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UJA Human Activity Recognition multi-occupancy dataset

Emiro De-la-Hoz-Franco
Universidad de la Costa – CUC
edelahoz@cuc.edu.co

Edna Rocio Bernal Monroy
Universidad Nacional Abierta y a Distancia - UNAD
edna.bernal@unad.edu.co

Paola Ariza-Colpas
Universidad de la Costa – CUC
pariza1@cuc.edu.co

Fabio Mendoza-Palechor
Universidad de la Costa – CU
fmendoza1@cuc.edu.co

Macarena Espinilla Estévez
Universidad de Jaén
mestevez@ujaen.es

Abstract

Activity Recognition Systems - ARS are proposed to improve the quality of human life. An ARS uses predictive models to identify the activities that individuals are performing in different environments. Under data-driven approaches, these models are trained and tested in experimental environments from datasets that contain data collected from heterogeneous information sources. When several people interact (multi-occupation) in the environment from which data are collected, identifying the activities performed by each individual in a time window is not a trivial task. In addition, there is a lack of datasets generated from different data sources, which allow systems to be evaluated both from an individual and collective perspective. This paper presents the SaMO – UJA dataset, which contains Single and Multi-Occupancy activities collected in the UJAmI (University of Jaén Ambient Intelligence, Spain) Smart Lab. The main contribution of this work is the presentation of a dataset that includes a new generation of sensors as a source of information (acceleration of the inhabitant, intelligent floor for location, proximity and binary-sensors) to provide an excellent tool for addressing multi-occupancy in smart environments.

1. Introduction.

A very high percentage of people use the Home Help Service (HHS) in Spain, they are elderly people who present a state of frailty or have a significant risk of suffering it in the future. HHS is based on the approach of keeping older people in their usual environment for as long as possible, covering those needs that may arise from situations of dependency. The HHS offers personal help and a series of services at home to people who have a certain level of dependency or who suffer a personal or family crisis. With this service it is intended that this person has an adequate degree of independence or autonomy in carrying out activities of daily life. And although it is not an exclusive service for the elderly, around 90% of the users of it are.

The basic objective of HHS is to increase personal autonomy in the usual way of life, it aims to develop to the maximum the possibilities of the elderly person to continue controlling their own life, even if it is someone who is dependent for certain activities of daily life. It is a service that is practically implemented in all municipalities, which is well known and highly valued by users and their families, and has proven its usefulness in guaranteeing the quality of life of the elderly.

In this proposal we set ourselves the objective of deepening the knowledge of the recognition Activities of Daily Life (ADL) and Recognition of Human Activities (HAR) as a solution that can help the monitoring of daily activities at home as a support to improve the quality of life of the elderly people.

The recognition ADL or HAR in assisted living indoor environments is an important basic service that requires the attention of researchers. From this line of research, different functional applications can be found that improve elderly people's quality of life. Therefore, as a baseline of research that supports future applied developments, it is necessary to recognize ADL in indoor environments.

The scenario becomes much more complex when in such environments several inhabitants interact simultaneously (multi-resident or multi-occupancy environments). Now adays, there are very few multi-

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occupancy datasets and even fewer generated from heterogeneous data sources. It is evident that merging heterogeneous data sources to obtain data sets is a complex task due to the heterogeneity and complexity of the data to be integrated [1,2]. Additionally, after a thorough review of the state of the art, the existence of a dataset that labels activities on two levels of granularity (detailed and general) has not been evidenced. The SaMO - UJA dataset; proposed in this study, presents a solution to these two situations: the integration of heterogeneous data and labelling of data instances on two levels of granularity.

The presented datasets will be a key tool to assess the performance of activity recognition approaches in an experimental context and build and apply models that facilitate HAR in real scenarios, seeking to improve people's quality of life. Such models are classified into Data-Driven Approaches (DDA) and Knowledge-Driven Approaches (KDA). Learning techniques are in the context of DDA. These approaches use a dataset with sensor data streams generated in a smart environment [3,37,39, 40]. Expert knowledge are in the context of KDA [4,35,36, 38]. These approaches use domain knowledge, ontologies or rule-based models to perform activity recognition.

