Detection of social isolation based on meal-taking activity and mobility of elderly people living alone

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Abstract

Social isolation is likely to be one of the most affected health outcomes for the elderly due to the COVID-19 pandemic especially for seniors living alone at home. Therefore, we seek to identify it based on detecting changes in the elderly such as malnutrition and lack of mobility. In this article we present our sensor monitoring system that was implemented for 15 days in the home of a 26-year-old student living alone as a first step to later deploy in the home of elderly people. Then, we present our results based on the data collected by sensors during the experiment. Our study showed the feasibility of automatic identification of the (1) meal-taking activity (shopping, cooking, eating and washing dishes) and (2) mobility (inside the home and the act of going out). These results are an intermediate step in assessing the social isolation status of the elderly based on these ADLs.

Keywords: Social isolation, Meal-taking activity, Mobility, monitoring systems.

I. INTRODUCTION

According to the UN (United Nations), people aged 65 and over will represent 16% of the world's population in 2050 [1]. Securing and supporting this population is therefore a growing concern, as advancing age encourages the appearance of risks of physical, cognitive and relational degradation. Indeed, an American report from the National Academies of Science, Engineering, and Medicine (NASEM), carried out before the COVID epidemic in 2020, points out that 24% of adults aged 65 and over living in the community in the United States (representing approximately 7.7 million people) were socially isolated [2]. With the COVID-19 pandemic, this number is increasing dramatically due to the stay-at-home orders, social distancing and banning visits for nursing home residents. While social isolation and loneliness are closely related, they do not mean the same thing. According to UK's National Institute for Health Research, isolation is a lack of social contact or support, whereas loneliness is the feeling of being alone and isolated (it is possible to feel lonely in a room full of people) [3]. The social isolation of the elderly is a risk factor for malnutrition [4], reduced mobility [5] and physical fragility [6]. Moreover, the desire to live independently at home increases significantly among the elderly due to attachment to their home and the cost of care in retirement homes. With the growing advances in technological monitoring system, elderly people can stay in their homes and their family feels safe and secure about them. Therefore, we focused on two activities of daily living (ADLs) that seem relevant for a predicting social isolation by detecting behavioral drift: (1) the meal-taking activity (shopping, cooking, eating and washing dishes) and (2) mobility (inside home and the act of going out).

The automatic classification of these ADLs can be challenged since every person has his/her own rhythm to do it especially the meal-taking activity process.

To meet these challenges, we are working on a monitoring system based on miniaturized sensors distributed in the person's living environment to detect changes in behavior (whether sudden or slow over time), and then to propose an intervention in line with the behavior, the person's abilities and his/her living context. For example, the elderly may begin to skip the dinner (compared to other days), the system notifies the caregivers/family of the situation and issues reminders to the elderly at the usual lunchtime to motivate them to eat.

Our work focuses on the following points: (i) Continuous and longitudinal monitoring through the deployment of low-cost, discrete, non-intrusive and miniaturized sensors in the individual's home; (ii) Automatic identification of processes related to home mobility and meal-taking. A learning phase will be carried out to model the behavior pattern of individuals; (iii) Establishing the link between these 2 activities and social isolation, a phenomenon that has been reinforced with the global COVID-19 crisis. This problem has been highlighted especially among the elderly who are living alone.

Our contributions can be summarized as follows:

-We introduce our sensor monitoring system and its deployment in a home of a person living alone. We show the feasibility of the system to monitor the targeted ADLs.

-We define the targeted ADLs and our approach for their automatic identification.
-We present the results of the sensor data analysis over 15 days for a test individual.

