Unifying and Analysing Activities of Daily Living in Extra Care Homes

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***Abstract*—This work presents the unification and formal analysis of occurring Activities of Daily Living (ADLs) identified by an intelligent well-being monitoring system used for elderly residents in extra care homes. The ADLs considered in this paper are: i) personal grooming and toilet, ii) preparation of breakfast, iii) preparation of lunch, iv) preparation of evening meal and v) sleep. These ADLs are examined as they exhibit multiple or similar occurrences during a typical day. The novelty of this work lies in the introduction of a unification approach that could help for the detection of normal and abnormal behaviour based on the execution of the ADLs from elders in extra care homes equipped with different types of sensors. To unify and detect these types of behaviour, temporal aspects of the ADLs' execution like their duration and time of day are scrutinised. Moreover, the formal analysis of the identified ADLs is conducted, using Petri Nets for the modelling of these activities and model checking for their verification. Finally, the verification results are used to indicate whether an abnormal behaviour takes places during an activity, which could be used as a measure for spotting potential health issues regarding the elders that reside in the monitored homes.**

***Index Terms*—Activities of Daily Living, Petri Nets, Formal Modelling and Verification**

I. Introduction

Nowadays, extra care homes are widely used as they offer security, reassurance and health support to the elders that live in these properties. In an environment like this, elderly people feel more confident to perform their daily activities as dedicated staff provides care services on a 24-hour basis in case of an emergency.

To improve the care services in the extra care homes, a monitoring system that consists of different types of non-intrusive sensors was installed into nine different premises of the extra care home provider involved in this research project. This system was not deployed to monitor elders that suffer from a particular disease or health issue, but it was mainly used to collect data related to their Activities of Daily Living (ADLs). For instance, the elders volunteered in the project face conditions like hard of hearing, vision impairment (i.e. partial vision loss), physical impairment, diabetes and others. The differentiation of the medical issues can affect the way that the ADLs are performed by each individual since the normal and abnormal behaviour can be defined differently in each case, which influences their detection.

The identification of undesired actions/behaviour that may affect the elders' well-being is examined considering activities that occur in different rooms of an extra care home. Thus, the monitored ADLs are: i) personal grooming and toilet, ii) preparation of breakfast, iii) preparation of lunch, iv) preparation of evening meal and v) sleep. It is worth mentioning that we consider these specific ADLs due to the fact that they exhibit multiple or similar occurrences during a typical day.

To collect the data needed for the observation of the aforementioned activities, we used an unobtrusive sensing system, the Canary Care [9]. This monitoring system consists of door, motion, temperature and light sensors. Further, the homes were equipped with other non-intrusive sensors like grid-eye and power consumption sensors, which were used to locate the residents in a room and identify the use of electric appliances respectively.

It should be stated that the unification of the ADLs was conducted by analysing the data collected from all the different sensors and by modelling the activities using Petri Nets, which resulted in useful remarks. The criteria used for the unification approach proposed in this paper are based on temporal aspects of the ADLs' execution like their duration, distraction period and time of day performed.

The rest of this paper is structured as follows: Section II presents the related work in the fields of ADLs, smart homes and their formal analysis. Section III describes the sensors installed in the nine extra care homes of the project. Section IV describes the unification of the ADLs considered and the Petri Net approach used for their modelling. Section V presents the verification results of the modelled ADLs. Finally, Section VI draws useful conclusions about the project outcome.

II. Background

The immense advance of the technology has resulted in the construction of ambient intelligent systems, the architecture of which comprises embedded technology [3], such as various types of sensors and actuators, to interact with their users targeting the improvement, detection or facilitation of their daily activities. The last two decades, these systems found application in many different real-world domains including both private and public environments like hospitals, universities, libraries, homes and companies [2].

Recent demographic results have shown that the elderly population is increasing dramatically compared to the growing of all the other age-groups [31], [32]. Thus, this observation raises the question of whether the society can support this ageing population, which usually suffers from chronic or progressive diseases (like dementia, Alzheimer, diabetes, etc.), by preserving or promoting its health and well-being [30]. In this case, the challenge lies in the fact that this age-group is quite diverse in terms of the health issues faced and the well-being status provided in each country [33].

