Combining Timed Data and Expert's Knowledge to Model Human Behavior *

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ABSTRACT

One of the major issues of monitoring activities in smart environments is the building of activity models from sensor's timed data. This work proposes a general theoretical approach to this aim, based on a Knowledge Engineering methodology and a Machine Learning process that are both funded on a general theory of dynamic process modeling, the Timed Observation Theory. In the proposed framework, activity recognition is an abstraction process where the activities are conceived as entities at different abstraction levels. This paper aims at showing that prior expert's knowledge about resident activities can be compared with posterior knowledge induced from timed data. The proposed approach is described through the database of the prototypical home of the GerHome project.

Keywords

Smart Environment, Human Activity, Dynamic Process Modeling, Machine Learning

1. INTRODUCTION

Physical or cognitive functional limitations and difficulties in activities of daily living (ADL) and in instrumental activities of daily living (IADL) increase with the age and, in general, are higher among people 60 years or more [29]. These restrictions affect the autonomy and the well-being of people in the last phases of life. Many older adults or people with disabilities wish to remain in their home for as long as possible even when their daily needs are affected. Certain surveys indicates that nearly 75 percent of respondents age 45 or older hope to stay in their homes as they age [1]. Under these considerations, and taking into account that the autonomy of a person depends not only of its capacities to accomplish acts of daily life, but also on the possibilities that the environment can provide, there is a growing interest in observing ADLs and monitoring health through smart environments [33, 6].

A smart environment *"is able to acquire and apply knowledge about an environment and also to adapt to its inhabitants in order to improve their experience in that environment"* [8]. An example of smart environment is a smart home as Aware Home [2], EasyLiving [5], MavHome [7, 17], CUS Smart Home [31], iDorm [16], QuoVADis [15], CASAS [28, 24] and GerHome [34, 35], where inhabitant behavior is recorded by sensors and monitored by a program in order to detect the activity carried out (such as cooking, eating, watching TV, etc.).

Activity monitoring consists of comparing resident behavior with activity models to determine the executed activity and to detect anomalies or behaviors that require automatic intervention of the environment. Nevertheless, the definition of models for human activity monitoring is one of the major issues due to the randomness of human behavior and, therefore, to the subjective notion of the concept *activity*.

The work presented in this paper proposes a general theo-

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retical framework which conceptually defines the notion of *activity* and relates Knowledge Engineering methodologies with Data Mining techniques to define and to identify resident activities. The application of this approach is illustrated through the GerHome project of Centre Scientifique et Technique du Bâtiment (CSTB, France). The aim of this project is to develop technical solutions to the problem of providing greater autonomy and better quality of life to the elderly at home; and thus, to work on the prevention of accidents such as fall down originating in the frailty increase of the person. The hold method is to track the frailty trends by monitoring the daily activity and to compare a learned model with sensor data recorded from effective activities. This research path leads the way to detect activity models and could offer an appropriate and reliable method to extract relevant and coherent daily activity patterns.

In Section 2, we introduce related works and the motivation of our approach. Section 3 presents the theoretical framework proposed for modeling and recognizing the resident's activities. Section 4 describes our proposal applied to the GerHome project. Finally, in Section 5, our conclusions are presented.

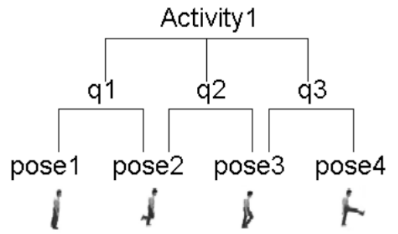
2. RELATED WORKS

Human activity recognition in perceptual environments involves severe challenges due to the erratic nature of human behavior. To determine what is being done can be complicated if different activities are executed at the same time; e.g., to cook while watching TV. Besides, the same detected action can be associated with several activities depending on the context in which it is carried out then, to discriminate what is the right activity is not trivial; e.g., to open sink water tap can be part of cooking or washing dishes. Moreover, activities can be interleaved: while washing dishes the phone rings, the activity is paused, the phone is answered and then, the activity is taken up again. Thus, to determine what a person is doing at a particular time is not a simple task.

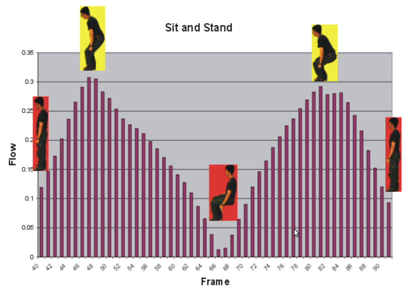
The problem lies in the meaning and the interpretation of the perceptual inputs due to the large gap that exists between the low level signals, as pixels, sensor signals, etc., and that one that is inferred in a higher level, for example, *washing dishes*.

