Perspectives in home TeleHealthCare system:

Daily routine nycthemeral rhythm monitoring from location data

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Abstract: **Free of most social constraints, elderly people tend to perform activities of daily living following the same sequence. This paper proposes a method for medical telesurveillance to detect and quantify a nycthemeral shift in this daily routine. While this common phenomenon is mostly mild, in acute cases, however, it may reveal a pathological behavior requiring a rapid medical examination. This method allows to compare two sequences of activities using the Hamming distance and to interpret the result according to the Gumbel distribution. It may be used to compare either consecutive sequences thereby taking into account evolution in the habits or a sequence to the person's individual activity profile to detect dementia's onset. In this early stage, only elementary activities were considered. That is the reason why location data were used to monitor the person's nycthemeral rhythm of activity. IR sensors placed in her own flat allowed us to follow-up the inhabitant's successive activities. Improvements of this method have already been planned. They include the use of a multi-sensors network to monitor both actimetric (location, movement, posture) and physiological nycthemeral rhythms (ECG, respiratory frequency) and to detect the use of particular items (fridge, chairs, bed). This more sophisticated sensors network will allow us to monitor more complex tasks execution and then to detect pathological behaviors such as perseveration in a task or wandering. On the other hand, multiplying sensors will require more storage capacities and the use of time-consuming data fusion tools. Therefore, a classification phase will be necessary to reduce as possible the number of relevant sensors.**

Health smart home; nycthemeral rhythm; elderly people monitoring; chronobiometry; alarm triggering

I. INTRODUCTION

Aging in place at home is a natural wish which is more and more difficult to fulfill because of the numerous cares most of elderly people need. The ageing of the population and the growing prevalence of neurodegenerative diseases synonymous of extreme dependence make matters worse. Every 7 seconds in the world, someone develops dementia which is in half the cases due to Alzheimer's disease, the main cause of admission in institution [1]. This kind of disease is characterized by a slowly and ineluctable impairment of the nervous system which results in a loss of abilities. Activities of daily living (ADL) require more and more help, their sequence is forgotten as well as the way to achieve them. Detecting these diseases' onset as soon as possible is very important to improve the efficiency of the treatments which aim at stabilizing symptoms and put the entry in dependence back. The general purpose is to support the person's autonomy and to maintain her/him in her/his own environment as long as possible. This last point is particularly important for the person's quality and expectancy of life. Unfortunately, no automatic and non-invasive mean of detection is available yet.

Within this context, the development of TeleMedicine/TeleHealthCare is critical for our society. To meet this need, scientists around the world have led many projects during the last decade [2]. In Grenoble, a project named 'HIS' was developed to monitor actimetric data of the watched person and trigger alarms if need be [3, 4]. A network of sensors was installed in an experimental platform to localize the person within the flat. This paper proposes in this context a new method of actimetry follow-up based on the calculation of the nycthemeral variability of the activity. During the monitoring, a learning phase is dedicated to the development of a personal actimetric profile [4] which would be refined all the process long. Censored or missing data may be approximated according to the model proposed by [5]. Then, sequences of activities may be compared day by day to point out an evolution of behavior as a mild change in habit or a weak nycthemeral shift common and non pathological among elderly people (e.g. a change is sleeping clock). Sequences of activities captured at home may also be compared to the profile of the patient to detect a worrying change in her/his cycle of activities like an abnormal perseveration, an important nycthemeral phase shift or even wandering. Finally, processes of decision-making are launched to eventually trigger alarms.

The second section of the present paper is dedicated to the rhythms which regulate the human being's functions and processes. It turns out that ADL are also rhythm-dependent and then are predictable in time. The follow-up of this activity cycle is based on location data collected by the AFIRM (Information Acquisition and Fusion and Network for Medicine) team from TIMC-IMAG Laboratory and RBI during the AILISA project [6]. Then, the methods used to study the sequences of activities are described in the fourth section. In particular, a procedure to detect and take into account a possible nycthemeral rhythm shift using the Gumbel distribution is introduced. In conclusion, perspectives for future are developed concerning the improvements of this method which have already been planned and their implementation.

