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A Simple, Non-Intrusive, Low-Cost Approach

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ABSTRACT

This paper presents an approach to verifying the activities of daily living of elders at their home. We verify activities, instead of inferring them, because our monitoring approach is driven by routines, initially sketched by users in their environment. Monitoring is supported by a lightweight sensor infrastructure, comprising non-intrusive, low-cost, wireless devices. Verification is performed by applying a simple formulae to sensor log data, for each activity of interest. The result value determines whether an activity has been performed.

We have conducted an experimental study to validate our approach. To do so, four participants have been monitored during five days at their home, equipped with sensors. When applied to the log data, our formulas were able to automatically verify that a list of activities were performed. They produced the same interpretations, using Signal Detection Theory, as a third party, manually analyzing the log data.

Categories and Subject Descriptors

K.4.2 [**Computers and Society**]: Social Issues—*Assistive technologies for persons with disabilities*; J.4 [**Social and Behavioral Sciences**]: Psychology

General Terms

Experimentation, Human Factors, Measurement, Performance, Verification

Keywords

Activities of Daily Living; Elders; Activity Recognition; Routines; Verification; Pervasive Computing; Sensors; Signal Detection Theory;

1. INTRODUCTION

Activities of Daily Living (ADL) are abilities defining the functional status of an individual. Verifying what ADLs are performed by an elder is a decisive factor to determine what kinds and what levels of assistance are needed for an individual and whether aging in place is desirable. The importance of this issue has led a number of researchers to develop a range of Ubicomp approaches that can monitor activities (e.g., [11, 17, 10]).

In this paper, we take these prior results one step further and apply them to the needs of caregiver professionals to monitor elders at their home. Specifically, our approach relies on the following key observation: as people age their daily activities are increasingly organized according to a routine to optimize their daily functioning [3]. As a result, their activities do not need to be recognized but should rather be *verified*. Deviations are a warning sign of degradation [3].

We have developed an approach to activity verification. This approach relies on a technological infrastructure that is simple, low-cost and non-intrusive. This infrastructure was deployed in four homes of elders of 83 years of age on average. The same set of sensors was used in the four homes and was placed at strategic locations with respect to their routines to verify the target activities. The analysis of the data collected during five weekdays show that they follow very strict routines that can easily be associated with their main activities.

The contributions of this paper are as follows.

1. An approach to activity monitoring via verification that is dedicated to elders;

2. A lightweight sensor infrastructure for activity verification;

3. An experimental study that validate the accuracy of activity verification.

In the remainder of this paper, Section 2 relates our approach to existing works. Section 3 presents our methodology to perform activity verification. Section 4 describes an experimental setting aimed to assess our approach. In Section 5, experimental data are analyzed and demonstrate their accuracy in a natural setting. Section 6 discusses the limitations of this work and outlines its applications. Finally, Section 7 concludes.

2. RELATED WORKS

This section presents key characteristics and requirements involved in the activity monitoring of elders.

Setting.

A lot of research has been addressing the monitoring of activities. Some works have taken place in an experimental setting: a home dedicated to experimental studies, which sometimes allow subjects to live in for a few days [14]. This experimental setting usually include cameras that allow the activities measured by sensors to be matched against the ground truth video annotations [14, 21].

In the context of elders, an unfamiliar setting is contradictory to a reliable assessment of activities. Indeed, as demonstrated by various studies [9], as their cognitive resources decrease, elders tend to optimize the remaining ones by increasingly organizing operations of their activities according to a strict routine. As a consequence, asking elders to perform activities in an unfamiliar setting compromises their optimization strategies. The resulting assessment of their functional status may be unrelated to their ability to live independently [9].

In a naturalistic setting, having multiple occupants in a home has been reported as introducing sources of errors in activity monitoring, even when different types of sensors are massively populating a home [14].

Activity variabilities.