Different works propose a characterization and a definition of human activity in smart environments. In particular, an activity can be considered in terms of space (activity location), of time (temporal patterns), of goals (intentions) and in terms of ethnographic data [3]. On the other hand, as proposed in [20], activities are directly linked with human acts which can be specified by constructing a probabilistic context-free grammar (PCFG), whose alphabet consists of poses (Figure 1(a)). Thus, activity recognition is based on a successive abstraction process where human activities are defined from the visual observation of body poses obtained from video data and, three levels of abstraction are conceived (Figure 1): continuous signal (optical flow), discrete event (body pose) and activity (sequence of discrete events). In [19], activities depend on temporal, logical and causal constraints linked with an intention and three abstraction levels are also presented: *low level sensory stimuli*, *notion of causality amongst some qualitative activity descriptors* and *notion of context-sensitive intent*. Similarly, [21] proposes three levels of abstraction as well: *movements as low-level semantic primitives*, *activities as sequences of states and movements* and *human behavioral actions as high level semantic events*.

The MavHome (managing and adaptive versatile home) project [32] is focused on providing smart environments, whose goals are to maximize the comfort of the inhabitants, minimize the consumption of resources, and maintain the safety of the



(a) Activity definition (*Pick Up*) [18]



(b) Motion patterns from sensor data (*Sit and Stand*) [20]

Figure 1: Activity definition by using PCFG

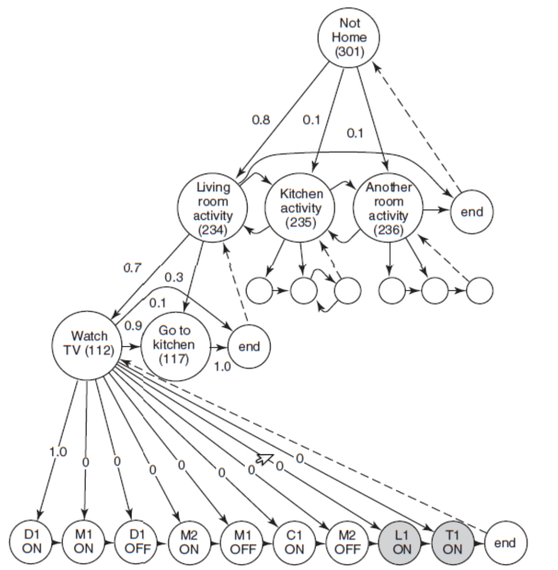


Figure 2: Activity hierarchical model constructed from MavHome data [9]

Table 1: Different notions of the concept *human activity* in smart environment.

Level	MavHome [32, 9]	CASAS [24, 26, 25, 27]	Semantic Levels [21]	Abstraction Levels [19]	PCFG [20]	Conceptual Activity
level 2	*activity* (space taxonomy)	temporal taxonomy	*behavioral action* (interaction with the environment, causal relationships)	*activities* (triples of context, behavior, state)	*activity*	*activity* (defined from a set of primary activities)
level 1	event sequence (start and end)	*abstract event level* (sequences of events, start and end)	*activity* (sequences of states and movement, knowledge related to statistics of temporal sequences)	*semantically meaningful activity-descriptors* (rules of causality, context-sensitive)	discrete event	*primary activity* (defined from a set of discrete events)
level 0	discrete event	*sensor level* (discrete event)	*human movement* (does not require contextual or temporal knowledge)	*low level sensory stimuli* (there is not notion of time, physical states or causality)	continuous signal	*discrete event*

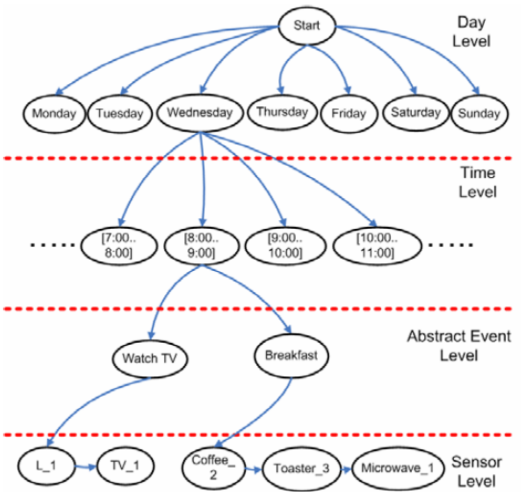


Figure 3: Example hierarchical activity model constructed from CASAS data [26]

environment and its residents. In this project, once again, three levels of abstraction are proposed (discrete events coming from sensors, event sequence and activity) and the move from an abstraction level to the other is based on models that are produced using a process of Knowledge Discovering from Databases (the Apriori algorithm [30] or Hiden Markov models, Figure 2). A similar approach is used in CASAS [27, 25, 26, 23], an adaptive smart home system that discovers and adapts to changes in the resident's preferences in order to generate satisfactory automation policies. In this case, a temporal point of view about the different levels of abstraction (Figure 3) is considered. It is to note that CASAS uses an algorithm of pattern adaptation miner (PAM) in order to adapt to changes in the behavior patterns.

