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Model-Based Approach for Anomaly Detection in Smart Home Inhabitant Daily Life

Kevin Fouquet, Gregory Faraut and Jean-Jacques Lesage

Abstract—Due to population ageing, the number of people requiring monitoring and specific health care increased. Nevertheless, due to social or financial reasons, most of this population prefers to stay at home. Thanks to recent improvement in Ambient Assisted Living (AAL) and smart home technologies, new opportunities emerge to develop Health at Home (HaH) solutions. One of the main objectives of HaH is to offer to smart home inhabitants a life and health quality similar to patients in specialized medical institutions. To achieve this task, it is proposed in this paper an approach to monitor frail people at home to detect behavioral changes which can be symptoms of health problems. The method is model-based, working with Stochastic Timed Automata as it is an efficient tool to model activity duration and ordering habits, which are key features of human behavior. Once a model depicting life habits is built, it is proposed to use normalized likelihood and probabilistic distribution to evaluate the consistency between the regular life habits and newly observed behavior. Appearance of a inconsistent behavior may testify the evolution or apparition of a medical symptom. A case study demonstrates the relevancy of the proposed approach, and several scenarios highlight the possibility to have clear enough information on inhabitant behavior to identify a limited number of responsible medical disorder.

I. INTRODUCTION

Thanks to the numerous major medical breakthrough of last decades, life expectancy has continuously risen in most regions of the world. This situation leads to an increase in the proportion of the elderly in global population. Over 30% of the population in Europe, North America and East Asia is expected to be aged over 60 years in 2050 [1]. This part of the population requires specific medical care as they are more likely to suffer from loss of autonomy and health problems. However, most of the elderly prefer to stay at home rather than moving to specialized institutions [2]. Consequently, innovative solutions have to be explored to ensure satisfying quality of life and medical-care to people in their home.

To achieve this task, Health at Home (HaH) is a field of research which focuses on improving medical care at home using smart home technology. Recent studies have considered inhabitant localization [3], [4], activity recognition [5] and life habits modeling [6]. These approaches allow medical staff to obtain significant information about the medical status of the inhabitant, as human behavior is influenced by his health [7].

In particular, these recent works enable new approaches for behavioral deviation detection. A behavioral deviation is

a change in inhabitant life pattern which can happen suddenly at a very specific moment (for instance after a fall) or which can evolve slowly on the long-term (for instance a gradual decline if he suffers from mobility disease). These changes in behavior might testify apparitions or development of diseases and are key information for medical staff, which can adapt their monitoring or adapt a treatment.

In this paper is proposed a method for behavioral deviation detection. It focuses on sudden changes in inhabitant behavior, also called anomalies. In order to make this approach versatile enough to be adapted to any dwelling and any inhabitant and to make communication with medical staff easier, a model-based approach is proposed. The model describes the regular life habits of the inhabitant by observing his activities carried out during a training phase.

Paper is structured as follows. Section II investigates existing works and their limits to identify human features which are relevant to consider for medical staff, and existing model considering them. Section III presents the global methodology and details about the model used for life habits representation. In section IV are presented the procedures for anomaly detection by comparing newly observed behavior with the previously generated model. Finally, section V proposes a case study on a real database to demonstrate the relevancy of the proposed approach. Last section concludes the paper and discuss the perspectives.

II. STATE OF THE ART

Anomaly detection in human behavior has been subject to many research for a few years. In particular, model-based approaches have been explored as these methods ease communication and can be adapted to various behavior and environment. Thus, [3] study inhabitant's displacement in his home to detect changes in his mobility. The authors introduce a room-to-room state transition model where probabilities are generated during a training phase and raise an alarm when a movement or inhabitant activity does not match the model. In [4], the authors also consider weighted directed graphs to depict usual mobility of the inhabitant and detect change in behavior by using page-rank algorithm at different times. However, these approaches only consider information given by the sensors deployed in the dwelling which offer low semantics level information, which makes difficult for medical staff to understand the nature of the deviation.