A systematic review of literature on sensor-based datasets was presented in [5]. Seven datasets were identified as the most widely used in the recognition of ADL: VanKasteren [6], CASAS Kyoto [7], CASAS Aruba [8], CASAS Multi-resident [9], UCI-HAR [10], Opportunity [11] and mHealth [12]. From these, only CASAS Aruba and CASAS Multi-resident are multi-occupancy and the Opportunity dataset is interleaved. In [5], a detailed compilation and analysis of the research based on the seven aforementioned datasets was presented, indicating for each of them: segmentation techniques, feature representation, classification, feature selection and quality metrics evaluated.

In this work, we present a multi-occupancy dataset called SaMO - UJA, which was collected in the UJAmI Smart Lab [34]. This dataset includes a new generation of sensors with heterogeneous data sources to provide a new point of view on the multi-occupancy problem. Concretely, we have included four information sources (binary sensors in some objects in the space, proximity between the inhabitant and the Bluetooth Low Energy (BLE) beacons in the space, acceleration of the inhabitant with the wearable device and intelligent floor for location) collected using different sensor technologies. The SaMO - UJA dataset is integrated by a Single-occupancy dataset, with data over 10 days, and a Multi-occupancy dataset, with data over 9 days, in total integrating 19 days of data collected in three sessions per day (morning, afternoon and night). The SaMO - UJA dataset contains 25 different types of activities grouped into 7 categories. There is a total of 620 activities (451 multi-occupancy and 169 single-occupancy).

This paper is organized into five sections: section 2 contains related works, section 3 outlines the proposed methodology, section 4 describes the process of data preparation, Section 5 contains conclusions and future works. Finally, the acknowledgments and references are presented.

2. Related research.

In the work [13], International Conference on Ubiquitous Computing and Ambient Intelligence UCAmI Cup is presented as a single-inhabitant dataset for researchers to analyze HAR using different machine learning methods and comparing their results with others colleagues. In the 1st UCAmI Cup, 26 authors from ten countries obtained the dataset.

This dataset integrated multiple activities of a single inhabitant in a smart lab at the University of Jaén (Spain) with a heterogeneous set of devices with sensors. The most relevant proposals were based on the techniques: bagging classifier [14], finite state machine [15], filtered classifier [16], finite automata and regular expressions [17], naive Bayes classifier [18] and hidden Markov model + definition-based model [19].

In [14], the dataset was processed using six classification methods (Decision Tree (C4.5), 1 Nearest-Neighbor (1-NN), Support Vector Machine SVM, random forest, AdaBoostM1 and bagging), developing the Cross Industry Standard Process for Data Mining methodology. In this experimentation, the accuracy in the recognition of the 24 activities was 92.10% with an evaluation model based on 10-fold cross validation. However, an accuracy of 60.10% was achieved on the test dataset.

A finite state machine is proposed in [15], carrying out activity recognition by means of binary sensor data. The presented model obtained a precision of 81.30%. To do so, a small subset of operations was used, providing an appropriate approach to the resource-constrained devices that are common in intelligent environments.

A method based on fusion was presented in [16], fusion is presented both at the feature level and at the decision level for heterogeneous sensors by pre-processing and predicting activities in the context of training and test data sets using filtered classifiers. The proposed fusion method obtained 94.00% precision for training dataset and 47.00% accuracy for test dataset.

In [17] was presented a method based on the user's behavioral models and activity sensor models in order to build weighted finite automata with regular expressions. So, the location of the inhabitant was obtained for each activity by means of the floor sensor data. This proposal achieved 90.65% precision in the test dataset.

A multi-event naive Bayes method was proposed in [18] for recognizing activities in real time. 24 types of activities were classified and the results obtained show a performance of true positives around 68.00%.