II. BACKGROUND AND RELATED WORK

Automatic classification of ADL is a crucial part of ambient assisted living (AAL) technologies. It enables to monitor the daily life of the elderly and to detect any change in their behavior to encourage them to live independently and safe in their home. Many studies in AAL focus on different ADLs, such as bathing, grooming, mobility inside and outside the home, eating... In this study, we focus on systems related to two main ADLs that we assume they could have connection with social isolation: the process of taking meals (food shopping, cooking, eating and dishwashing) and mobility (inside home and the act of going out).
Huynh et al. [7] propose a system composed of two types of non-intrusive sensors, a passive infrared (PIR) sensor in each room and a reed switch to detect the main door opening and closing. After a real deployment of the system in 50 flats of seniors living alone and the completion of a mental health and loneliness survey, this study demonstrates that the system can detect the outing behavior of the elderly people living alone and identify potential candidates with severe loneliness and depression problems based on the ratio of time spent inside and outside the flat.
Lussier et al. [8] propose a system composed of three types of sensors: passive infrared (PIR) sensors, magnetic contact sensors, and smart electric switches based on the request of Integrated Health and Social Services Centers (IHSSC) home care division of Montreal. The objective of the system is to improve the support provided to home care recipients who are at risk of self-neglect. Results from 3 older adults show that the system can collect data on the home care recipients' life habits, such as daily patterns related to eating, sleeping, personal care, inactivity and going outside.
Cippitelli et al. [9] present a solution to monitor the food and drink intake actions of elderly. It uses a depth and RGB camera placed on the ceiling. The depth information is applied to track the person's movements and the RGB stream is used to recognize specific elements located on the table during eating-related activities, such as glasses. The fusion of these processed data leads to the identification of specific intake behaviors. Experimental tests show the ability of the system to recognize intake actions.
While all these studies use different types of sensors and focus on monitoring of some ADLs, we consider it as an intermediate step to assess the social isolation status of the elderly. In addition, user acceptance of the elderly monitoring system is a compromise between user needs and perception, especially with respect to privacy. A study carried out to get older people's perspectives regarding the use of sensors [10] indicates that the older persons surveyed evaluated sensor monitoring positively because it gives them a sense of safety as an important premise for independent living. In addition, sensors that record their movements at home without cameras or sound recordings are not considered as an invasion of their privacy.
Therefore, this article proposes unobtrusive and passive sensor system that can assess the social isolation status of elderly based on the process of taking meals and mobility.

III. MOBILITY AND MEAL-TAKING ACTIVITY

A. Mobility

Mobility is defined as the ability to move freely or be easily moved. Mobility is very important to maintain self-care, independent and autonomous lifestyle of the elderly. Indeed, regular mobility and activity, even mild physical activity such as walking, enable to improve mental and cardiovascular health, control weight, maintain healthy bones and muscles, reduce the risk of falling and increase social interaction [11].
An American study on Time-Location Patterns realized in six cities indicates that adults aged 65 and over, spent 78% of their time at home. This result is understandable as older people are generally retired, have limited social contacts and therefore prefer to spend most of their time at home [12]. Thus, we will focus in our study on the monitoring of activities inside the home and the act of going out.

B. The meal-taking activity

Recognizing the activity of eating is very important for monitoring the health of the elderly. In fact, good nutrition has a huge impact on physical health, memory and mental function. And with age, eating well can boost immunity, fight illness-causing toxins, keep weight in check, and reduce the risk of heart disease, stroke, high blood pressure, type-2 diabetes, bone loss, Alzheimer's disease and cancer [13]. Unfortunately, malnutrition exists among older people and represents an issue that is not yet well investigated. According to the National Health Service of United Kingdom, among the 12.2 million older people, around one million over 65 are malnourished or at risk of malnutrition, most of them (93%) living at home, so their malnutrition goes often unnoticed [14]. Identifying all eating-related activities is the best way to analyze them correctly. The meal-taking activity consists of 4 ADLs: food shopping, cooking, eating and dishwashing.

Food shopping: Food shopping is the activity whereby a person goes to the market to buy different ingredients to cook or to buy ready-made meals. For the elderly, food shopping is not a simple activity, but it is considered as an important social event. In fact, for some older people living alone, this is the only opportunity

for social interaction. In [15], the authors mention that social aspect of food shopping is very important to older people and regular social interaction is recognized as a key element in maintaining both mental and physical wellbeing.

Cooking: Cooking is the activity of preparing food by combining, mixing, and heating ingredients. Cooking provides many physical, emotional, mental and health benefits. Indeed, this process begins with planning what to cook and what ingredients are needed and determines the need to go shopping. Then, the person mixes the required ingredients according to a recipe and takes care of the meal until it is well prepared. Continued home meal preparation by older adults has been associated with improved health and longevity. In addition, this activity can be an important means of social interaction when done for and with others [16].

