User Interaction Event Detection in the Context of Appliance Monitoring

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***Abstract*—In this paper we assess about the recognition of User Interaction events when handling electrical devices. This work is placed in the context of Intrusive Load Monitoring used for appliance recognition. ILM implies several Smart Metering Sensors to be placed inside the environment under analysis (in our case we have one Smart Metering Sensor per device). Our existing system is able to recognise the appliance class (as coffee machine, printer, etc.) and the sequence of states (typically Active / Non-Active) by using Hidden Markov Models as machine learning algorithm. In this paper we add a new layer to our system architecture called *User Interaction Layer*, aimed to infer the moments (called *User Interaction events*) during which the user interacts with the appliance. This layer uses as input the information coming from HMM (i.e. the recognised appliance class and the sequence of states). The User Interaction events are derived from the analysis of the transitions in the sequences of states and a ruled-based system adds or removes these events depending on the recognised class. Finally we compare the list of events with the ground truth and we obtain three different accuracy rates: (i) 96.3% when the correct model and the real sequence of states are known a priori, (ii) 82.5% when only the correct model is known and (iii) 80.5% with no a priori information.**

Keywords*—*User-Appliance Interaction; Intrusive Load Monitoring (ILM); Appliance Identification

I. Introduction

Researches estimate that in the United States 30% of the total energy consumption is due to lighting and to appliances in the residential sector [1]. Users have an important role in total energy consumption when choosing appliances (e.g. different energy efficiency labels) and how they use them. The analysis of the relationship between users and appliances could provide information about usual activities and how energy is consumed. This is possible through the monitoring of the appliances and the analysis of the activities.

There are mainly two methods for monitoring the electrical appliance consumption in a Smart Home / Building: the Non-Intrusive Load monitoring (NILM) and the Intrusive Load Monitoring (ILM). In the first case one Smart Meter is placed at panel level and the consumption of the whole household is collected. The contribution of single appliances can be recovered through some disaggregating algorithms [2]. This approach is not effective for the detection of appliances poorly contributing to the total electrical consumption [3]. ILM method relies on several Smart Metering Sensors placed in the monitored environment and measuring the electrical consumption of single appliances or aggregation of few of them. The term *Intrusive* underlines the fact that the Smart Metering Sensors have to be physically placed inside the environment.

The activity recognition task applied to the appliance monitoring could have different facets and levels of granularity, depending on the application:

1) **Activity of Daily Living (ADL) recognition**. Long-term activities, as eating, bathing, etc., usually involve the use of appliances. The main ADLs can be retrieved from the analysis of the electrical signatures. It has its major applications in health and elderly surveillance fields.
2) **Occupancy Detection**. The interaction with a non remote-controlled appliance implies the presence of a person close to it and can provide information about the spatial occupation. The field of application is mainly linked to energy efficiency: the occupancy detection could allow to apply energy saving measures.
3) **User-Appliance Interaction**. The User-Appliance Interaction events represent the finest level of granularity that could be achieved. Knowledge about when and how many times the user interacts with the appliances is inferred.

In this paper we present a new method for recovering the User-Appliance Interaction events, i.e. the moments in time in which a User has interacted with an Appliance. For sake of simplicity, in this paper we use the expression *User Interaction events*. Such a method has several fields of applications, like (i) user profiling [4], (ii) evaluation of the User-Appliance interactions [5], (iii) contribution to the ADL recognition in Smart Homes [6], (iv) energy saving through the indirect information about the occupancy. To accomplish this task, we add a module dedicated to the detection of the interactions to our existing system architecture based on Hidden Markov Models (HMM). The existing system is able to recognise the appliance class and the sequence of hidden states [7].

In Section 2 we provide details about related work dealing with activity recognition when using NILM and ILM. In Section 3 we present the system architecture, providing information about data, feature extraction and the module dedicated to the detection of the interactions. In Section 4 we explain the test procedure used for our module validation. In Section 5 we present and discuss the results. Finally in Section 6 we conclude the paper with an insight about our future works.

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II. Related Work

Existing research deals with the activity recognition when using NILM. The analysis of signals coming from a single Smart Meter can give important information about human activities, in particular ADLs. On the other hand NILM signals are quite simple to be obtained and information about ADLs could entail security problems and privacy violation. Noury et al. [8] develop a system for monitoring elderly people living at home through the energy consumption of the whole building. Their system is designed to retrieve an index related to the daily activities. The index provides a first-level alarm, that has to be confirmed by an expert. They detect activities of 13 elderly people during 9 months and prove the validity of the index with data gained from 12 elderly people during 6 months. Chen et al. [9] introduce the notion of Non-Intrusive Occupancy Monitoring (NIOM), using the data from a single electricity Smart Meter to infer occupancy. They relate the occupancy ground truth with the electrical load in two homes and develop a simple threshold-based algorithm for the occupancy recovering. They obtain an overall accuracy rate of about 90.6% and 79.1% for the two homes under analysis.