A hybrid method was presented in [19] that mixes a probabilistic model and a definition-based model. The probabilistic model is based on Hidden Markov Model with a neural network. The results obtained were not very promising as they reached an accuracy of 45.05%.

In our study, we present a new multi-occupation dataset that have been carried out in the UJAmI Smart Lab of the University of Jaén where a heterogeneous set of sensors collect environmental information.

This new dataset complements the initial dataset presented in [13] with new instances of activities that are carried out simultaneously by two inhabitants at the same time. We shall refer to this integrated dataset as the "Single and Multi-Occupation dataset", which we will call SaMO - UJA. Currently the identification of ADL in multi-resident indoor environments (also called multi-occupancy) has not been widely studied. The best-known multi-resident datasets are those that have been generated from the CASAS project [7] (Aruba [8], Cairo [20], Twor [20], Tulum [20] and ADL multi-resident [9]) and the ARAS dataset [21]. The ARAS dataset implies two datasets generated in two apartments, recording data over 1 month for two inhabitants.

Different studies are described below in which the multi-resident dataset of the CASAS family and the ARAS dataset have been evaluated, using several techniques for activity recognition. For example, a classifier based on Red Green Blue (RGB) activity image by using a Deep Convolutional Neural Network [22], Probabilistic Support Vector Machine [23], a method focused on dynamic Bayesian networks [24] and Random Forest [2, 25]. In addition, in [26-27] a complementary study is presented, which proposes the annotation of multi-resident datasets using the Long Short Term Memory method.

A very relevant issue in the recognition of activities is the unobtrusive and non-invasiveness of the devices in the smart environment [22]. For this reason, the authors proposed the use of RGB activity image by using the Cairo open dataset offered by the CASAS Project. Cairo was generated while two inhabitants with a pet were living for 55 days in a smart home. The results were very promising due to the fact that they reached up to 95.2% accuracy. This required pre-processing of the data, segmentation of activities and multi-conversion of images.

A method based on windows was presented in [23] to classify human activities for multiples inhabitant in smart environments. To do so, the presented methods are focused on the study of sensor data stream in order to detect the sensors most relevant to each specific window. Multiple spatial-temporal statistical features were processed to classify human activities. The data set used to test the presented method was the CASAS dataset (Aruba and Twor) as well as an artificial dataset by using the High-Bandwidth Motion Simulator (HBMS) simulator. A comparative study was conducted using multiple classifiers (SVM, Naive Bayes, logistic regression and Recurrent Neural Network (RNN)), the best accuracy was 92.0% with the P-SVM classifier with the HBMS dataset

A rule-based method to identify complex activity was proposed in [2] in a multi-inhabitant context in smart environments. The proposed method was based on a multi-label classification technique, using as base classifier an extension of the random forest method that generated the Enhanced Label Combination method. This proposal was tested by using the ADL Multi-resident dataset from CASAS of Washington State University (WSU) [20]. The main advantage of this proposal is its capability to address conflicts in the complex activity recognition in multi-inhabitant contexts with parallel as well as cooperative activities. The accuracy obtained reached up to 70.3% in the dataset used. Furthermore, a multi-label classifier was proposed to recognize the actions and monitoring the inhabitant in a multi-occupancy context [1] in the same dataset, obtaining 71.7% accuracy.

A method based on the approaches of multi-task learning and zero-shot learning was proposed in [28] to address the multi-occupancy context in smart environments. To do this, this method considers each activity of each inhabitant as a learning action, and learns all actions.

Multiple methods were proposed and compared in [21] with the ARAS datasets: Respective method for each inhabitant, the Cartesian product and average prototype method, Cartesian product and concatenation prototype model and, finally, multi-inhabitant with Unseen-Activity-Class recognition method with class tags, the highest accuracy obtained was 64.27% when applying this last method.

Dynamic Bayesian networks was proposed in [24] by using an extension of the Coupled Hidden Markov Models. To do so, vertices are added to the model to include single activities as well as multi-occupancy activities. The proposed method was tested using the multi-inhabitant dataset CASAS [7], identifying sensor events with associations as well as expert knowledge to recognize multiple-resident activities.

