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# Human home daily living activities recognition based on a LabVIEW implemented hidden Markov model

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## Abstract

The recognition of human daily living activities within a house represents an efficient tool to model its power consumption and is also a good indicator for monitoring the health status of the inhabitants. The problematic of activities recognition in smart homes has been extensively addressed in several studies. In this paper, we present an original interactive tool developed under LabVIEW environment with a graphical user interface allowing the modeling of the daily living activities, based on a machine learning Hidden Markov Model. After an overview of the advantage for the consideration of this model in current human activities, we examine how the associated scientific problematic can find an interest and a solution by the integration of machine learning tools. Thus, the application based on a Hidden Markov model approach, is presented and evaluated using two sets of experimental data from literature. Comparing with results obtained by other daily living activities recognition methods, we point out the very satisfactory recognition performance of the Hidden Markov Model and the likelihood of our development associated to a user-friendly graphical interface. This work opens the way to applications dedicated to the supervision of human daily living activities and / or to the management of the electrical consumption within a smart home equipped with non-intrusive sensors.

**Keywords** Daily living activities · HMM · LabVIEW · Machine learning · Sensor data · Smart home

## 1 Introduction

By generalization of the use of renewable energies combined with policies encouraging the reduction of energy consumption, especially by households, the diversification of energy resources and the human daily living activities supervision and managements are recently

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addressed by several studies as in [5, 10, 32]. In this context, numerous researches are concerned with the increase of the potentiality of smart homes, which were originally designed to increase comfort to the inhabitants or to provide indicators of elderly health status. But, as mainly concerned in this contribution, a second priority objectives ought in researches dedicated to human activity recognition systems for smart homes is the development of new approaches allowing an effective contribution to the reduction of greenhouse gas emissions and a reduction of the energy bill in a context of sustainability. Among these researches, we can specifically cite those reported in [16, 33, 34], related to new developments and integrative solutions for real-time and/or planned monitoring energy consumption in order to its optimization according to its availability, its price and the desired comfort of the inhabitants of the home. Since energy consumption in the home is closely linked to the habits of individuals [12], it is interesting to be able to model human behavior in a house by making it smart, thanks to a network of sensors (ultimately, using the many possibilities offered via the Internet of Things (IoT) as in [1, 2, 23], in order to know and predict (possibly remotely) the activities of the inhabitants without requiring their direct physical interaction with the system to preserve their privacy. Hence, from this observation, it follows the interest of having a reliable and practical situation model to remote recognition of human daily living activities in the home such as cooking, eating, sleeping ... and so on. However, the basic classical approach addresses this issue only through a contextual approach but not through the situational approach. Indeed, contextual models based on user and application needs are specified and implemented in a Top-Down approach by experts. In this approach, an expert manually associates the sensors, the contextual model and the expected services statically. But scenarios, due to new behaviors of the inhabitants, can emerge or disappear and must be integrated into the intelligent environment, others disappear. A static context model in a Top-Down approach is therefore not adequate, especially if we consider the great capacities to adapt to the needs of the users of the energy monitoring and management systems currently offered by smart environments.

The objectives of research in human activity recognition is therefore to develop Bottom-Up automatic learning methods for the realization of autonomous systems allowing them to evolve with the behavior and needs of users in an intelligent environment. This then amounts to replacing the contextual model with a situation model. This situation model lies on the results obtained by the classification and regression methods developed in the Machine Learning approach, already used in various applicative domains as in medicine [6, 9, 17–21, 26]. These methods and approaches for the development of situation models can also find their place as fundamental basic tools for the management of energy systems in smart homes (see as example Refs [8, 13]).

In the current contribution, the developed system concerns a machine learning model based on a Hidden Markov Model (HMM). This system allows the monitoring of the daily living activities related to the energy consumption. It is implemented under LabVIEW environment providing an interactive graphical user interface (GUI). This original system aims to predict in real time, from sensor data located at various parts in the house, the daily living activities without harming the privacy of the inhabitants. Before reaching the usual mode of prediction and daily monitoring, a procedure based on real sets of experimental data recorded upstream will be used in order to parameterize the model which, moreover, will allow to test and validate the performances and reliability of the global application.

For the current study, following this procedure, standard and quite universal studied cases of houses in developed countries were considered for validation as examples. The block diagram of Fig. 1 presents a standard home with the location of the sensors as well as a summary of the global approach.