For that reason, new techniques and tools were introduced to effectively detect, alleviate or tackle the medical issues faced by the elderly people and also improve their well-being. Hence, one of the innovations introduced was to incorporate the ambient intelligence into the healthcare [16], [27].

Examples of notable intelligent systems that have been built and employed in healthcare sector comprise research projects like the WSU CASAS [13], the ProSAFE [10], the SPHERE [34] and others [1].

The CASAS project at the Washington State University (WSU) introduces a health monitoring system for people with chronic medical conditions [13]. This system considers a variety of sensors, such as motion, door, light, temperature and power usage sensors. The goal of the project is to provide an activity recognition system trained to identify activities of daily living (ADLs) through the use of non-intrusive smart residential environments.

Another non-intrusive monitoring system for ageing population is suggested by the ProSAFE project [10]. This particular system contains a set of infrared motion sensor that has been installed into the different rooms of the smart home. The scope of this project is to develop a predictive model that will be able to sufficiently recognise abnormal behaviour during the execution of the ADLs [7].

On the contrary, the SPHERE project proposes a slightly obtrusive sensing system that comprises different types of sensors, which can be deployed in residential environments aiming to monitor the daily activities of the residents. Specifically, a combination of sensors is considered, including video monitoring components (e.g. video cameras), wearable sensors (e.g. wrist-worn motion sensor), and environmental sensors (e.g. door, motion, light, temperature, pressure and power usage sensors.) [34]. All these sensors are used to collect useful data regarding the detection of normal or abnormal behaviour with respect to the activities of daily living performed within those smart home environments.

To design and develop reliable intelligent systems that will be capable of faithfully and effectively monitoring the users' daily activities, the exhaustive understanding of their functioning is required. Consequently, the sensing systems and the activity recognition methods used in these environments have attracted the utmost attention of the researchers.

The sensing systems embedded in environments like the smart homes usually consist of a combination of sensors used in order to detect motion, temperature, light, power/water consumption and other environmental factors that could contribute to the accurate recognition of the ADLs [14]. Typically, the activity recognition that involves the use of these sensing systems can be can be categorised into two classes of activities monitoring, the dense and wearable sensing based respectively [11].

Dense sensors are embedded in the environment by being attached to objects used in the ADLs or to walls, cupboard, doors and other static points of the home in order to monitor the interactions that take place between the users and the smart environment during the execution of those activities of daily living. Dense sensors are widely used in applications of smart environments, since their main asset is their non-intrusive nature [10], [13], [18]. Further, according to [14], the adoption of the dense sensors has been proved to be very useful for the recognition of the ADLs, but their main disadvantage is that they cannot capture very detailed information about the performed activities, resulting in the need for acquiring more contextual information with respect to the activities, which usually derives from the data annotation.

On the other hand, the wearable sensors are not installed in the environment as they are put on the residents' body or clothing to support the detection of activities of daily living collecting data related to the body movement and position in a more precise way compared to the dense sensors [17], [20]. These sensors can monitor and collect data regardless of the location of the users. However, there exist certain limitations regarding their applicability in smart homes. This occurs due to the fact that these sensors lack acceptability from the users as they are not considered very reliable in terms of practicality, effectiveness and intrusiveness [11].

The operation of the smart homes is also dependent on the process of activity recognition, which is employed in this case to identify the ADLs that can be performed in those environments. It is noteworthy that the ADLs recognition is of high importance for the smart environments as it can be used as a means to identify or detect progressive medical and physical conditions related to the people monitored (e.g. sleep disorder [36], body sores [29] and essential tremor [35]). Mainly, this can result from the detection and observation of abnormal behaviours like fall detection [22], etc. Once the ADLs are identified using different techniques [8], [15], [28], both the sensors and ADLs can be modelled defining the structure and behaviour of the examined smart system. In the past, several research works carried out to detect ADLs and recognise potential abnormalities through the use of Markov decision models and one-class classification for the modelling of abnormal behaviour [19], [23]. Further, the formal modelling of the examined system's behaviour could also lead to useful observations about its functioning and interactivity.

The current literature shows that for the modelling and verification of the intelligent systems Petri Nets have been adopted successfully [21], [24], [25]. In this work, for the modelling and unification of the considered ADLs, we use the Time Petri Nets [5], which can effectively capture the interactivity of the smart extra care homes, the functioning of their sensors and the temporal aspects of the activities execution. Contrarily, it seems that there exist limited research and sources regarding the unification and classification of modelled activities of daily living in terms of their duration and time of execution.

