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► To cite this version:

Houda Najeh, Christophe Lohr, Benoit Leduc. Considering the mutual information criterion for sensor configuration selection in human activity recognition in smart homes. BS 2023: 18th Conference of IBPSA, Building Simulation, Sep 2023, Shanghai, China. pp.469-476, 10.26868/25222708.2023.1194 . hal-04208937

HAL Id: hal-04208937

<https://hal.science/hal-04208937>

Submitted on 15 Sep 2023

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Considering the mutual information criterion for sensor configuration selection in human activity recognition in smart homes

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Abstract

Ambient sensors of a smart home offer new services to occupants related to security, comfort and energy management. This makes it possible to estimate the practices of the occupants and determine energy consumption, by estimating the number of occupants per zone, their activities and routines, with a requirement for digital sobriety (i.e fewer sensors possible, but enough to ensure a service). The selection of a pertinent sensor configuration is an important aspect in human activity recognition (HAR). This problem includes the selection of the number and type of the sensors, as well as the identification of the most informative ones.

In this paper, we propose a novel approach to determine the most informative sensor types (among motion detection sensors and door contact sensors) based on the criterion of mutual information. The selected configuration of sensors is applied to recognize daily activities in real-time in a real-world dataset: Aruba, from the CASAS project. The simulation results show good performance of classification and a save of processing time.

Highlights

- Consider the mutual information criterion to select the minimum setup of sensors
- Recognize human activities in real-time with the selected setup of sensors.
- Save of the processing time with a minimum setup of sensors.

Introduction

In the literature, different simulation tools support engineers to optimize the building design (Tian et al. (2018)). It is demonstrated that the behaviors of residents in buildings are important to explain the discrepancy between the simulated and the actual energy consumption (Phan (2022)). Understanding the behaviors of occupants might reduce this gap. Recently, many researchers have focused on modeling human activities to improve the simulation performance (Alhamoud et al. (2015); Akbari and Haghghat (2021)). They estimate occupant activities and their related energy impacts.

Existing research works have focused on the data segmentation step to optimize the real-time processing time (Najeh et al. (2022); Bouchabou et al. (2021)). In this paper, we propose a complementary work which consists in recognizing daily activities in real time with a requirement for digital sobriety (i.e to add an offline step to select a minimum sensor configuration).

The selection of the most meaningful features is an important aspect for HAR. In the literature (Bouchabou et al. (2021),(Bouchabou et al. (2021))), researchers have used customized sensor configurations. They compare their activity recognition accuracy rates with existing techniques. However, the results of these comparisons are dependent on the features. Among many constructed features, some of them are not relevant depending on the considered estimation. The objective of selecting a minimum sensor configuration is not to exclude the other sensors from the house. The objective is to filter the sensors. So, that the algorithm goes faster with an acceptable compromise on recognition performance, but with a performance gain in terms of real-time processing time.

Information gain (IG) is a criterion for evaluating the contribution of one sensor to another (Phan (2022); Amayri (2017)). It evaluates how much information a feature provides regarding a variable (Lefkovits and Lefkovits (2017)). This criterion is useful to determine meaningful features when building an estimation model (Omuya et al. (2021)). To compute the information gain, it is necessary to discretize features which contain continuous values. Thus, a discretization step needs to be applied to discrete features comprising continuous values. In brief, we need two steps to select meaningful features: discretization of features and information gain estimation. These steps are done offline, by analyzing the setup of the house, and not in real time during the day. A challenge that needs to be addressed here is the number of selected sensors. There is no optimal number for all activities, and it is context-related. In fact, the number of sensors could be detected based on the predefined criteria (threshold of IG) or manually selected by using the knowledge.

The Elbow (Clayman et al. (2020); Shi et al. (2021))

and the Silhouette methods (Rousseeuw (1987); Subbalakshmi et al. (2015)) could be used to analyze the relationship between the number of sensors and the estimation performance. These analyses are useful to determine the optimal number of sensors. The question that arises is the following: Can two sensors together be more representative than one? The main contribution of this paper is to address this question.

In our study, different sensors were installed to estimate human activities. The sensor configuration includes motion detection sensors, indoor air temperature and door/window opening. The proposed approach in this paper starts by determining the most meaningful sensors. It is based on the criterion of mutual information. Then, classification algorithm is proposed which rely on real-time dynamic segmentation (Najeh et al. (2022)).