Eating: Eating provides energy to the body. It is very important for older people to stay as healthy and active as possible. Although good diet is recognized as important for successful aging, malnutrition is one of the greatest threats to the health, autonomy, and well-being of older adults [17]. For the elderly, malnutrition is not the consequence of a lack of food, but a deterioration of the desire to eat and is linked to various factors such as a decrease in taste and smell, difficulties in chewing, swallowing or eating independently, depression, loneliness and social isolation [18]. Monitoring the dietary activity of older persons is essential for their well-being.

Dishwashing: Dishwashing is about cleaning up the food left on the plates. This operation can be done manually by hand in the sink or automatically by the dishwasher. Even though dishwashing is a light activity, it may be a good physical activity for elderly and could help prevent early death. A Norwegian analysis of 36,383 cases from eight studies, with a mean age of 62.6 years and a median follow-up of 5.8 years, links higher activity overall, regardless of intensity level, with lower risk of premature mortality [19].

A time use survey over the period 2009-2010 carried out by the French National Statistics Office [20] revealed that the daily time related to the meal-taking activity among people aged 60 and over is almost 4 hours per day. In fact, men aged 60 and over, spend 24 minutes on shopping, 13 minutes on cooking, 154 minutes on eating and 13 minutes on washing dishes every day. By comparison, women aged 60 and over, spend 21 minutes on shopping, 72 minutes on cooking, 141 minutes on eating and 25 minutes on washing dishes every day. This result revealed that older men spend less time doing housework than older women, especially cooking, which is not surprising.

IV. SYSTEM OVERVIEW

A. System architecture

Figure 1 shows an overview of the system architecture. The main technological components of the system are: (i) home-distributed sensors to detect ADL; (ii) the gateway to transmit the data collected from the sensors to a Raspberry Pi; (iii) a Raspberry Pi for local storage, analysis and sending of analyzed results to the back-end server; (iv) the back-end server for storage and dissemination; and (v) the user interfaces in the form of a web application. The intelligence implemented on the Raspberry Pi analyzes the behavior of the elderly, motivates them to eat and move using a speaker in case of degradation of these activities and sends an alert to the caregiver in case of problem/emergency.

B. Deployment setup

The choice of sensors used in the system meets the requirements of a home environment and the elderly expectations: miniaturized and wireless sensors, unobtrusive, non-intrusive, easy to install, not requiring intervention from the elderly and long-term battery capacity. Considering these constraints, we have chosen three types of sensors: passive infrared (PIR) sensors, reed sensor and power meter sensor. The chosen PIR