Finally, for the verification of the unified activities, we examine safety and liveness properties related to the detection of normal and abnormal behaviour focusing on the completion and duration of the unified ADLs. All these properties are expressed in Computation Tree Logic (CTL) [12] and are model checked via the Charlie analyser [6].

III. Sensing System for Activities of Daily Living

The sensing system installed into the nine extra care apartments (provided by the sheltered accommodation partner) is a non-intrusive monitoring system as the type of sensors used were aiming to maintain the privacy of the people participating.

To set up this monitoring system, the following sensor equipment was considered: i) the Canary Care system, ii) grid-eye sensors and iii) power consumption sensors. Figure 1 shows all these sensors being installed into the real apartments. Figure 1(a) presents a Canary Care door sensor, Fig. 1(b) shows the grid-eye sensor and Fig. 1(c) displays the power consumption sensor.

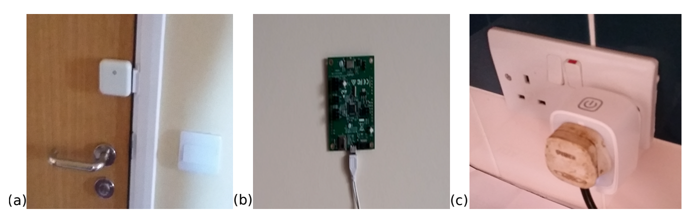

Fig. 1. (a) Canary Care door sensor, (b) Grid-eye sensor and (c) Power consumption sensor

The Canary Care system is a commercial product developed to support the caring of elders using wireless sensors. In this work, the system includes six multi-modal sensors that can work as motion, door, temperature and light sensors [9]. The information collected by these sensors is sent to the Canary Care server and portal (supported by the company) through the local hub that is located in each apartment. It is worth noting that the data transmitted (via Bluetooth 4.0) between the sensors, the hub and the server/portal is encrypted.

Moreover, the grid-eye sensor used is an infrared distance sensor that is designed for proximity detection using an 8×8 IR sensor array [26]. Specifically, this sensor utilises the thermal detection of humans and objects in order to determine their position in association with the location of the sensor. The technical characteristics of the grid-eye sensor include a field of view of 60° with a tolerance of $\pm 3^{\circ}$, a range of temperature measurement from -20°C to 100°C (with high gain and low gain accuracy being $\pm 2.5^{\circ}$C and $\pm 3^{\circ}$C respectively) and a frame rate of 10 fps. It is worth stating that the data captured is transmitted over the Bluetooth 4.0 standard.

Finally, the power sensors employed are typical wireless smart plugs that record the power consumption in watts, have the capability to be programmed to turn on/off at specific times and also to be controlled remotely using a Bluetooth connection [4]. The collected data is represented as a day/week/month summary that shows the consumption in kWh.

Having described the technical characteristics of the sensors, their placement is discussed explaining how they are embedded in the environment in order to monitor the activities performed by the elders. The basic idea is to position all these sensors in such a way that they could efficiently and unobtrusively detect the interaction of the residents with the smart environment during the execution of the ADLs.

Thus, the sensors are positioned only in rooms related to the considered ADLs and close to the doorways, monitoring in this way important areas and pathways between rooms in which these activities usually occur. Specifically, the six Canary Care sensors were installed in the hall, bedroom, living room and kitchen of each apartment acting as motion, light and temperature sensors. It is also worth mentioning that only two of these sensors were also used as door sensors, being placed on the main entrance of the apartment and the bathroom door[1].

Additionally, the grid-eye and power consumption sensors are used to further equip each apartment by installing them in the living room and kitchen respectively. The grid-eye is used to monitor the main seating area in the living room. Thus, the grid-eye sensor in conjunction with both the power sensor plugged in the TV and the Canary Care motion sensor located in this room are used to detect activities that occur in the living room by observing the dependencies among these sensors. Finally, another power sensor is used to monitor the usage of small electric appliances, such as microwave and kettle, that contribute to kitchen activities like the preparation of meals (i.e. breakfast, lunch and dinner).

