Behavioral telemonitoring of the elderly at home:

Persistent Actimetric Information from location data in Health Smart Homes

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Abstract — Supporting ageing in place and staying at home, delaying institutionalization, lightening the caregivers' burden, improving the elderly quality of life are as many expectations that tele-healthcare aims at coming up to. This paper discuss the ability to obtain a reliable pervasive information system at home from a network of localizing sensors allowing to follow the different locations at which a dependent (elderly or handicapped) person can be detected. It proposes a method for telemonitoring to detect abnormal changes in behavior which may lead to an early entrance in dependency. The tendency to perseverate is measured by a parameter of persistence in a task. The data recorded can be treated as the sequence of color coding numbers of balls (symbolizing activity-stations) taken in a Polya's urn, in which the persistence of the presence in an activity-station is taken into account by adding a number of balls of the same color as the ball just drawn. This method is illustrated through a longitudinal study of the successive locations of an elderly woman within her own flat. In this preliminary work, the records were captured by passive infrared sensors placed in each room allowing only the detection of elementary activities of daily living. The method was tested by varying the timebox width of the study (i.e. the duration of the watched activities) and in a second time by distinguishing the day of the week. In both cases, it provides interesting insights into the behavior and the daily routine of the watched person as well as deviations from this routine. We discuss the relevance of such a procedure to detect early sudden or chronic changes in the parameters values of the random process made of the succession of ball numbers and we use it to trigger alarms (in order to alert the care givers) and diagnosis the person's health and autonomy (in order to keep the person at home as long as possible but to see as soon as

possible the degradation of the person's health).

Index Terms—actimetry, behavioral modeling, biostatistics and time series of long recording at home, elderly monitoring, localization sensors, mobile and pervasive sensing, pervasive watching systems, Polya's urns, smart flats for elderly people.

Errare humanum est, perseverare diabolicum
(St Augustine, Hippo, 384).

1. Introduction

Advances in medicine have succeeded in allowing people to live longer and healthier. The demographic ageing of the worldwide population is considered as a direct outcome of such improvements. As a consequence policies which enable elderly people to stay at home or age in place are of increasing interest and the topic of research in a growing number of countries. In return, the prevalence of age-related diseases has increased in elderly people ageing in place, creating an increased need in infrastructures and medical caregivers at home we are already lacking. In particular, dementia which is in half the cases due to Alzheimer's disease (AD) affects another person each 7 seconds throughout the world and constitutes the main cause of institutionalization [1].

The course of dementia is slow but ineluctable. The neurological deterioration of the demented elderly is associated with cognitive decline, progressive disorganization, temporospatial disorientation trouble and therefore difficulties to perform activities of daily living without assistance [2,3]. Disturbances of some circadian (*i.e.* 24h±4h) rhythms like sleep/wakefulness, rest/activity cycles are also components of the behavioral symptomatology of dementia [4-7] and are major determinant of carers' burden and entrance in institution, which concerns an increasing proportion of elderly people in developed countries: the percentage of old people - aged above 65 - living in old age institutions varied in 2002 from 4% in Italy, 7% in France and Germany to 9% in Netherlands and Sweden and the percentage of this old people in the population will considerably increase by 28% (resp. 33%, 33%, 25%, 31%) in 2009 and to 50% (resp. 66%, 61%, 43%, 44%) in 2050 in France (resp. Italy, Germany, Netherlands, Sweden) (cf. Fig. 1 and [8-11]).

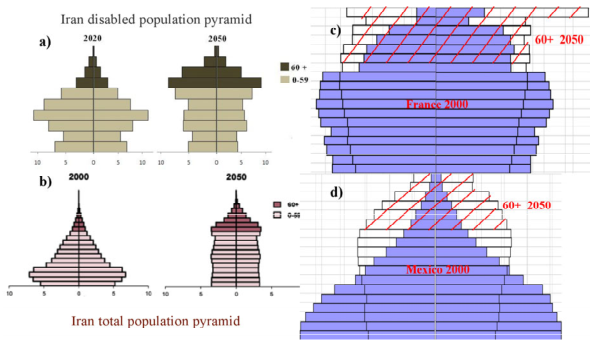

Fig. 1: Pyramids of the Iran disabled a)[10], total populations b)[11], whole population in France c)[9] and Mexico d)[9] between 2000 and 2050. It shows the demographic transition in 2000 for Mexico, the passage over 50% of the old people percentage in 2050 for France and over 30% of the old disabled percentage in disabled population in 2050 for Iran.