Users executing increasingly strict routines is a key observation to revisit what kind of activity monitoring is desirable. Indeed, the variabilities in realizing an activity has been a major challenge in a number of works (*e.g.,* [14, 13, 16, 11, 17, 10]). This challenge is typically addressed by spreading numerous sensors of different types and using a range of machine learning algorithms [17, 11]. But in fact, when a user follows routines, sensors could be placed at strategic locations; as well, collected data could be processed by simple algorithms because they would verify rather than infer activities.

Range of sensors.

When elders are being monitored continuously at their home, a range of sensors cannot be utilized. Typically, RFID tags cannot be used because they require that most, if not all, strategic objects be attached a tag [14, 19]. This situation is difficult to maintain without interfering with the person's life, as new objects get introduced in the home. Body-worn sensors are also delicate to introduce in naturalistic setting because they impose constraints on the user and may not deliver accurate data [14, 4, 10]. Regarding cameras, a majority of users consider them too intrusive [4, 10] in their daily life. When we interviewed elders about monitoring of their daily activities, they massively refused to have cameras installed at their home. Besides, as pointed out by Logan *et al.*, annotating videos is tedious and thus costly [14], preventing this approach to scale up to continuous monitoring of several participants.

When comparing various types of sensors in a naturalistic setting, Logan *et al.* reported that simple technology such as motion-based sensors are very successful in detecting activities [14]. Combined with well-identified routines, this situation can open up opportunities to use low-cost sensors.

Accuracy of activity monitoring.

Researchers have proposed various granularity at which activities can be monitored. For example, Lepri *et al.* distinguish between homogeneous and non-homogeneous activities (*e.g.,* watching TV *vs.* eating/drinking) and between an on-going activity and a completed activity [13]. For another example, Mihailidis *et al.* examine the various steps of hand-washing [16].

In fact, activities can be monitored at a variety of granularities.

Not surprisingly, the finer the granularity gets, the more complex the monitoring process becomes. In the context of home-based activity monitoring of elders, studies show that the granularity of the monitoring can be coarse-grained. More specifically, cognitive decline first impacts the instrumental ADLs (IADLs – *e.g.,* meal preparation) because they require high-level cognitive functions to initiate, plan and execute a task [9]; basic ADLs (BADL – *e.g.,* eating) are affected in later stages of cognitive decline, when elders have supposedly been already diagnosed by clinicians.

IADLs inherently involve numerous interactions with the environment to perform the sub-tasks of a given task (*e.g.,* breakfast involves preparing coffee by opening a drawer to reach for the coffee and turning on the coffee maker) [15]. This situation allows to track the execution of sub-tasks via interactions with sensor-equipped locations of the environment.

Summary.

We have outlined the behavioral characteristics of activities performed by elders at their home. These characteristics have allowed us to sketch requirements for home-based monitoring of activities of elders, taking into account their activity variabilities, the sensors needed, and the accuracy of the monitoring.

3. METHODOLOGY

We now present our methodology to perform activity verification. We define what we mean by an activity and list the activities of interest that will be monitored in our study. Then, we introduce the notion of routines, which are followed by users to perform activities. Routines are analyzed to determine key actions that characterize them. Finally, these key actions are associated with sensors that measure their occurrence.

Prior to presenting the methodology, we first examine the set of sensors that are used to measure the interactions of the user with the environment.

3.1 Sensors

Our approach relies on three types of sensors that have covered our needs in practice, while keeping the approach simple, low-cost and non-intrusive. These types of sensors are motion sensors, contact sensors and smart switches. Motion sensors detect motion in a specific area by orienting them at an appropriate angle. Contact sensors detect the opening of a room/cabinet door and a drawer. Smart switches are used to measure whether a connected appliance is functioning; a threshold can be set to prevent false positive (*e.g.,* the consumption of a clock built in the appliance). These three sensing functionalities are the building blocks of our approach to monitoring activities.

3.2 Activities

The notion of activity is fundamental to our work and needs to be defined in the context of our target population: elders. Specifically, we consider self-care activities for which individuals construct or reproduce solutions, involving manipulation of objects, situated in a specific place at home [15]. These activities are well structured [1], involving sequential steps that tend to be "compiled" by elders as a skill [20]. Accumulated reproduction of solutions, as well as aging related loss, probably explain why elders have preferences for routines. This phenomenon is called age-related *routinization* [3]; it precludes multiple activities to be conducted simultaneously [3].