This paper is structured as follows: The proposed methodology is detailed in Section "Followed methodology". Section "Case study" investigates the case study and the experimental results. Finally, concluding remarks are given in Section "Conclusion".

Followed methodology

This section describes the real-time HAR framework that integrates three steps: (1) selection of best features; (2) real-time dynamic segmentation method that determines the beginning and the end of each activity segment and (3) a classification step. These steps are preceded by a data pre-processing step. Figure 1 illustrates the proposed framework.

These steps are sequentially presented in the next sections.

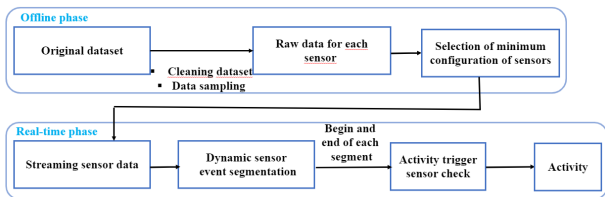


Figure 1: Proposed framework for human activities estimation

Selection of best features

The proposed methodology is based on the measurement of mutual information between the sensors and the activity. The computation of MI needs a discretization of features which contain continuous values. The following subsections describe the estimation of the Mutual Information (MI). Before detailing the calculation of MI, a reminder about the information theory is firstly presented.

Information theory is a probabilistic theory that quantifies the average information content of a set of messages between a source and a destination. In a more general sense, an information theory is a theory

aiming to qualify the notion of information content present in a set of data. In connection with HAR, MI aims to quantify the information content present in features regarding an activity.

The information is random (i.e uncertain). This uncertainty is taken as a measure of amount of information. In its transformations (encoding, transmission, decoding, etc.), information undergoes the effect of degradation. In connection with HAR, the topology of the houses, their equipment, and the manner an occupant performs an activity all have a great amount of variability, that increases the feature extraction difficulty.

Information theory Measurement of the quantity of information

The quantity of information is defined by Equation 1

$$H(x) = \log_2\left(\frac{1}{p(x)}\right) \quad (1)$$

The amount of information from the source is the average of the amounts of information, and it is defined by Equation 2. It is based on the notion of entropy (H) in the information theory. Entropy measures the disorder of the data categorized by a target. The higher the entropy is, the higher the disorder associated with this target is.

$$H(X) = - \sum_i^n p_i \times \log_2(p_i) \quad (2)$$

with

$$p_i = p(X = x_i) \quad (3)$$

where:

- $n \in \mathcal{N}$: the number of category of the target X.
- X : a discrete target with a value domain defined as $dom(X) = \{X_0, \dots, x_{n-1}\}$
- $H(X)$: the entropy of the target X
- $p(X = x_i)$: the probability for X to be equal to the value x_i

and X is a discrete variable whose domain is defined by $dom(X) = \{x_0, \dots, x_n\}$.

Mutual information is defined by Equation 4.

$$IG(x, y) = H(y) - H(y|x) \quad (4)$$

with $H(y|x)$: the conditional entropy of y given x .

When the IGs of features are determined, they are used to sort the features. Then the most meaningful features with the highest IGs are selected.

The following subsections detail the computation of MI of sensors regarding an activity.

Step 1 – Calculating probabilities

The first step consists in sampling data. In this work, the data are sampled with a sampling time equal to

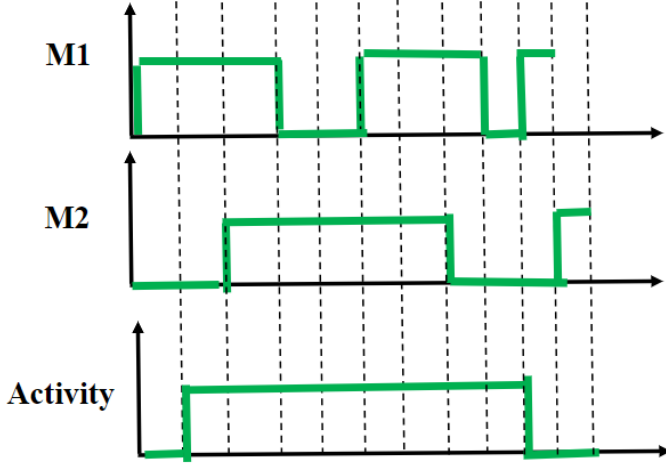


Figure 2: Sampled data

1 second. The calculation of probabilities consists in calculating the frequency of events over a period of time. The various cases are investigated as follows.