Following the rationale described above, a same or similar distribution of the sensors is considered for all the apartments, depending of course on the layout of the apartment equipped each time. Figure 2 shows an example of how the sensors are positioned in one of the apartments used.

It should be mentioned that this approach of positioning the sensors can result in useful observations about common patterns that could be extracted with respect to the way that ADLs are executed in different apartments from different people. Moreover, to identify the activities of daily living taking place in each monitored environment, we consider the dependencies of the installed sensors and examine the sequence in which they are activated each time that a specific activity is conducted.

[1]Note that no motion sensor was placed in the bathroom as the inhabitants raised concerns about their privacy. Therefore, the bathroom door sensor was used to externally 'detect' the bathroom activities.

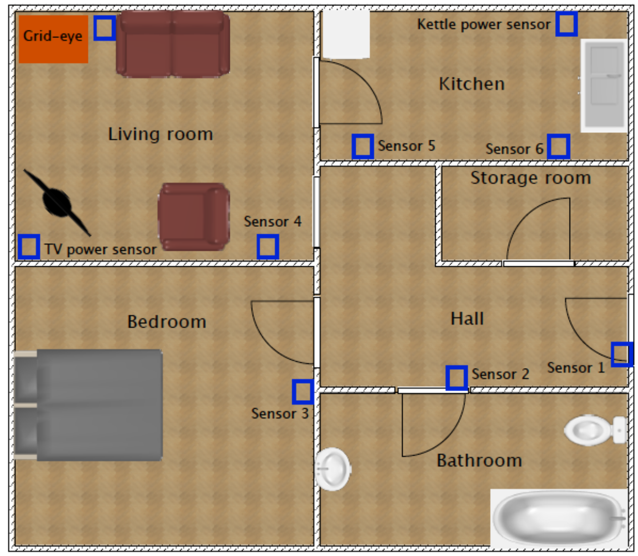

Fig. 2. The layout of one of the extra care apartments used.

IV. Unifying and Modelling of Activities of Daily Living

In this section, we present a unification of ADLs performed by elders, which derives from the data analysis/observation, the behavioural modelling and simulation of the smart environments (i.e. apartments) and the activity logbooks completed by the volunteers during the project. The unification proposed is based on temporal criteria like the duration of activity, duration of distraction and time of day executed.

Additionally to the time criteria, we also set the activities taken into consideration for this unification process. In this paper, these activities include tasks that are performed in different rooms and are repeated several times during a day. In general, the activities considered could be categorised into:

- (i) bathroom activities
  - (a) Personal Grooming
  - (b) Toilet
- (ii) kitchen activities
  - (a) preparation of breakfast
  - (b) preparation of lunch
  - (c) preparation of evening meal
- (iii) Bedroom activities
  - (a) sleep

It is worth pointing out that the execution of some of these ADLs exhibits similar behaviour, but maybe different duration or sequence of actions. For instance, the preparation of the meals could follow similar steps, but it may last more or less time depending on the occasion. This led to the idea of finding patterns that could be used to unify the way that these activities are performed by different people that live in separate places, facing different medical conditions.

To build an archetype/model that could effectively present the unification of the different ways of executing an activity, we follow certain steps relying on the data collected. Initially, we analyse the data that relates to the duration of the considered ADLs. To define it precisely, we compare the timestamps of the sensors' actual readings with the start and end time of the activity logbooks. At this point, it should be mentioned that all the Canary Care sensor readings are synchronised through the use of the hub timestamps, which indicate the time that readings were sent to the local hub from the sensors. Additionally, the timestamps of the other sensors' readings are generated and synchronised by a script running on a raspberry-Pi, which acts as a local server for the grid-eye and power sensors[2]. Also, it is worth noting that the logbooks were mainly used to delimit the duration of each activity approximating its starting and finishing time. Thus, to compute the duration of each activity with high accuracy, the information provided by the logbooks' records was cross-checked with the actual data collected from the system's sensors. In this way, conducting this comparison for all the repetitions of an activity in a day, we compute the average duration of every activity executed by the residents of all the monitored apartments (see Table I).

Observing the activities repeated several times during the day, it has been noticed that their average duration differs depending on the apartment each time. This results from the fact that people execute the same tasks in different ways due to the importance that they give to them each time or due to their physical condition. For instance, in apartments three and seven the average execution time for the personal grooming and toilet activities differs by 19.25 and 7.54 minutes respectively. As shown in the table below, this execution difference implies that different people that belong to the same age group perform these activities dedicating less or more time depending on the activity and the time of the day that this activity is conducted.

