Intelligent Environments 2018
I. Chatzigiannakis et al. (Eds.)

doi:10.3233/978-1-61499-874-7-234

Managing Multi-User Smart Environments Through BLE Based System

Daniele SORA [a], Juan Carlos AUGUSTO [b]
[a] *Dipartimento di Ingegneria Informatica, Automatica e Gestionale Antonio Ruberti, Sapienza Università di Roma*
[b] *Research Group on Development of Intelligent Environments, Department of Computer Science, Middlesex University London, London, UK*

Abstract. Smart and intelligent environment systems will be increasingly important in everyday life. Designing and developing them requires to face some research problems. A properly management of different types of sensors is very challenging but necessary in this area. A new wave of smart devices and systems brings customizable benefits for different users. Example of this are smart-phones, smart-bands, smart-watches, smart homes or smart cars. A successful combination of them bring interesting everyday life benefits.

One of the most important problems that needs to be solved in a practical way is the so called "multi-users problem ". Addressing it is fundamental for moving forward into a successful adoption in everyday life of the smart technologies mentioned before. Associating users and services in a spaces in which there are many possible combination of them, is a core task.

This work proposes a novel system based on interactions between Android smart-phones and Bluetooth Low Energy (BLE) technology beacons to deal with the challenges of a multi-user smart environment. We process data collected in a smart environment populated by many users. In particular we associate data collected and beacons. This processing generates database log traces containing measurements related to single user activities, helping in better matching services with users.

Keywords. Iot, BLE Beacon, habit mining, multiuser,intelligent environments

Introduction

Nowadays technological development in fields as information and communication is experiencing a very fast growth. Such high efficiency and performance levels were hardly predictable even few decades ago. This has brought two implications: more powerful tools have been designed, devices optimization allows a significant reduction in their dimensions and costs. This rapidly has allowed a widespread adoption of these micro-systems, involving also original everyday life aspects. This makes some areas of IT evolving as pervasive and ubiquitous. Sensors, actuators, smart appliances are all leading actors in the Internet of Things (IoT) paradigm application. Its deployment and implementation finds most interesting application into common spaces, as homes, offices or industries. They, enriched with sensors and appliances introduced above, can be turned into Smart (or Intelligent) Spaces: the universAAL [1] specification reports the smart space as "an environment centered on its human users in which a set of embedded networked artefacts, both hardware and software, collectively realize the paradigm of ambient intelligence".

This work introduces a novel system based on interactions between Bluetooth Low Energy (BLE) technology tools (BLE Beacons [2]) and smartphones. They are combined for managing data coming from a multiuser environment, allowing us to obtain many single-user traces in a multi-user populated domestic environment. Each trace is related to each user actions. These individualizations of actions support a better association between services and users.

The next sections are structured as follows: after an overview about relevant works, we explain a strategy to extract single-users traces from a multi-users smart environment, reporting also an explicative example. After that, implementation architecture and examples are described as well as the experiments conducted and their results.

Related Works

Intelligent Environments [3] have many appreciable potential benefits, but some problems are still open and need to be faced. Some of these problems are the difference and heterogeneity of sensors types, the amount of data generated by all the IoT devices connected and the presence of many users inside the environment. Particularly this last point is currently bottleneck to apply this paradigm into everyday life spaces. Carrying out contemporary different activities in many parts of the house by many people implies the generation of a dataset hardly exploitable by state of the art techniques designed for smart houses.

Researchers proposed different techniques to address this problem. In many cases the model complexity or the practical effort require makes these solution quite unpractical. In [4] the authors manage multi-user environments using a very dense hardware setting. They assumes users wearing many body sensors, but this has a huge impact under the practical aspect. Another strategy adopted in the past consists in deploying videocamera systems. This solution is adopted for instance in [5]. The limitation of this approach is correlated mainly to privacy issues and to the impossibility of install them in every space. More recent works adopted solutions linked to adding preprocessing logical layers on already existing activity recognition algorithm to improve their performance. For instance Roy in [6] uses spatiotemporal constraints to improve machine learning algorithms. However this is an approach strictly linked to two other specific systems, that does not allow the identification of users preferences. BLE proximity beacons have been exploited to localization purposes also by Faragher[2] and Rida [7]. In his work Palumbo [8] performs indoor smartphone localization exploiting their signals.