Meanwhile, some works in AAL considered activity recognition from sensor logs [5]. These works focus on identifying which activity is carried out by a smart home

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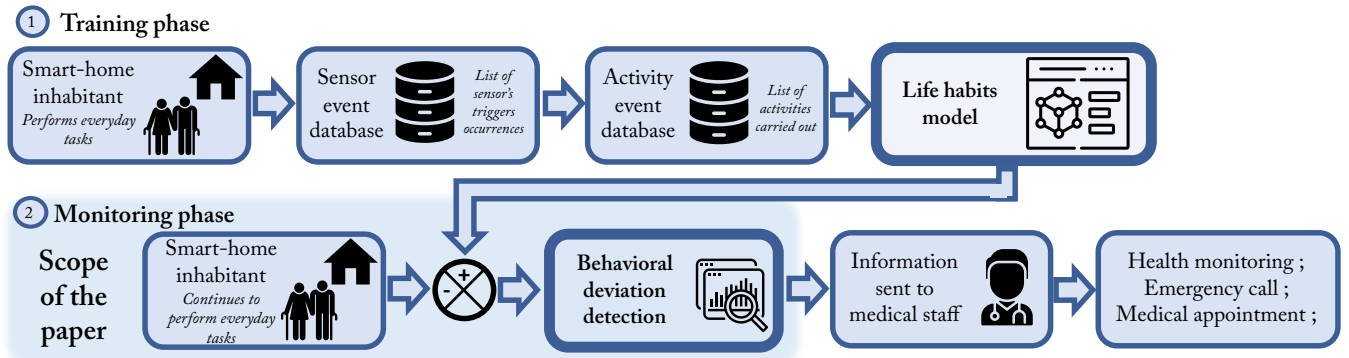


Fig. 1. Global methodology and paper contribution

inhabitant by observing the sensors he triggers. This approach offers opportunities for anomaly detection in human behavior by allowing a higher level of semantics, as knowing precisely which activity is faulty enables medical staff to better diagnose [7]. In this paper is proposed a new method for model-based behavior deviation considering the activities carried out by the inhabitant. To offer relevant information to medical staff, the proposed approach focus on activity ordering and activity duration which give very precise information about the health status of a human being [6], [7], [8].

Routine alteration is a frequent consequence of medical conditions evolution, and has been explored in [9]. The authors propose a model in which activities are decomposed into elementary actions with order or dependency relations to test and detect unexpected patterns. Yet, as the model has to be built by an expert this approach is hardly scalable, which is a massive problem as an important part of the population is expected to be aged 60 and over in the near future. Other works such as [10] also consider activity ordering through Hidden Markov Model. As the structure of these models does not possess intrinsic meanings by definition, they make communication with medical staff more difficult which reduce the main advantage of model-based approach.

On the other hand, many works study activity duration as a change in inhabitants' health status often disrupts the time allocated for specific tasks. Most of these works consider normal distribution or interval [10] whose characteristics are determined through a training phase. An anomaly is raised when an activity duration is out-of-bounds or when the probability to observe such time is lower than a given threshold. These works offer a relevant way to detect change in behavior but are often limited to the normal distribution, while most activities might be better modeled by other distributions, especially log-normal [6].

In this paper is proposed a new methodology for anomaly detection in smart home inhabitant behavior. Presented approach is model-based in order to ease communication with the different protagonists of HaH and to be versatile enough to be adapted to the numerous kinds of smart dwelling and to a huge number of inhabitants diseases. It consists in a high level of semantic approach as it considers directly the activity carried out by the inhabitant thanks to recent works

in activity recognition, and focus on activity ordering and duration as they are key features of health status of a human being.

III. GLOBAL METHODOLOGY AND LIFE HABITS MODEL

A. Methodology overview

Proposed methodology, shown in figure 1, is composed of two phases. During the training phase, the inhabitant of an equipped smart home carries out his everyday life. This paper focus on single inhabitant, but can easily be adapted to multi-inhabitant smart home if it is possible to distinguish them, for instance with embedded RFID sensors. Sensors are triggered and sensor events are registered in a sensor event database, which is used by existing activity recognition algorithms such as [5] to fill an activity event database. From this database is built the model representing inhabitant life habits which will be used as a reference for behavioral anomaly detection. This training phase is detailed in subsection III-B.

This paper focus on the second phase. During the monitoring phase, every daily tasks performed by the inhabitant are compared to the previously generated model in order to detect behavioral anomalies by observing activity ordering and duration. If an anomaly is detected, the information is sent to the medical staff who will evaluate its criticality and associate it with a potential health problem. If the anomaly is considered serious, medical care can be adapted, or an emergency call can be made to intervene.