II. AT THE HUMAN BEING'S TIME

Which is exceptionally remarkable in the human being is its ability to self-regulate: temperature, cardiac rhythm, muscular strength, hormone levels, menstrual cycle... Its processes and functions are very well-organized in time. Indeed, its physiological variables fluctuate around a near-constant value to maintain homeostasis (dynamical internal equilibrium). These fluctuations are periodical and regulated by internal biological rhythms. Rhythms are classified depending on their period. The most well-known have a period of about a day (24h±4h) and are termed as 'circadian'. In particular, a rhythm which lasts exactly 24h and is synchronized with the environmental light-darkness cycle (its *zeitgeber*) is called nycthemeral. To date, at least 170 human circadian variations have been studied [7, 8]. For many years, medicine has neglected biological rhythms, which change with the biological age [9]. Prescribed drugs only aimed at making a biological parameter reach its "constant" value. It is now admitted that watching rhythms is very relevant in medical surveillance, because preserving the integrity of the human time structure is critical to health.

Activities of daily living also follow periodical variations which are, in this case, adapted to both one's biological and social rhythms. The latter is synchronized with one's way of life and external schedules or clocks of the society. The periodical behavior of activities makes them be predictable-in-time. Therefore, it would be useless to monitor a person's actimetry ignoring these rhythms. On the other hand, the patient's nycthemeral activity rhythm is very sensitive to external cues, then her/his environment needs to be stable enough. Hospital suites seem to be well-adapted places to test model on rhythms [10, 11].

With advancing in age, some changes in annual and circadian rhythms are commonly observed, e.g. in the sleep/awake cycle, but these rhythms persist. In fact, the characteristics of some rhythms may change sensitively: the *mesor* or overall mean value of the rhythm may decrease (like the melatonin level) or increase (like the gonadotrophic hormone level in menopausal women) and the period may also be longer (suprachiasmatic nucleus) [12]. On the other hand, this phenomenon is acute in case of disease, in particular dementia-related ones. In Alzheimer's disease, the nycthemeral rhythm is known to be frequently very disturbed [13, 14].

III. THE HEALTH SMART HOME

A. *The experimental platform*

The HIS project located in the Faculty of Medicine of Grenoble takes the shape of a common 50m² flat (Fig.1) used as an experimental platform for both technological development and clinical evaluation [3, 4].

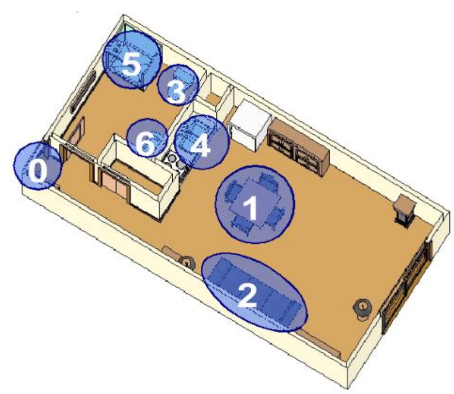


Figure 1. The experimental health smart home. IR sensors are placed in each room, allowing the monitoring of the inhabitant's successive location:
0. Entry hall
1. Living room
2. Bedroom
3. WC
4. Kitchen
5. Shower
6. Washbasin

The purpose of such a platform is to develop technologies to support ageing in place at home. In order to achieve it, this flat is equipped with smart sensors capturing all the day long measurements about the inhabitant (concerning her/his location, mobility, etc.) and her/his environment (temperature, hygrometry, illumination, etc.) while preserving her/his comfort and respecting ethical constraints. The network of sensors is linked to a master PC, located in a dedicated room of the flat, *via* a controller area network (CAN). Then, a software analyzes automatically the data transmitted and is able to develop an individual activity profile based on the recorded data, to detect abnormal deviations and to trigger alarms.

B. Location data

Within the framework of this study, the concept of HIS was transposed in a real flat of a residence for older adult in Grenoble [5, 15]. An infra-red motion sensors network was used to monitor a voluntary elderly woman's localization in time within her own flat during six months. Each room was equipped with a sensor and numbered (Fig.1, 2). Time-stamped locations were recorded at a sampling frequency of one second to form a corpus of experiments. These events were stored in a data bank as space separated numerals representing day, month, year, hour, minutes, seconds at a coded location captured respectively. For instance, the "03 08 2007 12 04 48 4" sequence means that, the 3rd of August 2007, at 12:04'48", the person was in the kitchen. A part of this corpus (20%) is used during the learning phase in order to provide a statistical occupation/activity profile of the person whereas the remaining 80% is used to test the model proposed [4]. This procedure allows to take into account each inhabitant's individual behavior and activity.