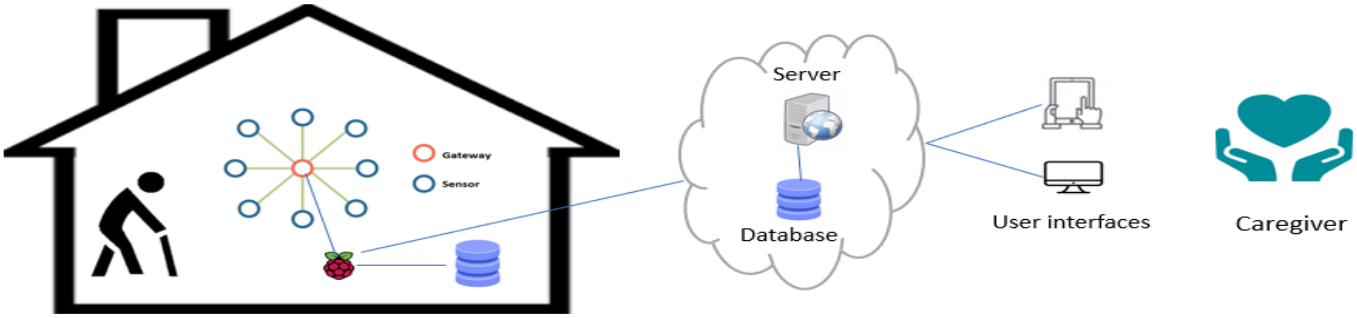

Figure 1. General architecture

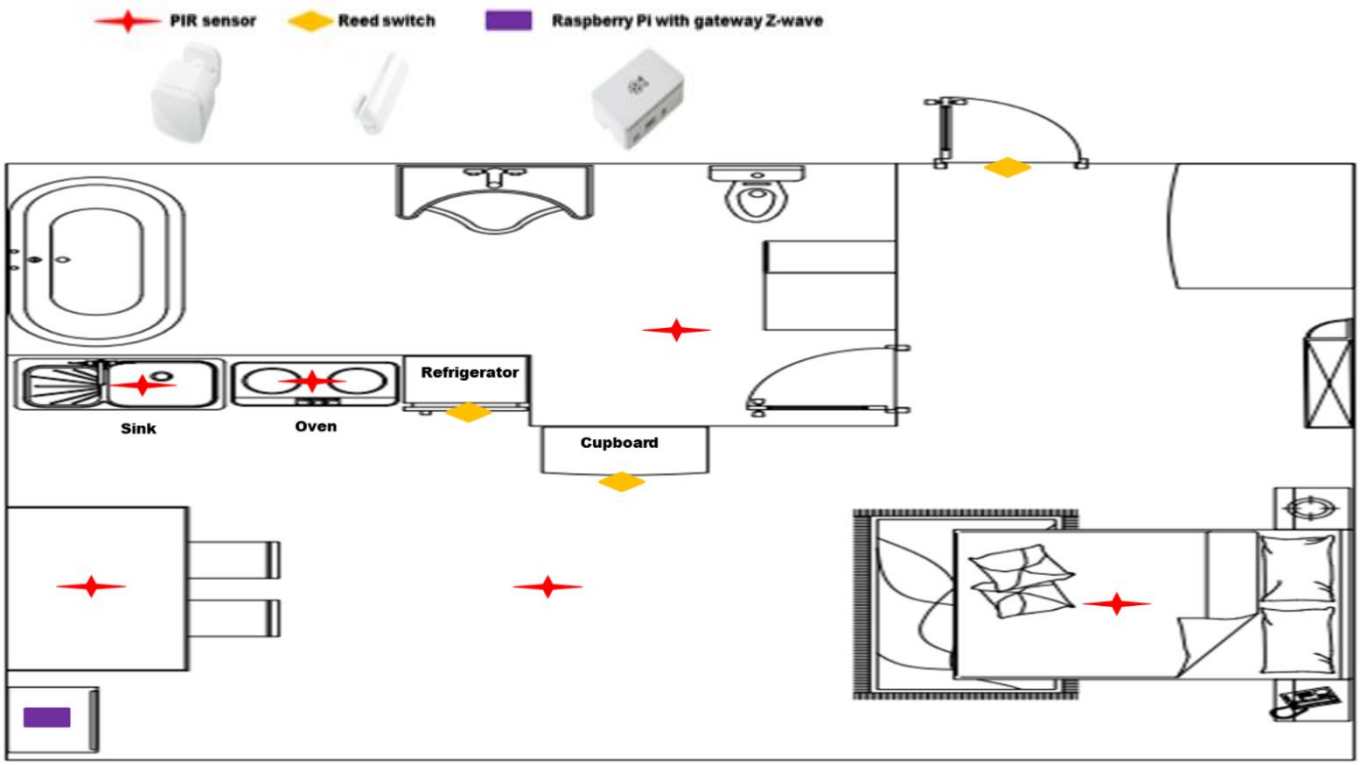

Figure 2. Distribution of sensors at home

Trisensor from Aeotec also includes temperature, brightness and humidity.

Each room in the home is covered by one PIR sensor with the addition of three PIR sensors on top of the sink, oven and dining table. The reed switch is installed in the outside door, refrigerator and cupboard. The power meter is equipped with most used electrical devices depending on the use of the person such as TV, toaster, microwave… In addition, a pack of Raspberry Pi with Z-wave gateway collects data from the sensor through Z-wave protocol. Since the sensors will be easily installed in specific locations, as mentioned above, the system will be indifferent to the type of house where it will be deployed. Figure 2 shows an example of a home installation. It represents the distribution of devices in a home young person. The temperature, luminosity, humidity and power meter sensors were not depicted in Figure 2 because we only use in this work data obtained from the doors and motion sensors.

V. DATA COLLECTION

The data used in this study was collected from the home of a young man. He is a 26-year-old student living alone and without any health disorders. The purpose of this experimentation is to validate the technical installation and the choice of sensors and to collect real data in the participant's home to develop and test our algorithm. No specific scenario was performed by the participant. The aim of this data collection is to know how these ADLs are realized by the person in real life in his home and to detect any problem when there is a change in his routine. The next step will be to deploy the system in the homes of elderly people living alone.