B. Life habits model

To be able to detect a deviation in the inhabitant's behavior, a model depicting his life habits has to be built from the training database. One month of training data is generally enough to know the routine of an individual. During this training phase, the inhabitant behavior might possess some anomalies. However, with regular medical check-up, it can be considered mainly sane.

As highlighted in the state of the art, activity ordering and duration are the most relevant human behavior features to observe in order to have significant information about inhabitants' health status. These features can be modeled using Stochastic Timed Automaton (STA).

A STA is a 3-tuple $\langle A, \mu, P \rangle$ where A is the STA structure such as $A = \langle L, l_0, X, \Sigma, \delta \rangle$ with:

- L is a finite set of location;
- $l_0 \in L$ is the initial location;
- X is a set of clocks;
- Σ is the alphabet;
- $\delta \subset L \times \Sigma \times R_X \times L$ is a set of transitions composed of a departure location, an event, a list of clocks to reset $R_X \subseteq X$ and an arrival location.

μ is the probability measure over location delay $\mu = (\mu_s)_{s \in L \times \mathbb{R}_+^X}$ and P is the probability defined on each transition $P: \delta \rightarrow [0, 1]$ and express the probability to observe successively the activities associated to the source and to the destination of a transition by generating its associated event. For each location, the sum of all probabilities from outgoing transitions is always equal to 1.

$$\forall l \in L, \sum_{l' \in L, \sigma \in \Sigma, r_X \subseteq X} P(l, \sigma, r_X, l') = 1$$

Automatic generation of a STA from an activity event database to represents inhabitants' life habits is presented in [6]. Details about this procedure will not be provided in this paper. The result of this generation is a STA whose each location represents a specific activity (except for the initial one). Probability associated to transitions express the probability to observe a specific ordered sequence of activity, and probabilistic distribution associated to each location represents the expected duration of the respective activity.

Any probabilistic distribution can be used to model activity duration. Yet, [6] highlights the efficiency and the wide coverage of the log-normal distribution. For every database, inhabitant and activity observed, log-normal distribution tends to offer a very precise representation of activity duration. In particular, results obtained by this distribution are more satisfying than normal and exponential distributions that are more commonly used. Consequently, in this paper is made the hypothesis that every activity duration is modeled by log-normal distribution.

An example of STA modeling an inhabitant's morning routine is depicted in figure 3.

IV. ANOMALY DETECTION

Once life habits model is built, it is proposed to monitor new behaviors and to compare theme with these life routines through the two indicators presented earlier: activity ordering and duration. If new observed behaviors are consistent with the model, the inhabitant is likely to carry out his everyday tasks as usual. Otherwise, it implies a change in his life routine. As stated earlier, these changes are key information for medical staff to detect potential health related problems or to detect an emergency.

A. Activity ordering

Testing activity ordering of a new behavior means computing a distance between a newly observed sequence of activity and the STA. Some existing techniques fulfill this task.

In particular, likelihood is a well-known tools which computes the probability that a model M generates a given sequence of event w . Let a_i be an activity. $\sigma_i \in \Sigma$ and $l_i \in L$ are respectively the event and the location associated to the activity a_i . Activity sequence $w = [\sigma_1, \dots, \sigma_n]$ is an ordered sequence of activity event. Its length denoted $|w|$ is the number of events composing the sequence. A path in the STA is a sequence of transition $\theta = ((l_1, \sigma_1, r_1, l_2), (l_2, \sigma_2, r_2, l_3), \dots, (l_n, \sigma_n, r_n, l_{n+1}))$ where $(l_i, \sigma_j, r_k, l_j)_{(i,j) \in [(1,m), (m,n), \dots, (o,p)], k \in [a,b, \dots, d]} \in \delta$ and its length $|\theta|$ is its number of transitions. The probability to fire such a path is:

$$P(\theta | M) = \prod_{k=1}^{|\theta|} P(\delta_k)$$

where δ_k is the k^{th} transition of θ .