In literature some works use more than one Smart Meter dedicated to an area of the home and monitoring the aggregation of more than one appliance. This case is classified as ILM, according to its definition. As stated in [10] ILM is used for the activity recognition. Lee et al. [11] use a small number of power meters instead of using one power meter per appliance to recognise the operating state of appliances in use. They make a model that associates several activities with the possible appliances in use: with that relationship they can detect the unattended appliances that are wasting energy without being concerned by the user activity. Users receive information about the appliance operating states, including the unattended appliances. Cho et al. [12] collect data from a Smart Socket (SMPT) that provide the location of the off-state appliances. They extract the activity from SMTPs and they provide the users with an analysis of their power consumption. They alert the users about their energy wasting and propose them energy saving measures.

Finally, when one Smart Metering Sensor per device is used, is the typical ILM case. The contribution of single appliances is directly acquired and no disaggregation algorithm is required. France et al. [13] record the electrical activity of lights and appliances for the recognition of ADL of elderly people. They monitor 13 elderly people for more than 6 months and calculate the probabilities of eating, toileting and bathing every day. They work up to well differentiate the diurnal and nocturnal activity and they discover that the eating activity is the most accurately detected ADL. Lee et al. [14] propose an automatic stand-by power reduction system based on the user-context profiling. Their system analyses the occupancy patterns tighter with the appliance utilisation. The system is able to predict the appliance usage and it applies energy saving measures by managing the stand-by power. They monitor several appliances in 4 homes and predict their activation and deactivation: as result, they save in 3 weeks between 27% and 44% of the total energy consumption.

Despite many years of research, the accuracy of systems dealing with aggregation of several signatures is still not precise enough, especially when working with small appliances [3]. The works previously mentioned propose solutions focused on the ADL recognition or the occupancy detection. Our solution is based on the identification of the User-Appliance Interaction events, which, as stated in the Introduction, retrieve the finest level of granularity. This work will constitute a good starting point for the development of several possible applications, as the application of energy saving measures, recognition of ADL, User profiling and improvement of the User-Appliance way of interaction.

III. System Architecture

A. Appliance and State Recognition System

In this Section we clarify the context of our work by presenting our system for the appliance and state identification based on HMM [7] and the ACS-F2 database used for its evaluation [15]. The system takes as input features coming from a Smart Plug and communicates with a PC that performs the feature extraction and the machine learning task. The system is able to detect in real time the appliance class and the state of the appliances. Another version of our system is able to perform appliance and state recognition directly on distributed devices by using the Internet-of-Things (IoT) paradigm [16].

The ACS-F2 database contains 450 electrical signatures coming from 225 appliances. Every appliance has been recorded two times for one hour, generating two signatures of one hour length each. The first hour of recording is called *first session*, in the same way the second one is called *second session*. The appliances are uniformly divided into 15 classes: mobile phone (via chargers), coffee machine, computer station (including monitor), fridge and Freezer, Hi-Fi system (CD players), lamp (CFL), laptop (via chargers), microwave oven, printer, television (LCD or LED), fan, shaver, monitor, lamp (incandescent) and kettle. The signatures are recorded at low sampling frequency (10^{-1} Hz). Six different features are available: real power (W), reactive power (var), network frequency (Hz), RMS current (A), RMS voltage (V) and phase of voltage relative to current (ϕ).

The ACS-F2 database has two interesting characteristics that make it different from the other databases:

- All the appliances belong to different brands and/or models without any repetitions inside the database and the classes are equally represented. This might simplify the construction of generic models using a fair number of different appliances per class.
- The database comes with two evaluation protocols (*intersession* and the *unseen appliance* protocol), that might help researchers to compare their results. More details can be found in [15].

For all the signatures we added information about their dynamic evolution by the inclusion of the *velocity* and *acceleration* coefficients (respectively comparable to the first and second derivative, as explained in [17]). The six original features and their coefficients contain not relevant and redundant information. We performed a feature selection based on the computation of the entropy and the information available from the theory of electricity. For the *intersession* protocol we were able to reduce the feature space by a half, while for the *unseen appliance* protocol we did not apply any modification [7].