The 9-sensor dataset contains 29,388 events recorded over 15 days for one month ((December 2020). The data is recorded in real time in a database of the DomoticZ software in the Raspberry Pi.

The PIR sensors detect movement in the motion area and the reed switch detects the opening or closing of the door. The PIR sensor works by sending a '1' signal when detecting a movement and '0' after 1 second of movement detection, with a refractory period of 5 seconds after movement detection. The reed switch sends a '1' signal when detecting the opening of the door and '0' when it detects the closing of the door. The Raspberry Pi and the Z-wave gateway uses DomoticZ, a home automation software, to collect and store data sent by the sensors through the wireless mesh network using the Z-wave wireless module of each sensor. The event logs in the database include date, time, sensor type and its status. The identification of the targeted ADLs will depend only on the data collected by these sensors.

VI. ADLS IDENTIFICATION

A. Home status

The first step in analyzing data from a home is to identify the status of the home when it is empty and when it is occupied, so the system focuses on the time when the home is occupied to identify the ADLs. Each time segment will be identified as 'the home is empty' or 'the home is occupied'.
Before determining the status of the home, we will define two transition of action:
'Enter': No movement detected inside the home then status change of the contact door sensor from '0' to '1' and back to '0', then immediate detection of movement inside the home by the PIR sensors.
'Exit': Detection of movement inside the home by PIR sensors then status change of the contact door sensor from '0' to '1' and back to '0' and no further movement detected in the home after closing the door.
We eliminate transitions that cannot be classified. For example, if the person goes out to collect their mail or through the garbage and leaves the door open, then goes home and closes the door, there is movement detection inside the home before opening and after closing the door.
Home status is an indication of whether the older person is inside or outside the home. The home status is identified as follows:
'The home is empty': it begins with the transition of 'Exit' and then ends with the transition of 'Entry'.
'The home is occupied': it begins with the transition of 'Entry' and then ends with the transition of 'Exit'.

B. Position inside the home

After eliminating time segments spent outside the home, we can identify which room is occupied by the elderly and the duration of their occupation.
Each room will be identified as occupied if the sensor of that room is triggered and the occupation status of that room will end if the person is detected by a sensor located in another room.
In our case, we will divide the home into three rooms: kitchen, bedroom and bathroom.
The bedroom is occupied when the PIR bed is triggered, the bathroom is occupied when the PIR bathroom is triggered, and the kitchen is occupied when the following sensor is detected: reed switch of the cupboard, reed switch of the refrigerator, PIR sink, PIR oven, PIR dining table and PIR living room (see Fig. 2). The PIR in the living room is added to the kitchen area because the home is small.

The main condition for changing the status of the home is to change the status of the door from 'closed' to 'open' and back to 'closed'.

C. Food shopping

An important action taken by anyone returning from a food shopping activity is to put his purchases in the refrigerator and/or cupboard. Therefore, we identify food shopping, on this base, through three consecutive actions: (i) Leaving the home (ii) Entering the home (ii) Opening the refrigerator and/or cupboard.

D. Preparing food

Preparing the food is identified by the execution of different actions with no specific order and no obligation to do them all: (i) Opening the refrigerator then closing it changes the status of the reed switch refrigerator from '0' to '1' and then backs to '0'(ii) Opening the cupboard then closing it changes the status of the reed switch cupboard from '0' to '1' and then backs to '0' (iii) Detecting movement in the area of oven by the PIR oven (iv) Detecting the presence of the person in the area of the dining table by the PIR dining table, with a duration of less than one minute (we consider that spending less than one minute at the dining table is an action related to food preparation such as putting down the plate, fork, etc.).

E. Eating food

The two activities of food preparation and eating are linked because the activity of food preparation is the trigger for food consumption. The identification of eating will be based on detecting the presence of the person in the dining table area, through the PIR dining table, with a presence time of more than one minute and after the food preparation activity.

The identification of food preparation and eating may depend on the profile of the elderly. For example, the person may buy a food prepared outside and therefore go directly to the activity of eating, or they can eat sometimes outside their home, etc. All these exceptions need to be considered in the development of the algorithm for identifying older people's ADLs.