A comparative study is conducted in [25] with multi-inhabitant activity datasets: ARAS dataset (HouseA and HouseB) [21], Tulum2 dataset and Cairo dataset. The best method was the tree ensemble with random forests by means of multi-label learning. The methods compared in [23] were evaluated using the following four metrics: F-macro, F-micro, hamming loss and subset loss.

The multi-occupancy Aruba dataset was used [26-27] to propose a Long Short Term Memory model in order to perform annotations and identify characteristics. The authors proposed the use of multiple classical methods: logistic regression, SVM, multinomial naive Bayes and, finally, Gaussian naive Bayes to classify the activities in the new generated dataset. The accuracy achieved was 79.5%.

On the other hand, an example of feature extraction can be by sliding windows [28] is very agile (2.5 s). This has been shown to be suitable for evaluating inertia activity data and the delay in the response to estimating the classification is negligible. The set of features extracted from the inertial sensors included maximum and minimum values, averages and standard deviation, which had proven to be efficient and suitable to describe inertial sensors in Activity Recognition (AR) and allow the identification and recognition of actions or objectives of the inhabitant.

Most of these studies present datasets, some annotated others not, collected from binary sensors and proximity sensors. In our proposal, we present and evaluate an annotated dataset containing ADL collected in a multi-resident environment from four data sources (binary sensors in some objects in the space, proximity between the inhabitant and the BLE beacons in the space, acceleration of the inhabitant with the wearable device and intelligent floor for location). This paper introduces a novel dataset analysis that includes a new generation of sensors as a source of information call SaMO. Some of the advantages that can be highlighted with respect to our work are:

• The proposal includes the use of sensors together with the definition of a wide range of HAR in multiple occupancy conditions.

• Uses different technologies and sources of information,

• It integrates 30 sensors, 15 BLE beacons, wearable devices and Smart Lab Floor with 40 models which generate heterogeneous data.

• Two levels of class labeling are defined for the recognition of activities, which allowed the identification of 25 types of activities grouped into 7 categories.

According to the revised literature, none of them generate datasets from four data sources, in addition, most of them use binary sensors, accelerometer and gyroscope, none of them contain an intelligent floor for the location.

3. Methodology.

In this proposal, single and multi-occupation activities (SaMO – UJA dataset) are integrated in the labeled dataset by means of heterogeneous data sources generated in the UJAmI Smart Lab of the University of Jaén [34]. Four data sources make up the sensor information:

1) Sensor data stream generated by 30 binary sensors that were located, categorized into three sensor types: wireless magnetic sensor that works with the Z-Wave protocol (detecting opening and closing of doors, and use of TV remote control, medicine box or bottle of water); wireless PIR motion sensor that works with the ZigBee protocol (detecting whether an inhabitant has moved inside or outside a range of 7 meters from the sensor with a sample rate of 5 seconds) and wireless pressure sensor that works with the Z-Wave protocol (detecting pressure when the inhabitants use the sofa, chairs or bed).
2) Location information generated by a set of 15 BLE beacons [29] as well as a wearable device worn by inhabitants. The BLE beacons model sticker was estimated [30] for proximity with a sample frequency of 0.25 Hz. The wearable device reads the Received Signal Strength Indicator (RSSI) from several BLE beacons, to identify the proximity between the inhabitant and, for example, a beacon located on the toothbrush or the medicine box.
3) Acceleration data generated from the same wearable device. The acceleration of the inhabitant data collected through an Android application installed on the wearable device [31] of the inhabitant with a sample frequency of 50 Hz (acceleration data of the inhabitant collected in three axes expressed by meter per second squared).
4) Location data generated by the smart lab floor with 40 modules that provides location data. SensFloor® [32] that consists of a suite of capacitive sensors (formed by 40 modules that are distributed into a matrix with 4 rows and 10 columns, each module composed of eight sensor fields).

