2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 24-27 September 2018, Nantes, France

Location of persons using binary sensors and BLE beacons for ambient assitive living

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***Abstract*—In ambient assistive living (AAL) it is of a paramount importance to be able to detect, localize and estimate the activities of persons living at their homes. Specially, estimating an accurate person's localization and detailed movement patterns in everyday activities, are very valuable for health monitoring and safety assessment. The indoor positioning and navigation (IPIN) research community mainly concentrates on the use of radio beaconing for trilateration with WiFi, Bluetooth or UWB, acoustic beaconing, inertial pedestrian dead-reckoning, and the fusion of several approaches, using fingerprinting or Bayesian estimators. In the area of activity recognition (AR) authors use different kind of sensors such as smart floors, binary sensors attached to common objects, or infer the proximity to objects using Bluetooth beacons. In this paper we want to join these two different field approaches (IPIN and AR) by proposing an indoor localization method that make use of smart floor information, binary sensors, and the signal strength received at a smartwatch coming from BLE beacons deployed in a smarlab. We use the smart floor as a ground truth in order to estimate location accuracy of persons in a totally unobtrusive way. The localization results, for a person moving in the smart livinglab during 10 days, showing accuracies below 1.5 meter in 80% of the cases. The proposed approach can help the tracking of multiple persons living together and also serve as a complement to improve the performance of location-aware activity recognition algorithms.**

***Index Terms*—Indoor localization, Bluetooth tags, BLE beacons, RSSI, capacitive floor, smart-watch, particle filter, AAL.**

I. Introduction

Indoor localization is still an open problem. Many different approaches using distinct technologies have been proposed to obtain a usability similar to GPS outdoors [1], [2], [3]. The most difficult challenge for pedestrian navigation is to find an accurate-enough indoor location method, valid for extended areas, robust to environmental conditions, and at the same time as simple as possible. Different approaches can be used for the location of persons indoors: 1) Solutions that rely on the existence of a network of receivers or emitters placed at known locations in the environment and other sensors on the persons to be located (beacon-based solutions or Local Positioning Systems-LPS) [4], [5], 2) Solutions that mainly rely on dead-reckoning methods with sensors only installed on the person to be located (beacon-free solutions, or Pedestrian Dead Reckoning-PDR) [6], [7], [8], [9], [10]. All these methods, typically used in the Indoor Positioning Navigation (IPIN) domain, allow, apart from an accurate localization, the individual identification of persons since users are tagged with unique ID sensors.

Other localization solutions do not require the user to carry any device with him. These approaches are called device-free solutions. Some categories are: 1) Tomographic solutions that create a mesh of radio links crossing an area to detect subareas where a significant signal attenuation comes from [11], 2) Pressure sensors, such as capacitive floor to detect the activity of the persons within a small area in a house, or the position of persons on beds or sofas [12], 3) Contact ON/OFF binary sensors that detect when a person is opening a door or removing an object from a predefined default position, 4) energy dis-aggregation analysis at the main power supply socket or at individual electrical appliances. All these methods, typical in the Activity Recognition (AR) domain, allow to infer the presence and position of persons, but not its identity. Other unobtrusive sensor type, such as vision cameras, are not considered in these scenarios due to privacy concerns.

This paper explores how we can join different approaches coming from the Indoor Positioning Navigation (IPIN) field with those more common in the Activity Recognition (AR) area. We propose a fused indoor localization method that make use of binary sensors and the signal strength received at a smartwatch coming from BLE beacons deployed in a smartlab. The combination of both approaches make the positioning more robust and also has the potential to allow the identification of different users without confusion, so making it possible a multi-tracking approach. We use the smart floor as ground truth for position tagging. As we will present later, the localization results, for a person moving in the smart livinglab during 10 days, show accuracies below one and a half meter in 80% of the cases. Considering the potential impact of this contribution, the presented approach can help to improve the multiple tracking of different persons living together and also serve as a complement to improve the performance of location-aware activity recognition algorithms.

This paper presents a description of the smartlab in section II, the localization approach in section III, the results with the localization performance in section IV, and final discussion with future work, and some conclusions in sections V and VI.

II. SmartLab test bed

This section shows the test bed used for the location strategy presented in this paper. Next subsections detail the site of the test beds, which is called UJAmI, a description of the kind of smartfloor used, a presentation of the Bluetooth tags under use, and the binary (ON/OFF) sensors.

A. Site: UJAmI SmartLab

The University of Jaén's Ambient Intelligence (UJAmI) SmartLab[1] [13] represents an innovative space that plays a key role in the implementation of new ground-breaking research within the realms of Ambient Intelligence. UJAmI SmartLab is a smart apartment deployed by the Advanced Studies Centre in Information and Communication Technologies and Engineering (CEATIC) of the University of Jaén (Spain).

This apartment has multiple and heterogeneous sensors and actuators that are connected to a unified middleware. The aim of the UJAmI SmartLab is to have a real apartment which was sensitive, adaptive, and responsive to human needs, habits, gestures, and emotions which subsequently underpinned assistive technology based solutions in the home.