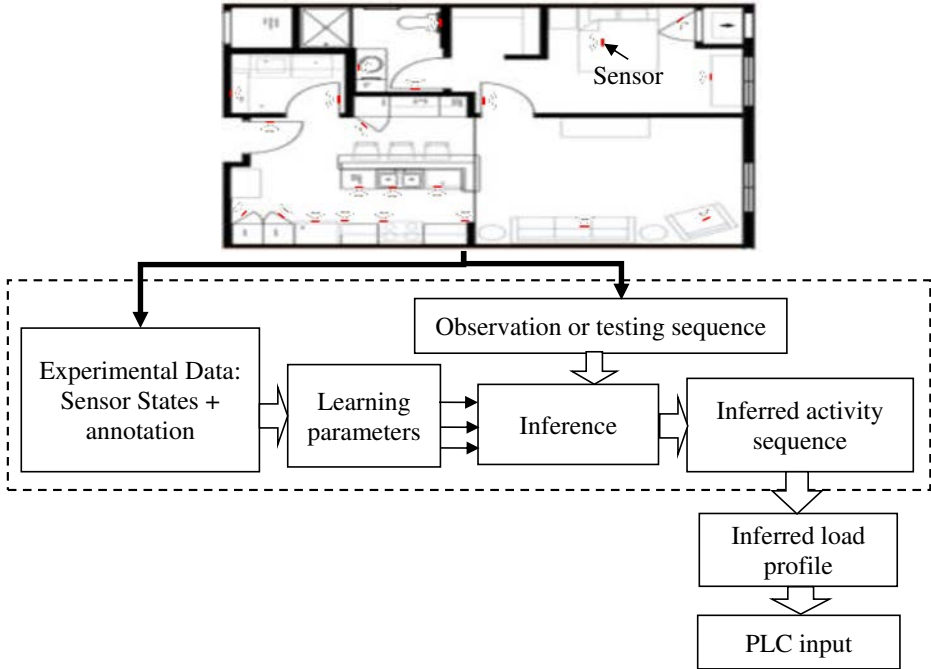


Fig. 1 Plan of a standard home and synoptic of the considered Bottom-Up modeling approach

After the description of the model, the method and its associated graphical user interface and of the set of experimental data, we will present, in the following, the obtained validation results.

Since the developed application mainly concerns the optimal management of energy consumption, and as shown in Fig. 1, among the three types of sensors allowing meeting the challenges of detecting human activity in a house, we will only consider direct environment components and infrastructure systems such as electrical systems providing in real-time, data on electrical consumption. For information, the third sensor technology integrates portable devices worn by residents to control the physiological state or movement of the person.

## 2 Methods and LabVIEW implementation

The method implemented in the current work is based on that originally presented by Kasteren et al. in Refs [29, 31]. We have adapted and developed it to be implemented under LabVIEW environment. This choice of LabVIEW environment was done as it provides efficient software analysis and user-friendly interactive tools in the form of a GUI. Within these specific developments and from inputs based on experimental data sets, it can provide various and easy possibilities for processing these data, for the extraction of HMM parameters, their validation then the application to the prediction in real-time. Thus, as it is requested in a LabVIEW program, we have developed a Virtual Instrument, VI, consisting in two main parts being the block-diagram and the GUI [3].

Figure 2 summarizes the various steps of the application. It should be noted that the development of this application required programming techniques which are, in the community of LabVIEW developers, considered as advanced programming techniques.

In addition to the use of some functions available in the LabVIEW library, subroutines (sub-VIs) dedicated to performing certain specialized tasks have been developed and added to the user library as shown in the hierarchical representation of the main diagram presented in Fig. 3. These dedicated VI and sub-VIs will be described in the following.

## 2.1 Type of experimental data

The experimental learning data inputs of the application are of two types: the annotation of the human daily living home activities and the data providing from ubiquitous sensors installed at different places in the house. They constitute two chronological data series and are recorded into two tables respecting both formats presented in Tables 1 and 2.

## 2.2 Data processing and discretization

In this step, the raw experimental data obtained from the sensors is discretized in time slices of duration  $\Delta t$  [27, 29] chosen long enough to be discriminative but short enough to provide high accuracy labeling results. Thus, at each sensor is associated a single feature  $x_t^i$  indicating the value of the feature  $i$  at the time slice  $t$  as  $x_t^i \in \{0, 1\}$ .

The values of the features can either be represented by their raw values obtained directly from sensors, or be transformed, as proposed by Kasteren et al. in Refs. [29, 31], according to

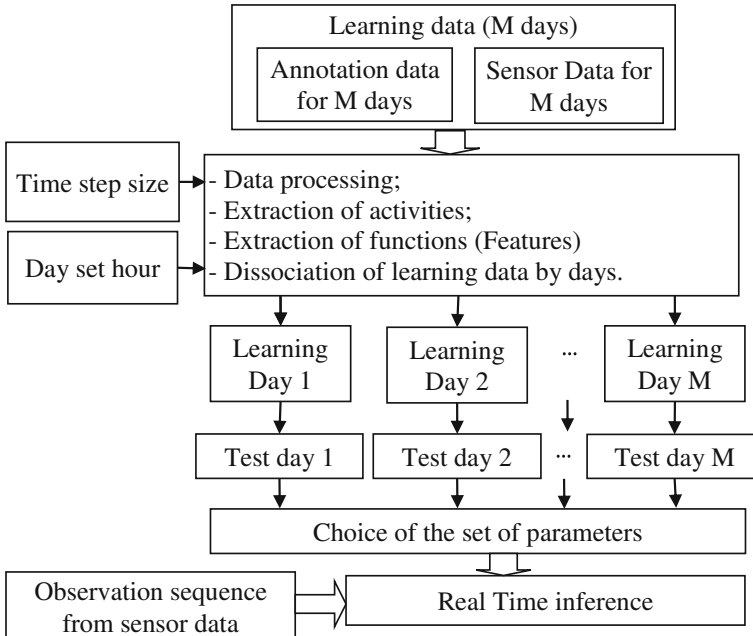


Fig. 2 Synoptic of the diagram of the implemented GUI illustrating the overall modeling process