If the sequence of activity event w is generated by firing θ , θ is said to be fireable by w . Additionally, θ is said to be valid if its probability $P(\theta | M)$ is greater than 0. Let $\Theta_M(w)$ be the set of all valid paths in M which are fireable by w . In that case, likelihood can be defined by:

$$P(w | M) = \sum_{\theta \in \Theta_M(w)} (P(\theta | M))$$

The more important the likelihood is, the more probable the model may produce the given sequence. Thus, likelihood is a relevant tool to compare a sequence of activity with life habits. However, this technique has the disadvantage to give low probabilities if inhabitant life habits are diverse, as the sum of outgoing probabilities of each location has to be equal to 1. Thus, having a low likelihood probability does not necessarily mean that the observed behavior has no consistence with life habits.

To counterbalance this drawback, normalized likelihood was defined in [5]:

$$\|P(w | M)\| = \frac{P(w | M)}{\max_{v \in \Sigma^{|w|}} [P(v | M)]}$$

with $P(w | M)$ the likelihood defined earlier and $\Sigma^{|w|}$ the set of all sequence of activity events of length $|w|$.

Thanks to this normalization, the most probable path through the model (which corresponds to the most appeared life routine) will have a normalized likelihood equal to 1. Other life routines will get a score relative to this main habit, included in $[0, 1]$. The more important is the normalized likelihood, the higher is the confidence that the observed behavior matches with life habits.

B. Activity duration

The same way, duration of newly observed activities has to be compared with the expected ones according to the probabilistic distributions described in the model. If duration fit with the distribution, it means the inhabitant is likely to carry out his activity as usual. Otherwise, it means that the inhabitant behavior changed which can indicate various health troubles depending on the activity (loss of appetite, sleep disturbance, mobility problems, etc.) [7].

Detecting anomalies by comparing observed duration and expected distribution as already been explored by [11]. In their work, the authors consider normal distribution exclusively, and compute a distance between the duration and the expected mean in number of sigma. Then they define a threshold in number of sigma beyond which an anomaly is detected. This threshold depends on the quantity of expected healthy behaviors to be observed. For instance, a threshold of 3σ means 99.74% of the newly observed behavior are normal. A threshold of 2σ stands for 95.44%, etc.

This work can easily be extended to log-normal distribution by considering the logarithm of observed duration. Thus, a time distance to evaluate the coherence between a duration t and the model associating activity duration with log-normal distribution can be defined by:

$$\text{time distance}(t) = \frac{\log(t) - \mu}{\sigma}$$

where μ and σ are such that e^μ and e^σ are the parameters of the log-normal distribution. If this time distance exceeds a thresholds fixed by the medical staff depending on the expected amount of abnormal behavior, an anomaly is detected.

V. CASE STUDY

In order to demonstrate the relevancy of the proposed approach, a test on a real case study is proposed. Numerous databases are publicly available online. DOMUS database has been chosen as it considers morning routine of inhabitants which is often well-defined.

A. Database description

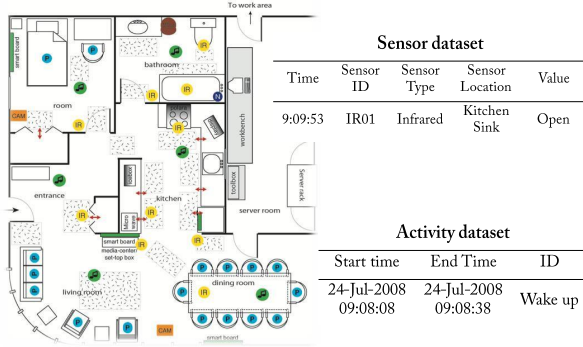


Fig. 2. DOMUS smart home plan and examples of sensor and activity events.

In the DOMUS database 6 participants are asked to carry their morning routine for 10 days. The smart home is equipped with pressure detectors, infrared movement detectors, door and switch contacts, lamp light switches, and flow meter. For this case study, only first user's behavior is studied. All sensor events generated during the performance of the morning routine are labeled with the occurrence time, the name, the type and the localization of the sensor, and a value depending on the sensor's type. It is then possible to use these events to generate an activity database, thanks to activity recognition algorithms such as [5]. In figure 2 is

depicted the smart home plan as well as the sensors locations and instances from sensor and activity datasets.