Proposed System

In this section an overview and a description of the system is provided. A first important step consists in describing the hypothesis and assumptions considered. Smart spaces techniques can involve a very wide range of different environment typologies. However this work is strictly focused on domestic environments. There are many other applica-

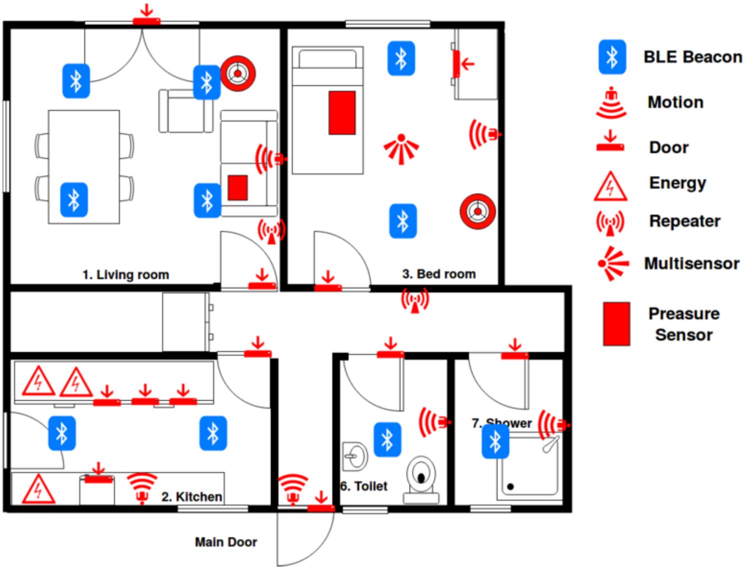


Figure 1. Smart Home Map

tions that can obtain great benefits from intelligent environments paradigm, as for instance, private or public offices, and also this work can be extended to cover these scenarios, but by now our designing proposals, algorithms and test are related to private domestic environments, the so called smart house.

Environment model

Considered scenarios will be always multi-users. In the literature this feature is subject to many conceptions. In this work a space in which many individuals act independently both in different parts of the house and in the same areas is represented through the term "multi-users". The inhabitants (users) set is $H = \{H_1, \ldots, H_P\}$ with $|H| = P \in \mathbb{N}, P > 1$.

The environment model we refers to in this paper is shown in Figure 1. It is the smart home section of the Smart Spaces Lab at Middlesex University in London. It is containing the classical rooms of a common house: living room, bed room, kitchen toilet and shower. Each room is equipped with all the typical appliances and furnitures that can be found in common houses. Moreover each room is enriched with a set of heterogeneous sensors: motion Passive Infra Red based, doors contact, energy monitoring and multisensor device including temperature, humidity level and light intensity. This sensors set can be formalized as: $S = \{S_1 \ldots S_m\}$ with $|S| = m$ total number of installed sensors. Each sensor is associated to a state. We indicate the state of a sensor $S_i, 1 \leq i \leq m$ using the notation $S_i[t]$ where t is a temporal indication. Moreover the set of the possible states is $S_i[t] \in \{0, 1\}$. This means that the state activation is considered as a boolean value (not activated/activated).

The users, acting inside the environment, cause sensors activations records. They are collected by the smart home system, paired with activation time stamp ts and stored into a list, $A = [\langle ts_w, A_w \rangle], w \in \mathbb{N}$. When assigned to a user H_i, they are going to compose data traces $T_{H_i} = \{A_1^{H_i}, A_2^{H_i}, \ldots, A_{L_{T_{H_i}}}^{H_i}\}$ with $|T_{H_i}| = L_{T_{H_i}} \in \mathbb{N}, 1 \leq i \leq P$. Notice that $L_{T_{H_i}}$ is different for each user, since it depends on the user's activities. Hence, since multi-users assumptions, more than one trace will be produced. The set of data traces will be $T = \{T_{H_1}, T_{H_2}, \ldots, T_{H_P}\}$ with $|T| = P, P \in \mathbb{N}$. This last formula implies $|T| = |H|$, so, we are imposing a trace for each user. This is not automatically obtained just recording activation data, but it is the final goal of this work. By now the dataset produced by this kind of environment would be a confused interleaving of different $T_{H_i}, 1 \leq i \leq P$, without the possibility of reconstructing the different traces.