All of these approaches include the idea of hierarchical abstraction, and define three levels of abstraction (Table 1): discrete events, sequence of discrete events and a taxonomic classification at the highest level. Nevertheless, these definitions about the concept *activity* depend mainly on the techniques used to build models for activity recognition.

We propose then a general paradigm to define a conceptual notion of human activity that is not subject to a particular application and which considers three levels of abstraction: at level 0 timed observations or *discrete event*, at level 1 *primary activities* as specific timed observation sequences, and finally *activity* as sequences of primary activities. Besides, we present a general procedure to define activity models which combines Knowledge Engineering with Data Mining. The advantage of our approach is to facilitate the definition of the principles of a general abstraction process from data.

3. A THEORETICAL FRAMEWORK FOR MODELING HUMAN ACTIVITIES

Our proposal is based on relating a Knowledge Engineering Methodology to a Timed Data Mining technique, i.e. the Timed Observations Modeling For Diagnosis (TOM4D) methodology [22, 14, 13] and the machine learning process called Timed Observations Mining For Learning (TOM4L) [4, 12]. Both TOM4D and TOM4L come from the mathematical Theory of Timed Observations [11] that provides a theoretical framework to facilitate the dynamic process modeling for monitoring, diagnosis and control.

3.1 Human Activities As Observation Classes

In this framework, a process is an arbitrary set $X(t) = \{x_i(t)\}_{i=1...r}$ of time functions $x_i(t)$ defined on $\mathbb{R}$ (i.e. sig-

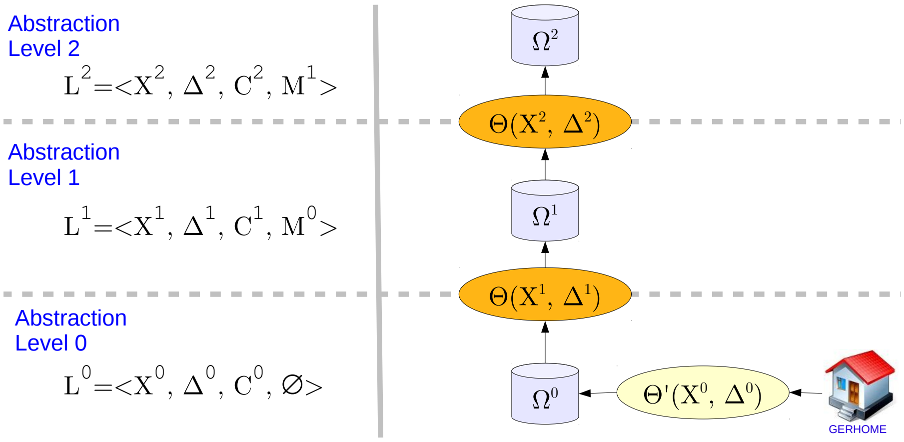


Figure 4: Activity abstraction process

nals provided by sensors). A *timed observation* is a couple (δ_i, t_k) which corresponds to the assignation of a predicate $\theta(x_i, \delta_i, t_k)$ where δ_i is constant and $t_k \in \mathbb{R}$ a time stamp. When making an abuse of language, such a predicate can always be interpreted as the predicate $EQUALS(x_i, \delta_i, t_k)$ (i.e. $x_i(t_k) = \delta_i$). A monitoring program $\Theta(X, \Delta)$ is a program Θ that analyzes the set of time functions $x_i(t)$ associated to the set of variables $X = \{x_i\}_{i=1...r}$. The aim of a monitoring program is to write timed observations (δ_i, t_k) in a database whenever a time function $x_i(t) \in X(t)$ satisfies some predicate $\theta(., ., .)$. Generally speaking, such a predicate is satisfied when $x_i(t)$ matches against a behavioral model [10] that can be as simple as the switch of an interrupter or, requiring complex techniques, such as signal processing techniques for artificial vision.

Definition 1. Let X be a set of variable names of a process $X(t) = \{x_i(t)\}_{i=1...r}$ and let $\Delta = \bigcup_{x \in X} \Delta_x$ be such that Δ_x is a set of values assumable by the variable $x \in X$ via a program Θ. An observation class C_i is a set of pairs (x, δ) such that $x \in X \wedge \ \delta \in \Delta_x$.

In other words, an observation class C_i associates variables $x \in X$ with constants $\delta \in \Delta_x$. For simplicity reasons, an observation class is usually defined as a singleton $C_i = \{(x, \delta)\}$. This allows to formally define usual notions of events:

- A discrete event is a pair (x, δ) with $x \in X$, $\delta \in \Delta_x$, denoting that the value δ is assumed by the variable x. A discrete event corresponds then to a singleton observation class $C_i = \{(x, \delta)\}$.
- A discrete event occurrence is a triplet (x, δ, t_k) with $x \in X$, $\delta \in \Delta_x$, $t_k \in \mathbb{R}$ denoting that the value δ is assumed by the variable x at the time t_k. A discrete event occurrence is then a timed observation (δ, t_k) of an singleton observation class $C_i = \{(x, \delta)\}$.