B. Model and training data generation

Following protocol defined in subsection III-B, an STA is generated from user 1 behavior. Activity duration is modeled by log-normal distributions. Model is depicted in figure 3. By using tools such as likelihood, it appears sequence of activities [Wake up, Use Toilet, Preparing Breakfast, Having Breakfast, Washing dishes, Other activities] is the most probable sequence to occur. This sequence is very likely to be user 1's usual life routine

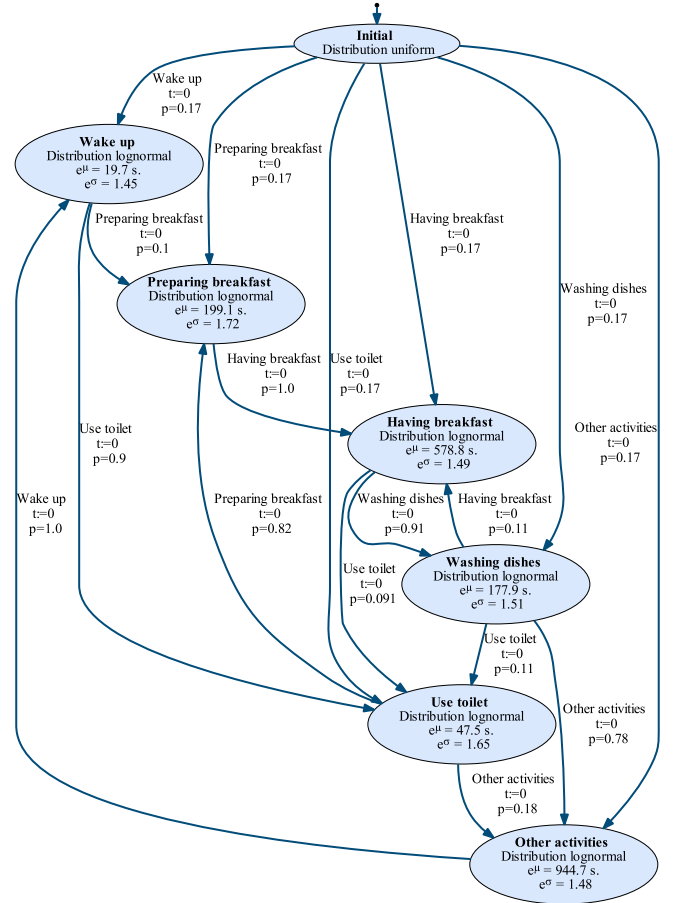


Fig. 3. STA model depicting life habits of User 1 from DOMUS.

To test presented methodology, labeled database of sick inhabitants are necessary. To the best of our knowledge, there is no public database of this sort. Therefore, it is proposed to artificially build scenarios depicting symptoms evolution to be the most representative of real life observations.

Three scenarios are proposed to test the proposed methodology: In first scenario, The inhabitant carries out its activity as usual. In the second one, the inhabitant suffers from a loss of appetite. Loss of appetite is an important feature for medical staff to observe as it often mirrors the health status of a patient [7]. Finally, scenario 3 depicts an inhabitant suffering from urinary tract infection which is a common

TABLE I
ACTIVITY SEQUENCE AND DURATION FOR EACH SIMULATED SCENARIO.

	Scenario 1	Scenario 2	Scenario 3
Symptoms and disease	Good Health	Loss of appetite	Urinary Tract Infection
Generated activity sequence	Usual life routine: [Wake up, Use Toilet, Preparing Breakfast, Having Breakfast, Washing dishes, Other activities]	Usual life routine: [Wake up, Use Toilet, Preparing Breakfast, Having Breakfast, Washing dishes, Other activities]	Usual life routine with one to three additional "Use toilet" activity randomly carried out every day
Generated activity duration	Randomly generated according to STA distribution	Activity Preparing and Having breakfast duration are multiplied by a random factor $f \in [0,1]$ Other duration are randomly generated according to STA distribution	Randomly generated according to STA distribution