The UJAmI SmartLab measures approximately 25 square meters, being 5.8 meters long and 4.6 meters wide. It is divided into five regions: hall, kitchen, workplace, living room and a bedroom with an integrated bathroom (See Figure 1).

There are more than 130 smart devices deployed in this apartment that allow the analysis of the behaviour of its inhabitants. A list of the most representative smart devices are indicated as follows:

- Environmental sensors: Interruption, movement, pressure, presence, arrival, NFC tags, flood, brightness, temperature and CO2 sensors.
- Wearable devices: Smart watches, acceleration sensors and gyroscope sensors.
- Actuators: Light bulbs, led strips, alarm, speakers and Schlage lock.
- Smart Devices: Smart fork and a smart cookies.
- Indoor location: Smart floor, beacons, stickers and leap motion.
- Vision cameras: IP cameras, Web cam and a Kinet.
- Screens: Smart TV and electronics tables.
- Health devices: Smart Body Analyzer and smart watch.
- Brain interfaces: BrainLink Macrotellect, Emotiv Insight and Emotiv Epoc+.

A web-based system for managing and monitoring smart environments was proposed in [14], which integrated most of the environmental sensors and actuators of the UJAmI SmartLab. This system is based on MySQL and allowed the integration with Open Hub, offering the advantages to process the information, accessible services and analytic capabilities.

[1] http://ceatic.ujaen.es/ujami/en/smartlab

a)

b)

c)

Fig. 1. UJAmI SmartLab at Jaén University. From top to bottom: a) 3D model view, b) bed/living-room, and 3) hall/kitchen views.

B. Capacitive Floor

The UJAmI smartlab is equipped with capacitive floor in order to sense the activity and presence of the user in the environment. The capacitive measurement principle has several advantages over the more traditional pressure sensors: the capacitive sensor reacts from a certain distance without direct touch, and there is no restriction on the floor covering (the only exception is conductive material, because of its shielding of the capacitive measurement). The modules used are the registered *SensFloor* product, which is based on smart textiles with a thickness of 3 mm, and it is installable underneath flexible, as well as rigid, flooring. So, the sensor modules remains invisible and does not interfere with the material of the floor covering.

The whole area of the UJAmI SmartLab is covered by 40 modules that are distributed in a matrix of 4 rows and 10 columns. Each module has a dimensions of 1.12 x 0.56 meters.

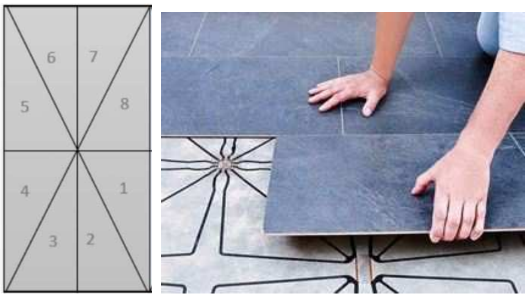


Fig. 2. Floor details: Left) the eight sectioning of one *SensFloor* module. Right) Installation detail (*SensFloor* is covered by the desired floor).

TABLE I
BLE BEACONS IN THE DEPLOYMENT.

ID	Description	MAC	X	Y	Power(dB)
1	TV controller	dd26da1d4f5de2b4	1.2	2.5	-12.0
2	Book	fc399ca08834564b	0.3	3.3	-12.0
3	Entrance door	ed5db2070ac93626	4.5	4.6	-12.0
4	Medicine box	6f9f4861f45eb83d	4.7	0.0	-16.0
5	Food cupboard	06099f1be94516d9	5.5	1.5	-12.0
6	Fridge	b141ab754dad1e55	5.1	1.4	-12.0
7	Pot drawer	a909c2973133b421	5.2	1.2	-12.0
8	Water bottle	d895f89352efda14	5.7	1.7	-12.0
9	Garbage can	829ad3c09f1ee8be	4.9	2.3	-12.0
10	Wardrobe door	8108b9e0bcd42be1	0.6	1.7	-12.0
11	Pyjama drawer	fc0a68ebcdb1ab7c	0.6	1.7	-12.0
12	Bed	472c18626db5d102	1.4	0.9	-12.0
13	Bathroom tap	b3a04300d937b129	3.0	1.1	-12.0
14	Toothbrush	b924c01610110ab4	3.1	0.9	-16.0
15	Laundry basket	768a0ca423a37319	4.6	0.6	-12.0

A module is composed of eight sensor fields, each sensor in a module is associated with an id-number, as indicated in Fig.2 left. The distribution of the 40 modules by 4 rows and 10 columns can be seen in Fig.3, by the numbers (from 01 to 10 horizontally, and 01 to 04 vertically) in the periphery of the smart-lab floor-map.

C. BLE/Smart-watch

In our testbed the inhabitant carries a smart-watch attached to his wrist, and several BLE beacons (Estimote) are distributed in the environment (a total of 15 tags are used). The received BLE signal strength (RSS) from the beacons to the smart-watch can be used to infer the proximity to each beacon, and also to infer the position of the person in the environment if we know the location of the different beacons. We know the exact position of each BLE beacon and the corresponding MAC identification number, as presented in table I. The transmission power of these beacons are also indicated, and should be taken into account when receiving RSS signals, since two beacons (4.'Medicine box' and 14.'Toothbrush') generate weaker signals than the others.