Our notion of activity comprises three key criteria that are at the basis of our verification process

Criterion 1: An activity is situated in a room. This criterion raises a need to measure motion in a given room during the activity.

Criterion 2: To conduct an activity, the user interacts physically with the environment, following a routine. This situation requires that the expected interactions be measured.

Criterion 3: Age-related functional decline leads elders to conduct one activity at a time. This observation suggests that, to match an activity, measures of environment interactions should only pertain to that activity. In other words, if interactions involve more than one activity, they should not be considered as forming an activity.

Our study covers both types of daily activities: basic and instrumental. We chose to study two BADLs: getting dressed and taking a shower. And, we targeted one IADL: meal preparation. The main reasons to choose these activities are as follows. First, they are among the activities that are sensitive to age-related functional decline [9], as well as routinization [2]. As a result, there is a rich collection of articles reporting on the monitoring of these activities (*e.g.,* [4, 17]). Second, they allow to exercise many dimensions of our approach, illustrating different sensing functionalities, locations, and activity requirements.

3.3 Routines

We now detail how activities are instantiated with respect to users and their environment. Our goal is to determine what environment interactions are performed by a user when conducting an activity of interest. To be accurate, this phase is conducted at the user's home by a member of our research group, trained in ergonomics, and more specifically in activity analysis. The experimenter asks the user to sketch each activity of interest. This sketching phase reveals a list of *markers* that characterizes the activity. For example, participants are asked how they prepare breakfast in the morning. Ms. Dupont (a fictitious name) shows each drawer she opens and each appliance she uses. The experimenter asks questions as the activity is sketched, to assess the degree of certainty of the collected information. For example, "Do you make coffee every morning?", "Do you always put your coffee in this cabinet?". For each routine, a set of markers is chosen. In the case of Ms. Dupont, we assess that making a coffee is an essential part of breakfast; this is our first marker. She takes milk in her coffee; this is our second marker. She gets a clean mug from a specific cabinet; this is our third marker.

Guidelines to choose robust markers include the degree of certainty of a given environment interaction and its uniqueness (*e.g.,* coffee is only made once a day using a specific appliance). It could be argued that the more markers used to monitor an activity, the more certain one can be that this activity has been performed. However, in practice, not all markers are validated. For example, one can imagine that a clean mug may not always be in a specific cabinet; it can sometimes be taken from a dishwasher, preventing this marker to be validated.

3.4 Sensor placement

The list of markers collected in the previous stage is used to determine what sensors should be used and where they should be placed. Of course, markers and sensor placement are intimately intertwined, in that markers are not chosen independently of available sensor functionalities, and the feasibility of placing a device at the right point in the physical environment. In the case of Ms. Dupont, we use a smart switch to determine when the coffee maker is turned on. We place a contact sensor on both the fridge and a specific cabinet to determine respectively, when some item (possibly milk) is taken from the fridge and a clean mug from the cabinet.

Putting it all together. To determine that environment interactions form an activity, (1) a subset of the activity's markers need to be validated via sensors (Criterion 2), over a period of time, during which, motions are observed in a specific room (Criterion 1), with no interleaving environment interactions from another room (Criterion 3).

Let us now turn our attention to the BADLs of interest. They require coarse-grain measurements. The shower activity does not offer many alternatives, considering the available sensor functionalities: it is detected by a motion detector, oriented such that as few motions outside the shower cabin are observed. In this case, false positives can be ignored based on the duration of the detected activity.

Regarding the activity of getting dressed, based on our analyses, the key marker is getting clean clothes. This environment interaction can be detected by placing a contact sensor on the door of a strategic piece of furniture (*e.g.,* a wardrobe). However, this marker has not the uniqueness property: door opening is likely to be detected many times during the day. This situation is discussed further in Section 6.