Of the seven datasets mentioned above and detailed in [5], as the most widely used in the recognition of ADL, none are generated from four data sources. Most of them are generated from binary sensors, accelerometers and gyroscope. None contains an intelligent floor for location and although some of them mention the use of motion sensors [7-9], there is no evidence that they are BLE beacons. Our work features the use of these sensors together with the definition of a wide range of HAR under multi-occupancy conditions.

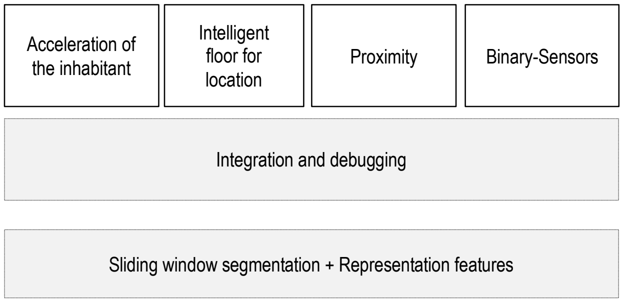

Figure 1. Applied methodology.

As indicated in Figure 1, the data were collected and debugged, reducing the time in which no relevant activities were carried out. For feature representation, a sliding window with a fixed size of 30 seconds was established. The resulting dataset was randomly distributed into two datasets: one for training, with 70% of the data instances and another for testing with 30%. In order to reduce the amount of data, different feature selection techniques were applied within each dataset.

4. Data preparation.

Single and multi-occupation datasets were collected in the UJAmI SmartLab, the dataset is publicly available in https://cutt.ly/qf5MuZw and contain data from four sources (acceleration of the inhabitant, intelligent floor for location, proximity and binary-sensors). The single-occupation dataset [13] contains 246 activity instances collected over 10 days. The dataset was divided into two sets: training and test. The subset used for training contains 169 instances recorded over seven days and the subset used for testing contains 77 instances recorded over three days. The multi-occupation dataset contains 451 activity instances collected over 9 days. Just like in the single-occupation dataset, data was collected for each day in the morning, afternoon and evening sessions. Table 1 contains a count of activities of the multi-occupation dataset and the single-occupation datasets by activity type.

Table 1. Integration of single/ multi-occupation dataset activities – Training set (7 days)

Activity	Multi-occupation	Single	Total
Shower	91	6	97
Brush teeth	43	21	64
Use toilet	33	10	43
Get dressed	17	15	32
Take medicine	6	7	13
Dinner	18	7	25
Lunch	18	6	24
Breakfast	16	7	23
Take snack	7	5	12
Prepare breakfast	15	7	22
Prepare dinner	12	7	19
Prepare lunch	14	6	20
Go home	9	12	21
Leave home	3	9	12
Visit in the SmartLab	0	1	1
Sleep	18	14	32
Relax on sofa	32	1	33
Play videogame	29	1	30
Read book	9	0	9
Watch TV	28	6	34
Work at table	8	2	10
Do dishes	10	2	12
Put washing machine on	7	6	13
Take out trash	8	0	8
Throw waste in bin	0	11	11
Total	**451**	**169**	**620**

After integrating and debugging the datasets, the data instances of the four information sources were grouped into sliding windows of 30 seconds. For the single-occupation dataset, 1529 instances were generated and 3249 for the multi-occupation dataset. The activities were grouped by categories, according to their affinity and the total activities were calculated by category, see Table 2.

Table 2. Description data using a 30 second sliding window

Category	Activities	Multi-occup.		Single-occup.		Total Act.	N.
Personal care and cleaning	Shower	237	554	24	273	261	827
	Brush teeth	151		100		251	
	Use toilet	76		28		104	
	Get dressed	67		84		151	
	Take medicine	23		37		60	
Have food	Dinner	146	473	127	347	273	820
	Lunch	186		110		296	
	Breakfast	115		97		212	
	Take snack	26		13		39	
Food preparation	Prepare breakfast	94	371	66	295	160	666
	Prepare dinner	109		84		193	
	Prepare lunch	168		145		313	
Out of home	Go home	25	34	41	80	66	114
	Leave home	9		35		44	
	Visit in the SmartLab	0		4		4	