F. Dishwashing

Dishwashing is identified by detecting the presence of the person around the sink, by the PIR sink.

Figure 3. Number of events detected by sensors

VII. RESULTS

Figure 3 shows the number of sensor activations during this test period. The periods of 8 to 9am, 12 to 2pm and 7 to 10pm contain the greatest number of events detected by the sensors, especially the detection of the person around the oven, and this is comprehensive because it seems that this time corresponds to meal preparations.

In addition, we can see that between 10pm to 8am, the greatest number of sensor activations is the PIR bed, and this shows that the person is in his/her bed awake then asleep (between 1 to 8am shows that few events are detected by the sensors and this point out that the person is sleeping and does few movements in bed).

These results depend a lot on the daily rhythm of the elderly that is why the system should be personalized.

Even so, a person's daily pattern can vary from day to day, as shown in Figure 4, especially on weekends and weekdays.

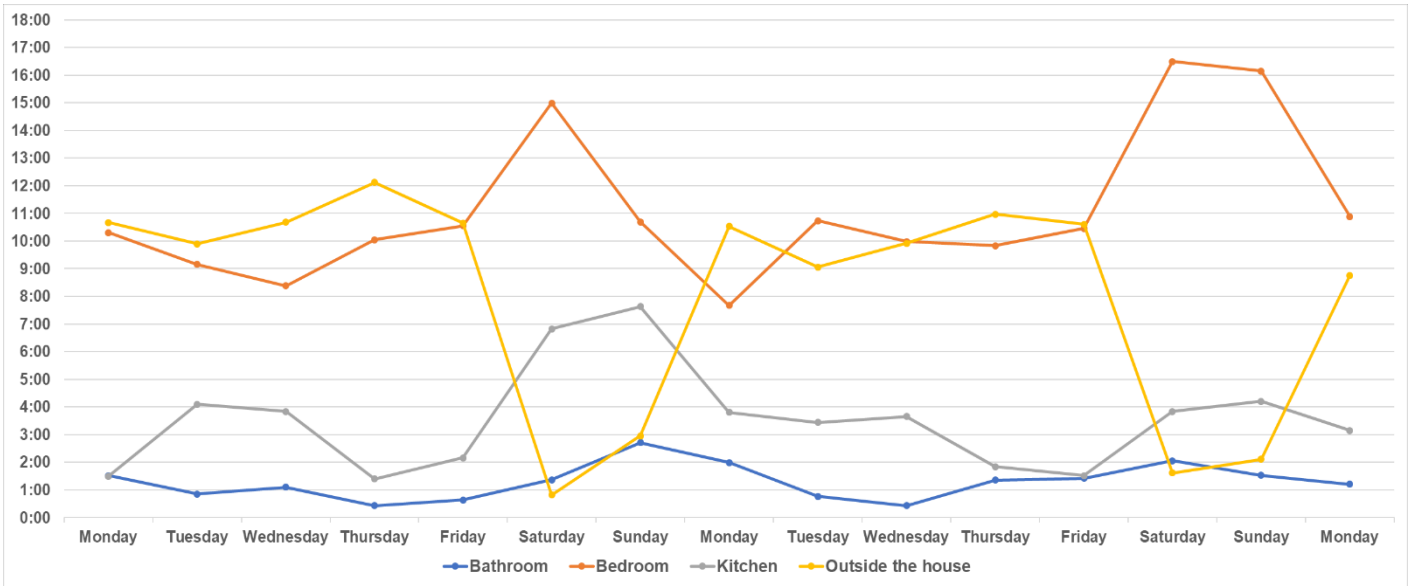

Figure 4. Distribution of time spent inside and outside the home

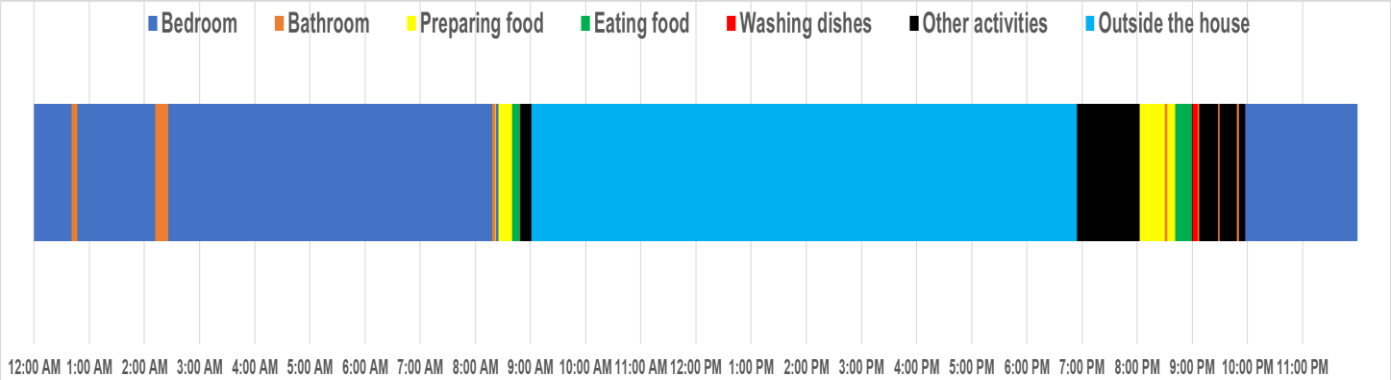

Figure 5. Distribution of time spent inside and outside the home

In our case, there is a big difference in the time spent outside the home respectively from 8h45m on the last Monday to 1h36m on the second Saturday. This difference is logic because the person being followed is a student and he attends his studies during the week. In addition, there is a pattern of duration of time outside the house. In fact, the average time outside the house on the weekday is 10h21m with a maximum of 12h7m and a minimum of 8h45m.

Regarding meal-taking activity, the person spent an average of about 3h31m in the kitchen with a significant increase on weekends (the person spent 7h37min in the kitchen on the first Sunday, and this difference makes sense given that the person eats their lunch outside the home on weekdays and weekends can be an opportunity to prepare meals with longer preparation, uneasy to prepare during weekdays). Overall, the person's daily presence in the kitchen reflects the regularity of the meal-taking activity.

Regarding hygiene, the person spent an average of about 1h17m in the bathroom with a maximum of about 2h42m and a minimum of 0h25m.Therefore, the duration of this activity was distributed relatively evenly over the entire test period.