The notion of observation class also contemplates different levels of abstractions; that is to say, a particular set $C^\ell = \{C_1^\ell, ..., C_n^\ell\}$, $n \in \mathbb{N}$ of observation classes C_i^ℓ can be defined for any level of abstraction ℓ ($\ell \in \mathbb{N}$). Thus, the following definitions are introduced.

Definition 2. Let X^ℓ be a set of abstract variables belonging to an abstraction level ℓ and let $\Delta^\ell = \bigcup_{x^\ell \in X^\ell} \Delta_{x^\ell}^\ell$ be such that $\Delta_{x^\ell}^\ell$ is a set of values assumable by the variable x^ℓ. An abstract observation class at the abstraction level ℓ is a singleton $C_i^\ell = \{(x^\ell, \delta^\ell)\}$, with $x^\ell \in X^\ell$ and $\delta^\ell \in \Delta_{x^\ell}^\ell$.

Definition 3. A behavioral model M^ℓ defined at abstraction level ℓ is a set of n-ary timed relations between observation classes defined at the abstraction level ℓ.

The move from an abstraction level $\ell - 1$ to the level ℓ is made when associating a particular set of behavioral models (at level $\ell - 1$) to a given observation class C_i^ℓ (at level ℓ). Considering this as a general principle, Definition 4 specifies the notion of abstraction level.

Definition 4. An abstraction level ℓ is a structure $L^\ell =< X^\ell, \Delta^\ell, C^\ell, M^{\ell-1} >$ where

- X^ℓ is a set of variable names defined at level ℓ,
- Δ^ℓ is a set of values assumable by the variables,
- C^ℓ is the set of observation classes belonging to the level ℓ, such that each observation class $C_i^\ell \in C^\ell$ is a singleton and,
- $M^{\ell-1}$ is a behavioral model defined at level $\ell - 1$.

Consequently, the variables $X = \{x_i\}_{i=1...r}$ of a process $X(t) = \{x_i(t)\}_{i=1...r}$ are associated with the lowest level 0: $L^0 =< X^0, \Delta^0, C^0, M^{-1} >$ where $X^0 = X$ and, naturally, $M^{-1} = \emptyset$ since there is not observation classes in a previous level and so no behavioral models can be defined with the timed observation paradigm. At level 1,

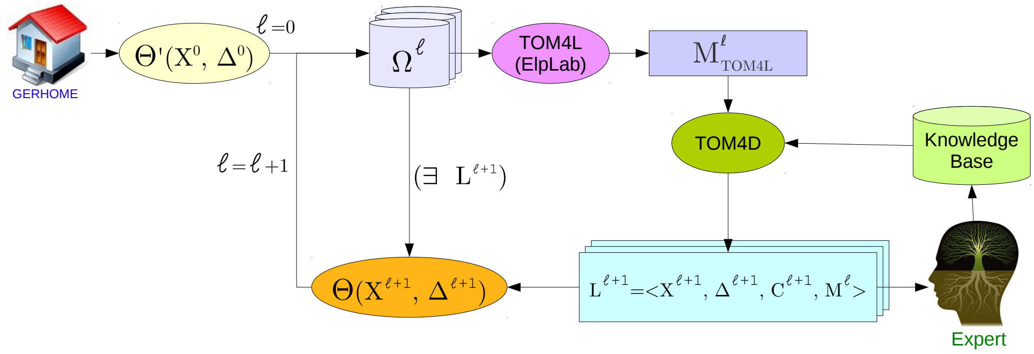


Figure 5: Definition of activity models (**Expert symbol has been taken of www.civicore.com**)

$L^1 =< X^1, \Delta^1, C^1, M^0 >$ where the variables and the observation classes are abstract. Each class of C^1 is associated with a behavioral model of M^0; that is, a set of n-ary relations included in M^0. Similarly, at level 2 where $L^2 =< X^2, \Delta^2, C^2, M^1 >$, variables and observation classes are abstract and each observation class of C^2 is associated with a sub-set of M^1.

The definition of these abstraction levels allows to specify: the different types of *discrete events* (sensor data) as observation classes at level 0 ($C_i^0 \in C^0$), each *primary activity* as an observation class at level 1 ($C_i^1 \in C^1$) and; finally, an *activity* as an observation class at level 2 ($C_i^2 \in C^2$).