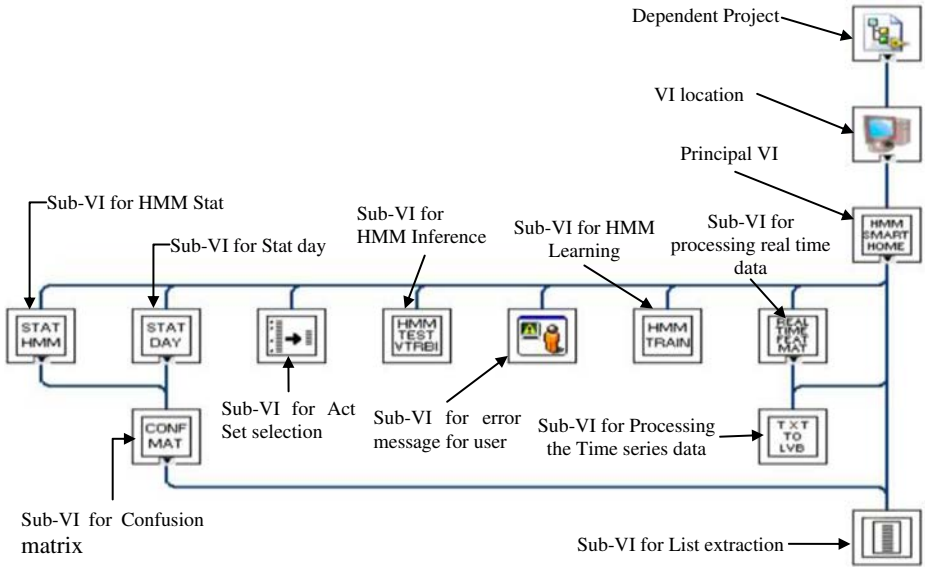


Fig. 3 VI Hierarchy of the principal program showing the main developed sub-VIs icons

one of the two other possible procedures of representation: the “Last Fired” and the “ChangePoint” procedures as illustrated in Fig. 4.

In the “Last Fired” procedure, the last fired sensor, i.e. the sensor that gives the value “one” last, remains at this value until another sensor fires. In the “ChangePoint” procedure, a sensor will give “one” when its state changes, i.e. when it changes from zero to one or vice versa; otherwise it remains at zero.

In a house with  $N$  sensors installed, the observation at time slice  $t$ , over a set of  $T$  time slices is represented by the following vector:

$$\vec{x}_t = (x_t^1, x_t^2, \dots, x_t^N)^T \quad (1)$$

and the associated activity label for the time slice  $t$  is represented by  $y_t$  as  $y_t \in \{1, 2, \dots, Q\}$  for  $Q$  possible activities (states of the HMM).

Consequently, in the application under LabVIEW and thus in the corresponding GUI, the observation time series  $X_{1:T}$  will be represented by a binary matrix of dimensions  $N \times T$  and the activity labels time series  $Y_{1:T}$  by a vector of numbers with  $T$  elements. These two series of experimental data observed in a definite number of days will then be dissociated in order to attribute to each experimental day its sub-series  $X_{1:T}$  (and  $Y_{1:T}$ ). This dissociation is done by choosing 03:00 as the reference time for the beginning of a day as  $t$  that time, there is the minimum of human activities in standard homes.

Table 1 Temporal data format of the annotation of human activities

Start date and time	End date and time	Activity number
dd-mmm-yyyy hh:mm:ss	dd-mmm-yyyy hh:mm:ss	number
⋮	⋮	⋮

**Table 2** Format of the temporal data of the activity of the sensors

Start date and time	End date and time	Sensor number	State
dd-mmm-yyyy hh:mm:ss	dd-mmm-yyyy hh:mm:ss	number	1
⋮	⋮	⋮	⋮

So, for each day,  $d = 1, 2, 3, \dots$ , in an observation panel composed of  $D$  days, and for the number  $T'$  of items in the time series of each day we obtain the observation time series:

$$X^d_{1:T'} = (\vec{x}_1, \vec{x}_2, \dots, \vec{x}_{T'}) \quad (2)$$

and the corresponding activity label series:

$$Y^d_{1:T'} = (y_1, y_2, \dots, y_{T'}) \quad (3)$$

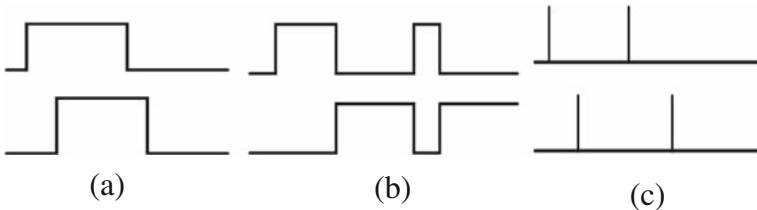
Finally, on the total number of learning days  $D$ , we will obtain for the observation time series, a binary matrix  $X$  of dimensions  $D \times N \times T'$  and for the activity labels time series, a matrix  $Y$  of dimensions  $D \times I \times T'$ .