4. DESCRIPTION OF THE EXPERIMENT

In this section, we present an experiment aimed to validate whether elders follow strict routines in their daily activities. To do so, (1) we assess to what extent the participants of our study follow routines by administering a questionnaire; (2) we describe the data collected by our methodology and why they are relevant for our goal.

Participants	A	B	C	D	*Mean (SD)*
Age	77	77	87	93	*83.5 (7.89)*
Gender	F	F	F	F	
Education years	7	8	12	10	*9.25 (7.89)*
Family status	S	W	W	W	
MMSE [0 − 30]	28	28	26	26	*27 (1.15)*
Time-based IADL [5 − 15]	5	5	7	5	*5.5 (1.00)*
Self-reported IADL [9 − 45]	12	16	24	18	*17.5 (5.00)*
Routinization [0 − 40]	15	19	15	24	*18.25 (4.27)*

SD=Standard Deviation; F=Female; S=Single; W=Widowed.
Interval notations are used for score ranges.

Figure 1: Participant profiles

4.1 Participants

To test our research assumptions, it is critical to include community-dwelling, very old adults. To do so, we have collaborated with a public home care service for elders, and have had access to the medical file of their beneficiaries. As described in Figure 1, four participants, aged 83.5 on average (SD= 7.89) have been recruited according to specific exclusion criteria: dependency syndrome; neurological or musculoskeletal disease or systemic disorders. The main inclusion criterion was cognitive integrity with an MMSE score [8] greater than 24. According to the Helsinki declaration (WMA, 2008), approval was sought and obtained from the ethics committee of the University of Bordeaux. All participants provided a written consent form prior to the participation in our study.

We have assessed their functional status for some activities of daily living. First, we evaluated their performance in IADLs, using the time-based IADL assessment test [18]. A participant is asked to perform an activity with a time limit. If the activity is achieved without error and without exceeding the time limit, a score of 1 is

given. A score of 3 means that the participant has major difficulties to perform the activity. We tested our participants on five different activities; this gave scores ranging from 5 (ideal performance) to 15 (major difficulties). In Figure 1, we observe that three of our participants obtain ideal scores (5), and one shows very minor difficulties (7). We conclude that our participants show no difficulties in performing IADLs and have a high level of autonomy.

We also asked them to self-assess their functional status, using the 9-item IADL scale [12]. For each item, the participant assesses her performance: 1 denotes no difficulties and 5 denotes major difficulties. This tool shows that we have a variety of participants in the way they see themselves performing ADLs; it ranges from 12 to 24, on a scale of 45.

Finally, we evaluated the degree of routinization of our participants using the routinization scale defined by Bouisson [5]. We observe that our participants show a variety of routinization degrees. In particular, the participants B and D are more routinized than the two others.

In summary, our participants perform well in their ADLs, although they perceive themselves as experiencing difficulties. From these data, we can expect our participants to perform their ADLs on a regular basis. The variation in the routinization degrees play a key role to assess whether our verification approach covers a wide spectrum of behaviors.

4.2 Data Collected

Logs of the sensors placed in the participants' homes have been collected for 5 weekdays. The same set of sensors has been used for all participants. However, they have not necessarily been used the same way to monitor the activities of interest. For example, participants may or may not take milk from the fridge to make breakfast.

Sensor logs consists of the sensor identifier, a changed status, and a timestamp. The sensor identifier corresponds to a sensor type (motion detector, contact sensor and smart switch) and its location. We selected the logs pertaining to the sensors located in the rooms corresponding to the activities of interest, namely, kitchen, bedroom, and bathroom.

In Figure 2, we show the apartment of Ms. Dupont, populated with sensors corresponding to the activities of interest and related rooms. In Figure 3, we display an example fragment of a log. This table consists of three column showing sensor types, the status and the time stamp; the room information is omitted because the fragment is limited to a sequence of events only occurring in the kitchen (similarly for the date of the time stamp). All columns are self-explanatory. Notice that the level of information delivered by motion sensors have been raised with a software layer. The goal is to obtain two statuses: the first time and the last time a presence is detected in a room. To do so, we need to keep a state to know whether some motion detected in a room is the first occurrence. Furthermore, the last presence is a room is determined by the first environment interaction detected in another room or by an absence of motion for a period of time. This high-level sensor is referred to as a presence detector.