The reader can notice that the figure shows another sensor type not included in the list. Bluetooth Low Energy (BLE) beacons, especially in this work, are modeled as particular sensors. In fact they do not produce directly a record, but their presence is exploited to create distinguished traces assigning properly each record. Due to these characteristic, it is opportune defining differently the beacon set B as $B = \{B_1, \ldots B_n\}$ with B finite set and $|B| = n$ number of beacons in the system. When a user H_i enters into a proximity beacon domain B_{id}, the system creates an association between H_i and B_{id}. An association is expressed as a coupled value $\langle ts, B_{id} \rangle$ where ts the time stamp indicating when the association happens and B_{id} is the beacon involved. For each user, the multi user management system generates an association list $\Lambda^{H_i} = [\langle ts, B_{id} \rangle, \ldots], 1 \leq id \leq n$ and ts is a progressive number. The set of all the association lists is $\Lambda = \Lambda^{H_i}$ *for each* $i : 1 \leq i \leq P$

It is interesting to point out how they are distributed into the environment. In fact, differently from the sensors S_i, deployed in according to their utility (i.e. pressure sensors on chairs and bed, energy consumption meter on outlets and so on), the beacons are equally distributed into the rooms. The amount of installed beacon, is the minimum necessary to cover each room. In this work we assume they are uniformly distributed in space, so each of them covers comparable areas. In other words, the house surface is divided into domains $D = \{D_{B_1}, \ldots, D_{B_n}\} = \{D_1, \ldots D_n\}, |D| = n$. Each corresponds to a beacon. Vice versa each beacon has his own domain: it can be indicated $B_i \leftrightarrow D_i$ with $1 \leq i \leq n$.

Since the domains represents in practical terms spatial disjoint areas, the sensors can be associated to one and only one domain $D_i, 1 \leq i \leq n$. So the sensor set S can be subdivided into subsets $S = S^{D_1} \cup S^{D_2} \cup \ldots \cup S^{D_n}$ s.t. $S^i \cap S^j = \emptyset, 1 \leq i \leq R, 1 \leq j \leq R, i \neq j$.

However there are some cases in which the sensor, due to their technical functionality, cover more than just one domain. As example think about PIR sensors: they usually are utilized to cover whole rooms, in the example shown in Figure 1 they would be detected in more than one domain in rooms 1, 2 and 3. To model this eventuality the notation used is the following: if the activation area of a sensor S_k covers a set of domains $\delta_{S_k} = \{\delta_1 \ldots \delta_f\} \subseteq D, f \in \mathbb{N}, f \leq n$, the projection of S_k on δ_{S_k} is defined as $\pi = S_k^{\delta_1}, \ldots, S_k^{\delta_f}, |\pi| = f$. The state of a sensor S_k is computed using the formula

$$S_k[t] = S_k^{\delta_1}[t] || \ldots || S_k^{\delta_f}[t] \tag{1}$$

In other words, this is the boolean operation OR, it means that to activate S_k it is enough to activate one of its projections.

Assumptions

The definitions introduced above, describe the model used to represent the environment. Since we want to provide a matching between each activation A and the user that caused it with his activity, we need to consider space inhabitants as sensor provided. But adding very complex devices to people strongly limits the user experience system level. For this reason in this work we make the following hypothesis:

- to each user in H correspond one and only one smart-phone device registered on the system capable to communicate with beacons through low energy bluetooth signals
- users bring the smart-phone always with themselves while performing activities into the home

These hypothesis are very reasonable since the smart-phone is an increasingly common device in our everyday life. They have a crucial role in the system: they scan the area near them checking if there is any beacon nearby. If there is one, it communicates this information to a server that stores the data. If there is more than one beacon, the smart-phone chooses the nearest one. The information exchange is performed only when the nearest beacon is different from the last sent.

The beacon proximity is computed evaluating RSSI (Receive Signal Strength indicator) of the beacons BLE [7]. Periodically each smartphone H_i scans BLE devices and detects the nearest one choosing maximum RSSI. It is the most reasonable measure indicating the distance between a signal sender and a signal receiver, since it indicates the strength or the received signal. It is particularly significant if the beacons domain is homogeneous, all have the same specifications and the same transmission power. When the nearest beacon changes, H_i sends information to the system. They are stored into Λ^{H_i}.