The passage of a level $\ell - 1$ to a level ℓ, where each class of C^ℓ is associated with a behavioral model of $M^{\ell-1}$, can be accomplished by a program $\Theta(X^\ell, \Delta^\ell)$ which analyzes the flow of timed observations at level $\ell - 1$. In other words, $\Theta(X^\ell, \Delta^\ell)$ assumes the matching of the flow of timed observations at level $\ell-1$ against the models in $M^{\ell-1}$, and records the corresponding timed observation (δ^ℓ, t_k) in a database. Figure 4 illustrates these concepts in the context of the GerHome project where a monitoring program Θ' registers a set Ω^0 of sequences of discrete events, considered as timed observations at level 0, from sensors that perceive the process *"the resident's behavior at home"*. For its part, $\Theta(X^\ell, \Delta^\ell)$ ($\ell = 1, 2$) writes occurrences of observation classes defined at level ℓ, from a model $M^{\ell-1}$ that allows to recognize the behavior at level $\ell - 1$ and interpret it as more abstract activities at the higher level.

3.2 Activity Model Definition Process

The abstraction process requires to establish the different levels; and therefore, to define behavioral models M^ℓ. To this aim, we propose a procedure of activity definition based on the combination of learning from data using Data Mining techniques (TOM4L process), and the use of expert's knowledge through Knowledge Engineering (TOM4D methodology). Figure 6 shows the logic-precedence structure of the process of model construction where the relations are between passive entities (as knowledge base, process model and timed observations) and conceptually active entities (as TOM4D, TOM4L, the expert and the monitoring program Θ). Thus, an passive entity can be obtained trough an active entity which can require another passive entity. In the figure, a model can be built from *a priori* knowledge by means

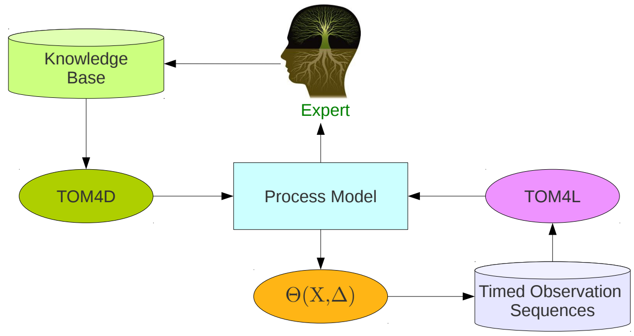


Figure 6: Structure of logical precedence in the construction of models from data (**Expert symbol has been taken of www.civicore.com**)

of the methodology TOM4D or from timed observations in a database through TOM4L. Knowledge can come from experts' knowledge or can be new knowledge acquired from the built models validated by experts. In turn, the timed observations are obtained through a monitoring program Θ which uses models to detect changes in the process and thus, it writes timed observations in a database. This structure of logic precedence allows to organize the available elements to carry out a procedure of model definition.

Figure 5 illustrates the process of definition of the inhabitant's activities for the GerHome project, where an monitoring agent Θ' produces the timed observations in Ω^0 (i.e. coming from sensors). The application of the TOM4L process (through the software ElpLab) to timed observations in Ω^ℓ (at level ℓ) produces a behavioral model M^ℓ_{TOM4L} representative of these observations. This model is analyzed through the TOM4D methodology and a source of knowledge (documents, data, experts, etc.) in order to define a behavioral model of interest $M^\ell \subseteq M^\ell_{TOM4L}$ and the abstract observation classes linked to this one (i.e. activities at the next level $\ell + 1$). Thus, the abstraction level $L^{\ell+1} =< X^{\ell+1}, \Delta^{\ell+1}, C^{\ell+1}, M^\ell >$ can be specified in order that an agent Θ detects in Ω^ℓ occurrences of M^ℓ and registers occurrences of observation classes $\Omega^{\ell+1}$. In a similar way, a new application of TOM4L on $\Omega^{\ell+1}$ begins the cycle to define the activities of the next level which are later validated by experts.

The TOM4L process provides both a general matching program $\Theta(X^\ell, \Delta^\ell)$ and a general algorithm to discover models M^ℓ at any abstraction level. The next section illustrates the application of the TOM4L process to the GerHome project.

4. APPLICATION

Previous works on GerHome implement systems for monitoring elderly activities from video event and environment event [33, 34, 35]. The first efforts to define activity models were carried out in a manual way from scenarios defined by experts. Nevertheless, the randomness of human behavior leads to that the manual definition of activities is extremely complex. Consequently, we aim to define activities by means of using the TOM4L automatic techniques combined with available knowledge interpreted trough the TOM4D methodology.

Activity definition is accomplished from data registered by sensors in the laboratory GerHome. This laboratory is an apartment made up living room, bathroom, kitchen and room, where different kinds of sensors record inhabitant behavior (Figure 7).