- Case of 1 variable

In this case, we are interested in the measurement of the mutual information of one sensor regarding the activity, such as illustrated in Figure 2.

M1 is a binary sensor. So, two probabilities are possible: $P(M1=0)$ and $P(M1=1)$ and they are defined respectively by Equations 5 and 6.

$$P_1 = P(M1 = 0) = \frac{\text{counter}(M1=0)}{\text{number of samples per day}} \quad (5)$$

$$P_2 = P(M1 = 1) = \frac{\text{counter}(M1=1)}{\text{number of samples per day}} \quad (6)$$

- Case of 2 variables

In this case, we are interested in the measurement of the mutual information of the two sensors together regarding the activity, such as illustrated in Figure 2.

M1 and M2 are two binary sensors. So, four probabilities are possible: $P(M1=0 \& M2=0)$, $P(M1=0 \& M2=1)$, $P(M1=1 \& M2=0)$ and $P(M1=1 \& M2=1)$ and they are defined respectively by Equations 7, 8, 9 and 10.

$$P_1 = \frac{\text{counter}(M1=0 \& M2=0)}{\text{number of samples per day}} \quad (7)$$

$$P_2 = \frac{\text{counter}(M1=0 \& M2=1)}{\text{number of samples per day}} \quad (8)$$

$$P_3 = \frac{\text{counter}(M1=1 \& M2=0)}{\text{number of samples per day}} \quad (9)$$

$$P_4 = \frac{\text{counter}(M1=1 \& M2=1)}{\text{number of samples per day}} \quad (10)$$

- Case 3: Case of more than two sensors

In this case, we iterate the method (Case 2) by taking the variables two to two.

Step 2 – Entropy Calculation

Two cases are investigated.

- Case of 1 variable

The entropy of sensor M1 is defined by Equation 11

$$H(M1) = P(M1 = 0) \times \log_2(P(M1 = 0)) + P(M1 = 1) \times \log_2(P(M1 = 1)) \quad (11)$$

- Case of 2 variables

The entropy of both sensors M1 and M2 is defined by Equation 12

$$H(M1\&M2) = P(M1 = 0\&M2 = 0) \times \log_2(P(M1 = 0\&M2 = 0)) + P(M1 = 1\&M2 = 0) \times \log_2(P(M1 = 1\&M2 = 0)) + P(M1 = 0\&M2 = 1) \times \log_2(P(M1 = 0\&M2 = 1)) + P(M1 = 1\&M2 = 1) \times \log_2(P(M1 = 1\&M2 = 1)) \quad (12)$$

Step 3 – Information Gain Calculation

The measurement of the MI of variable regarding an activity is calculated as following. Since sensor data and activity data are binary, several cases are considered and are summarized in Table 1.

Table 1: Possible cases

	Activity=0	Activity=1
M1=0	c1=count (M1=0 & Activity=0)	c2=count (M1=0 & Activity=1)
M1=1	c3=count (M1=1 & Activity=0)	c4=count (M1=1 & Activity=1)

Equation 13 illustrates the measurement of $MI(\text{sensor}, \text{activity})$.

$$MI(M1, \text{activity}) = H(\text{activity}) - (\ln(c1) / \ln(\text{Activity})) * \text{entropy0} - (\ln(c2) / \ln(\text{Activity})) * \text{entropy1} - (\ln(c3) / \ln(\text{Activity})) * \text{entropy0} - (\ln(c4) / \ln(\text{Activity})) * \text{entropy1} \quad (13)$$

Selection of the most meaningful sensors

Once the MI between two sensors together regarding an activity as well as the mutual information of each sensor alone regarding an activity are determined; two cases are considered:

1. Case 1: $MI((\text{Sensor 1}, \text{Sensor 2}), \text{activity}) \geq MI(\text{Sensor 1}, \text{activity}) + MI(\text{Sensor 2}, \text{activity})$
In this case, Sensor 1 and Sensor 2 are used to recognize the activity
2. Case 2: $MI((\text{Sensor 1}, \text{Sensor 2}), \text{activity}) < MI(\text{Sensor 1}, \text{activity}) + MI(\text{Sensor 2}, \text{activity})$
In this case, the sensor that has the max of $MI(\text{sensor}, \text{activity})$ is the most significant sensor to recognize the activity. So, this one is kept while the other is discarded.