5. DATA ANALYSIS

In this section, we first define a set of formulas, dedicated to daily routines, which is applied to sensor log data to determine whether specific routines are performed. These formulas are then applied to log data across the four participants over weekdays to demonstrate their accuracy.

5.1 Routine Formulas

Routine formulas leverage our notion of activity, introduced in
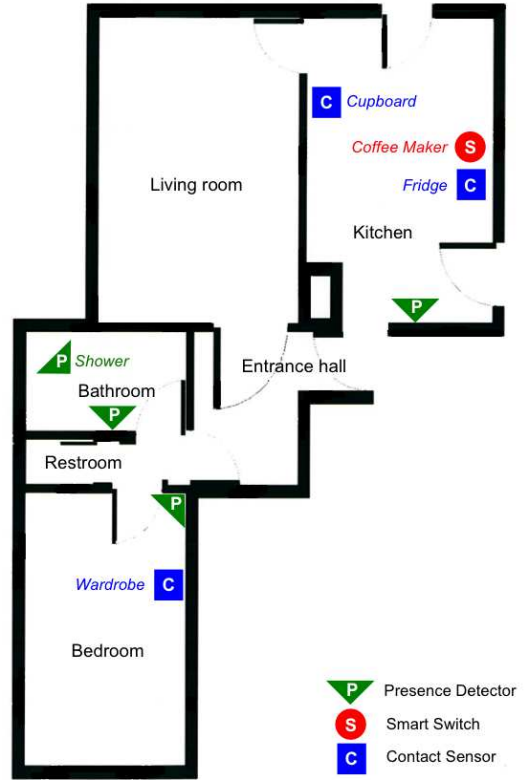

Figure 2: Apartment layout of Ms. Dupont

Section 3, and the criteria associated with this notion. In particular, our routine formulas are grounded in the area of ontological activity modeling and representation (*e.g.,* [6]). Specifically, our formulas are knowledge-driven, in that they rely on the fundamental attributes of an activity. Namely,

Spatial context. This is the room (*i.e.,* the location) where the activity takes place. In our work, because sensors have a fixed location, sensed interactions are situated by definition.

Temporal context. This context comprises two dimensions: (1) the time of the day at which the activity occurs; this information is specific to each participant, and (2) a minimal duration over which the activity is supposed to be performed.

Environment interactions. There are interactions related to markers of the target activity, and associated with sensors for the purpose of

Sensor Type	Status	Time
Presence detector	Presence	09:10:23
Contact sensor - Fridge	Open	09:13:31
Contact sensor - Fridge	Closed	09:13:34
Smart switch - Coffee maker	On	09:14:16
Contact sensor - Cupboard	Open	09:14:58
Contact sensor - Cupboard	Closed	09:15:03
Smart switch - Coffee maker	Off	09:16:38
Presence detector	Absence	09:16:47

Figure 3: Fragment of activity log of Ms. Dupont

our work.

Further defining our notion of a routine formulae, we now examine what result it produces. A formulae verifies an activity by producing a *score*, whose value ranges between 0 and 1. The value 0 means that the activity has not been performed, according to the participant's routine. The value 1 indicates that the sensed measures match the participant's routine.

To specify our first formulae, let us consider on the activities of interest: getting dressed (GD). The time of the day at which this activity occurs is on the morning, as declared by all our participants, and a marker of this activity is the action of getting clean clothes from the wardrobe, thus equipped with a contact sensor. The resulting activity-specific formulae is defined as follows.

$$Sc^{GD} = T^{GD} \times M^{GD}$$

Where Sc^{GD} is the score for the activity getting dressed; T^{GD} is the time of the day, which takes value 1, if it is within the expected time frame of the day, and value 0, otherwise; and, M^{GD} is the marker of this activity, which has value 1 if the sensed interaction occurred, and value 0 otherwise. We did not consider the duration of the activity because presence can be detected in the bedroom for a number of reasons, not necessarily related to dressing, even though the wardrobe may be used.