Traces extraction algorithm

The elements described by now can provide all the ingredients necessary to compute single user activations traces. What we know is the evolution of the beacons associations of each user and the global activations dataset. The methodology for merging the data is described in the Algorithm 1.

Summarizing, the algorithm assigns to a given user all the sensor activations that happens into the domain of the beacon associated to him/her at that time. The algorithm can partially assign to different traces T^{H_i} and T^{H_j} the same activations, and this potentially can generate traces suffering of some kind of noise. This can happen when:

- it is dealing with cross-domain sensors
- two (or more) different users are performing actions very nearly and they are associated to the same beacon.

In the first case it occurs due to cross-domain sensors peculiarity: the activation of the sensor in a domain, implies the activation of all the projection sensors into the other domain interested by the sensor.

The second point, instead is given by the system design. It is probable that if two users are very near each other, they are performing or the same activity together or two activities in the same area. So having the activations duplicated into their traces does not add noise but instead improves their quality.

Algorithm 1 Algorithm devised for single user activations traces extraction from multi-user data log and beacon association set

Input: H users set
Input: Λ set of association lists
Input: A activations list
Output: T single user traces set
for all $H_i \in H$ **do**
  $\Lambda^{H_i} \leftarrow \Lambda.get(H_i)$
  $\alpha \leftarrow \Lambda^{H_i}[0], \alpha = \langle ts, B_{id} \rangle$
  for all j s.t. $1 \leq j < |\Lambda^{H_i}|$ **do**
    $\beta \leftarrow \Lambda^{H_i}[j]$
    $\delta \leftarrow \alpha.B_{id}$
    for all $A_w \in A$ s.t. $\alpha.ts \leq A_w.ts < \beta.ts$ **do**
      if $A_w.sensor \in S^{D_\delta}$ **then**
        $T_{H_i}.add(A_w)$
      end if
    end for
    $\alpha \leftarrow \beta$
  end for
  $T.add(T^{H_i})$
end for

Example

To explain how the algorithm works, we can refer to a scenario example. The Table 1 contains a graphical representation of the system state during the action execution for two different users $H = \{H_1, H_2\}$. The left table contains data related to H_1, the right one to H_2. Each table contain the sensor activations and the beacon associations grouped by beacon domains. The notation for the sensor activation is S_{ij} and indicates the activation of the j-th sensor of the i-th domain. In case of cross-domain sensors, $S_{ij}^{\delta_i}$ indicates the projection of the same sensor in different domains. The columns labeled with $t_1 \dots t_\infty$ represent the state evolution in time. If there is an activation (or a beacon association) from domain D_i of the sensor S_{ij} in time t_k, then the corresponding cell has 1, empty cell means 0 (no activation).

To project the example to the map in Figure 1, we can consider B_1 the beacon in the north-east of the living room and B_3 the south-east one. The sensors $S_{13}^{\delta_1}$ and $S_{33}^{\delta_3}$ are projections of the PIR sensor S_{1333} (it influences both the domains). Notice that S_1333 is not reported into the table, since its value can be inferred using Formula 1. The As indicated in the table S_{11} is the window sensor, S_{12} is the lamp sensor, S_{31} is the door sensor and S_{32} is the sofa sensor.

The behavior of H_1 is: t_1 open windows, t_2 and t_3 turn off the lamp, t_4 open the door, t_5 close the door.

The behavior of H_2 is: t_1 and t_2 enter room and stay on the sofa, t_3 close the window, t_4 turn on the light and t_5 stay on the sofa.