It should be noted that at this stage that if a new activity is considered, it will corresponds to the IDLE activity attributed to the time slices when no activity corresponding to the starting set is detected.

### 2.3 The hidden Markov model

We already mentioned that the interactive tool allowing the modeling of the daily living activities developed in the current application is based on a machine learning Hidden Markov Model, HMM. We remember that a HMM can be seen as a special case of Markov chains which are random processes whose transitions are given by a stochastic matrix and which verify the Markov property, i.e. that the next state depends only on the previous one. In a HMM, the states are not observable (they are hidden) but each of them can randomly emit one of the elements of a set of visible symbols [27]. There is therefore a set of hidden states and a set of observable symbols. In the current application, the hidden variables correspond to the activities and the observable variables correspond to the sensor data. According to the notation proposed by Rabiner et al. [22], Fig. 5 gives a simple graphical representation of a HMM highlighting the transition probabilities between the states ( $a_{ij}$ ) and the observation probabilities ( $b_j(k)$ ).

Within the notations of the variables adopted above, we can say that the fundamental role of the model is the establishment of a correspondence between a sequence of observations  $X_{1:T}$  and a sequence of activity labels  $Y_{1:T}$  on the whole  $T$  time slices. We report in Fig. 6, the

**Fig. 4** Example of sensor response with **a** Raw values, **b** Last Fired, **c** ChangePoint representations [29, 31]

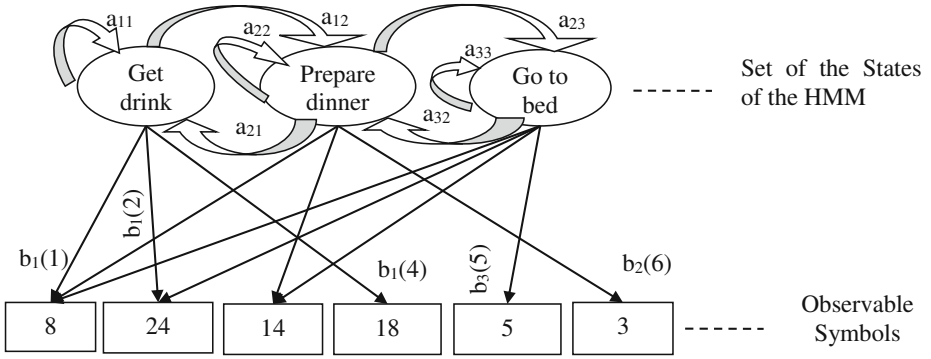


Fig. 5 Graphical representation of a HMM given on an example

graphical representation used for the interconnection between the sequence of states, and the sequence of observations, of the discretized data [29, 31].

To have the possibility to apply the HMM, and thus to be in agreement with the main Markov property, the following two hypotheses have to be considered in the application [22]:

- The activity  $y_t$  at time slice  $t$  depends only on the activity,  $y_{t-1}$ , at time slice  $t-1$ ;
- The observable variable,  $\vec{x}_t$ , at time slice  $t$  depends only on the activity  $y_t$  at this time slice  $t$ .

The corresponding joint probability is factorized as follows:

$$p(y_{1:T}, X_{1:T}) = p(y_1) \prod_{t=1}^T p(\vec{x}_t | y_t) \prod_{t=2}^T p(y_t | y_{t-1}) \quad (4)$$

A HMM with its parameters is noted  $\Lambda = (A, B, \pi)$  such that [7]:

- $A = \{a_{ij}\}$  is the matrix of transition probabilities, such as  $a_{ij} \equiv p(y_t = i | y_{t-1} = j)$ ;
- $B = \{b_j(k)\}$  is the matrix of observation probabilities, such as  $b_j(k) \equiv p(\vec{x}_t = \vec{x}_k | y_t = j)$ ;
- And  $\pi = \{\pi_i\}$  is the vector of initial probabilities, such that  $\pi_i \equiv p(y_1 = i)$ .

With  $i, j = 1, 2, \dots, Q$  (number of total activities) and  $k = 1, 2, \dots, K$  (number of total observations).