As machine learning algorithm we used HMM. This choice has been made mainly for two reasons. In the first place, HMM are

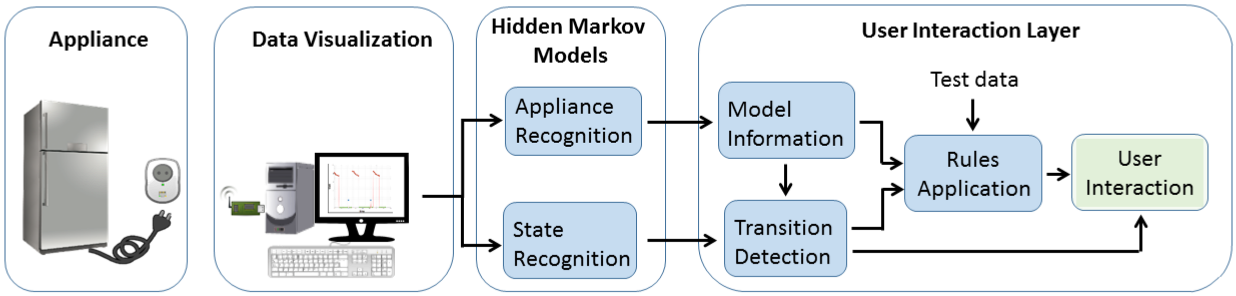

Fig. 1: The system architecture: the appliance, recorded with a Smart Plug, communicate with a PC on which a HMM-based algorithm runs. The output of HMM (i.e. the appliance class detected and the sequence of states) is taken as input of the *User Interaction Layer* that finds the User Interaction events.

well-known to provide excellent performances when applied to temporal signals having stationary stretches. This is exactly the case when dealing with electrical signatures, given their state-based nature that fits well with HMM state-based approach. Secondly, when using consciously the HMM algorithm, we can associate every hidden state with a real state of the appliances. In such way, we can retrieve the state sequence through the alignment of the Viterbi algorithm, that is implicitly used by HMM.

This system has been already presented and is able to run in real-time. We also implemented an interface showing the identified appliance and its actual state (the last of the state sequence) [7]. The state sequence could give information about the User Interaction events with the appliance, but it depends on the appliance class and the type of category which it belongs to. In the next paragraph we define the appliance categories according to the User Interaction events.

B. Categories Definition

For the majority of the appliances, User Interaction events can be recovered through an analysis of the state sequence. Usually an interaction with the device implies a command to the device that will bring to the transition of the state of the appliance. HMM technique can potentially retrieve this information from the hidden state transitions.

The difficulty in retrieving the user interaction events depends on the category the device belong to. Several categorization are possible. Hart [18] proposed a categorisation depending on the operational state: two-state devices, multi-state appliances and continuously variable devices. Lee et al. [14] proposed another separation based on the temporal usage of home appliances: *Background Appliances*, *Occupancy-Reactive Appliances* and *User-Interactive Appliances*. In this paper we refer to the following separation proposed by Zaidi et al. [19]:

- **Usage dependent appliances** (UDA). The devices change their state depending on the interaction with the user (e.g. microwave). An User Interaction usually corresponds to a change of state.
- **Fixed operation appliances** (FOA). The device is characterised by a pre-established sequence of operations that are started by the User. If every fixed operation is represented by a hidden state, the User Interaction will imply a change from a specific state to another but will not involve the other transitions.

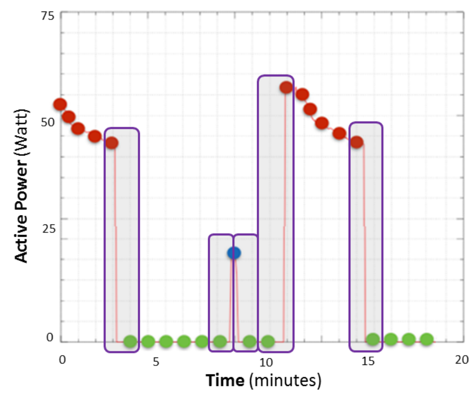

Fig. 2: The trend of the active power of a fridge is represented. We used points of different colours according to their state: green for a non-compression phase, red for the compression phase and blue for the door opening. The state transitions are highlighted by using rectangular boxes.