The PIR sensor value $S_{1333}[t] = S_{13}^{\delta_1}[t] || S_{33}^{\delta_3}[t], \textit{for each } t : t_1 \leq t \leq t_5$

Table 1. Tabular representation of activities progress combining Beacon Domain Areas, Beacon and Sensors for two different users. For facilitating interpretation W = window, L = lamp, D = door, S = sofa

Domain Area	Sensor	t_1	t_2	t_3	t_4	t_5
D_1	B_1	1	1	1		
	S_{11} (W)	1				
	S_{12} (L)		1	1		
	$S_{13}^{\delta_1}$(PIR)	1	1	1		
D_2	B_2					
	S_{21}					
	S_{22}					
D_3	B_3				1	1
	S_{31}(D)					1
	S_{32}(S)					
	$S_{33}^{\delta_3}$(PIR)				1	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮
D_n	B_n					
	S_{n1}					
	S_{nm}					

Domain Area	Sensor	t_1	t_2	t_3	t_4	t_5
D_1	B_1			1	1	
	S_{11}(W)			1		
	S_{12}(L)				1	
	$S_{13}^{\delta_1}$(PIR)			1	1	
D_2	B_2					
	S_{21}					
	S_{22}					
D_3	B_3	1	1			1
	S_{31} (D)					
	S_{32} (S)	1	1			1
	$S_{33}^{\delta_3}$(PIR)	1	1			1
⋮	⋮	⋮	⋮	⋮	⋮	⋮
D_n	B_n					
	S_{n1}					
	S_{nm}					

The list A produced would be: $A = [\ \langle t_1 : S_{11}\rangle, \langle t_1 : S_{1333}\rangle, \langle t_1 : S_{32}\rangle,\ \langle t_2 : S_{1333}\rangle\ \langle t_2 : S_{12}\rangle,\ \langle t_2 : S_{32}\rangle,\ \langle t_3 : S_{1333}\rangle,\ \langle t_3 : S_{12}\rangle,\ \langle t_3 : S_{11}\rangle,\ \langle t_4 : S_{1333}\rangle, \langle t_4 : S_{31}\rangle,\ \langle t_4 : S_{11}\rangle,\ \langle t_5 : S_{1333}\rangle,\ \langle t_5 : S_{31}\rangle,\ \langle t_5 : S_{32}\rangle\ ]$, representing a portion of sensor database log.

Moreover the multi-users management system would produce also two beacons association lists: $\Lambda^{H_1} = [\langle t_1, B_1\rangle, \langle t_4, B_3\rangle]$ and $\Lambda^{H_2} = [\langle t_1, B_3\rangle, \langle t_3, B_1\rangle, \langle t_5, B_3\rangle]$. Applying Algorithm 1 to H, A and Λ, the result set $T = \{T_{H_1}, T_{H_2}\}$ will be:

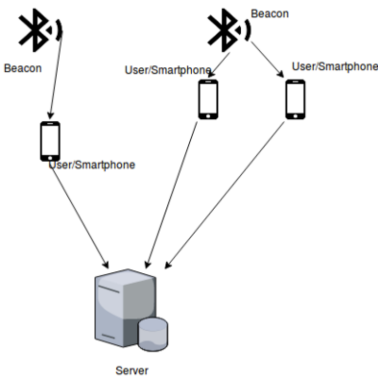
- $T_{H_1} = \{\ \langle t_1 : S_{11}\rangle, \langle t_1 : S_{1333}\rangle,\ \langle t_2 : S_{1333}\rangle\ \langle t_2 : S_{12}\rangle,\ \langle t_3 : S_{1333}\rangle,\ \langle t_3 : S_{12}\rangle,\ \langle t_3 : S_{11}\rangle,\ \langle t_4 : S_{1333}\rangle,\ \langle t_5 : S_{1333}\rangle, \langle t_4 : S_{31}\rangle,\ \langle t_5 : S_{31}\rangle,\ \langle t_1 : S_{32}\rangle\ \}$
- $T_{H_2} = \{\ \langle t_1 : S_{1333}\rangle, \langle t_1 : S_{32}\rangle,\ \langle t_2 : S_{1333}\rangle,\ \langle t_2 : S_{32}\rangle,\ \langle t_3 : S_{1333}\rangle,\ \langle t_3 : S_{12}\rangle,\ \langle t_3 : S_{11}\rangle,\ \langle t_4 : S_{1333}\rangle,\ \langle t_4 : S_{32}\rangle,\ \langle t_5 : S_{1333}\rangle,\ \langle t_5 : S_{31}\rangle,\ \langle t_1 : S_{11}\rangle\ \}$