The BLE beacon distribution at UJAmI Smartlab, which are mostly attached to fixed objects, can be seen in Fig.3.

BLE beacons were not efficiently distributed for localization purposes. Note that the irregular distribution does not guarantee a low positioning Dilution of Precision (DOP), meaning that the positioning error expected from them is larger than if optimally distributed. They if fact were placed at points where the user is expected to interact the most with objects, so the deployment was conceived for facilitating activity recognition labor, not location.

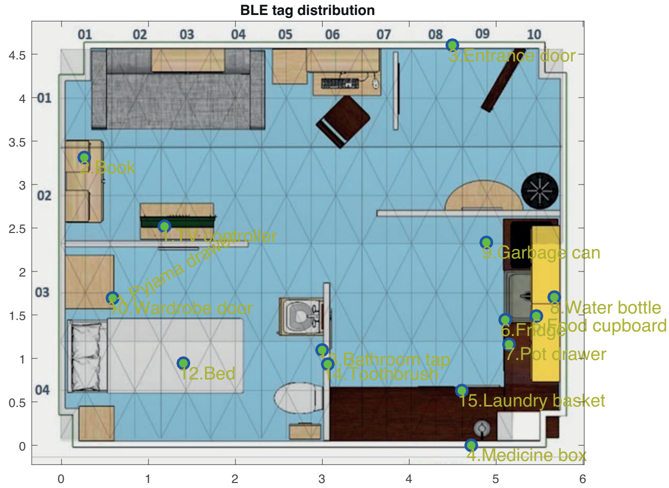


Fig. 3. Deployment of BLE beacons for localization. The 20 modules of the smart floor are depicted with row and column number on the floormap boundary. X-Y axis units in meters.

For registering the Received Signal Strength (RSS), in our test-bed we used a smart-watch model LG-W150, that incorporates a Qualcomm Snapdragon 400 processor with 1.2GHz CPU. The Bluetooth version is 4.0 and it also has Wi-Fi connectivity that is used for data streaming. This smart-watch also has inertial sensors (9-Axis Gyro/Accelerometer/Compass), a barometer, and heart rate monitor, that can be exploited in future works.

D. Binary sensors

A total of 26 binary sensors are distributed in key points in the environment where the user interacts the most. See Fig. 4. The position of the binary sensor is translated when necessary to the most probable position of the user when activating one sensor. For example, if we use the microwave, which has a contact sensor on the door, the true position associated to the user is not the actual position of the sensor, but the closest position to that sensor that is naturally accessible to the user (e.g. at a 0.6 m distance on the floor close to the microwave).

Other binary sensors available in the UJAmI smartlab, which are medium-range motion detectors (PIR or infrared), where not used for measurement since give not accurate information of where the user is located.

III. LOCALIZATION APPROACH

Once it is clear the problem to solve, and the kind of sensors and environment we want to deal with, in this section we explain the implementation details of the fusion process among BLE RSSL-based positioning and the Binary sensors for user's localization. The localization approach is based on a Bayesian

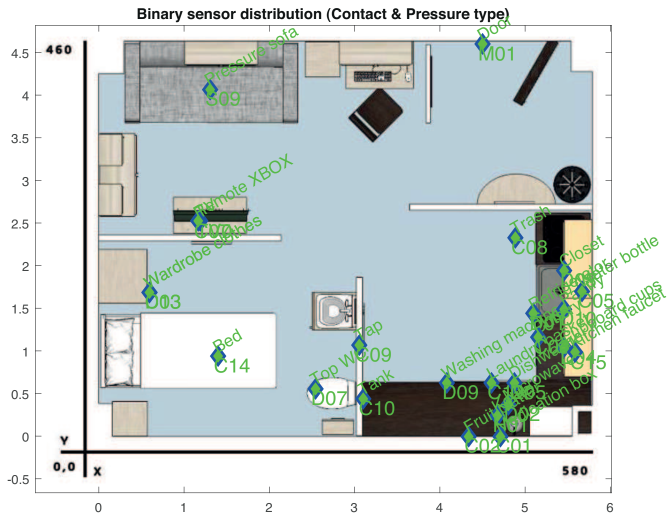
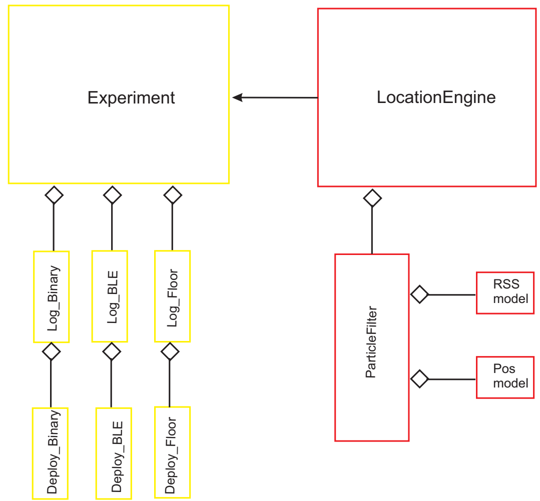