  For instance, a washing machine could be switched off (state 1), wash (state 2), rinse (state 3), spin (state 4) and maintenance wash (state 5). In this case the transition from state 1 to 2 implies User Interaction, but not the other transitions. In some cases FOA could be modelled by grouping a certain number of hidden states in one, for instance the washing machine could be ”off” (state 1) or ”on” (state 2).
- **Thermostatically controlled appliances** (TCA). TCA are appliances that either provide heating or cooling depending on the temperature of a certain environment, for instance fridges. In this case the electrical consumption is not directly depending on the user activity. However, in certain cases, other sources of consumption could be activated when interacting with users: for instance, fridge internal lamp is automatically switched on when the door opens.

Finally we have to consider that some appliances can be battery based. In particular some UDAs as the laptop change their energy consumption depending on their usage and the battery charge level of the battery, making hard to identify the single contributions.

C. *User Interaction Layer*

The system described in the previous paragraph is able to detect the appliance class and the state sequence without explaining the User Interaction with the appliances. For this reason we created an additional layer, called *User Interaction Layer*, that takes as input the output of the HMM and which is able to provide the User Interaction events. In Figure 1 we represent the new system architecture: the output of the HMM algorithm is taken as input of the *User Interaction Layer*.

In most cases User Interaction event involves a change of the operational appliance mode and therefore a change of its state. Depending on the modelling choice, this change could correspond to a change of the model hidden state. As a consequence, the analysis of the transitions of the state sequence could provide information on the User Interaction events. Not all the transitions recovered by the state sequence are User Interaction events, but depend on the appliance class and its category (UDA, FOA or TCA). This information is available from the output of the HMM: the winning appliance class and consequently the category to which it belongs to. In Figure 2 we show the concept of the Transition Detection: the trend of the active power of a fridge is represented using points of different colours depending on their state (green (state 1) for a non-compression phase, red (state 2) for the compression phase and blue (state 3) for the door opening). The transitions of states are potential indicators of User Interaction events. The HMM provide additional information on the recognised class (Fridge), therefore we know that only the transitions involving the state 3 are due to User Interactions.

By using the information coming from the Transition Detection and the winning model, we are able to determine if an user has interacted with device or not for almost all cases. For the remaining ones, the system shows some limitations: (i) the user interaction happens inside the same state (Interaction without transition) and (ii) under specific conditions the transitions have different meanings and have to be filtered (Transition selection).

Interaction without transition. This circumstance occurs when we choose to model a device with a lower number of hidden states than necessary, therefore a single state of the model could represent more than one real state. As a consequence, state transitions do not detect all User Interactions. To detect the missed interactions, we applied certain rules on portions of the signal having a stationary hidden state. For instance, the Fan class of the ACS-F2 database includes devices of different brands and/or models with a different number of real states, for example mechanical fan with 2, 3 or more power levels. Given the heterogeneity of the devices, we decided to represent the Fan class with a 2-state HMM: "active" and "not active" states. If a specific fan has more than 2 power levels, these are grouped inside the "active" state. As a consequence, when the user increases or decreases the fan speed without passing through the "not active" state, the interaction is not automatically detected. The Fan case is reported in Figure 3A. This problem is solved by analysing the portions of the signal having a stationary hidden state. With a simple rule-based system we are able to recover the User Interactions events that do not have a transition in the state sequence.

Transition selection. This circumstance occurs when the transition from one state to another has different meaning depending on the context: in some cases the transition can be caused by the User Interaction but not in others. For the selection of the transitions linked to User Interactions we applied a rule-based algorithm on the portions of the signal corresponding to the transitions. For instance, for the mobile phone class we used a model with two hidden states: one for the charging phase ("on") and the other for the charged phase ("off"). The transition from "off" to "on" states means an User Interaction event (typically the user plugs the device or is using it). The transition from "on" to "off" could have two reasons: the device is charged or the device has been unplugged. In the first case, no user interaction event should be notified, while the opposite should occur in the latter case. Using a rule-based system, we verified if some conditions are satisfied: if the difference of the active power between the two states exceeds a threshold, the device has probably been unplugged (User Interaction), in the opposite case the device is fully charged (no User Interaction). The mobile phone case is reported in Figure 3B.

For solving the system limitations (Interaction without transition and Transition selection) we applied a simple rule-based system. In both cases the rules are determined by using decision trees with binary splits for classification. The decision trees are built by using the examples in the training data. The decision trees can be translated in a sequence of conditions (rules), for instance for the printer class we obtain the following rules:

if $\Delta P < 8.7225$ **then**
    if $\Delta Q < -5.4495$ **then**
        class = 1
    else
        class = 0
    end
else
    class = 1
end

where ΔP is the velocity coefficient of the active power, ΔQ is the velocity coefficient of the reactive power and $class$ determines if the event should be considered or not.