Segmentation

Once, the minimum set up of sensors is determined using the criterion of mutual information, the second step of the proposed framework (Figure 1) consists of carrying out the recognition. In this paper, we used a real-time dynamic segmentation on streaming data which also provides the recognition step. It integrates the spacial correlation between events and decides if two sequential sensor events belong or not to the same segment of activity. This avoids events from very different zones to be in the same window. This method is published in Najeh et al. (2022) and it allows determining the beginning and the end of each segment when new events are inscribed and provides the label of the recognized activity.

Let $E = \{e_1, e_2, \dots, e_n\}$ a sequence of events, where e_i represents the i^{th} event. Each $e_i \in E$ contains a vector of information $\langle T_i, s_i, V_i \rangle$ where T_i , s_i and V_i represent respectively time stamp of the i^{th} event (Date; Year:Month:Day), Time (Hour:Minute:Second), sensor name of the i^{th} event and sensor value of the i^{th} event.

The concept of dynamic segmentation is the following. For each incoming event, the question that arises is if the incoming event belongs to the current segment, or it is the beginning of a new segment? It is based on the measurement of the Pearson Product Moment Correlation (PMC) coefficient Xu et al. (2022) which measure the linear correlation between two sensor events.

Figure 3 illustrates an example of identification of the beginning and the end of activities' segments, i.e how to process the real-time dynamic segmentation.

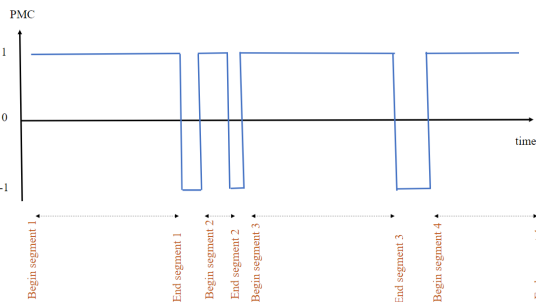


Figure 3: Real-time Human Activity Recognition Framework

Once the correlation between events is determined, for each incoming event, as long as the correlation is always equal to 1, it means that this event belongs to the current segment. As soon as the correlation is different to 1, the last sample corresponds to the end of the segment and as soon as it goes back to 1, this moment corresponds to the beginning of a new segment.

Case study

In this section, the objective is to verify that (1) the HAR is faster, and that (2) the accuracy is not too degraded. We compare using a dataset available in the community, with and without calculation of the minimum setup.

Testbed

The case study is performed on Aruba dataset, which contains human activities collected in a smart apartment by the Center for Advanced Studies in Adaptive Systems (CASAS) Cook et al. (2012). The apartment accommodates a woman adult. It has frequent visits of the woman's children and grandchildren through the year. The set-up for the sensor network includes 5 temperature sensors, 3 door contact sensors and 31 detection motion sensors. The sensors' identifiers begin respectively with "T", "D" and "M". The configuration of sensors in the apartment is shown in Figure 4.

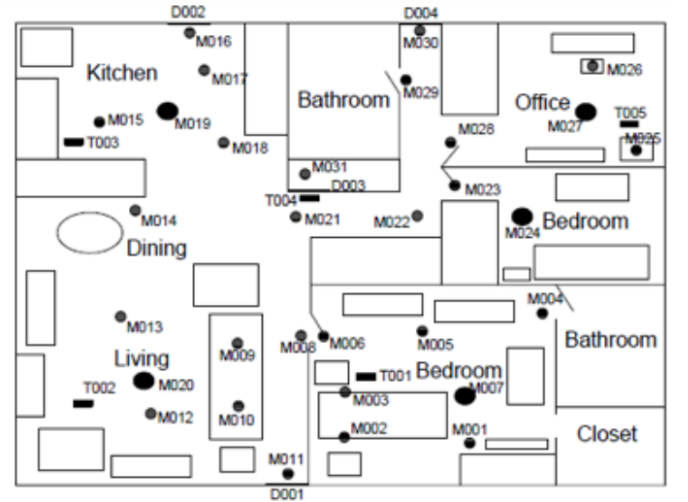


Figure 4: Simulation Results

The following activities are considered within the dataset. The number in parentheses is the number of times the activity appears in the data: Sleeping (401), Bed to Toilet (157), Meal Preparation (1606), Eating (257), Enter Home (431), Work (171), Relax (2910), Wash Dishes (65) and Housekeeping (33). The home inhabitant noted their activities, providing ground truth annotations. Table 2 summarizes the floor map of the dataset.