Fig. 4. Deployment of 26 Binary sensors. X-Y axis units in meters.



a)

```
% ..................................................................
%          Define EXPERIMENT
% ..................................................................
experiment=Experiment('UCAmI2018','Training',[1:7]);    % Indicate site name, dataset ('Training' or 'Test'),
                                                        %                      and specific days [1], [1:7]
%experiment.loadSensorData(Log_Activity());             % Log_file with Activity Ground truth
experiment.loadSensorData(Log_Binary(Deploy_Binary())); % Log_file with Binary data stream (and deploy)
experiment.loadSensorData(Log_BLE(Deploy_BLE()));       % Log_file with BLE data stream (and deploy)
experiment.loadSensorData(Log_Floor(Deploy_Floor()));   % Log_file with Floor data stream
%experiment.loadSensorData(Log_Acce());                 % Log_file with Acceleration data stream
%experiment.loadMap(Map('SmartLab'));                   % Map includes RoIs with walls and passable segment

% ..................................................................
%            LOCATION ENGINE
% ..................................................................
locationengine=LocationEngine(experiment);         % Pass experiment object for easier communication
locationengine.loadBayesFilter(ParticleFilter());  % Choose a Bayes filter: ParticleFilter() or EKF()

% Execute on-line Location estimation at measurement rate
while(experiment.dataAvailable)                    % Repeat as many times as da available in Log_files
    visualize=false;
    locationengine.process_measurement(experiment.get_next_measurement,visualize);  % Input next measurem.
end
locationengine.compute_CDF();                      % Shows localization error
```

b)

Fig. 5. Location software design: a) Class diagram, b) Matlab main program.

estimator implemented using a particle filter. Next sections details the software object architecture used for localization, and the details of the location engine that includes a particle filer, two measurement models for: the RSS-BLE ranging and Binary pinpointing, and also a motion model.

A. The localization software object architecture

The implementation of the localization method is coded using an object oriented paradigm in Matlab. Two main classes are defined: Experiment and LocationEngine (see Fig. 5a). We instantiate one experiment object and load as many sensor data logfiles as needed. Three different logfiles are inserted into the experiment containing the information recorded from: Binary sensors, BLE beacons and the smart floor. The deployment classes include all the specific sensor Ids, labels, positions and other features; the logfiles contain the data streams with timestamps and sensor states or RSS measurements.

The Matlab coded implementation can be seen in Fig. 5b. The locationengine class is instantiated in order to perform the localization making use of the experiment object that was previously created. The locationengine object is populated with a ParticleFilter object that implements all weighting of particles based on the category of measurements received and the measurement models. In a real-time fashion, the locationengine object is fed with upcoming new measurements that comes from the three different sources (binary sensors, BLE beacons or the smart floor). After the processing of all data samples in the defined experiment, the positioning error and a Cumulative Distribution Function (CDF) is generated in order to evaluate the performance (we will show some of the CDF in next section). Different tests can be generated with more or less logfiles by simply commenting or uncommenting the corresponding lines of code.

B. The particle filter approach

The overall fusion approach implemented in the locationengine object is depicted in Fig. 6. The Bayesian approach is composed of a prediction and a correction iterative process. The prediction term is triggered by a normal-speed walking random movement model. For the measurements models we use the RSS data that give information about the ranging of the user to the BLE beacons (trilateration approach) and also the position information that is derived from the set of binary sensors. The presented particle filter framework also is capable to add additional information such as the partitioning of the environment with the walls or doors defined in a map.

C. The BLE RSS-based measurement model

We know that the person to be located is carrying an smartwatch, and several BLE beacons are disseminated along the environment. When we measure, at time k, the signal strength RSS$[k]$ at the watch from one BLE beacons, we can update the weights of each particle p as:

$$P(\mathrm{RSS}[k])|\hat{r}^{(p)}[k]) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{RSS}}}\exp\{-\frac{|\delta\mathrm{RSS}^{(p)}|^2}{2\sigma^2_{\mathrm{RSS}}}\} \quad (1)$$

where $\delta\mathrm{RSS}^{(p)} = \mathrm{RSS}[k] - (\mathrm{RSS}_0 - 10\beta\log_{10}(\|\hat{r}^{(p)}[k] - r_{\mathrm{tag}}\|))$ being β the path loss exponent (equal to 2 in ideal open-space conditions), RSS_0 the expected signal strength at a reference distance of 1 m (-72 dBm in our case), and r_{tag} the known position of the BLE beacon. A typical value for the standard deviation of BLE RSS is about 6 dB ($\sigma_{\mathrm{RSS}} = 6$ dB).