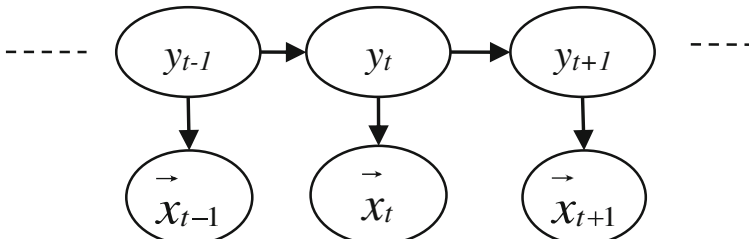


Fig. 6 Interconnection between the sequences of states and the observations of the HMM



## 2.4 Learning

The Baum-Welch algorithm is known to be the reference algorithm for learning the parameters of a HMM [22]. Its application to this approach would require  $2^N$  parameters for the distribution of observation to consider all possible combinations, thus requiring a large number of learning elements, even with a reduced number of features. For this reason, Kasteren et al. [31] have introduced another learning method in which each feature is modeled independently of the others. Within this novel method, we will have  $N$  parameters for each activity and each feature will be modeled by an independent Bernoulli distribution whose maximum likelihood parameter is  $\mu_{ni}$  for the  $n^{\text{th}}$  feature in the state  $i$ . Thereby, the transition distribution is modeled by  $Q$  multinomial distributions, one for each activity and finally, the vector of initial probabilities follows a multinomial law. The parameters of the model will therefore be:

$$a_{ij} = \frac{\sum_{t=2}^T \delta(y_t, j) \delta(y_{t-1}, i)}{\sum_{t=2}^T \delta(y_{t-1}, i)} \quad (5)$$

$$\mu_{ni} = \frac{\sum_{t=1}^T x_t^n \delta(y_t, i)}{\sum_{t=1}^T \delta(y_t, i)} \quad (6)$$

$$\pi_i = \delta(y_1, i) \quad (7)$$

Where,  $\delta(i, j)$  is the Kronecker delta function, giving 1 if  $i = j$  and 0 otherwise.

## 2.5 Inference

One of the main applications in which HMMs are positively considered is in decoding or inference problematic as in the present work. It consists of finding the best state sequence of the model that would have emitted an observation sequence i.e. in our case, the best time series of activity labels. This series corresponds to the sequence which allows the maximization of the probability  $P(Y_{1:T} / X_{1:T})$ . The algorithm that can provide a solution to this problem is the Viterbi one that has been detailed in several references as in Refs. [11, 22].

In the current application, the Viterbi algorithm is implemented in the LabVIEW developments as a sub-VI that is called in the “test” and “real time inference” steps in the block diagram of Fig. 2.

## 2.6 Performance evaluation of the model

The performances of the implemented HMM are evaluated by four “performance indices” extracted from the confusion matrix. These are the Precision, the Recall, the F-Measure, and the Accuracy, defined by the following equations [14, 21, 30]:

$$precision = \frac{1}{Q} \sum_{i=1}^Q \frac{TP_i}{TI_i} \quad (8)$$

$$recall = \frac{1}{Q} \sum_{i=1}^Q \frac{TP_i}{TT_i} \quad (9)$$

$$F\text{-Measure} = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (10)$$

$$accuracy = \frac{\sum_{i=1}^Q TP_i}{Total} \quad (11)$$

The format of the confusion matrix is given in Table 3 where the lines represent the true values of the labels (activities) and the columns those inferred by the model [14]. The confusion matrix is a tool for measuring the performance of a machine learning model by checking in particular how often its predictions are accurate compared to reality in classification problems [25]. The Precision index provides information on the proportion of positive identifications that are actually correct [28], the Recall index is linked to the proportion of actual positive results that has been correctly identified [24], the F-Mesure index is the weighted average of Precision and Recall indices [4] and the Accuracy refers to a measure of the degree to which the predictions of a model match the reality being modeled [15]. We thus note, for all indices, the pertinence of the results as: true positive TP, total true TT, total inferred TI, and the Errors E.

For a correct development and implementation of the HMM method in the current application, we introduce the method “Leave-one-day” proposed by Tapia et al. [27]. This method consists in the selection of one destination day to be inferred among the whole day range D, and in the repetition of this sequence for all the D days. The experimental data providing by the D-1 days are used to learn the parameters of the model for the specific d day. It results of this procedure a set of parameters and an observation sequence matrix for each test day.

The previously defined performance indices (Eqs. 8 to 11) will then be calculated for each test day, and the averages of these values and their standard deviations will then allow an overall assessment of the model’s performance.

**Table 3** Confusion matrix format

INFERRED LABELS TRUE LABELS	1	2	3	
1	TP <sub>1</sub>	E <sub>12</sub>	E <sub>13</sub>	TT <sub>1</sub>
2	E <sub>21</sub>	TP <sub>2</sub>	E <sub>23</sub>	TT <sub>2</sub>
3	E <sub>31</sub>	E <sub>32</sub>	TP <sub>3</sub>	TT <sub>3</sub>
	TI <sub>1</sub>	TI <sub>2</sub>	TI <sub>3</sub>	TOTAL