Figure 5 shows an example of activities detected during a day. It represents 7 activities detected by the sensors (other activities corresponding to those different from the 6 others like playing the piano, cleaning the table after the meal, etc.). It shows the targeted ADLs such as preparing food, eating it, washing the dishes, going outside the home. In fact, he spent, 15m29s and 36m9s in preparing food then 8m26s and 17m43s eating it for breakfast and for dinner, respectively. And he washes the dishes for 5m21s in the evening.

The extraction of this information allows us to have a good insight on the person's daily pattern and thus to detect changes in their behavior (whether sudden or slow over time). Our system will work, using different conditions related to meal-taking activity and mobility, at two level of data analysis. For example, in the first level which is the real time level and based on the model built during the learning phase (one or two weeks/week ends), the system will trigger the loudspeaker to motivate the elderly person to eat if he/she makes an unusual delay of this activity (nutrition is very important for the health of the elderly that is why we need to motivate him/her in real time). And if he/she does not respond to our motivation, we inform the caregiver of this state by sending an alert in the web application. And for the second level, which is the long-term analysis, the data model evolution can reveal a degradation of the time of eating activity. We can conclude from this degradation that he starts to eat less than usual. An alert will be sent to the caregiver and an intervention from him is so necessary.

VIII. Conclusion

In our study, we presented a sensor-based monitoring system composed of PIRs and a reed switch to monitor the activity pattern of people at home.

Analysis of the data collected during 15 days of follow-up for a person living alone allowed us to detect the meal-taking activity (shopping, cooking, eating and washing dishes), mobility (inside home and the act of going out) and the difference of daily pattern between the weekend and weekday.

The system aims to automatically identify the meal-taking activity and mobility to identify social isolation of the elderly. It will respond to each case accordingly to the level of change in their behavior by motivating them to eat and move around and triggering an alert in case of a problem.

In a next step, we will use AI for automatic identification of ADLs, perform tests in the homes of elderly people living alone and detect those cases with abnormal patterns likely to be linked to social isolation problem.

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