Implementation and experiments

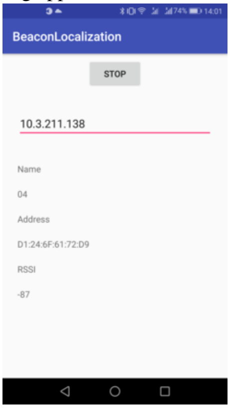
The system described in the previous section has been implemented into the smart house model illustrated in Figure 1. The Figure 2a shows the beacons subsystem architecture. All the devices catch the BLE signals and communicate to the server where the strongest one came from. A screnshot of the application performing that is shown in Figure 2b. The top IP field contains the address of the server, "Name" field is the beacon number of the nearest beacon while the "Address" field contains its the MAC address. "RSSI" shows the value of the RSSI signal computed for the nearest beacon.

The BLE beacons have a different behavior respect to the other sensors: indeed while the former have a simpler structure and just emit a signal indicating their presence, the latter after sensing the environment send actively the information to a central server. Due to this different characteristics, beacons are managed by another subsystem. Its structure is illustrated in Figure 2a. The beacons are installed in each room uniformly distributed accordingly to the surface they need to cover. They just send their signals, that are caught

Figure 2. Beacons system architecture and running application screenshot



(a) Beacons subsystem structure architecture



(b) Running beacons application screenshot.

by the smartphones. They run a custom application developed to understand which is the nearest beacon. Each time the nearest beacon is identified, the information is sent to the server. The beacons utilized in this work are very simple. They are fully standalone Bluetooth Smart proximity beacon using iBeacon and AltBeacon technology. Their consumptions are very low, they can last until 9 months with their most energy consumption configuration (high advertising rate).

As explained before, each smartphone represents a users. In our experiments the smartphones utilized are all Android smartphones. The application developed can run on Android version ≥ 5.0 because they are BLE optimized. Three devices have been tested, a Samsung Galaxy S4, Android version 5.0, a Nexus 7 tablet, Android version 6.0 and a Honor 8, Android version 7.0.

The server collect the smartphones measurements and stores the beacon history into different files. To distinguish the smartphones it considers their IP address as unique key. This works only for static address configuration. In fact if the goal is to store user data to utilize them along different sessions and analyze his behavior, a dynamic IP addresses configuration is not good because there is no warranty about the IP assignment in two different sessions.

To evaluate the results, the following procedure has been followed: first two experimenters perform activities into the smart house illustrated in Figure 1. Manually analyzing the log, a ground truth trace for each user is computed. Than the Algorithm 1 is applied and the results for each user are compared with the ground truth. The metric to evaluate them is the Jaccard similarity index between the traces obtained and the correspondent ground truth. Given $\bar{T}^{H_i}$ the ground truth trace, the Jaccard similarity is computed $J_{H_i} = \frac{\bar{T}^{H_i} \cap T^{H_i}}{T^{H_i} \cup T^{H_i}}$.

Two are the scenarios tested:

- two users H_1, H_2 perform activities at the same time in different parts of the house. The first user keeps tidy the living room, then he moves in the kitchen and there he prepares a tea. The second user moves from the kitchen to the bedroom and there he makes the bed. Both users never act in the same room at the same time.

Table 2. Experimental results, Jaccard similarity value between the ground truth traces and the computed traces.

	H_1	H_2
Scenario 1	87.4%	86.6%
Scenario 2	77.1%	75.5%

- two users H_1, H_2 perform activities at the same time. They are partially performed also in the same room. H_1 prepares a tea in the kitchen. In the meanwhile H_2 enters in the kitchen to wash hands, then move quickly to living room and then sits on the bed in the bedroom.

The results obtained in the experiments is shown in Table 2.

Conclusions and future works

The goal of this work is to provide a feasible solution to the multi-users intelligent environments problem. The main idea is to be able to distinguish between different users, for building the data traces of the sensor activations correlated to their activities. Naturally, the optimal result would be to obtain a log related to a given user containing only the correct measurements.