### 3 Graphical user interface

The current human daily living activities recognition application was developed taking into account the user-friendly possibilities offer through the GUI by LabVIEW to provide a simple and convivial interface dedicated to the final user. In the startup session of the program, the interactive graphical user interface (GUI) is displayed and during all the process, the full background software development is hidden for the user. The GUI consists of two main pages accessible by direct activation with a pointing device as a mouse pointer. The first page is associated to the inputs. In this page, the user enters the experimental learning data by uploading measurement files and the set of activities considered by selecting the labels in the dedicated list. The second page is associated to the results. It is dedicated to the visualization of the test day resulting data that must be selected in the whole D-day range by incrementing the dedicated button. The length of the time slices (discretization time) with based unit in second, is also to be introduced from the dedicated control. This second page consists of four sub-pages. The first sub-page is the “Feature Graph” sub-page displaying the superposed graphs of the sensors firing activities (Features) as function of time. Thus, each graph corresponds to one sensor which value is one when it fires and zero else. The second and third sub-pages are the “HMM Train” and the “HMM Test” sub-pages displaying the parameters and the test results respectively with comparison graph between real activities and those inferred by the model. The performance indicators defined in Eqs. 8–11 are also displayed in the “HMM-Test” sub-page for the selected destination test day. Finally, the sub-page “HMM Real time inference” is reserved for the prediction results of a sequence of activities linked to another sequence of observation of the sensor data that could be done in real time (instantaneous reading of the activities of the sensors).

As example, the corresponding pages related to the current application for a specific day are shown in Figs. 7 to 11. In Fig. 7, the page “Inputs” includes 25 occurrences of daily living activities existing in the referenced house. In the sub page “Feature Graph”, Fig. 8, we show as example, the behaviors of the various sensors obtained for the first test day proposed in the Kasteren data set (Note: as we will see below, Home A in [31] will correspond to Dwelling-A in the current contribution) with “ChangePoint” feature representation procedure and 1 min of time slice length. The considered sensor features are:1- Microwave, 2- Hall-Toilet door, 3- Hall-Bathroom door, 4- Cups cupboard, 5- Fridge, 6- Plates cupboard, 7- Front door, 8- Dishwasher, 9- Toilet Flush, 10- Freezer, 11- Pans Cupboard, 12- Washing machine, 13- Groceries Cupboard, 14- Hall-Bedroom door. The “HMM Train” in Fig. 9 displays the calculated HMM parameters for the same day, mainly by the values of the three matrices ( $A$ ,  $B$  and  $\pi$ ). The “HMM Test” sub-page, in Fig. 10 displays the graphs of real activities and those predicted as a function of time with the performance indicators for the tested day as well as the mean and standard deviations of these same indicators on all the learning days. Finally, the sub-page “HMM Real time inference”, Fig. 11, presents the prediction results deduced from the model.

### 4 Validation and discussion

Among the above-presented example, the developed tool has been applied for validation to several sets of experimental data found in the literature. Especially, we applied our model on input data series providing by Van Kasteren et al. [31] recorded in the house named by the



Fig. 7 View of the “Inputs” page of the GUI: Introduction of experimental data and selection of activity labels

authors “Home A” and, providing by Ordóñez et al. [21], on a second one named by the authors “Set A”. These two series of data are named Dwelling-A and Dwelling-B, respectively, in the current contribution.

As explained above (§ II.E), using the “leave-one-day” method, the activities of each tested day are inferred by the HMM model for which the set of parameters is learned with the experimental data providing from the other studied days of the chosen panel. Each inferred activity sequence is compared with the real activity sequence of the corresponding tested day. The results can be shown in the sub-page “HMM Test” as it appears in Fig. 10.

We thus observed the “leave-one-day” results obtained with each of the three procedures of feature representations, that are, as a reminder, the Row, Last fired, and ChangePoint (§ II.B) for two discretization time lengths ( $\Delta t$ ), equal to 10 min and 1 min, respectively. The mean values and standard deviations on all days of measurements for both dwellings are presented in Table 4.



Fig. 8 Example of view of the “Feature Graph” sub-page of the GUI (See comments in the text for the sensor feature labels)

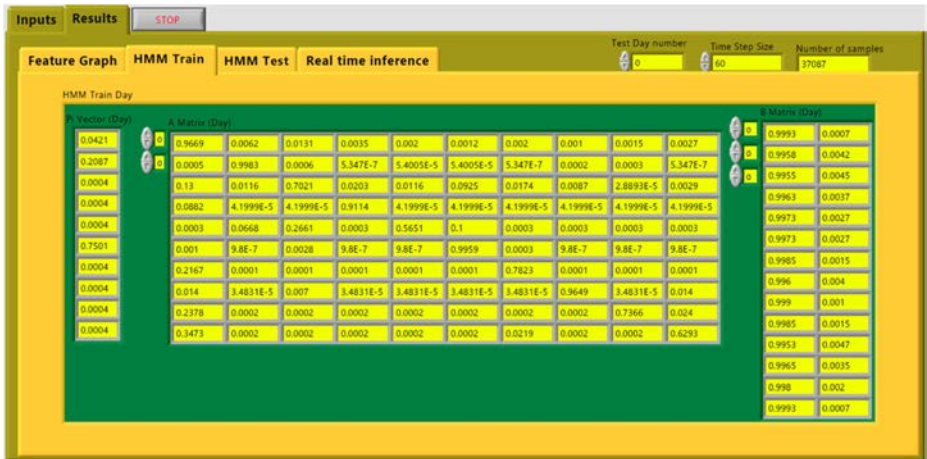


Fig. 9 View of the “HMM Train” sub-page of the “Result” page of the GUI

At first glance, we notice that the implemented model behaves differently for both sets of experimental data. This difference is attributed to the dispersion between the values obtained for one and the other of the two sets for each performance index.