Apts	Per. Grooming	Toilet	Breakfast	Lunch	Ev. Meal	Sleep
Apt 1	25	5.5	29.68	34.67	32.18	451
Apt 2	43	9.76	46.07	40.43	58.9	489
Apt 3	45.5	5.4	30	74.16	45	561
Apt 4	10.96	6.2	18	24.07	12.5	501
Apt 5	32.39	7.5	38.8	53.15	47.89	474
Apt 6	33.85	7.2	39.81	50.88	38.33	586
Apt 7	26.25	12.94	23.61	30.58	27.1	283
Apt 8	48.56	15.69	41.53	46.16	35.3	405
Apt 9	33.44	8.7	32.28	43.99	37.41	486
Avg duration	33.22	8.77	33.31	44.23	37.18	470.67
St. deviation	11.7	3.52	9.06	14.67	13.17	88.66

TABLE I
AVERAGE DURATION AND STANDARD DEVIATION OF ACTIVITIES PER APARTMENT (IN MINUTES).

Next, we examine each activity with respect to the number of steps required for its execution by every individual. This will enable us to find all the different variations of a successfully performed activity. Furthermore, it could reveal cases of abnormal behaviour through the delayed completion or not of an activity, which is usually caused by a distraction. To specify whether a behaviour is abnormal or not, we set a time threshold, for which this distraction is considered negligible or not[3]. If this time threshold is exceeded significantly, then this fact could point to a worrying situation for the elderly person that executes the activity.

Therefore, to identify all the possible variations of the ADLs, we model and simulate the behaviour of the system (i.e. interactions between the users and the smart apartments via ADLs) according to the data collected. For the modelling of the ADLs, the Time Petri Nets class is used, as it enables the temporal analysis of the developed behavioural models. To examine further the sensors' readings, we use a simulation tool to represent the sequence of sensors activated for each variant of the ADLs considered. This tool is developed in MATLAB taking as input the layouts of the apartments and the respective sensor data. It is worth noting that the modelling and simulation of the data also allowed the definition of a time threshold for the execution of each activity examined. This threshold is defined by the *standard deviation* of the mean values obtained from each apartment with respect to the considered ADLs, denoting a period of time during which a delay in the execution of the ADLs is acceptable. If this threshold is exceeded, then we consider this specific behaviour as abnormal even if the activity is eventually completed[4].

Now, following the steps of the unification approach described earlier, we first extracted all the possible variations of the ADLs for each of the apartments. Then, we unified all the variants of the ADLs produced from the diverse behaviour of the residents by presenting their behaviour and interactions as a sequence of actions required for each alternative. The unification of the ADLs is explicitly defined in the list below:

(i) Personal Grooming:
 (a) $Grooming\_no\_distractions$
 (b) $Grooming$, $Bedroom\_act$, $finish\_Grooming$
 (c) $Grooming$, $short\_visit$, $finish\_Grooming$
 (d) $Grooming$, $Bedroom\_act$, $cont\_Grooming$, $Liv-Room\_act$, $finish\_Grooming$
 (e) $Grooming$, $Kitchen\_act$, $cont\_Grooming$, $Bed-room\_act$, $finish\_Grooming$
 (f) $Grooming, Bedroom\_act, cont\_Grooming$, $Bed-room\_act2$, $finish\_Grooming$

(ii) Toilet:
 (a) $Toilet\_no\_distractions$
 (b) $Toilet$, $Bedroom\_act$, $finish\_toilet$
 (c) $Toilet$, $hall\_act$, $finish\_toilet$
 (d) $Toilet$, $Bedroom\_act$, $hall\_act$, $finish\_toilet$

(iii) preparation of breakfast
 (a) $Breakfast\_no\_distractions$
 (b) $Breakfast$, $Bedroom\_act$, $finish\_breakfast$
 (c) $Breakfast$, $LivRoom\_act$, $finish\_breakfast$
 (d) $Breakfast$, $Toilet\_act$, $finish\_breakfast$
 (e) $Breakfast$, $short\_visit$, $finish\_breakfast$
 (f) $Breakfast$, $Bedroom\_act$, $cont\_breakfast$, $Liv-Room\_act$, $finish\_breakfast$
 (g) $Breakfast, LivRoom\_act, cont\_breakfast$, $Liv-Room\_act2$, $finish\_breakfast$