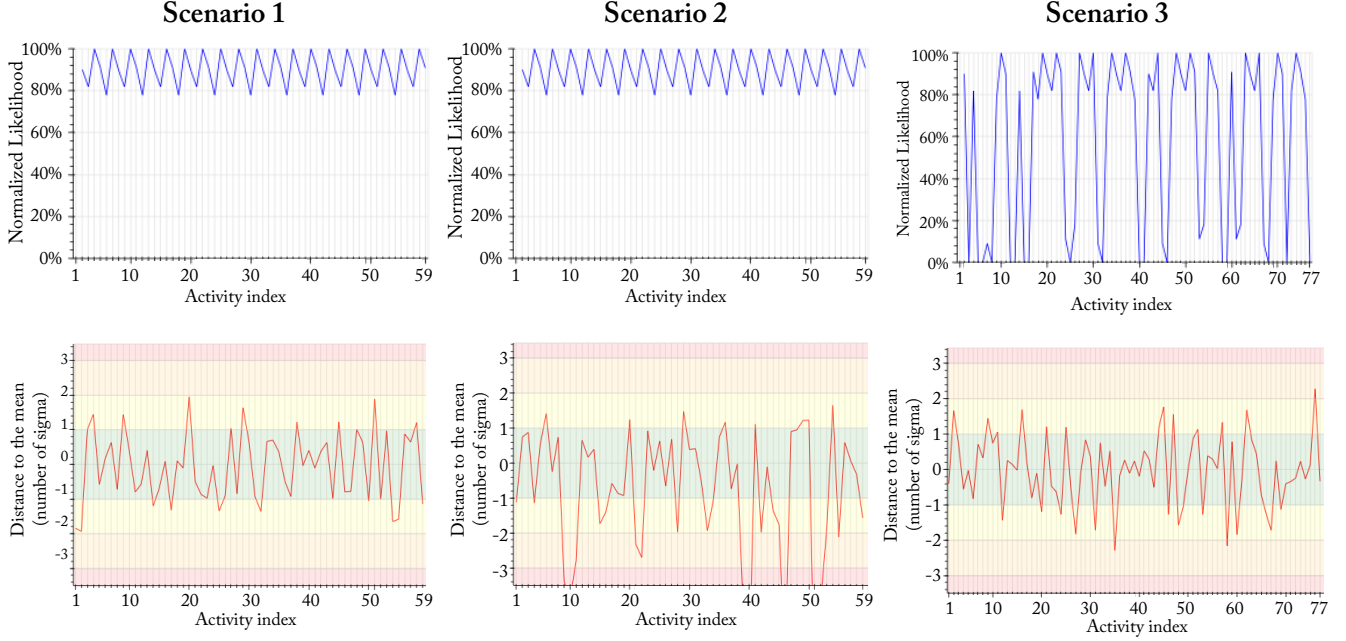


Fig. 4. Normalized likelihood (above) and time distance (below) for each activity with each scenario.

Scenario 1 & 2 Index - Activity		Scenario 3 Index - Activity	
1, 7, 13, 19, 25, 31, 37, 43, 49, 55	Wake up	1, 10, 19, 27, 34, 41, 48, 55, 63, 70	Wake up
2, 8, 14, 20, 26, 32, 38, 44, 50, 56	Use Toilet	2, 3, 5, 7, 11, 12, 13, 15, 20, 24, 25, 28, 31, 35, 40, 42, 45, 49, 53, 56, 58, 61, 64, 67, 71, 72, 77	Use Toilet
3, 9, 15, 21, 27, 33, 39, 45, 51, 57	Preparing Breakfast	4, 14, 21, 29, 36, 43, 50, 57, 65, 73	Preparing Breakfast
4, 10, 16, 22, 28, 34, 40, 46, 52, 58	Having Breakfast	6, 16, 22, 30, 37, 44, 51, 59, 66, 74	Having Breakfast
5, 11, 17, 23, 29, 35, 41, 47, 53, 59	Washing dishes	8, 17, 23, 32, 38, 46, 52, 60, 68, 75	Washing dishes
6, 12, 18, 24, 30, 36, 42, 48, 54	Other activities	9, 18, 26, 33, 39, 47, 54, 62, 69, 76	Other activities

Fig. 5. List of index and associated activity

disease in the older population [12]. Details about these scenarios and their artificial generation are given in table I.

Activity duration are generated by the random variate function from the Scipy library on Python 3.6. Each scenario is ten days long.

C. Results

Results for each scenario are depicted in figure 4. The list of activities index is stated in figure 5. Activity ordering

is evaluated by computing normalized likelihood for each activity in relation to the previous occurred event. For instance, in scenario 1 the second event "Use toilet" follows activity "Wake up". It consequently possess a likelihood of 15.3% ($17\% \times 90\%$) and a normalized likelihood of 90% ($\frac{17\% \times 90\%}{17\% \times 100\%}$). Activity duration is evaluated according to subsection IV-B. If an activity evaluation reaches a threshold defined by the medical staff, for instance 10% for activity ordering and 2σ for activity duration, an anomaly is detected.