Let us examine our second activity of interest, namely, taking a shower (TS). This formulae is defined as follows.

$$Sc^{TS} = T^{TS} \times D^{TS}$$

The time of the day is also pertinent in this formulae. Furthermore, this activity requires a minimal period of time over which this activity is performed; D^{TS} takes value 1, if this minimal duration is reached and value 0 otherwise. This duration is based on a unique marker, which corresponds to the presence detector, placed in the shower.

Lastly, we investigate the activity of preparing breakfast (BP). Its formulae is given below.

$$Sc^{BP} = T^{BP} \times \frac{A^{BP} \times 4 + \frac{S_1^{BP} + \ldots + S_n^{BP}}{n}}{5}$$

This formulae reflects the constraint that breakfast preparation occurs at a specific time of the day T^{BP}. Furthermore, it accounts for the fact that this preparation often includes a major marker, corresponding to an appliance (*e.g.,* a coffee machine, a kettle) that can be monitored (A^{BP}). To account for its importance, this marker is weighted by multiplying it by 4. It is added by the rest of the markers of this activity, which are averaged (S_i^{BP}). In our experiment, these markers range from 1 to 3.

To illustrate this formulae, consider Ms. Dupont's morning routine. Preparing breakfast consists of making coffee, sensed by a smart switch (a major marker) and taking a clean cup from a specific cabinet and milk from the fridge, both monitored by a contact door. As can be noted, duration is ignored in our formulae because this activity consists of a few markers that are to be validated over the time of the preparation.

Note that, although conceptually grounded, in practice, the formulas that we have presented are the result of a series of refinements, driven by the analysis of the sensor-log data, collected from our participants. To assess the accuracy of our formulas, we now need to apply them to the log data, across our participants.

5.2 Analysis

We now analyze the results of applying our routine formulas on the log data of our four participants. First, we test the accuracy of the formulas with the calculation of two specific indices: the sensitivity and the response bias indices, respectively A' and $B''D$ for non-parametric data [7]. Second, we assess our methodology to perform activity verification.

5.2.1 Sensitivity indices

Sensitivity indices are used in Signal Detection Theory to measure performance in Yes/No tasks (see Stanislaw and Todorov [22]). To do so, participants of such tasks discriminate signals (stimulus is present) and noises (stimulus is absent). In the presence of a stimulus, `yes` responses are correct and termed *hits*. In the absence of a stimulus, `yes` responses are incorrect and termed *false alarms*. Then, hit and false alarms rates are used to calculate the indices. A' measures the ability of the participant to correctly discriminate the presence or the absence of a stimulus. This index is contained between 0 (extremely low sensitivity) and 1 (extremely high sensitivity). B''_D measures the general tendency of the participant to respond `yes` or `no`. B''_D is contained between -1 (tendency to respond yes and produce false alarms) and 1 (tendency to respond no and miss stimuli).

In the present experiment, the formulas take the role usually played by human participants in Yes/No tasks. Thirty sets of sensor logs were randomly selected from the data collected at participants' homes. They covered an entire morning. Our version of the Yes/No task was conducted as follows. In a first step, we recruited a naive human observer to judge whether our participants perform the three activities of interest. The results of this judgment were used as a base line. Then, scores of activities were computed using our formulas, from which A' and B''_D were calculated.

Results for meal preparation showed the following values $A' = 1.00$ and $B''_D = 0.00$. That is, all the responses of the formulas were correct, according to our base line (*i.e.,* the naive observer). The formulae can be considered as extremely sensitive and perfectly matches the observer in the case of the activity of meal preparation.

Results for taking a shower showed the following values $A' = 0.94$ and $B''_D = 1.00$. Most of the responses of the formulae were correct. The formulae can be considered as highly sensitive. The response bias index indicates that the formulae is conservative (*i.e.,* our formulae has a tendency to respond No). This situation means that our formulae may miss stimuli.