(iv) preparation of lunch
 (a) $Lunch\_no\_distractions$
 (b) $Lunch$, $Bedroom\_act$, $finish\_lunch$
 (c) $Lunch$, $LivRoom\_act$, $finish\_lunch$
 (d) $Lunch$, $Toilet\_act$, $finish\_lunch$
 (e) $Lunch$, $short\_visit$, $finish\_lunch$
 (f) $Lunch, LivRoom\_act, cont\_lunch$, $LivRoom\_act2$, $finish\_lunch$

(v) preparation of evening meal
 (a) $EvMeal\_no\_distractions$
 (b) $EvMeal$, $Bedroom\_act$, $finish\_EvMeal$
 (c) $EvMeal$, $LivRoom\_act$, $finish\_EvMeal$
 (d) $EvMeal, LivRoom\_act, cont\_EvMeal$, $LivRoom\_act2$, $finish\_EvMeal$

[2]The sensors are polled every 0.25 seconds for a reading, the sensor time and server time cannot be more than 0.25 apart, which is negligible for the purposes of human activity recognition.

[3]Note that the time threshold is dependent on the activity conducted and its average duration.

[4]For the modelling process in the Time Petri Net models, the value of the time threshold is set equal to the standard deviation plus five percent.

(vi) Sleep
   (a) $Sleep\_no\_distractions$
   (b) $Sleep$, $toilet\_act$, $finish\_sleep$
   (c) $Sleep$, $kitchen\_act$, $finish\_sleep$
   (d) $Sleep$, $toilet\_act$, $kitchen\_act$, $finish\_sleep$
   (e) $Sleep, toilet\_act, cont\_sleep$, $toilet\_act2$, $finish\_sleep$
   (f) $Sleep, toilet\_act, cont\_sleep$, $kitchen\_act2$, $cont\_sleep2$, $kitchen\_act$, $finish\_sleep$

The list of ADLs presented above includes all the alternative ways of executing them according to the patterns extracted from all the apartments. The unification of ADLs does not necessarily imply that all these variants apply to all the residents or that their execution time has the same duration or threshold. For example, Fig. 3 shows the behavioural model of the sleep activity as it is performed by the resident of the apartment one[5].

These ADLs variants can be used to detect normal and abnormal behavioural patterns that could indicate potential health issues. To do this, we analyse the distractions or intermediate actions that occur during the execution of the ADLs. As already mentioned, if all the intermediate actions are conducted within the set time thresholds, then this denotes a normal behaviour. Otherwise, if their execution exceeds these thresholds, then this possibly indicates an abnormality.

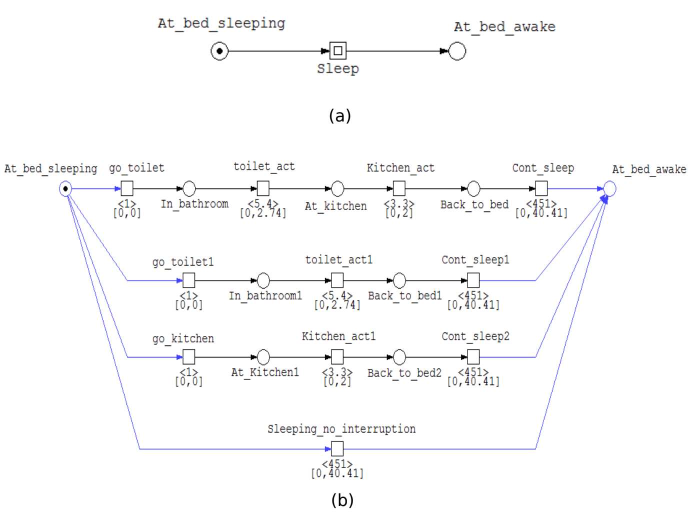

Fig. 3. Apt 1: (a) Unified representation of sleep activity and (b) Variants of sleep activity with duration and threshold.