Table 2: Floor map of Aruba

Residents	1
Rooms	7
Number of sensors	39
Type of sensors	M, T, D
Number of activities	12
Number of days	219

Selection of the best configuration of sensors

This section deals with the determination of the most relevant sensors for each activity in Aruba’s dataset. In this paper, only the selection of meaningful features for two activities is detailed. Results for other activities are omitted for reason of space.

Case of the Work Activity

Figure 5 shows the sampled data of sensors M025, M026, M027 and M028 installed in the office setting where the activity “Work” occurs as well as the sampled data of activity Work.

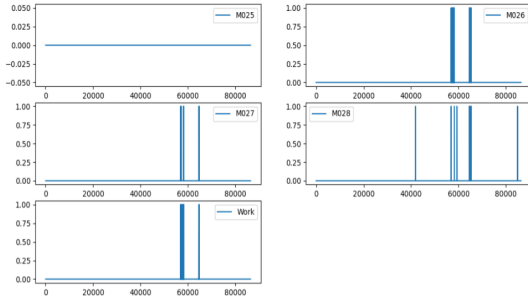


Figure 5: Real-time Human Activity Recognition Framework

Table 3 summarizes the Mutual Information for each sensor alone regarding the activity “Work”.

Table 3: Mutual information 1 Sensor/ Work

Sensors	IG
M025	0
M026	0.4815
M027	0.0944
M028	0.0117

The values of MI of both 2 sensors regarding an activity are represented in Table 4.

Table 4: Mutual information 2 Sensors/ Work

(Sensors, Work)	MI
MI((M025, M026), Work)	0.0075
MI((M025, M027), Work)	0.0025
MI((M025, M028), Work)	0.0003
MI((M026, M027), Work)	0.008
MI((M026, M028), Work)	0.0074
MI((M027, M028), Work)	0.0025

Mutual information between M026 and M027 is the higher. However, the constraint $MI((M026, M027),$

Work) $\geq IG(M026, Work)+IG(M027, Work)$ is not satisfied. In this case, Only the sensor M026 is meaningful to recognize the activity “Work”.

Case of the Sleeping Activity

The sensors installed in the bedroom in which the activity “Sleeping” in occurred are: M001, M002, M003, M005, M006 and M007. The values of MI of each 2 sensors regarding an activity are represented in Table 5.

Table 5: Mutual information 2 Sensors/ Sleeping

(Sensors, Sleeping)	MI
MI((M001, M002), Sleeping)	0.001
MI((M001, M003), Sleeping)	0.0011
MI((M001, M005), Sleeping)	0.0009
MI((M001, M006), Sleeping)	0.0019
MI((M001, M007), Sleeping)	0.0035
MI((M002, M003), Sleeping)	0.0004
MI((M002, M005), Sleeping)	0.0002
MI((M002, M006), Sleeping)	0.0012
MI((M002, M007), Sleeping)	0.0034
MI((M003, M005), Sleeping)	0.0002
MI((M003, M006), Sleeping)	0.0013
MI((M003, M007), Sleeping)	0.0037
MI((M005, M006), Sleeping)	0.0011
MI((M005, M007), Sleeping)	0.0053
MI((M006, M007), Sleeping)	0.0041

Table 6 summarizes the information gain for each sensor alone regarding the activity "Sleeping".

Table 6: Mutual information 1 Sensor/ Sleeping

(Sensor, Sleeping)	MI
IG(M005, Sleeping)	0
IG(M007, Sleeping)	0.0032

Mutual information between M005 and M007 is the higher. The constraint $MI((M005, M007), Sleeping) \geq IG(M005, Sleeping)+IG(M007, Sleeping)$ is satisfied. In this case, both of sensors M005 and M007 are meaningful to recognize the activity “Sleeping”.

Aggregation of results

In conclusion, the minimum configuration of sensors contains the following sensors (see Table 7):

To test the efficiency of the minimum sensor configuration selection framework, the selected configuration is used for real-time HAR recognition. A comparison between the performance of recognition with a minimum configuration and a complete configuration in terms of processing time and classification performance is discussed further below.

Table 7: Minimum configuration of sensors

Activity	Most representative sensors
Sleeping	M005 and M007
Work	M026
Bed to Toilet	M004 and M005
Eating	M014 and M020
Relax	M009 and M020
Housekeeping	M031
Meal Preparation	M015 and M017
Wash Dishes	M015
Enter/Leave Home	M030 and D004

Segments of activities with the minimum configuration of sensors

Once the beginning and the end of each segment is determined, a classification step consists of recognizing the activity based on the concept of trigger sensor and the time delta between the beginning and the end of the segment Najeh et al. (2022).