Rest	Sleep	100	499	92	232	192	731
	Relax on sofa	399		140		539	
Entertainment	Play videogame	541	1218	30	207	571	1425
	Read book	141		0		141	
	Watch TV	408		106		514	
	Work at table	128		71		199	
Domestic cleaning	Do dishes	34	100	12	95	46	195
	Put washing machine on	29		16		45	
	Take out trash	37		0		37	
	Throw waste in bin	0		67		67	
Total			**3249**		**1529**		**4778**

For each of the data sources of the dataset, the following description feature representation was generated in the sliding windows. First, the inhabitant acceleration data (see table 3) are structured into timestamp, device, X, Y and Z columns. The last three correspond to the acceleration measurements in the spatial axes. For each of the three axes a feature representation was generated from the following calculations [33]: arithmetic mean, range, standard deviation, skewness and kurtosis.

Table 3. Excerpt from an acceleration of the inhabitant

TIMESTAMP	DEV.ID	X	Y	Z
2018/01/16 11:13:01.766	d36b03135c9	-0.36474	-6.83032	10.0050
2018/01/16 11:13:01.767	d36b03135c9	-1.0990906	-4.79272	8.4983
2018/01/16 11:13:01.768	d36b03135c9	-0.73965	-3.5930	9.4552
2018/01/16 11:13:01.780	d36b03135c9	-0.52661	-4.0048	9.4111

Second, capacitance data (see Table 4) are obtained from the intelligent floor for location, by the individuals' interaction with it (see Fig 2). The data are structured into timestamp, device and capacitance value. As the feature representation for the intelligent floor for location data, we include the count of times that each tile was activated in the sliding window.

Table 4. Excerpt from an intelligent floor for location

TIMESTAMP	DEV.	CAPACITANCE							
16/01/2018 11:14:44	3,04	4	4	15	21	17	20	2	11
16/01/2018 11:14:44	4,04	0	-2	-1	-1	0	0	4	-1
16/01/2018 11:14:44	1,07	-1	0	-1	-2	1	0	-10	1
16/01/2018 11:14:44	3,04	-6.	47	13	17	15	18	3	7

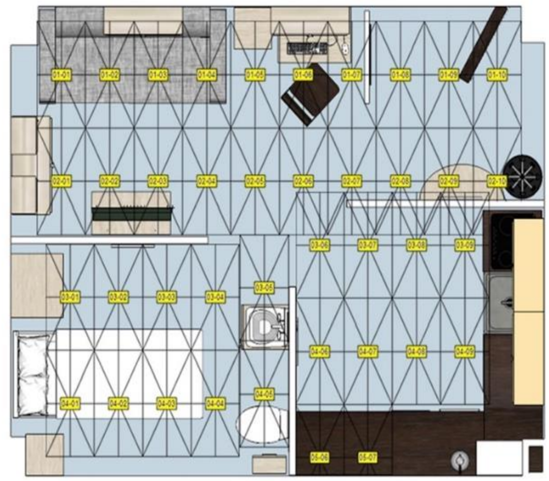

Figure 2. Layout of the intelligent floor for location in the UJAmI SmartLab [24].

Third, user proximity to objects and rooms (see table 5) was obtained from the Received Signal Strength between the wearable device worn by the individual and BLE beacon objects. The location of BLE objects within the smart lab are shown in the indoor environment (see Fig 3). Proximity data is structured into timestamp, device ID, ID, object and RSSI columns. RSSI is used to generate the feature representation of proximity. The features computed from the RSSI of each smart object in the sliding window are: arithmetic mean, range and standard deviation.