Figure 2. Activity generic sensors (infrared volumetric sensors indicated by arrows).

IV. Activities monitoring

A. Activities of daily living modelling

To detect easily deviations from the daily routine, the activities of daily living (sleeping, eating...) are classified into four categories:

- A: Ambulatory Activity (between rooms at home)
- G: Generic Social or Cultural Activity (reading, watching TV, receiving family or friends, etc.)
- C: Cooking & Eating (dedicated activities)
- U: Unassigned to a Specific Activity (resting or sleeping)

As the considered activities are very elementary, each room is supposed to be dedicated at only one kind of activity. Therefore the location and the category of the activity are assimilated e.g. being in the kitchen (room 4) means that the patient is "Cooking & Eating" (activity C). Data were recorded at each second. We choose to consider the dominant (in time) activity of an hour only. Then, each hour is labeled with the letter (A, G, C or U) corresponding to its dominant activity.

B. Measurement of the dissimilarity between two sequences of activities

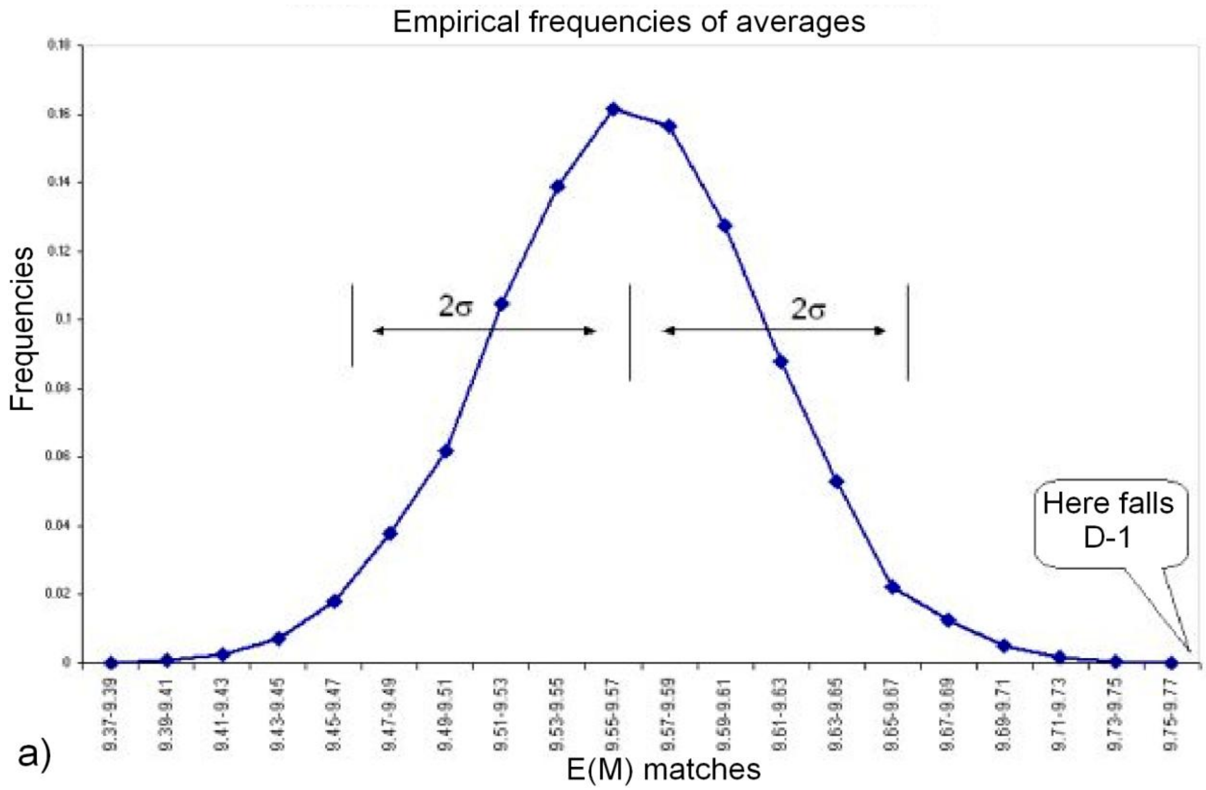
To detect abnormal deviation from the activity profile or a temporal shift between sequences consecutive in time, we need to quantify the dissimilarity between two sequences. To manage to do it, the classical Hamming distance d_H is employed. This distance is generally used to compare equal length strings as followed. For a finite alphabet A and a fixed integer n, A^n is the set of strings of length n on the alphabet A, i.e. $A^n=\{x=(x_1,\ldots,x_n) : \forall\ i\in\{1,...,n\}\ x_i\in A\}$. The rotation of $x\in A^n$ is obtained by applying a circular permutation (we will denote by the symbol σ) to its first component: $\sigma(x) = \sigma(x_1,x_2,...,x_n) = (x_2,...,x_n,x_1)$. It is equivalent to a shift of the origin of phases. Then the Hamming distance is:

$$d_H(x, y) = \min_{k=1,\ldots,n} \mathrm{Card}\left\{ i \in \{1,\ldots,n\} : x_i \neq \sigma^k(y)_i \right\}.$$

C. Nycthemeral phase shift detection

In this part, we aim at defining a criterion of comparison between two sequences of activities. A random variable M is introduced as the number of matches between the activities sequences of two consecutive days, e.g. by denoting x, y the sequence recorded respectively at day D_t and at the previous day D_{t-1}: $M = n - d_H(x, y)$.

The probability law of M is assumed to be the circular Gumbel distribution which is generally used to model the distribution of the extreme value of a large collection of random observations ruled by the same arbitrary distribution. Let us suppose that the daily activities were recorded at 22 times (by considering that the hours 24, 1 and 2 correspond to the same sleeping activity) which corresponds to sequences of length n=22. The expected number of matches E(M) is less than the maximum number of matches observed by comparing 22 independent chains of length 22, because a change of the origin of phases on the ring does not correspond strictly to a new chain tossing. Then, we can write: $P(M<k)>P(\cap_{i=1,\ldots,n}(X_i<k))$, where $0\leq k\leq 22$ and the X_i's are independent identically distributed (i.i.d.) random variables, having as common distribution, the binomial law B(22; ¼). A variable X which follows B(22; ¼) represents the number of matches between two independent sequences of length 22 by supposing that the occurrence of each activity A, U, G, C has the probability ¼ and there is 22 times in the lapse recording. If n increases (i.e. if the temporal sample is refined, e.g. from hours to minutes), then the circular Gumbel distribution tends to the



a)

Hours	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
D-1	C	A	A	G	A	U	G	A	A	U	G	G	U	A	C	U	G	C	C	A	U	U
D1	U	C	A	G	G	U	A	A	G	U	G	U	U	C	A	C	U	G	C	C	A	U
σ(D1)	C	A	G	G	U	A	A	G	U	G	U	U	C	A	C	U	G	C	C	A	U	U

b)

Figure 3. Empirical behavior of the number of matches between sequences of activities
a) Empirical distribution of the mean number E(M) of matches calculated between 500 activities sequences D1,…,D500 and 30 000 random sequences, showing that the following match between D1 and D-1 is significantly better than a random match ($p < 10^{-3}$).
b) Comparison of two consecutive activities sequences. The maximum of matches (12) is obtained for a nycthemeral phase shift equal to 1.

$\sup_{i=1,..,n} X_i$ distribution, and asymptotically in n, E(M) may be estimated as follows:

$$E(M) = \sum_{k=1}^{n} P(M \geq k) = n - \sum_{k=1}^{n} P(M < k)$$

$$\approx n - \sum_{k=1}^{n} P(\bigcap_{i=1}^{n} X_i < k) = n - \sum_{k=1}^{n} P(X < k)^n$$

The mean μ (respectively variance σ^2) of X is equal to n/4 (respectively 3n/16). Therefore, the following quantities can be neglected with an approximation less than 2%, taking into consideration that X is asymptotically Gaussian:

- $P(X \geq k)^n$ for $k > i(\mu+3\sigma)+1=I$
- $P(X \leq k)^n$ for $k < i(\mu+2\sigma)-1=I'$,

where i(x) is the nearest integer less than x. Thus, we have:

$$E(M) \approx n - \sum_{k=I'+1}^{n} P(X<k)^n = n - \sum_{k=I'+1}^{n} (1-P(X \geq k))^n$$

$$\approx n - \sum_{k=I'+1}^{n} (1 - n \cdot P(X \geq k)) = n - (n - I' - 1 + 1) + n \cdot \sum_{k=I'+1}^{I} P(X \geq k)$$