The trigger sensors for each activity are determined by a statistical study carried out beforehand offline. For such an activity, the sensor triggered at the start of the segment must correspond to the list of triggering sensors for this activity and the time delta must correspond to the usual duration of this activity. The usual duration of each activity is also determined offline by a statistical study on the duration of the activities. Table 8 summarizes the segments of activities classified with a minimum configuration of sensors.

Segments of activities with the total configuration of sensors

Table 9 summarizes the segments of activities classified with the complete configuration of sensors.

Discussion

This section analyses the performance of the classification with the two configurations. This discussion focuses on the analysis of the processing time of the segmentation and classification algorithm using a full configuration and a minimum configuration of sensors, as well as the classification results.

Processing Time

Activity recognition with a complete configuration and a minimum configuration of sensors is done on the same computer, with the same algorithms, but we have fewer sensors (35%), and less calculation (59.75%). In fact, the processing time related to the application of the algorithm using a global configuration of sensors is equal to 121.13 seconds (121.12 sec for the segmentation and 0.01 sec for the classification). It is equal to 72.38 sec with a minimum configuration of sensors (72.83 sec for segmentation and 0.0062 sec for classification).

Figure 6 shows the evolution of processing time regarding the number of sensors.

Table 8: Results of classification with a minimum configuration of sensors

Activity Name	Real Activities	Simulated Activities
Sleeping	00:03:50 to 05:40:43 05:43:45 to 08:01:12	00:03:50 to 05:40:27 05:43:45 to 08:00:21
Bed to toilet	5:40:51 to 05:43:30	05:40:51 to 05:43:24 08:57:48 to 09:02:48 13:32:00 to 13:33:24 15:21:21 to 15:22:49 23:38:36 to 23:42:36
Work	15:47:48 to 16:10:33 17:55:24 to 17:57:47	15:47:48 to 16:10:23 17:55:24 to 17:57:46 18:06:57 to 18:09:03
Relax	09:29:23 to 09:34:05 14:46:25 to 15:13:24 16:15:57 to 16:21:58 17:06:21 to 17:27:12 17:28:26 to 17:33:54	08:08:38 to 08:10:40 09:30:10 to 09:34:01 14:46:25 to 15:13:25 16:15:57 to 16:18:30 16:18:33 to 16:21:53 17:06:17 to 17:19:50
Eating	09:56:41 to 09:59:04 09:59:47 to 10:02:48 15:25:35 to 15:28:42 17:35:16 to 17:37:11	09:36:08 to 09:44:04 09:56:41 to 10:03:17 10:46:25 to 10:48:37 11:35:35 to 11:38:11 15:25:35 to 15:28:39 17:35:16 to 17:37:08 17:44:13 to 17:45:19
Meal Preparation	08:11:09 to 08:27:02	08:16:28 to 08:24:27 08:33:52 to 08:35:45 09:03:00 to 09:26:41 09:48:52 to 09:53:02 09:48:54 to 09:50:46 09:54:58 to 09:56:27 13:54:44 to 14:13:19 15:23:00 to 15:25:33 16:25:02 to 16:27:24 16:21:59 to 16:31:26 16:47:37 to 16:48:54 16:32:53 to 16:34:13 17:50:38 to 17:51:42 16:36:10 to 17:06:00 18:20:05 to 19:45:14 17:27:13 to 17:27:55 21:36:36 to 23:25:59

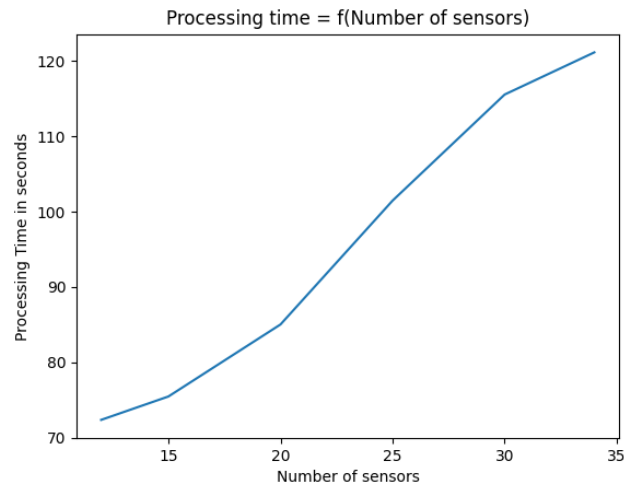


Figure 6: Sampled data

So, if we consider an implementation of this algorithm on an embedded system, the use of a minimum con-