Results for getting dressed showed the following values $A' = 0.93$ and $B''_D = 0.39$. Most of the responses of the formulae were correct. The formulae can be considered as highly sensitive. The response bias index indicates that the formulae is slightly conservative in that it misses very few stimuli.

In summary, our formulas are accurate in that they almost always detect whether an activity of interest is present in a given log data, as compared to our naive observer.

5.2.2 Longitudinal assessment of activity verification

So far, we have demonstrated that our formulas are accurate in detecting activities for a given sensor log. However, we have not determined whether a formulae would find many occurrence of an activity within a day. For example, detecting that the shower is taken is useful, but this is even more valuable if this activity is detected only once (if indeed the user does not take than more shower per day).

The goal of this section is to assess our formulas in a longitudinal manner. That is, showing how many occurrences of an activity is detected each day. To do so, we consider sensor-log data from our participants, over 5-weekday mornings (from Monday to Friday). These log data are used to invoke our formulas. For each partic-

ipant's data log, the formulas are applied as many times as there presence detected in a room associated with an activity of interest. Because of this wide-range application of the formulas, a lot of the computed scores show that the activities of interest have not been performed. We investigated what would be a threshold that would allow to filter out the irrelevant scores. In fact, this threshold is obvious to set because we observed that there are no scores below 0.8. Examining the log segments corresponding to a 0.8 score, we are able to match them against the routines. This situation can be explained by the way the formulas are defined in that they always include major markers that characterize a routine. For the activity of getting dressed and taking a shower, the scores detect an activity of interest with a value equal to 1 (all criteria are met) or necessarily discard the log segment with a value equal to 0. For the activity of breakfast preparation, values of scores above the threshold are between 0.8 and 1, combining the criteria of the time of the day and the major marker of the activity.

Importantly, our strategy does not discard meaningful sequences of actions, nor does it generate spurious scores. This behavior is illustrated by our experiment. For example, in Figure 4, we display how many times a score above the threshold is produced by the formulas for a given participant over the five weekdays. Thereafter, these scores are called *valid scores*. The analysis of the data gathered for all of our participants showed that for the activity of breakfast preparation, the number of valid scores was 1.15 per day in average (SD = 0.49), for a total of 12.95 of computed scores in average (SD = 5.09). For the activity of taking a shower, the number of valid scores was 0.60 per day in average (SD = 0.76), for a total of 6.00 computed scores in average (SD = 2.88). For the activity of getting dressed, the number of valid scores was 0.70 per day in average (SD = 0.86), for a total of 8.30 computed scores in average (SD = 2.64).

The ratios of valid scores per computed scores were 0.10 in average (SD = 0.05) for the activity of breakfast preparation, 0.09 in average (SD = 0.11) for the activity of taking a shower, and 0.08 in average (SD = 0.10) for the activity of getting dressed.

We observe that our approach is reliable for breakfast preparation because this activity is mostly detected once a day for our four participants. Taking a shower exhibits the same performance, even though this activity does not occur every day. Getting dressed is also detected. However, this activity is sometimes detected many times a day, and sometimes not detected at all.

Examing the entire sensor log of some of our participants over 4 weeks,[1] we notice that our formulae for taking a shower shows a periodicity for this activity. In constrast, the activity of getting dressed does not exhibit the same results.

6. DISCUSSION

We first discuss the limitations of our approach and then outline the main perspectives.

6.1 Limitations

Single occupant. Our approach is dedicated to monitoring a single occupant of a home. This choice stems from the fact that caregiving professionals report that when elders live as a couple, one of them can monitor the other one that may need assistance. Therefore, we thought that our work would be more useful in the case of an elder living alone. Furthermore, as mentioned in Section 2, experimental studies have shown that monitoring multiple occupants in a home introduce sources of errors.