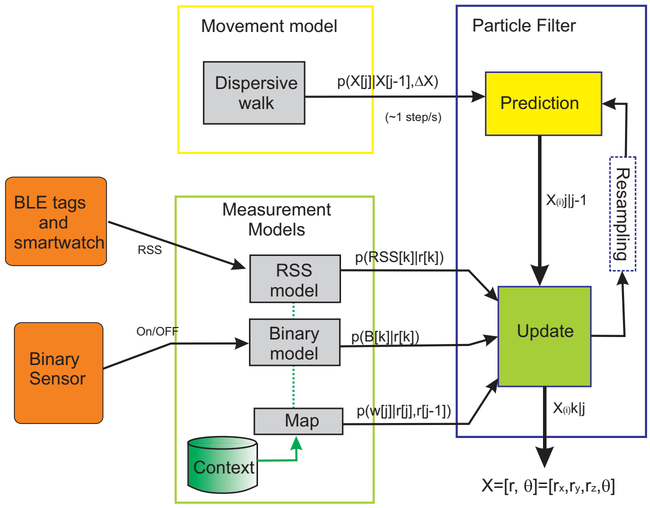


Fig. 6. General fusion framework for BLE-RSS ranging and binary sensors.

D. Binary measurement model

When at a given time k a binary sensor b is sensed, as on/off or pressure, we decide that a person is on that position $r_b[c]$, so we can apply the following measurement model:

$$P(r_b[k])|\hat{r}^{(p)}[k]) = \frac{1}{\sqrt{2\pi}\sigma_{r_b}} \exp\{-\frac{|\delta r_b^{(p)}|^2}{2\sigma_{r_b}^2}\} \qquad (2)$$

where $\delta r_b^{(p)} = |r_b[c] - \hat{r}^{(p)}[k]|$ is the distance between the particle positioned in $\hat{r}^{(p)}[k]$ at time k and the binary position $r_b[c]$ identified by b. and σ_{r_b} is the uncertainty on the binary position that accounts for 0.5 meters in our implementation.

E. Motion model

A simple pedestrian movement model is used. It assumes than a person can be static or can move not faster than a given maximum speed. The orientation change is unmodeled assuming that a person can change his orientation without being detected by any binary sensor or RSS-based range from a BLE beacon. We implement it in the particle filter approach by distributing the particles randomly around its current position, with a standard deviation proportional to the maximum displacement speed of a person, typically less than 0.6 m/s. We add to the XY particle coordinates white zero-mean noise with 0.3 meters standard deviation once every second.

IV. Results: Localization performance

This section shows the localization results generated after executing the algorithms presented in last section. In order to understand the results we will also describe the dataset.

A. Data set

The dataset includes 10 days of recording in the UJAMI smartlab [15]. Each of these days are segmented into three operative periods/hours (morning, evening and afternoon) and labeled in our logfiles names ending with 'A', 'B' or 'C'. For each day and period we have independent data logfiles as can be seen in the folder structure in Fig. 7a. An example of the content in each logfile is shown in the same figure 7 under letters: b, c and d; respectively for smart floor, BLE beacons and binary event streams.

The smart floor logfile includes a timestamp, a module identification (row and column), and eight capacitance values. The values of the 8 sensors in a module represent the capacitance change. The first of these eight values is for the sensor with the id-number 1 and the last sensor is with the id-number 8, following the coding expressed in Fig. 2.

The BLE beacons logfile includes the timestamp, the MAC address, a description, and the signal strength RSS value. On the other hand, the binary event logfile includes the timestamp, a string code, the sensor's state, and the inhabitant name (in our case always the same person named 'Mario'). The state of each binary sensor can be 'Open'/'Close' for contact sensors, 'Pressure'/'No Pressure' for pressure sensors, and 'Movement'/'No movement' for motion sensors.

The motion sensor category are rejected and not taken into account since they are based on PIR (Infrared) and do not give valid information for position pin-pointing. For the rest of binary sensors, the used position is a modification of the real sensor position. The following table II, shows the binary sensor details as contained in the DeployBinary class. Note that the X* and Y* columns set the potential person's position used when the sensor is activated. The 'type' column indicates with the coding: 0, 1, 2, respectively: contact, motion or pressure type sensors.

B. Localization using the smart floor

The localization using capacitive floor is assumed to be the most accurate, since person's localization is directly linked with the stepped floor tiles. However the floor sensors only generate signals when there is a change in the person posture. If the person remains static, standing, on a chair, on a sofa, or on the bed, no signal is generated by the floor tiles, so a location filter would be needed in other to continuously estimate the person's location. If the inhabitant receives a visit, multiple readings can be generated from distant modules, so potentially confusing the estimation.

In Fig. 8 we see the trajectory in magenta color which is a trail of consecutive locations. Also a red circle, an arrow and some small lines, that represent the location uncertainty, the heading and the distribution of particles that all contribute in a weighted way to compute the user location.

From the trajectory Fig. 8, it is clear that the user enters/leaves the smartlab through the door, seats down in the sofa, go to the dressing cabinet (coordinates [1,2] m), gets up and goes to bed by the right side of the bed ([1,0.4] m), and specially past most of the time at the kitchen preparing breakfast, lunch and dinner. We know this since all datasets also has annotated activities.