Table 9: Results of classification with a complete configuration of sensors

Activity Name	Real Activities	Simulated Activities
Sleeping	00:03:50 to 05:40:43 05:43:45 to 08:01:12	00:03:50 to 04:14:32 05:43:53 to 07:53:22
Bed to toilet	5:40:51 to 05:43:30	05:40:51 to 05:43:24 08:57:48 to 09:02:48 13:32:00 to 13:33:24 15:21:21 to 15:22:49 23:38:36 to 23:42:36
Work	15:47:48 to 16:10:33 17:55:24 to 17:57:47	15:48:10 to 15:51:26 15:56:02 to 16:08:31 18:06:57 to 18:09:03
Relax	09:29:23 to 09:34:05 14:46:25 to 15:13:24 16:15:57 to 16:21:58 17:06:21 to 17:27:12 17:28:26 to 17:33:54	08:08:38 to 08:10:40 09:30:10 to 09:34:01 14:46:57 to 15:10:24 15:10:31 to 15:13:23 16:15:57 to 16:18:30 16:18:33 to 16:21:53
Eating	09:56:41 to 09:59:04 09:59:47 to 10:02:48 15:25:35 to 15:28:42	09:36:08 to 10:03:17 10:46:25 to 10:48:37 11:35:35 to 11:37:00 15:25:35 to 15:28:39 17:35:16 to 17:37:08 17:44:13 to 17:45:19 23:28:27 to 23:31:29
Leave Home	11:41:34 to 11:41:43 11:43:53 to 11:43:58	11:41:37 to 11:43:30
Enter Home	11:43:30 to 11:43:34 11:47:48 to 11:47:52	11:43:55 to 11:47:48
Meal Preparation	08:11:09 to 08:27:02 08:33:52 to 08:35:45 09:48:52 to 09:53:02 09:54:58 to 09:56:27 15:23:00 to 15:25:33 16:21:59 to 16:31:26 16:32:53 to 16:34:13 16:36:10 to 17:06:00 17:27:13 to 17:27:55	08:11:15 to 08:23:23 15:14:38 to 15:19:03 16:38:00 to 17:04:14 17:37:40 to 17:44:07 17:46:54 to 17:55:10 17:58:05 to 18:04:12 19:45:15 to 19:47:36 23/2439 to 23/27/40

figuration of sensors is more advantageous in terms of computation time.

Performance of the Classification

Sleeping Activity The recognition rate of Sleeping activity with both a minimum and a complete configuration of sensors is equal. The start and end times of simulated and ground truth activities are almost identical, and the rate of false positives and false negatives is almost negligible.

Bed to Toilet Activity For 24 hours, the “Bed to toilet” activity is labeled only once. However, the number of simulated activities detected is 5 in the case of recognition with a complete and minimal configuration of sensors. The start and end time of the first simulated activity corresponds to the GT activity, with a negligible rate of false negatives (6 seconds). This is explained by the fact that the occupant forgets to label the activity.

Enter/Leave Home Activity Activities Enter Home and Leave Home are very short activities. The number of real activities labeled is equal to two with a lag of 10 seconds between the first and the second “Leave Home” activity and 4 min between the two “Enter Home” activities. Recognition with a complete configuration of sensors makes it possible to detect these activities, but since the duration between activities is short, each simulated activity corresponds to the union of two real activities separated by a few seconds. The recognition with a minimum configuration of sensors does not detect short activities.

Work Activity The recognition algorithm with a minimum configuration of sensors allows detecting three “Work” activities. The first two practically correspond to the actual labeled activity, with a negligible false positive rate (10 seconds and 1 second respectively for the first two activities). The third simulated activity is explained by the fact that the occupant may have forgotten to label the activity. The recognition algorithm with a complete configuration of sensors makes it possible to estimate the first activity but in two sub-segments separated by an interval of approximately 5 minutes (from 15:48:10 to 15:51:26 and from 15:56:02 to 16:08:31 instead of 15:47:48 to 16:10:23). The second real work activity is not detected. The recognition rate for the work activity is lower with a full configuration.