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[1]Unfortunately, sensor logs of participants did not cover the same number of weeks, leading us to only consider one week.
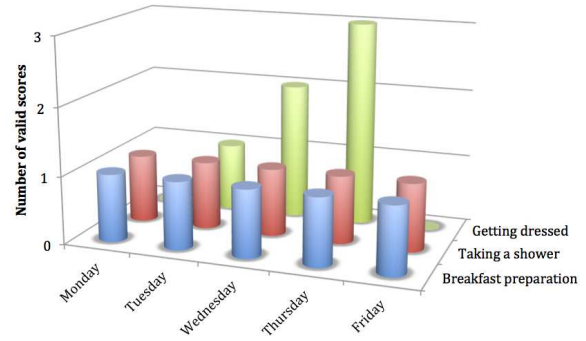

Figure 4: Longitudinal scores of a participant

Number of sensors. Our experimental study involves few sensors. This strategy is problematic for some activities such as getting dressed. Indeed, there might not be enough measures to detect a meaningful pattern. For example, opening the wardrobe may occur for a number of reasons. To recognize the activity of getting dressed, more sensors would be needed to account for other markers of this activity. For example, other doors and drawers could be used to account for additional steps of this activity.

Length of the experiment. Our conclusions could also be strengthened by considering sensor data log over a longer period of time. For example, in Section 5, we noticed that the activity of taking a shower B''_D showed that our formulae tends to miss stimuli (*i.e.,* too conservative). But in fact, we applied this formulae to data log, covering a longer period of time, whenever participants had been recruited earlier. With these additional data, the shower formulae perfectly matches our base line. This suggests that more log data increase the confidence in our formulas to accurately verify activities with respect to Signal Detection Theory.

Assessing the accuracy of our approach. Our signal processing methodology presented in Section 5 could be strengthened by adding multiple observers. We could then compute means of their judgements and compare them to the scores of the formulas. Yet, the consistence of the comparison for a unique observer is very encouraging.

Granularity of activity monitoring. Our approach focuses on whether an activity is performed. Currently, we ignore in what order the steps of the activity are performed, the duration of each step, . . . This granularity may not match the requirements of some applications. For example, if the quality of the activity needs to be assessed, the granularity of our work is not sufficient.

6.2 Perspectives

Sample size. We are continuing to collect data from our participants and recruiting more participants. As a result, we will soon be able to further the processing of the log data to strengthen our statistical evaluation.

More activities. We are adding more activities in the participants we are monitoring. In particular, we are including all meal preparations. These additional activities will allow us to assess the scalability of our approach.

Applications. We are developing applications that can leverage the routine formulas to remind users of activities of interest. The

present work is essential to assess whether activity verification is accurate enough and thus enables an application to send meaningful reminders to a user.

Screening. Another perspective for activity verification is screening. We plan to use our approach to analyzing the evolution of a routine (order of the steps, duration, time of the day, ...) and the evolution of the routines with respect to each other (order of the routines, occurrences, ...). These analyses should be useful indicators to assess the evolution of the functional status of users.

7. CONCLUSIONS

We have presented an approach dedicated to elders aimed at verifying activities, instead of inferring them. Our approach is knowledge-based in that it relies on collecting routines that are initially sketched by users at their home. The resulting knowledge about how activities are performed by elders is reliable because their age-related functional decline increases their degree of routinization.

Then, we have introduced markers that characterize key actions of routines and sensors that measure these actions. Based on these routines, we have defined formulas to verify whether an activity has been performed with respect to sensor log data.

We have validated our approach by conducting an experimental study addressing three daily activities and involving four participants of 83 years of age on average. This study involves a sensor infrastructure that consists of low-cost, non-intrusive, wireless devices. We have collected sensor logs from our participants' home during five weekdays. This study have showed that our formulas produce the same results as a third party, manually analyzing the log data. Using Signal Detection Theory, we also showed that our formulas are accurate and reliable. Furthermore, this approach gives a methodological support to assess the relevance of the knowledge used to define the formulas. For example, asserting that the coffee maker is a key marker of the breakfast preparation can be checked by Signal Detection Theory, and more specifically by the value of A'.

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9. REFERENCES

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