C. Localization using binary sensors

If we run the algorithm presented in last section, but using in this case only binary event streams, we obtain the trajectory

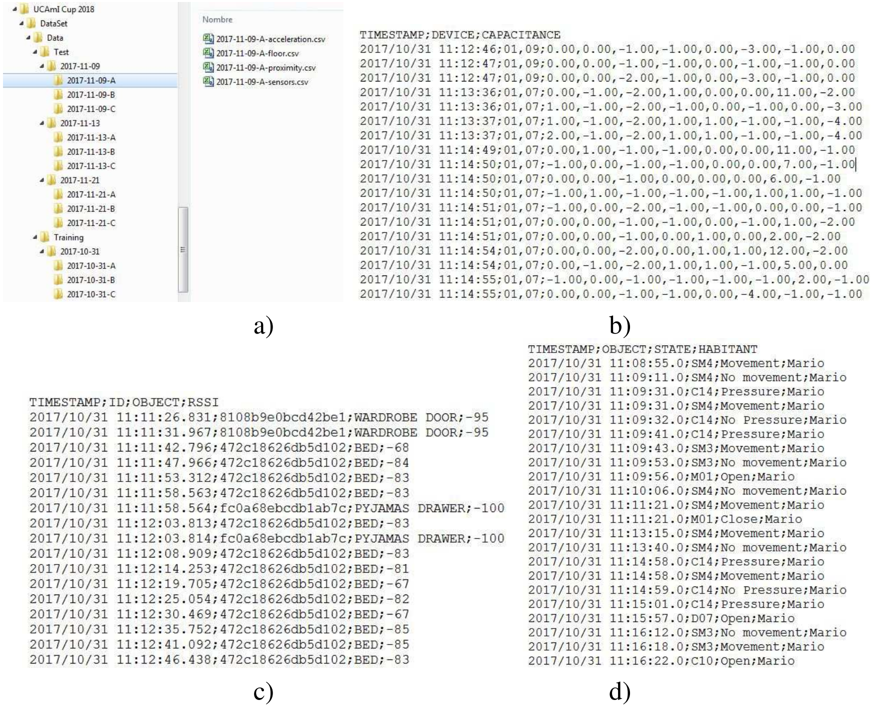


Fig. 7. The dataset with the sensor information. A total of 10 days are available. As shown in the directory structure (a) different separated files with specific formats are recorded per data type: smart floor (b), BLE beacons (c) and binary sensors (d) data streams in csv files.

TABLE II
BINARY SENSORS IN THE DEPLOYMENT.

ID	Code	Description	X	Y	type	X*	Y*
1	M01	Door	4.5	4.6	0	4.5	4.0
2	TV0	TV	1.2	2.5	0	1.2	3.0
3	D01	Refrigerator	5.1	1.4	0	4.8	1.4
4	D02	Microwave	4.8	0.4	0	4.8	0.8
5	D03	Wardrobe clothes	0.6	1.7	0	1.0	1.7
6	SM1	Sensor Kitchen move.	5.8	2.6	1	5.8	2.6
7	SM2	Motion sensor bed	0.1	0.4	1	0.1	0.4
8	SM4	Motion sensor bedroom	1.5	0.0	1	1.5	0.0
9	SM5	Motion sensor sofa	1.6	2.5	1	1.6	2.5
10	D04	Cupboard cups	5.5	1.0	0	5.0	1.0
11	D05	Dishwasher	4.9	0.6	0	4.8	0.8
12	D07	Top WC	2.5	0.6	0	2.5	0.6
13	H01	Kettle	4.7	0.2	0	4.7	0.8
14	D08	Closet	5.5	1.9	0	4.9	2.0
15	D09	Washing machine	4.1	0.6	0	4.0	0.8
16	SM3	Motion sensor bathroom	2.7	1.3	1	2.7	1.3
17	D10	Pantry	5.5	1.5	0	4.9	1.5
18	C01	Medication box	4.7	0.0	0	4.7	0.8
19	C02	Fruit platter	4.3	0.0	0	4.3	0.8
20	C03	Cutlery	5.2	1.2	0	4.9	1.1
21	C04	Pots	5.2	1.2	0	4.9	1.1
22	C05	Water bottle	5.7	1.7	0	4.9	1.7
23	C07	Remote XBOX	1.2	2.5	0	1.2	3.0
24	C09	Tap	3.1	1.1	0	2.5	1.1
25	C10	Tank	3.1	0.4	0	2.7	0.5
26	C12	Laundry basket	4.6	0.6	0	4.6	0.8
27	C13	Wardrobe clothes	0.6	1.7	0	0.8	1.7
28	C14	Bed	1.4	0.9	2	1.4	0.9
29	C15	Kitchen faucet	5.6	1.0	0	4.9	1.0
30	S09	Pressure sofa	1.3	4.1	2	1.3	4.1
31	C08	Trash	4.9	2.3	0	4.9	2.3