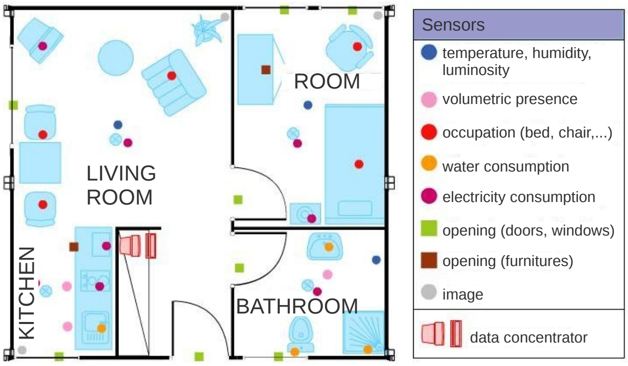


Figure 7: GerHome layout with sensors

GerHome's logs, as depicted in Figure 8, are timed data of the form "yymmdd-hhmmss.mss/Msg" where "yymmdd-hhmmss.mss" (like `080313-122225.825`) is a time stamp t_k and "Msg" (like `USAGE.KITCHEN.MICRO_WAVE_OWEN.begin`), is a constant δ associated with an observation class C_i^0. The ElpLab software, which implements the TOM4L approach, uses a natural number i to identify the class.

```
[...]
080313-122225.825/USAGE/KITCHEN.MICRO_WAVE_OWEN/begin
080313-122226.145/OPENCLOSE/KITCHEN.REFRIGERATOR/open
080313-122228.929/OPENCLOSE/KITCHEN.REFRIGERATOR/close
[...]
```

Figure 8: GerHome's logs

In particular, a spatial taxonomy is considered for the purpose of analyzing behavior in each area of home, so logs are classified according to the different spaces (Figure 7).

In this section we describe how the activity definition can be carried out by means of complementing knowledge about activities with data analysis. On the one hand, from *a priori* knowledge, the different abstraction levels of an activity can be specified; and thus, to analyze if the activity is representative of the available data. On the other hand, to analyze the available data to extract behavioral models and then, to define activities at different levels of abstraction.

4.1 From a priori Activity Definition to Data Analysis

Documents, set of data, information transmitted by experts and common sense allow to interpret sensor signals and to define what sequences of events determine an activity. Once this established, each activity can be validate by experts and collated with the resident's behavior registered in a database. Activities in the living room will be considered in order to illustrate part of the process of activity definition in which the starting point is *a priori* knowledge.

The living room of GerHome has five sensors registering the resident's behavior: three detecting presence and other two detecting use of the phone and use of the TV. Each message of a timed data registered from sensors is interpreted through TOM4D as a variable that assumes a particular value; that is to say, as an observation class. For example, the messages `PRESENCE.LIVING_ROOM.CHAIR.1.true` and `PRESENCE.LIVING_ROOM.CHAIR.1.false` are interpreted as a binary variable x^0_{L1} (`PRESENCE.LIVING_ROOM.CHAIR.1`) that takes values $true$ or $false$. Thus, the observation classes $C^0_{1027} = \{(x_{L1}, false)\}$ and $C^0_{1028} = \{(x_{L1}, true)\}$ can be specified. Similarly, the other variables in the living room are identified: x^0_{L2} (`PRESENCE.LIVING_ROOM.CHAIR.2`), x^0_{L3} (`PRESENCE.LIVING_ROOM.ARMCHAIR`), x^0_{L4} (`USE.LIVING_ROOM.TEL`) and x^0_{L5} (`USE.LIVING_ROOM.TV`); and so also, the corresponding observation classes: $C^0_{1029} = \{(x^0_{L2}, false)\}$, $C^0_{1030} = \{(x^0_{L2}, true)\}$, $C^0_{1025} = \{(x^0_{L3}, false)\}$, $C^0_{1026} = \{(x^0_{L3}, true)\}$, $C^0_{1037} = \{(x^0_{L4}, begin)\}$, $C^0_{1038} = \{(x^0_{L4}, end)\}$, $C^0_{1039} = \{(x^0_{L5}, begin)\}$ and $C^0_{1040} = \{(x^0_{L5}, end)\}$.

Considering *a priori* knowledge on alternative activities in the living room and a certain notion on them, *watch TV* is proposed as a possible activity made up of sitting down and turning on the TV. Hence, an abstract class C^1_{101} of level 1 can be specified to represent the activity *watch TV* and it can be associated with behavioral models of level 0, which are composed of at least the observation classes C^0_{1028}, C^0_{1030}, C^0_{1026} (linked to sit down) and C^0_{1039} (linked to turn on the TV). Therefore, although the models in principle are not known, some relation is supposed between the observation class 101 and the classes $1028, 1030, 1026, 1039$ as Figure 9 illustrates.

From data and given a particular observation class, the TOM4L process allows to discovery the behavioral sequences that finish in the given class, and to find the time constraints $[0, \frac{2}{\lambda}]$ where $\frac{1}{\lambda}$ is the average times between two observation class occurrences. Then, taking in account the relations that would define *watch TV* (Figure 9), the study of the class 1039 (to turn on the TV) is carried out.