It can be seen in Table 4 that the “Last Fired” feature conversion procedure, when the Dwelling-A data set, for a time step of 10-min duration is concerned, the model gives better inference results ( $86.78\% \pm 14.43\%$  of accuracy,  $72.13\% \pm 15.68\%$  of recall and  $67.43\% \pm 18.77\%$  of precision) than with the two other procedures. On contrary, for a time step of one minute duration, with this same data set, the “ChangePoint” procedure will ensure a better model inference, thus providing significantly higher values of the performance indices ( $92.32\% \pm 5.79\%$  of accuracy and  $70.32\% \pm 16\%$  of precision). However, for the Dwelling-B data set, the “Row” procedure provides a better model inference within the two time step sizes with higher performances for one minute ( $92.64\% \pm 9.19\%$  of accuracy,  $73.27\% \pm 9.43\%$  of recall and  $75.73\% \pm 11.97\%$  of precision). Thus, some fundamentals can be firstly concluded of this first part of the analysis. Indeed, we clearly see that the obtained results point out the

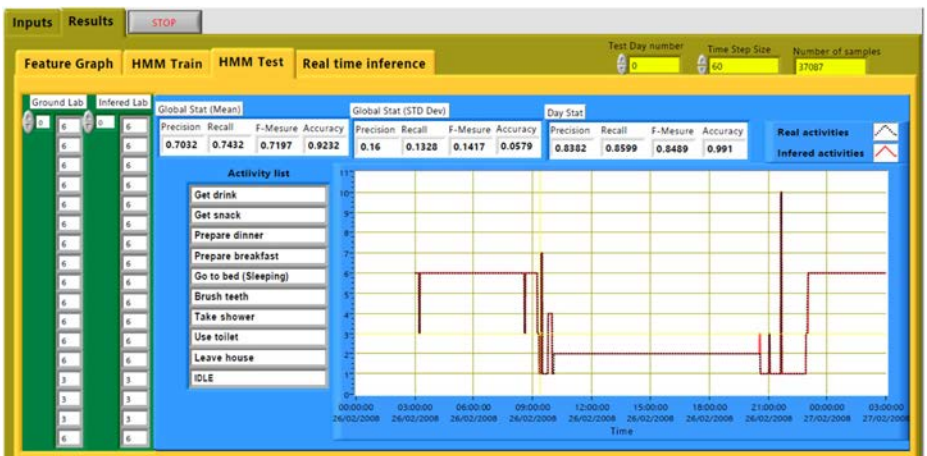


Fig. 10 View of the “HMM Test” subpage of the “Result” page of the GUI

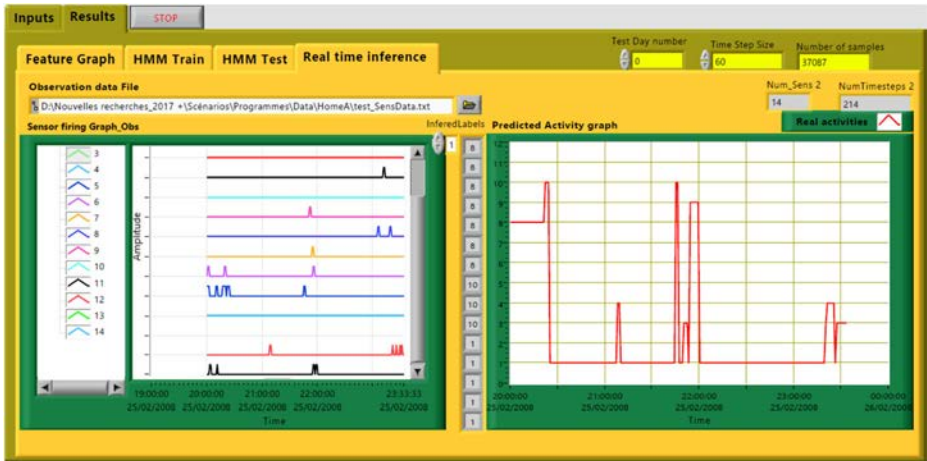


Fig. 11 View of the “Real Time Inference” subpage of the “Result” page of the GUI

huge influence of the length of discretization time step ( $\Delta t$ ) and the non-equivalence of the conversion procedures. But, we cannot definitely classify the procedures in terms of performances as these last are straight forwardly linked to the data sets themselves. We attribute these discrepancies between results obtained with both data sets to the influence of the number of learning days, the number of activities considered and the number of sensors.