Finally, $E(M) = I' + n \cdot \sum_{k=I'+1}^{I} P(X \geq k)$

If n=22, then μ=5.5, σ=2.03, I'=8, I=12 and E(M) is estimated by:

$$E(M) = 8 + 22 \cdot \sum_{k=9}^{12} P(X \geq k)$$

$$\approx 8 + 22 \cdot (0.043 + 0.013 + 0.003 + 0.0007) \approx 9.32$$

We can notice that the distribution of the $\sup_{i=1,..,n} X_i$, hence the circular Gumbel distribution, behaves like a single Gaussian variable with a suitably chosen variance.

Let us suppose that the 22 activities recorded at day D_{t-1} corresponds to the sequence:

UCAGGUAAGUGUUCACUGCCAU

Then, we can compare the other days to this reference sequence by using the circular Hamming distance and the significance of the result will be given with respect to the circular Gumbel distribution, whose empirical mean is approximately Gaussian of mean 9.55 (Fig. 3a). For instance, by comparing the sequence D1 to the reference sequence D-1, the number of matches found is 12, with a nycthemeral phase shift of 1 (Fig. 3b), which is significantly better than the mean match with a random sequence ($p<10^{-3}$). An alarm will be triggered only in case of a significant difference observed after correction of the nycthemeral phase shift which cannot be considered as pathological in older adult.

D. An individual statistical activity profile

From the 20% of the corpus dedicated to the learning phase, a statistical activity profile is established taking into account an initial individual daily routine. To achieve this goal, a statistical method proposed by Virone *et al.* [4] is used. The circadian cycle of occupation of each room is determined as follows. For each hour of each day, the time spent in a given room is calculated thereby obtaining temporal series of occupation for each time slot. Finally, the mean and the standard deviation of each series are calculated, normalized and plotted depending on the hour of the day. By superimposing the curves of each room, a good estimation of the inhabitant's habits is obtained.

Referring to the same profile, all the watching long may lead to mistakes with time. Apparition of a non-pathological nycthemeral rhythm shift is very common in elderly people and hence must not cause alarm triggering. The comparison day by day of the activities sequences may show whether the shift is punctual or installed. In the second case, it would be interesting to make the profile evolve with the person's behavior. Thresholds have to be determined to decide if the observed shift is temporary or not.

V. CONCLUSION

A. A new tool for telemedicine

Human being's functions and processes are very well-organized in time as well as its activity. These rhythms which regulate life evolve with aging. Their characteristics (mean level, period) sensitively change but rhythms remain identical. In case of dementia-related diseases as Alzheimer's, however, an acute dysregulation of circadian rhythms frequently appears in particular in behavioral cycles [14]. This paper is focused on the detection and quantification of the nycthemeral activity rhythm shift. A statistical approach is then introduced to measure the similarity between two sequences of activities. The sequences are compared using the Hamming distance. Then, the result is interpreted according to the Gumbel distribution used to model the probabilistic law of the number of matches between two sequences. In general, a nycthemeral shift is non-pathological. In this case, the tool provided may be used to adjust the origin of phases of two sequences to make the comparison easier or to compare sequences day by day thereby detecting new habits and then completing the actimetric profile. On the other hand, if the disturbance is important (sharp rupture in respect to the profile), this shift may be used as a marker of entrance in pathology and/or trigger alarms either by informing the person him/herself using biofeedback systems [16], or by initiating a telephone call or email message to a central assistance).

B. Perspectives for the future

The development of technologies for telemonitoring aims at improving the person's quality of life by preserving her/his autonomy as longer as possible. These systems have to obey to technical, economical and ethical constraints while ensuring the person's comfort and security. This paper proposes a method for monitoring the person's activity. However, it happens that due to either sensor failure or auto-censure some data are missing. A method as proposed recently by Fouquet *et al.* [5] may be used to overcome this difficulty and would be integrated shortly.