Figure 10 shows the behavioral model associated with the class C^0_{1039} where the discovered model consists only of turning on and turning off the TV. This indicates that only the variable x^0_{L5} is involved in the behavior; that is to say, only the use of the TV as Figure 12(a) graphics (where *true* and

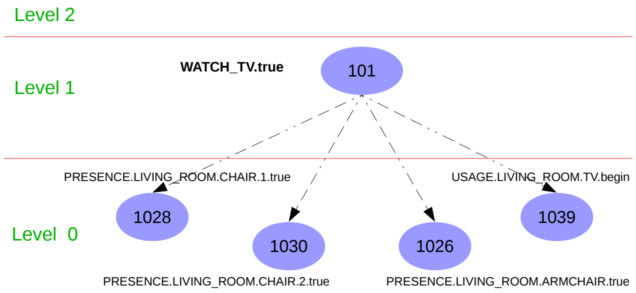


Figure 9: Activity Definition - Watch TV

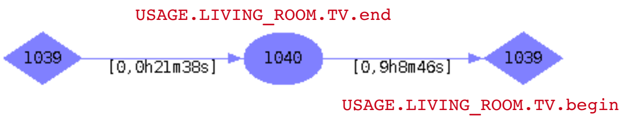


Figure 10: Behavioral model associated with the class 1039

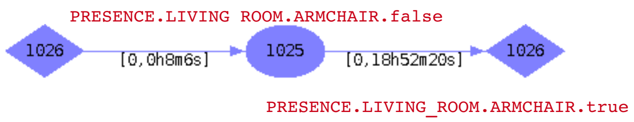
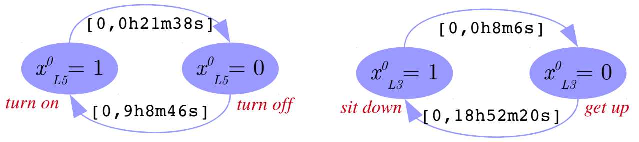


Figure 11: Behavioral model associated with the class 1026



(a) use of the TV (b) use of the armchair

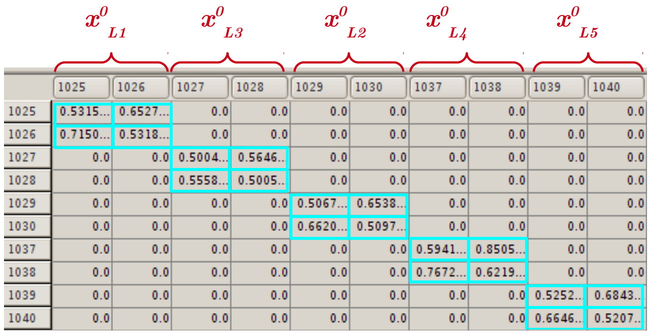
Figure 12: Graphical representation of behavior associated with the classes 1039 and 1026

false are represented like 1 and 0).

A similar result on the use of the armchair is obtained by studying the observation class C^0_{1026} where the found behavior consists only of sitting down and getting up of the armchair (Figure 11). Once again, there is only one variable (x^0_{L3}) involved in the discovered behavior as Figure 12(b) graphics.

These outcomes do not represent the intuitive idea about the behavior in a living room where if the resident actuates in the environment should exist some relation between the different variables (or sensors).

TOM4L defines the BJ-measure [12] that allows to establish how strong is the relationship between the different observation classes. Figure 13 shows this measure between the observation classes of the living room, calculated from the available data, where columns and rows identify the mentioned classes. Note that the relations that exist are only those between the classes linked with the same variable.



	1025	1026	1027	1028	1029	1030	1037	1038	1039	1040
1025	0.5315...	0.6527...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1026	0.7150...	0.5318...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1027	0.0	0.0	0.5004...	0.5646..	0.0	0.0	0.0	0.0	0.0	0.0
1028	0.0	0.0	0.5558...	0.5005..	0.0	0.0	0.0	0.0	0.0	0.0
1029	0.0	0.0	0.0	0.0	0.5067...	0.6538..	0.0	0.0	0.0	0.0
1030	0.0	0.0	0.0	0.0	0.6620...	0.5097..	0.0	0.0	0.0	0.0
1037	0.0	0.0	0.0	0.0	0.0	0.0	0.5941...	0.8505...	0.0	0.0
1038	0.0	0.0	0.0	0.0	0.0	0.0	0.7672...	0.6219...	0.0	0.0
1039	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5252..	0.6843..
1040	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6646..	0.5207..

Figure 13: Strength of relationship between observation classes

This explains the previously obtained models (Figures 10, 11) and allows to suppose that the available logs are not representative of a real-life watch TV activity.

The experts validated this deduction and thus, the robustness of the TOM4L approach was verified. Therefore, an *a priori* definition of activity can be proposed by experts and collated with data in order to establish the adequacy of its definition.

4.2 From Data Analysis to Activity Definition

For the analysis of data, behavior executed in the kitchen is considered where there are 14 sensors and thus, 24 observation classes. The study is concerned with the use of the stove (`PRESENCE.KITCHEN.STOVE.true`, classID=1024).