This paper describes a first implementation of the proposed system: its effectiveness and precision depend on a lot of factors, that can have an impact more or less important. Most of them are related to beacons. They impacts mainly for three factors:

- **Technology:** the proximity BLE technology is evolving. There exists new protocols and formats, for instance Eddystone. They can provide more data and metadata useful for improving precision.
- **Installation:** the beacons position is very important, since if the beacons are too far each other, some sensors could be uncovered and the granularity could be too coarse. On the contrary if they are too near each other, the coverage areas are going to overlap and it becomes difficult for the smartphone (but also for an human) to understand which is the nearest proximity beacon. In our experiments, the minimum distance between two beacons in the same room is $1,5$ meters. The maximum is strongly dependent by sensors installation density, in our scenario is $3,5$ meters.
- **Exploitation:** by now the nearest beacon information is mined just looking at the maximum RSSI value given by all the reached beacons. So each beacon is analyzed independently from the others. Other more complex algorithms that involves triangulation techniques between many beacons can bring more precision in localizing the users and, consequently, in separating the user traces.

The technological limits are the main responsible of the errors occurred: the recognizing of beacon change can be slower of the sensor triggering. In that case the measurement correlated can be lost (decreasing the precision). The simple RSSI measurement can also bring a wrong nearest computation for short time, causing measurements losses or wrong associations. Moreover there could be interferences from beacons installed in neighbour rooms: this is a rare event since the BLE signal is quite weak and walls and obstacles make it also weaker, so interferences in other rooms from farer beacons are not probable. However if they could happen, the effects on the performances are similar to the ones described above.

For readability and brevity, we just presented a scenario example. However the possible inhabitant activities combinations are very variegated. There could be actions in which activities involve completely different sensors or other in which all the users act in a very small area. In the latter case, probably users are associated to the same beacon, implying overlapped traces.

Next steps will involve in exploiting the traces obtained with this technique. They can be useful in many applications as for instance providing a clean database for training and testing other state of the art activity recognition or habit mining techniques. It would be interesting also to check the dirty measurements impact in applying these techniques, comparing the results between a single user database application and multi user multi traces obtained with this technique.

References

[1] Mohammad-Reza Tazari, Francesco Furfari, Álvaro Fides-Valero, Sten Hanke, Oliver Höftberger, Dionisis Kehagias, Miran Mosmondor, Reiner Wichert, and Peter Wolf. The universAAL reference model for AAL. *Handbook of Ambient Assisted Living*, 11:610–625, 2012.

[2] R. Faragher and R. Harle. Location fingerprinting with bluetooth low energy beacons. *IEEE Journal on Selected Areas in Communications*, 33(11):2418–2428, Nov 2015. ISSN 0733-8716. doi: 10.1109/JSAC.2015.2430281.

[3] Juan C. Augusto, Vic Callaghan, Diane Cook, Achilles Kameas, and Ichiro Satoh. "intelligent environments: a manifesto". *Human-centric Computing and Information Sciences*, 3(1), 2013. doi: 10.1186/2192-1962-3-12.

[4] Liang Wang, Tao Gu, Xianping Tao, Hanhua Chen, and Jian Lu. Recognizing multi-user activities using wearable sensors in a smart home. *Pervasive and Mobile Computing*, 7(3):287–298, 2011.

[5] Juyeon Lee, Jonghwa Choi, Dongkyoo Shin, and Dongil Shin. Multi-user human tracking agent for the smart home. In Zhong-Zhi Shi and Ramakoti Sadananda, editors, *Agent Computing and Multi-Agent Systems*, pages 502–507, Berlin, Heidelberg, 2006. Springer Berlin Heidelberg.

[6] Nirmalya Roy, Archan Misra, and Diane Cook. Ambient and smartphone sensor assisted adl recognition in multi-inhabitant smart environments. *Journal of Ambient Intelligence and Humanized Computing*, 7(1):1–19, Feb 2016. ISSN 1868-5145. doi: 10.1007/s12652-015-0294-7. URL `https://doi.org/10.1007/s12652-015-0294-7`.

[7] M. E. Rida, F. Liu, Y. Jadi, A. A. A. Algawhari, and A. Askourih. Indoor location position based on bluetooth signal strength. In *2015 2nd International Conference on Information Science and Control Engineering*, pages 769–773, April 2015. doi: 10.1109/ICISCE.2015.177.

[8] F. Palumbo, P. Barsocchi, S. Chessa, and J. C. Augusto. A stigmergic approach to indoor localization using bluetooth low energy beacons. In *2015 12th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, pages 1–6, Aug 2015. doi: 10.1109/AVSS.2015.7301734.