To go further, the experimental platform will be equipped with other kinds of sensors which will allow us to follow-up both actimetric (postures, number of steps) and physiological variables (ECG, respiratory frequency). These last variables will be captured thanks to embedded sensors sewed within a waistcoat which needs to be in direct contact with the skin. This waistcoat named Visuresp® was developed by the PRETA (Experimental, Theoretical and Applied cardio-respiratory Physiology) team of the TIMC-IMAG Laboratory and the RBI Society. The respiratory signals measurements are obtained by a non-invasive method: impedance plethysmography. An algorithm developed by RBI provides an estimation in time of the volume of air present in lungs. This algorithm is available in static conditions and needs to be extended to ambulatory capture. Actimetric data are provided by a 3D-accelerometer to follow up the posture of the patient in time. Using only one cloth was a condition we impose ourselves to ensure the patient's comfort. Observing both physiological and activity data will allow us to monitor their respective circadian rhythms. The characteristics (Acrophase, i.e. localization in time of the maximum amplitude value, Mesor, Period, Amplitude [17]) of the circadian physiological cycles studied will be monitored in time to detect an eventual disorder. As far as the activity cycle is concerned, it would be interesting to consider more complex tasks [18, 19]. However, this will require more sensors like magnetic switches placed on doors, relevant items and also below chairs and bed. Moreover, data fusion techniques will be necessary to deal with information from a multi-sensors network like the ones proposed by Hong *et al.* [18] or also Demongeot *et al.* [15, 20]. On the other hand, multiplying sensors will increase considerably the quantity of data leading to time for treatment and storage problems. A classification phase will probably be necessary to distinguish relevant sensors from the others. These perspectives are summed up in Figure 4.

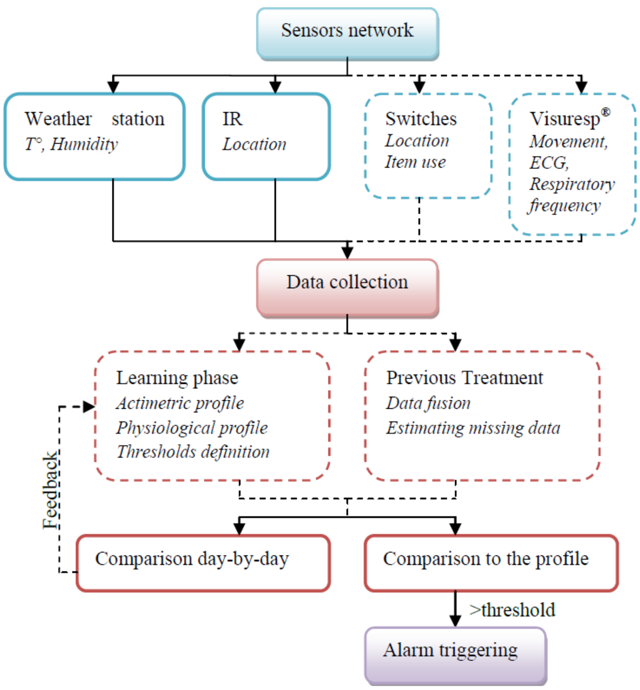


Figure 4. Method proposed to study both physiological and behavioral circadian rhythms. Plain lines represent what is already implemented or installed while dashed lines represent what remains to integrate.

Such a monitoring system would allow us to detect pathological behavior like deviation from routine, perseveration in task, wandering while monitoring the patient's main physiological variables. The ECG signal may even be used to detect a possible anxiety at nightfall common in Alzheimer sufferers. Nevertheless, all the perspectives above mentioned are related to the early detection of dementia's onset. Those who are interested in what we can do to extend the entrance in institution of elders with onset dementia may also feel concerned. These patients suffer from disorientation and forget gradually the sequence of ADL. By combining the profile of the patient before the beginning of her/his disorders and the prediction ability of the system, one may imagine a cognitive assistance in performing ADL like the one developed by Bouchard *et al.* [21, 22, 23]. Before managing to do it, further works are needed.

Finally, biological and social rhythms cannot be neglected any longer. Further understanding rhythms is crucial. However, they are difficult to observe because of the external cues which may affect them. Thereby overcoming this difficulty, the first measurements and tests on the model proposed will occur in a hospital suite of the Center of Gerontology, University Hospital of Grenoble. This kind of environment is particularly stable and activities are regulated by the medical staff. IR sensors placed at relevant points of the room (doors, bed, bathroom) will provide data on the watched person's behaviors. This preliminary experiment will be a first step toward the validation of the method proposed before its testing in real conditions.

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