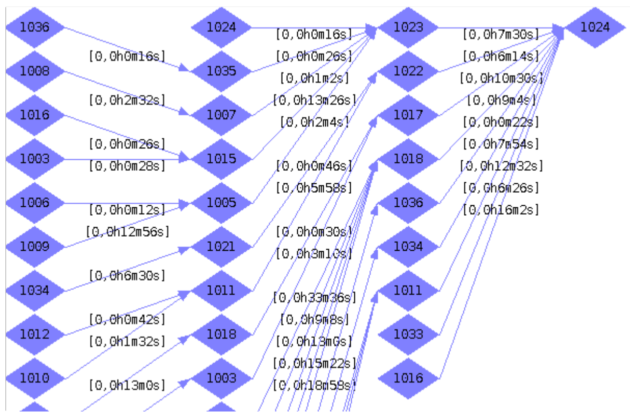


Figure 14: Model tree portion of the class observation 1024

The TOM4L process provides a set of 50 n-ary relations that describes the occurrences of the class 1024 (Figure 14). The figure 15 shows one of these 50 n-ary relations. The proposal is then to use these relations in order to define activities in other level of abstraction.

The n-ary relations and their observation classes are analyzed and then grouped with different criteria defined from the mentioned analysis, according to the TOM4D methodology. For example, the model m^0_1 that describes the behavior

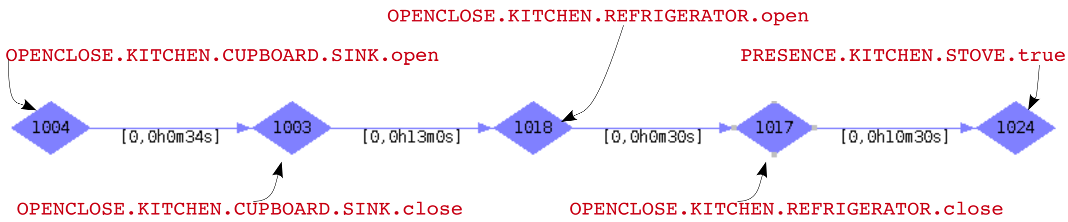


Figure 15: n-ary relation (behavioral sequence) associated with the class 1024

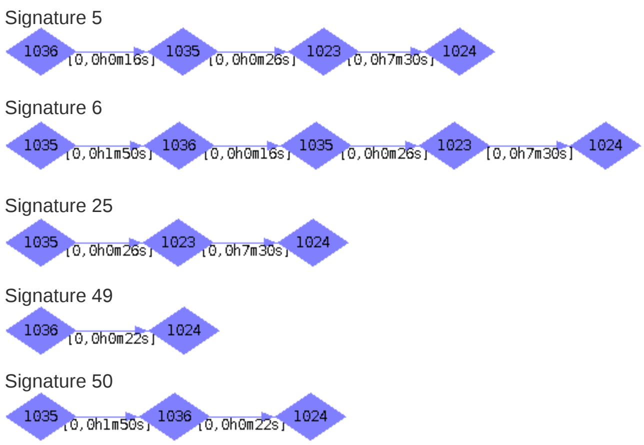


Figure 16: Models (n-ary relations) associated with activity A1

Table 2: Activity definition at abstraction level 1 from n-ary relations

Signature ID (model M^0) Level 0	Activity	Observation Classes Level 0	Abstract Class Level 1
5, 6, 25, 49, 50	A1	1023, 1035, 1035, 1024	111
2, 3, 7, 9, 12, 13, 14, 15, 17	A2	1003, 1004, 1017, 1018, 1024	112
0, 4, 8, 17, 24, 26, 27, 34	A3	1005, 1006, 1007, 1008, 1009, 1010, 1011, 1012, 1023, 1024	113
37, 43, 48	A4	1033, 1034, 1024	114
...	...	...	...

associated with using the stove is given in Figure 16, and an activity identified as A1, is associated with this model. An abstract observation class, let us say 111, representing this activity is specified and is linked with the aforesaid model. Table 2 shows different activities and their abstract classes specified defining the level $L^1 =< X^1, \Delta^1, C^1, M^0 >$. ElpLab allows to record the occurrences of the classes C^1 of the level L^1, and the same approach can be done to define $L^2 =< X^2, \Delta^2, C^2, M^1 >$.

5. CONCLUSION

In this paper, a general theoretical framework to model and recognize resident activities was presented. Based on the areas of Knowledge Engineering and Timed Data Mining, this framework conceives human activities as entities at different levels of abstraction and generalizes thus, the notion of *activity*. This generalization allows that the definitions of resident activity and the process of activity recognition are independent of any Data Mining technique or particular implementation. Besides, a general procedure to define the different abstraction levels and their behavioral models from data and experts' knowledge was described.

We applied our proposal to the GerHome's timed data coming from the sensors of a home prototype, in order to show that *a priori* Expert's knowledge can be collated with the timed data of a data base and, inversely, when *a priori* Expert's knowledge is not available, behavioral models can be found from timed data and then validated by Experts. We are now applying our approach to homes where activities are made by residents in different real-life context such as hospital or nursing room.

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