IV. Test Methodology

We perform some tests on the data coming from the ACS-F2 database in order to determine the accuracy of our system in the recognition of the User Interactions. We recover the ground truth by finding manually the user interactions in the signals. This task is simple for some categories having a clear distinction among the states (kettle, lamp, etc.), while is difficult for some others having complex electrical consumption trend in time (computer station and laptop). In the latter case, we select only the clear interactions. We divide the appliances by using the categorisation of Zaidi [19]. As UDA we have mobile phone (via chargers), computer station (including monitor), Hi-Fi system (CD players), lamp (CFL), laptop (via chargers), television (LCD or LED), fan, shaver, monitor, lamp (incandescent); as FOA we have printer, coffee machine, microwave oven and kettle; as TCA the fridge and freezer. Hi-Fi system and fan have problems of Interaction without transitions, while mobile phone those of Transition selection; the signatures belonging to these three classes are

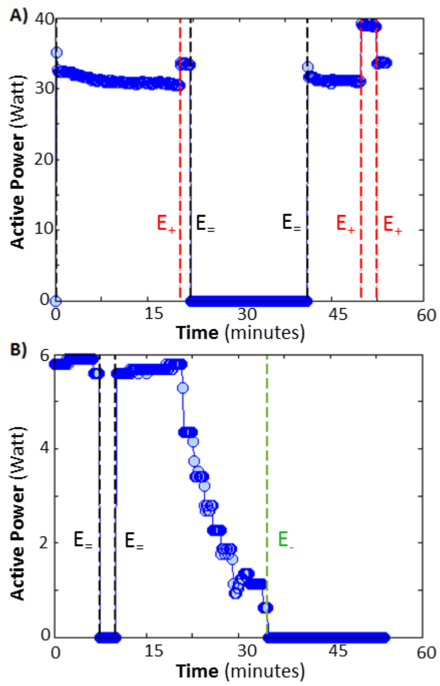

Fig. 3: A) Fan signature having 3 power levels and B) mobile phone signature. In black the events detected by the analysis of the transitions ($E_=$). In red the events added (E_+) and in green (E_-) the one removed by the rule-based algorithm.

treated with the rule-based system.
We compute the accuracy rate in three different tests:

1) When the correct model and the real sequence of states are known a priori. In this case we measure the performance of our system making the hypothesis that the HMM is performing a perfect Viterbi alignment with a perfect appliance class recognition.
2) When only the correct model is known. In this case we measure the performance of our system making the hypothesis of an HMM performing a perfect appliance class recognition and we use the computed Viterbi alignment.
3) With no a priori information. In this case we use the computed appliance class recognition and Viterbi alignment.

For each test we measure the accuracy rate of the correct detection of the User Interaction events. We consider the detection correct when the elapsed time between the real and the detected interaction is under 30 seconds (corresponding to 3 samples distance with the sampling frequency of 10^{-1} Hz). For the misclassifications we separate false positive (FP) and false negative (FN): in the first case an interaction is not detected when it occurs, in the second an interaction is detected when not present. Given the difficulty of the task, we perform the test following the *Intersession* protocol, the simplest between the two described with the ACS-F2 database.

V. Results and Discussion

As first step, we run the HMM algorithm to determine the appliance class identifications and state sequences. This information is sent to the User Interaction Layer that recover the User Interaction events. We obtain an accuracy rate of 96.5% for the appliance class recognition and 97% for the state recognition.
As a next step, we send the test data and the HMM outputs to the User Interaction Layer to perform the three tests presented in previous Section. In Table I we show the results obtained after the User Interaction Layer.

		Test 1			Test 2			Test 3		
class	**type**	TP	FP	FN	TP	FP	FN	TP	FP	FN
Hi-fi	UDA	49	3	3	37	15	17	37	15	17
Television	UDA	40	3	0	38	5	3	38	5	3
Mobile P.	UDA	16	4	5	10	10	3	10	10	3
Coffee M.	FOA	39	0	0	34	5	7	34	5	7
Computer	UDA	22	5	2	22	5	0	22	5	0
Fridge	TCA	14	0	0	9	5	0	9	5	0
Lamp Inc.	UDA	54	0	0	54	0	0	54	0	0
Laptop	UDA	23	2	0	13	12	4	13	12	17
Oven	FOA	59	0	0	59	0	4	59	0	4
Printer	FOA	45	0	0	37	8	26	37	8	28
Fan	UDA	107	4	0	106	5	0	106	5	0
Kettle	FOA	55	0	0	55	0	0	55	0	0
Lamp CFL	UDA	58	0	0	57	1	1	57	1	1
Monitor	UDA	62	0	0	61	0	5	61	1	4
Shaver	UDA	155	0	0	152	3	13	149	6	13