It is also worth noticing that although some of the ADLs (i.e breakfast, lunch and evening meal activities) follow similar behavioural patterns, their variants consist of different distractions or number of steps. This could occur because of the different time of the day that they are performed. For instance, the evening meal activity includes no distractions like short visits as its execution occurs in evening times where the visits tend to be less frequent or very rare. But, this is not the case for the breakfast or lunch activity[6]. Knowing this, we can collect useful information about the way that elders behave under normal conditions during the different times of the day.

All the aforementioned ADLs variants are used to provide a 'global' and unified behaviour for the elders that could contribute to the successful detection of abnormalities. To achieve this, we first need to define the overall durations and time thresholds for the activities based on the respective durations (average) and time thresholds (standard deviation) set by the 'local' behaviours extracted from each apartment. Finally, the unification of the ADLs helps the creation a global behavioural model that could be used for the ADLs' analysis.

V. Verification of Unified Activities of Daily Living

In this section, we present the model checking of safety and liveness properties that are used for the detection of normal and abnormal behaviour. The properties verified are expressed in Computation Tree Logic referring to both structural and temporal dependencies of the performed activities. In particular, we verify the following properties taking as case example the sleep activity presented in Fig. 3.

Starting with the structural analysis of the model, we examine whether all the variants of the sleep activity are available implying that it can be potentially completed. To check this, we verify the following CTL propositions:

(i) $AG(At\_bed\_sleeping \rightarrow AX((In\_bathroom \rightarrow EX(At\_bed\_awake)) \vee (In\_bathroom1 \rightarrow EX(At\_bed\_awake)) \vee (At\_kitchen \rightarrow EX(At\_bed\_awake)) \vee At\_bed\_awake))$
(ii) $AG((Back\_to\_bed \rightarrow \neg(Back\_to\_bed1 \vee Back\_to\_bed2)) \rightarrow EF(At\_bed\_awake))$

The first property examines whether all the variants are available as options and the second one that these variants exclude each other. Both properties evaluate to true showing that the environment can detect all the different ways of potentially executing and completing the sleep activity exhibiting normal behaviour.

Now, to detect possible abnormalities, we present two properties of the system, where the temporal aspects of the sleep activity execution is checked:

(i) $A((In\_bathroom \wedge At\_kitchen \wedge Back\_to\_bed)\ U_{\leq 491} At\_bed\_awake)$
(ii) $A(At\_bed\_sleeping U_{\leq 491} At\_bed\_awake)$

In this case, these properties examine if there always exists a path for which the duration of the sleep activity is less than the the average duration (i.e. 451) plus the standard deviation increased by five percent (i.e. 40.41) regardless whether we follow the activity with distractions or not. The outcome that is obtained is false indicating that an abnormal behaviour could occur as the acceptable time threshold can be exceeded.

Following the same logic, we can generally analyse the models of all the ADLs separately for each apartment or we can model check the properties of interest using a behavioural model that represents all the unified ADLs. In both cases, the unification of the ADLs facilitates the detection of abnormal behaviours that could indicate useful remarks about the medical condition of the monitored people.

VI. Conclusion

This paper proposes a unification approach that is based on the data analysis, modelling, simulation and observation of ADLs conducted by elders in real extra care homes. This approach introduces an efficient way of unifying activities that are executed by people that suffer from several different health issues. The unification of the ADLs could help the trained monitoring system to effectively detect

[5]The model of Fig. 3 is extracted from the complete model of apartment one that presents the entire behaviour of the system including all the unified activities.

[6]In terms of modelling, even if different unified activities have a common or same sequence of steps (e.g. breakfast, lunch and evening meal), they can be distinguished through the sequential representation of the system's behaviour and the precedence weight of each activity in the Time Petri Net model.

abnormal behaviours that are related to the variations of the ADLs considered in the unification model as they could be identified using through temporal and structural limitation imposed by the approach as regards their execution. It is worth noting that the formal modelling and verification in this work is used to examine the human behaviour through the unified ADLs models used and also validate the presence of potential abnormalities related to undesirable medical incidents.

To improve the proposed unification of the ADLs and provide a universal approach for the construction and analysis of unified activities using Petri Nets, time series and Stochastic Petri Nets will be considered to further analyse the collected data and enable a more accurate prediction of potential abnormalities with respect to the temporal aspects of the examined ADLs.

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