Table 5. Excerpt from a proximity

TIMESTAMP	DEVD.ID	ID	OBJECT	RSSI
2018/01/16 11:13:01.929	30586a1-e1f0-382f-	472c1	BED	-93
2018/01/16 11:13:07.314	30586a1-e1f0-382f-	b141ab	FRIDGE	-99
2018/01/16 11:13:12.579	30586a1-e1f0-382f-	472c18	BED	-71
2018/01/16 11:13:12.580	30586a1-e1f0-382f-	b141ab	FRIDGE	-97

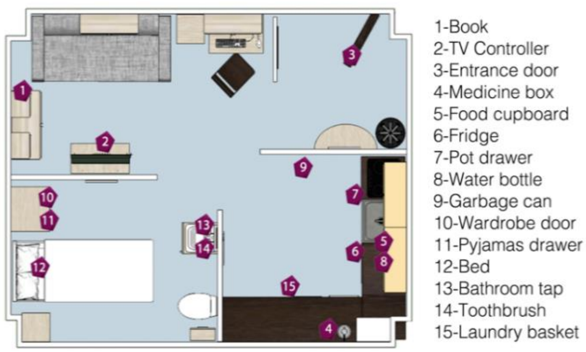

Figure 3. Layout of the BLE beacons in the UJAmI SmartLab.

Fourth, the data from binary sensors (see Table 6) collected in the smart lab identify the interactive events between individuals and sensors. 30 binary sensors were deployed in the indoor environment (see Fig 4).

The data from binary sensors is structured into timestamp, object and state columns. The possible values of the latter depend on sensor type: magnetic contact (open or closed), motion (movement or no movement) and pressure (pressure or no pressure).

In order to translate this information into feature representation, the count of activations (open, movement or pressure) for each object was computed in the respective sliding window.

Table 6. Excerpt from a binary-sensors

TIMESTAMP	OBJECT	STATE
2018/01/16 11:12:48.0	SM4	Movement
2018/01/16 11:13:04.0	SM4	No movement
2018/01/16 11:13:48.0	SM4	Movement
2018/01/16 11:13:58.0	SM4	No movement
2018/01/16 11:13:59.0	SM4	Movement
2018/01/16 11:14:53.0	C09	Open
2018/01/16 11:15:05.0	C09	Close

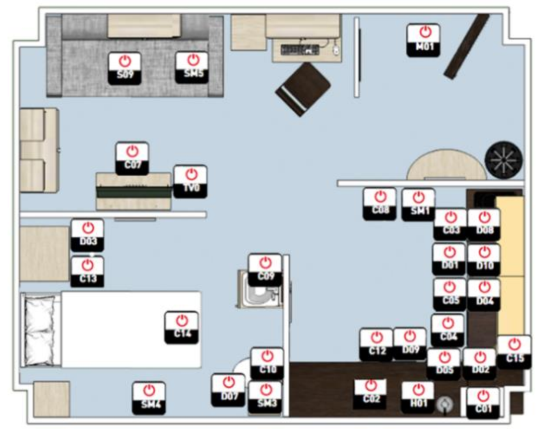

Figure 4. Layout of the binary sensors in the UJAmI SmartLab.

Following, we describe the id sensors with the objects that are illustrated in Figure 4: M01 Door, TV0 TV, SM1 Motion sensor–Kitchen, SM3 Motion sensor–bathroom, SM4 Motion sensor–bedroom, SM5 Motion sensor–sofa, D01 Refrigerator, D02 Microwave, D03 Wardrobe, D04 Cupboard cups, D05 Dishwasher, D07 Top WC, D08 Closet, D09 Washing machine, D10 Pantry, H01 Kettle, C01 Medication box, C02 Fruit platter, C03 Cutlery, C04 Pots, C05 Water bottle, C07 Remote XBOX, C08 Trash, C09 Tap, C10 Tank, C12 Laundry basket, C13 Pyjamas drawer, C14 Bed, C15 Kitchen faucet and, finally, S09 Pressure sofa

The integration of several data sources, through the timestamp field, allowed us to generate the fixed time windows and the feature representation generated from the raw features. The resulting SaMO – UJA dataset has 4778 data instances with 134 features, identifying the category as the class criterion (see Table 7).