TABLE I: Results (in terms of number of events) obtained when applying the *User Interaction Layer* for the three tests: Test 1 when the correct model and the real sequence of states are known a priori, Test 2 when only the correct model is known and Test 3 with no a priori information.

In the first test we obtain an accuracy rate of 96.3%. Having the a priori information about the correct model and the sequence of states, the *User Interaction Layer* performs well. Several classes attain the 100% of accuracy rate. In the second test we obtain an accuracy rate of 82.5%. We notice a drop in the performances when we let the HMM compute the alignment with the Viterbi algorithm. The small error rate in the state recognition (about 3%) has a great impact in the accuracy rate of the User Identification events. This is explained by the importance of recovering the correct state sequence for the computation of the state transitions. In fact, it directly influences the User Interaction events detection through the Transition Detection phase. In the third test we obtain an accuracy rate of 80.5%. We notice a small deterioration in performances compared to the previous case. The difference is small because the accuracy rate computed on the appliance detection is quite high (96.5%) and misclassifications among similar models provide similar sequences of states.
Finally we notice that our system of rules improves the results for the class on which it has been applied: in the three tests we have a mean improvement of the 25.8% for the Hi-Fi class, of the 16.5% for the mobile phone class and of 18% for the fan class. In particular the rules related to the *Interaction without transition* improve the FP, while those related to the *Transition selection* improve the FN.
We remark that some classes are more challenging than others, as Hi-Fi, computer and laptop. This observation can be explained by the fact that the appliances belonging to these classes require high level of interaction with the User and during the labelling phase the errors are more frequent. Finally we ascertain that the mobile phone, even after the application of the rules, remains a difficult class for the event identification.

VI. Conclusion

In this paper we deal with the recognition of the user interaction events in ILM context. In a previous work [7], we developed a system based on HMM able to recognise the appliance category and the sequence of states of an electrical device. In this work we add a new layer, called *User Interaction Layer*, able to retrieve the User Interaction events. We use the ACS-F2 database [15], that contains the electrical signatures of 225 appliances uniformly spread into 15 appliance classes. All the appliances belong to different brand and/or models and are recorded with a low sampling frequency of $10^{-1}Hz$.

The *User Interaction Layer* uses the information about the recognised appliance class and the sequence of states coming from HMM. As first step, the transitions between states are recovered from the sequences. We select the transitions corresponding to User Interactions depending on the winning appliance class. This method shows some limitations and for certain appliance classes we use a rule-based system to refine the list of User Interaction events. We separate two cases: (i) the user interaction happens inside the same state (Interaction without transition) and (ii) when the transitions have different meaning depending on the context (Transition selection). For both cases the solution consists in a rule-based system respectively able to find extra-events inside portions of signatures with stationary hidden state and filter events that should not be considered.

We compare the list of User Interaction events with the ground truth and we obtain three different accuracy rates: (i) when the correct model and the real sequence of states are known a priori, (ii) when only the correct model is known and (iii) with no a priori information. We report the number of correct event detections, the number of false positives and false negatives. As expected, the best case is when the a priori information about the correct model and state sequence is used. In terms of accuracy rate, we obtain 96.3%. In the second case, we observe a drop in the performances in terms of accuracy rate, achieving 82.5%. This drop is due the to difference between the real state sequences and the computed state sequences that has a significant influence in the computation of the transitions. In the last test (with no a priori information) the system achieves an accuracy rate of 80.5%. We observe a small difference with the previous test because the accuracy rate computed on the appliance detection is quite high (96.5%) and because misclassifications among similar models provide similar sequences of states.

In conclusion, we demonstrate a simple way of extracting information about User Interaction events starting from an existing modelling system based on HMM. Even if the ACS-F2 database contains several signatures, more data could increase the reliability of our system. Such problem could be solved by including other signatures coming from other databases, as the Tracebase [20] or ECO data-set [21]. We plan to use smart and more complex algorithms for the rule computation that should lead to better performances. We also plan to apply energy saving measures by using the information coming from the *User Interaction Layer*.

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