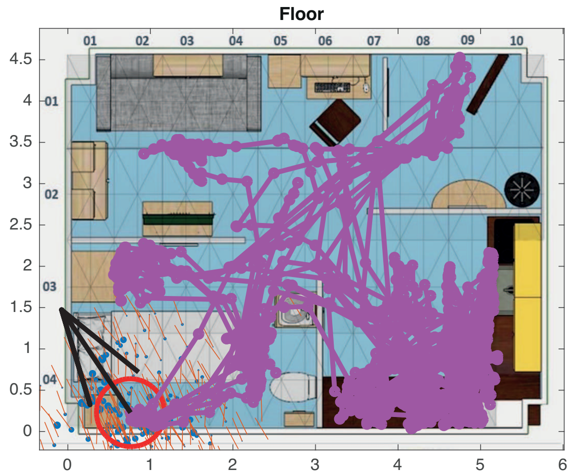


Fig. 8. Trajectory generated using just Floor data.

that is presented in Fig. 9. It is a trajectory of a person along a whole first day in the database (date: 2017-10-31). Some sudden jumps are detected and the crossing of one wall (bedroom/Kitchen). The density of estimations is low since not so much binary events occur in a day of activities.

D. Localization using BLE beacons

In Fig.10 we can see an example of BLE beacon installed in the smartlab. The beacon model used was the *Sticker* from Estimote. A total of 15 BLE beacons were installed by gluing them to everyday common objects. The RSS data

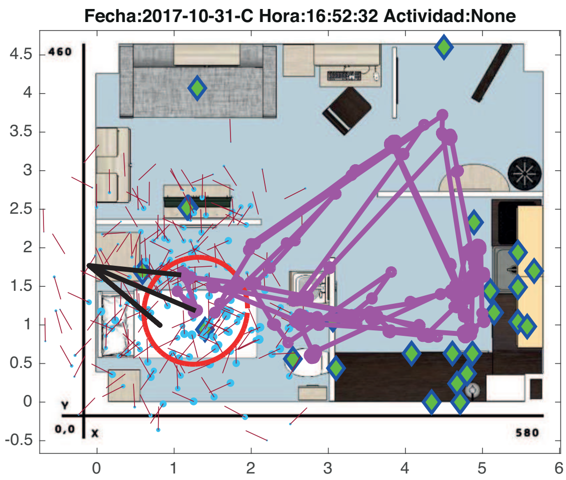


Fig. 9. Trajectory generated using just Binary data.

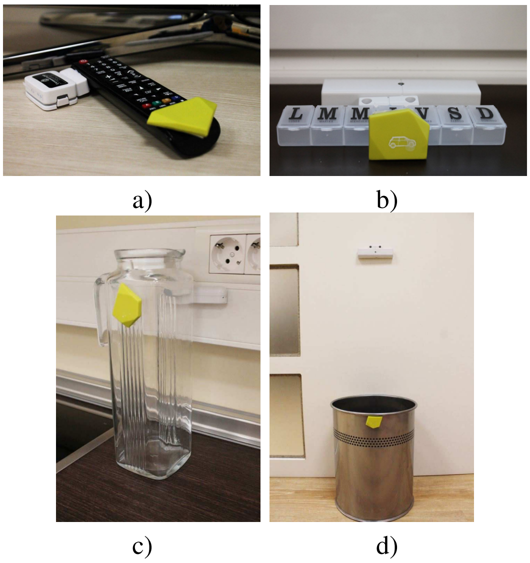


Fig. 10. Examples of some Estimote BLE beacons (yellow) and binary swirches (white) deployed at some points in the smartlab.

was collected through an Android application installed on the smartwatch of the inhabitant. RSS readings are registered with a sample frequency of 0.25 Hz.

It is important to mention that some BLE beacons are attached to objects that have a fixed position, but others tags could be transported since the object can, in a natural and unpredictable way, be moved by the inhabitant. For example, the remote control or the water bottle (Fig.10 a and c) could be moved by the inhabitant. This makes even more difficult the location estimation labor using BLE beacons.

The trajectory of one day using only RSS data is presented in Fig. 11. We can infer on a first look that is richer than the binary sensors only case. In next section we will show the Cumulative Distribution Function (CDF) of all approaches in order to see the error in meters.

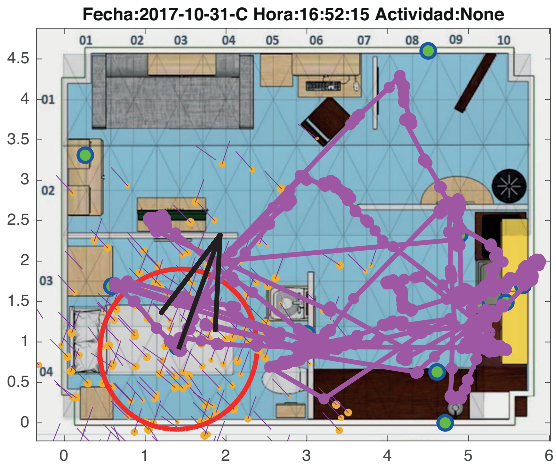


Fig. 11. Trajectory generated using just RSS data from BLE beacons.