Conclusion

This work proposes a framework to select a minimum configuration of sensors which are the most representative to estimate occupants’ activities. The objective of selecting a minimum sensor configuration is not to exclude the sensors from the house but to filter the sensors as input to the real-time HAR algorithm so that it goes faster with a compromise on recognition’s performance, but with a gain of performance in terms of processing time in real time. Mutual Information Criterion is applied to select the most meaningful sensors.

Once the minimum configuration is selected, a real-time human activity recognition framework in a building context is adopted to test the efficiency of the most representative selected sensors. It is a two-step methodology: (1) real-time dynamic segmenta-

tion and (2) classification.

The dynamic sensor-event segmentation approach is performed by calculating the Pearson Product-Moment Correlation (PMC) coefficient between events. The classification is based on the triggering sensor and segment duration check. The triggering sensor of the event is the very first sensor of an activity. In this work, it is not required to be discriminating (just the fact that it is the first), but it happens that we find that it is generally quite good at discriminating.

The simulation results show that the results show that for a 35% reduction in the number of sensors (i.e. from 34 sensors in full configuration to 12 sensors in minimum configuration), 59.75% of processing time is saved. Future works will be around testing the efficiency of this method on different hardware architectures, considering the cost of each solution.

Acknowledgment

The work is supported by the HARSHEE project, funded by the “France Relance” program and the Delta Dore company.

References

- Akbari, S. and F. Haghighat (2021). Occupancy and occupant activity drivers of energy consumption in residential buildings. *Energy and Buildings* 250, 111303.
- Alhamoud, A., P. Xu, F. Englert, A. Reinhardt, P. Scholl, D. Boehnstedt, and R. Steinmetz (2015). Extracting human behavior patterns from appliance-level power consumption data. In *European Conference on Wireless Sensor Networks*, pp. 52–67. Springer.
- Amayri, M. (2017). *Estimation de l'occupation dans le bâtiment*. Ph. D. thesis, Université Grenoble Alpes (ComUE).
- Bouchabou, D., S. M. Nguyen, C. Lohr, B. Leduc, and I. Kanellos (2021). Fully convolutional network bootstrapped by word encoding and embedding for activity recognition in smart homes. In *International Workshop on Deep Learning for Human Activity Recognition*, pp. 111–125. Springer.
- Bouchabou, D., S. M. Nguyen, C. Lohr, B. LeDuc, I. Kanellos, et al. (2021). Using language model to bootstrap human activity recognition ambient sensors based in smart homes. *Electronics* 10(20), 2498.
- Clayman, C. L., S. M. Srinivasan, and R. S. Sangwan (2020). K-means clustering and principal components analysis of microarray data of 11000 landmark genes. *Procedia Computer Science* 168, 97–104.
- Cook, D. J., A. S. Crandall, B. L. Thomas, and N. C. Krishnan (2012). Casas: A smart home in a box. *Computer* 46(7), 62–69.
- Lefkovits, S. and L. Lefkovits (2017). Gabor feature selection based on information gain. *Procedia Engineering* 181, 892–898.
- Najeh, H., C. Lohr, and B. Leduc (2022). Dynamic segmentation of sensor events for real-time human activity recognition in a smart home context. *Sensors* 22(14), 5458.
- Omuya, E. O., G. O. Okeyo, and M. W. Kimwele (2021). Feature selection for classification using principal component analysis and information gain. *Expert Systems with Applications* 174, 114765.
- Phan, H. (2022). *Modélisation de l'activité des ménages dans le bâtiment résidentiel instrumenté*. Ph. D. thesis, Bordeaux.
- Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics* 20, 53–65.
- Shi, C., B. Wei, S. Wei, W. Wang, H. Liu, and J. Liu (2021). A quantitative discriminant method of elbow point for the optimal number of clusters in clustering algorithm. *EURASIP Journal on Wireless Communications and Networking* 2021(1), 1–16.
- Subbalakshmi, C., G. R. Krishna, S. K. M. Rao, and P. V. Rao (2015). A method to find optimum number of clusters based on fuzzy silhouette on dynamic data set. *Procedia Computer Science* 46, 346–353.
- Tian, Z., X. Zhang, X. Jin, X. Zhou, B. Si, and X. Shi (2018). Towards adoption of building energy simulation and optimization for passive building design: A survey and a review. *Energy and Buildings* 158, 1306–1316.
- Xu, Z., G. Wang, and X. Guo (2022). Online activity recognition combining dynamic segmentation and emergent modeling. *Sensors* 22(6), 2250.