Table 7. Dataset structure - feature representation of the SaMO – UJA dataset

Sources	Raw features	Generated features	Description
All	Timestamp	Time	Window set in 30 seconds (one feature)
Acceleration of the inhabitant	X, Y and Z	Xmean, Xrank, Xstd, Xskew, Xkur, Ymean, Yrank, Ystd, Yskew, Ykur, Zmean, Zrank, Zstd, Zskew and Zkur.	Arithmetic Mean, range, standard deviation, Skewness and kurtosis (15 features)
Intelligent floor for location	Device	F1_1, F1_2, F1_3, F1_4, F1_5, F1_6, F1_7, F1_8, F1_9, F1_10, F2_1, F2_2, F2_3, F2_4, F2_5, F2_6, F2_7, F2_8, F2_9, F2_10, F3_1, F3_2, F3_3, F3_4, F3_5, F3_6, F3_7, F3_8, F3_9, F4_1, F4_2, F4_3, F4_4, F4_5, F4_6, F4_7, F4_8, F4_9, F5_6 and F5_7.	Counting by contact with tile (40 features)
Proximity	Object, RSSI	1_Book_mean, 1_Book_rank, 1_Book_std, 2_TV_controller_mean, 2_TV_controller_rank, 2_TV_controller_std,3_Entrance_door_mean, 3_Entrance_door_rank, 3_Entrance_door_std,4_Medicine_box_mean, 4_Medicine_box_rank, 4_ Medicine_box_std,5_Food_cupboard_mean, 5_ Food_cupboard_rank, 5_ Food_cupboard_std, 6_Fridge_mean, 6_Fridge_rank, 6_Fridge_std, 7_Pot_drawer_mean, 7_Pot_drawer_rank, 7_Pot_drawer_std, 8_Water_bottle_mean, 8_Water_bottle_rank, 8_Water_bottle_std, 9_Garbage_can_mean, 9_Garbage_can_rank, 9_Garbage_can_std, 10_Wardrobe_door_mean, 10_Wardrobe_door_rank, 10_Wardrobe_door_std, 11_Pyjamas_drawer_mean, 11_Pyjamas_drawer_rank, 11_Pyjamas_drawer_std, 12_Bed_mean, 12_Bed_rank, 12_Bed_std, 13_Bathroom_tap_mean, 13_Bathroom_tap_rank, 13_Bathroom_tap_std, 14_Toothbrush_mean, 14_Toothbrush_rank, 14_Toothbrush_std, 15_Laundry_basquet_mean, 15_Laundry_basquet_rank and 15_Laundry_basquet_std.	Arithmetic Mean, range and standard deviation by object (45 features)
Binary sensors	Object, state	M01, TV0, SM1, SM3, SM4, SM5, D01, D02, D03, D04, D05, D07, D08, D09, D10, H01, C01, C02, C03, C04, C05, C07, C08, C09, C10, C12, C13, C14, C15 and S09.	Count by object (30 features)
	Inhabitant		One feature
	Activity	**Category** and activity	Two features
		Total	**134 features**

5. Conclusions.

This paper presented the SaMO – UJA dataset, which contains Single and Multi-Occupancy activities, collected in the UJAmI Smart Lab of the University of Jaén (Spain) from different sensor technologies and information sources: binary sensors in some objects in the space, proximity between the inhabitant and the BLE beacons in the space, acceleration of the inhabitant with the wearable device and intelligent floor for location.

The SaMO - UJA dataset has two levels of class labelling for the identification of activities: a level with greater granularity called activity (shower, brush teeth, use toilet, get dressed and take medicine, among others), which allows us to represent a total of 25 different types of activities, and a more general level called category (personal care and cleaning, have food and food preparation, among others), which groups the aforementioned activities into seven major categories.

Our future works are focused on presenting different models for learning HAR based on the sensor information and features described in the previous section. In order to evaluate the impact of different configurations in machine learning methods, we developed several case studies with the SaMO – UJA dataset.

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