Nevertheless, with this new user- friendly tool allowing in an easy way to obtain practical results for the Precision, the Recall, the F-Mesure and the Accuracy, the user or the applications using the results of this analysis will have access to the three representations, thus offering the possibility, manually or automatically, of using the best independently of the data set and achieving the highest accuracy for the Hidden Markov Model. Moreover, our results are quite close to those initially obtained by the authors with their original experimental data, as in the case of Van Kasteren et al. [31] who performed their analysis with a method developed under Matlab.

Thus, the tool can be used as a functional, or even industrial and commercial product, thus considered as a black box in future projects in a smart home energy management system. For a complete study of the energy consumption of his home, an inhabitant or an energy manager simply needs to enter the experimental data recorded on several days. Then, considering the activity labels in terms of electrical power needs by their relative loads, the user will obtain as outputs, the load profiles corresponding to each test day and a prediction of the energy consumption. For a specific and real-time prediction, he can choose as inputs, a single set of parameters. Indeed, for the latter, the application offers him the possibilities, from the sub-page “Real Time Inference” (cf: Fig. 11) to validate the set of parameters of the HMM and start the prediction.

## 5 Conclusion

The present manuscript outlined the development of an original and interactive graphical tool allowing the modeling, test, and user-friendly prediction of human daily living activities in a smart home. This tool was developed under LabVIEW. The inputs of the application are two

**Table 4** Performance results (Precision, Recall, F-Measure and accuracy) obtained for two studied cases

Data Set	Activity labels		Precision (%)		Recall (%)		F-Measure(%)		Accuracy (%)	
	$\Delta t$ (mm)		$\Delta t$ (mm)		$\Delta t$ (mm)		$\Delta t$ (mm)		$\Delta t$ (mm)	
Dwelling A: one person apartment with 14 sensors, 25 test days	10	1	10	1	10	1	10	1	10	1
	Change: 63.00±	Change: 70.32±	Change: 70.27±	Change: 74.32±	Change: 66.16±	Change: 71.97±	Change: 83.75±	Change: 92.32±		
	16.86	16.00	15.17	13.28	15.65	14.17	11.69	05.79		
	Last: 67.43±	Last: 54.23±17.7	Last: 72.13±	Last: 67.81±	Last: 69.51±	Last: 59.9±15.8	Last: 86.78±	Last: 87.12±		
	18.77	Row: 30.35±	15.68	13.84	17.25	Row: 29.85±	14.43	11.39		
	Row: 46.34±	1967	Row: 54.89±	Row: 30.65±	Row: 49.43±	18.53	Row: 59.22±	Row: 38.35±		
	23.76		22.76	16.70	22.73		28.57	22.41		
	Get drink									
	Get snack									
	Prepare dinner									
Dwelling B: 4 rooms house with 12 sensors, 14 test days (13 days obtained after separation)	10	1	10	1	10	1	10	1	10	1
	Change: 50.25±	Change: 63.61±	Change: 61.82±	Change: 63.77±	Change: 55.18±	Change: 63.58±	Change: 68.59±	Change: 76.05±		
	13.25	05.96	11.77	04.51	12.37	04.50	06.59	11.00		
	Last: 44.94±	Last: 58.79±	Last: 57.51±	Last: 61.00±	Last: 50.21±	Last: 59.71±	Last: 52.96±	Last: 68.06±		
	11.73	13.46	12.09	10.99	11.68	11.99	22.94	15.97		
	Row: 64.57±	Row: 75.73±	Row: 74.75±	Row: 73.27±	Row: 69.18±	Row: 74.39±	Row: 91.63±8.5	Row: 92.64±		
	11.47	11.97	12.83	09.43	11.83	10.39		09.19		
	Leaving									
	Toileting									
	Showering									
Sleeping										
Breakfast										
Lunch										
Dinner										
Snack										
Spare-Time/TV										
Grooming										
IDLE										

time series data obtained from a ubiquitous sensor network for the features and by annotations for the activity labels. The procedure is based on a Hidden Markov Model due to its time modeling abilities. Experimental results are presented in a graphical user interface using LabVIEW. The results obtained from true input data provided by literature are closer to those provided by similar studies. Among the validation of our application, it proves the efficiency of the chosen approach, as compare for example to the pure sequential approach currently used in recognition process.

From the validation results, we noted that the choice of the feature representation procedure depends on the experiment itself, hence the need to apply the three procedures, i.e. the Row, Last fired, and ChangePoint procedures to a set of experimental data to be able to choose the proper one for each data set.

One of the originalities of our tool is its development under LabVIEW environment, thus offering interactivity and friendliness to the user thanks to the GUI. The obtained results, associated with interactive graphical tools demonstrate the possibility to integrate such tools in a smart-home for either the prediction or the management of the energy consumption as function of the human activities, based on experimental datasets of human activities recorded off-line in the considered environment. Moreover, this development under LabVIEW opens the door for real-time monitoring with the integration of a real-time sensor data acquisition module. In addition to this perspective for future work, and based on the discriminating possibilities offered by the implemented model, it would be valuable to consider non-binary sensors allowing greater reliability of the prediction of the energy consumption with the true human activity in a smart-home.

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