For scenario 1, as the sequence of activity tested is consistent with the usual life routine of the inhabitant, normalized likelihood fluctuates between 78% and 100% and no anomaly is detected. Considering activity duration, most are included in $[-1, 1]$ (green area) meaning the observed behavior is perfectly normal. Only activity "Use toilet" the first day is slightly shorter than expected, and activities "Use toilet" and "Preparing Breakfast" are longer than expected respectively the 4th and 9th day. Yet, these deviations' amplitude are not more than 2σ (-1.93, 1.96 and 1.89), and are consequently considered as benign.

Concerning scenario 2, normalized likelihood is the same as activities are executed is the same order. However, dura-

tion study highlights a more disturbed behavior. In particular, activity "Preparing breakfast" is shorter than expected the 2nd, 3rd, 4th, 6th, 7th, 8th, and 9th day (respective distances are -3.39, -1.74, -2.32, -1.937, -4.26, -1.76, -7.24). On the other hand, activity "Having breakfast" is shorter than expected everyday except day 10 (-1.15, -3.89, -1.39, -2.70, -1.98, -1.05, -6.05, -5.90, -3.90). These anomalies are sent to medical staff. As the deviations' amplitudes are severe and repeated several days in a row, a health problem can be deduced. The behavior deviation only concerns meal-related activities, thus eating disorder can be expected. Additionally, as the activity duration study reveals that these activities are shorter than expected, the loss of appetite is the privileged scenario. Other activities are punctually longer or shorter than expected ("Washing dishes" the 1st day, and "Other activity" the 7th day), but as these deviations appear once and have a low amplitude (below 2σ), they do not signify a massive change in inhabitant routine.

Finally, scenario 3 possess a more chaotic normalized likelihood which testifies a change in activity ordering. By observing more closely the activities, it appears that the sequences which possess a low normalized likelihood are ["Use toilet", "Use toilet"] (0%) 5 times, ["Having breakfast", "Use toilet"] (9.1%) 4 times, ["Use toilet", "Having breakfast"] (0%) 3 times, ["Preparing breakfast", "Use toilet"] (0%) 3 times, ["Washing dishes", "Use toilet"] (11.1%) 3 times, ["Use toilet", "Other activities"] (18.2%) 3 times, ["Use toilet", "Washing dishes"] (11.1%) 5 times, and ["Other activities", "Use toilet"] (0%) 2 times. As "Use toilet" appears in all of these sequences, it can then be concluded that the inhabitant may suffer from a urinary problem. Yet, it should be noted that normalized likelihood offer no information about activity frequency. Medical staff has no information if activity "Use toilet" is executed more or less often than expected. Activity duration seems to be consistent with the usual life habits as no activity deviates from the expected behavior, except for activity "Use toilet" the 5th and 8th day (-2.30 and -2.17 respectively) and "Other activity" the last day (2.29). Yet, as these deviations are of different natures and not recurrent, they are not likely to express a health problem.

VI. CONCLUSION AND DISCUSSION

In this paper, a method for anomaly detection in behavior of smart home inhabitants has been introduced. It consists in creating a model depicting life habits of a smart home inhabitant to compare it with new daily activities to detect unexpected behavior, as they might testify of a change in the inhabitant's health status. This method focuses on activity ordering and duration, which are key information about health status of an individual, by using normalized likelihood and probabilistic distribution to evaluate each carried out activity. Thus, it makes possible to know precisely the amplitude and the nature of a behavioral deviation, and ease diagnostic for medical staff. Proposed approach is versatile enough to be adapted to any inhabitant, home equipment, and to focus on specific activities depending on his medical history.

A case study presents several scenarios depicting real life symptoms, artificially generated from a real inhabitant routine presented in DOMUS database. These scenarios highlight the efficiency of the approach, and testify to the precision of the obtained information since it is possible to identify the symptoms which caused the deviation in behavior.

Further works will consider long-term behavioral deviations, that is to say detecting inhabitant's decline in execution of his daily routine by observing trends in the presented indicators to allow for preventive actions. Moreover, other indicators than activity ordering and duration could be taken into consideration such as activity time.

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