management feature, where the polling rates as well as the localization WiFi sampling intervals are depending on the smartphone’s state and its current battery level. The user can still choose a desired polling rate in the settings but when the phone battery reaches levels below 50%, the polling rate is reduced by half, and furthermore if the battery life goes below 20% the sensing and localization functions are both disabled. We plan to further improve power efficiency by batching data that are not critical to automation before sending them to the server and by activating the localization only when a user move has been detected.

**IV. SYSTEM DEPLOYMENT AND EVALUATION**

In this section, we explain how the system is deployed and evaluated in an indoor office environment at the Computer Science department of University of Geneva.
A. System Deployment

We deployed the system at the TCS-Sensor Lab in the Computer Science department of University of Geneva with an office area of nearly 260 m\(^2\). In order to cover the area of the 4 office rooms and the in-between corridor with WiFi signals that are sufficient to feed the localization algorithm, we have deployed 5 WiFi access points strategically. Each room has multiple sensors (e.g., humidity sensor, illuminance sensor, etc) and electrical appliances as actuators (e.g., desk fans, desk lights, and electrical curtains). Each actuator is paired to a sensor mote via a solid state relay [32]. The relay is connected to the 220V power supply, to the actuator and to the sensor mote. The relay receives a 3V output from the mote once a location match is detected on the app, thanks to the accurate indoor localization mechanisms. The current generated from this voltage then enables the relay’s underlying circuit and the correlated appliances will be switched on automatically. During the experiments, a person walks through the office areas holding a smartphone with the Smart Syndesi app installed and enabled (as shown in Figure 7).

B. Evaluation

This section includes two types of experiment evaluations: a functional one, and a non-functional one. The function evaluation is to validate the prototype functionalities, while the non-function one is about the evaluation of the indoor localization accuracy.

For the functionality evaluation, when the person holding the smartphone enters an office, the actuators of that office should be automatically triggered based on the user preferences. As shown in Figure 8, the "environment control" feature correctly triggers the specific appliances based on user settings, displaying in its interface the automation status based on the current location/office. The interface of "Node Manager" will also present the actuators that are in the current room and their status for manual triggering, as shown in Figure 9.

For the evaluation of the accuracy of the room recognition, as well as the automated environment control, an experiment scenario and walking path have been defined. As shown in Figure 7, the experiment consists of a person holding the smartphone and walking through the office areas following a predefined path (shown as green dash line). From the starting point, the person holds the smartphone and enters office rooms one by one, triggering the "relocate" function on the defined "check points" on the ground (shown as number 1-6 in Figure 7). During that time, the mobile app is configured to have the environment control function enabled so the expected outcome is the enabling/disabling of the corresponding electrical appliances as the location changes. As WiFi received signal strength depends on the smartphone hardware components, for the evaluation of the algorithm, we used 3 smartphone models from different manufacturers, as shown in Table I.

![Figure 8: Appliance Automation.](image)

![Figure 9: Nodes Manager.](image)

**Table I: Smartphone Models**

<table>
<thead>
<tr>
<th>Model</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Samsung Note 3</td>
<td>Android 5.0; Quad-core 2.3 GHz Krait 400; Wi-Fi 802.11 a/b/g/n/ac; 3GB RAM</td>
</tr>
<tr>
<td>Sony Xperia Z5</td>
<td>Android 7.0; Quad-core 2.0 GHz; Wi-Fi 802.11 a/b/g/n/ac; 3GB RAM</td>
</tr>
<tr>
<td>LG Nexus 5X</td>
<td>Android 7.1.2; Hexa-core 1.8 GHz Cortex-A53; Wi-Fi 802.11 a/b/g/n/ac; 2GB RAM</td>
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The experiments were run 20 times for each phone and for every checkpoint we gathered metrics on the room recognition and appliance actuation. As results shown in Figure 10, the overall accuracy of the room recognition was far greater than 90%, which proves the efficiency of the deployed localization system. In particular, we notice that check points 1, 3, 5, 7 and 8 which are all located inside the 4 offices achieved perfect score. This is an important result since when it comes to localization misses, a corridor miss is far less critical since it is basically transitive state. Regarding the actuation of office appliances, in the case where the office room was correctly detected, the system demonstrated robustness and reliability as there were almost no fails in the steps followed by the phone-server-WSAN to enable the automation, as shown in the results figure.
V. CONCLUSION

In this paper, we presented an indoor location-aware smart environment system. The system consists of an indoor localization module, a wireless sensor and actuator network for electrical appliance management, and a gateway interconnecting office appliances, localization engine with smartphone users. Thanks to the accurate indoor localization module, the system is able to identify people’s indoor locations in real-time, which then trigger the automation of office appliances. We have implemented the prototype, and deployed the system in an indoor environment with 4 office rooms in the Computer Science department of University of Geneva. We have performed multiple experiments with different smartphones models to validate the system functionalities and performance. Evaluation results show that the estimated indoor locations are of high accuracy, and the automation of office appliances can be triggered by the estimated indoor locations in real-time.

In the future, an envisioned milestone is to offload the localization algorithm computations to the cloud/edge servers that are deployed in the smart environments. In this way, we can deploy the full tracking system and even experiments with more advanced machine learning techniques and algorithms which were overly demanding in power and computational resources to be implemented on a mobile device. Moreover, we plan to enhance the system with more power-efficient management as well as security features to make it privacy-preserving.

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