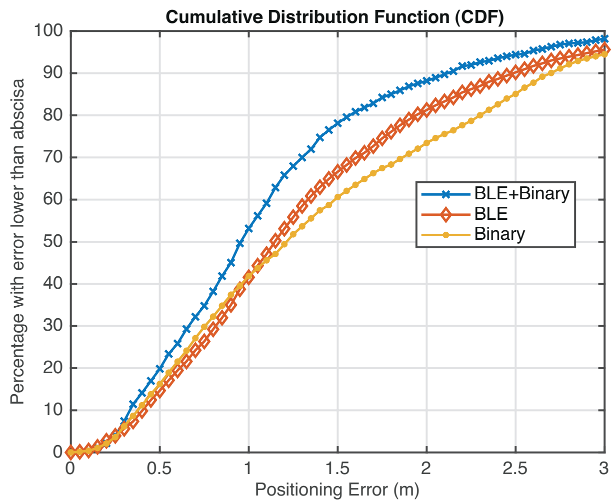


Fig. 12. Cumulative distribution function (CDF) showing localization errors for different sensor set-ups: BLE, Binary and both Fused.

E. Localization CDF using different sensors

The localization results using only RSS data from BLE beacons, only Binary event streams, and also a both data sources (BLE+Binary) together, is presented in the CDF in Fig. 12. It can be seen that the BLE performance is better than the Binary positioning (2 meter error or less in 80% of the cases, and 2.3 m, respectively). The use of both fused data streams gives a solution that outperforms each individual measurements (1.5 m in 80% of cases).

The detailed estimation for an specific time interval is shown in Fig. 13. Note that the ground-truth used from the smart floor is not as continuous as desired and that the fused version is more continuous so providing a greater location availability.

The good news is that fusing RSS data from BLE beacons with some binary event detection has the potential to estimate with decent accuracy (less than 1.5 meters) the position of a person in different areas of the smartlab, and has the potential

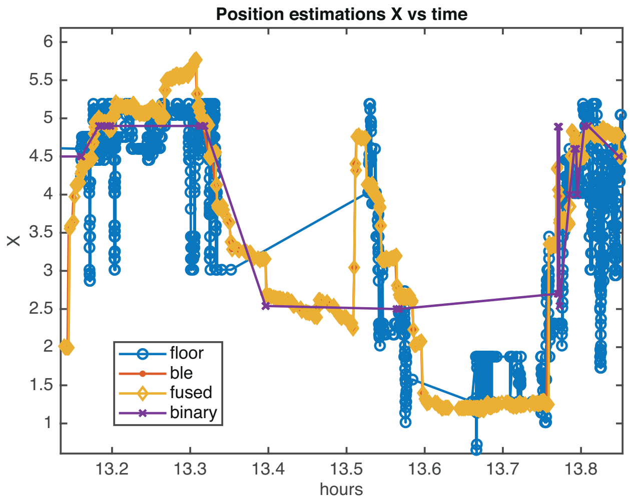


Fig. 13. Position estimation (X coordinate) for different methods.

to distinguish multiple inhabitants living together.

V. Discussion and Future Work

In this work we have localized a single person moving in a smartlab. A more realistic case should be to localize several peoples moving in the same space. The binary event streams or the floor-based information can not directly identify the person, however the RSS data stream from BLE beacons which comes from different smartwatches can give the information needed to correctly locate each person without confusion. This type of multi-user localization will be studied in future works by the authors.

In our datasets we had at our disposal logfiles from smartwatch's accelerometers, but not from gyroscopes or magnetometers. We finally did not use the accelerometer information, since it was not too informative for displacement estimation, being acceleration coupled with hands manipulation in on-place activities. In future works we would like to record all inertial information (3-axis accelerometers, gyroscopes and magnetometers, with an update rate of at least 50 Hz) in order to perform pedestrian dead reckoning (PDR) estimation. In this way we will be able to improve the location information of each user, or even being able to study more parameters about the walking or moving characteristics of the users and probably detect in advance, health issues, such as the beginning of forthcoming mobility impairment.

VI. Conclusions

In this paper we have presented the integration of expertise into two different fields (Indoor positioning and navigation-IPIN and Activity Recognition-AR) by proposing an indoor localization method that makes use of smartfloor information, binary sensors, and the signal strength received at a smartwatch coming from BLE beacons deployed at the UJAmI smartlab. We used the capacitive floor detections as the ground truth in order to estimate the person's location accuracy. The localization results, for a person moving in the smarthouse during 10 days, show accuracies below 1.5 meters in 80% of the cases. These accuracies are not absolute, since the floor used as ground truth also has some errors. Anyway, the proposed BLE+Binary location approach can help the tracking of multiple persons living together and also serve as a complement to improve the performance of location-aware activity recognition algorithms.

Acknowledgment

The authors thank the financial support received from projects: TARSIUS (TIN2015-71564-C4-2-R (MINECO/FEDER)), REPNIN+ (TEC2017-90808-REDT) and Tomoloc (CSIC-PIE Ref.201750E003).

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