Detecting early dementia onsets is then critical for the person management and for the treatment effectiveness at weakening the symptoms. However, no automatic and non-invasive mean of detection is yet available [12, 13].

Fig. 2: infrared sensors (arrows) for localizing dependent people in a health smart home

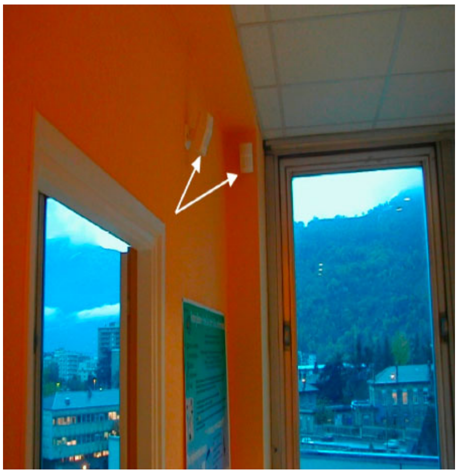

Fig. 3: pressure sensors (FSA Seat 32/63 pressure mapping system, Vista Medical Ltd.).

During the last decade, tele-healthcare systems have been developed through many projects to support ageing in place at home and improve the quality (and expectancy) of life of the elderly [14, 15]. Since about 12 years [16-18], many experiments have been achieved for watching dependent people at home, in particular elderly and handicapped persons. For instance, in Grenoble, during the AILISA project [19], a flat inhabited by an elderly woman, 80-year-old, was equipped with Passive InfraRed (PIR) sensors to monitor her successive locations around the clock (Fig. 4). In order to acquire data necessary to permit alarms triggering, numerous sensors have been invented, in particular for localizing the person at home or in the surroundings. These localizers are on people's body (*e.g.* the GPS or the accelerometers), in the flat rooms (on walls, *e.g.* infrared or radar detectors, *cf.* Fig. 2, or on floors, bed or chairs, e.g. the pressure sensors, *cf.* Fig. 3), on doors (e.g. magnetic switches) or in gardens and streets (*e.g.* video-cameras). The sensors network is very important to follow up dependent people during their walk trajectories inside their home or outside. No matter if the space/time data are acquired on healthy elderly people or on patients suffering from a neuro-degenerative disease, the sensors recording must be very well calibrated, to give birth to specific profiles of the time series corresponding to the successive locations in rooms inside flat or in specific places inside a room [20]. A big hope comes from such ambient information to be able to detect a progressive stereotyped behavior (for the early diagnosis of a chronic disease like the Alzheimer one) or a sudden fall on the ground. The optimal use of pervasive information implies fusion and scoring from the primary data, in order to detect minimal changes in time profiles: a way to do that is to considerably simplify the information by giving a color coding number to the different locations (relevant for the watching), and to follow up the succession of these numbers, *e.g.* by interpreting them as the succession of colors of balls drawn from a Polya's urn: in this kind of urn, the persistence (or *a contrario* the unstability) of an action in a location is represented by adding $n_i(k(i))$ $k$balls of color $k(i)$, when a ball of color $k(i)$ has been obtained at time i. If $n_i(k(i))$ depends only on i through k, the random process constituted by the succession of the $n(k(i))$'s is called homogeneous and a change in homogeneity can be detected by estimating the $n(k)$'s and testing their significant consecutive differences. We will give in the following elements of material and methods in order to describe more precisely the data collection and treatment procedures, and then we will discuss the pertinence of such a research protocol and its implementation in the current life of dependent people at home.

2. Biological background

Clocks are everywhere. There exists a time for everything: opening/closing time, work time, spare time, released time, seed-time, reaction time, arrival time, …… Between environmental time givers (*Zeitgebers*) like the day/night alternation, seasons, etc. and the clocks of the society, it is difficult to escape from time. Notwithstanding, physicists and mathematicians manage to do it. They elude time as soon as it makes things too difficult (*e.g.* in non-autonomous differential equations). For a long time, physicians tried to neglect it too but it is now admitted that rhythms are very relevant for medicine. Indeed, human being's functions and processes are very well-organized in time: heart rate, hormone levels, temperature, blood glucose level, etc. Up to now, circadian rhythms, mediated by the suprachiasmatic nucleus (the biological clock of the mammalian brain), have been studied in at least 170 human variables [21,22]. Dysfunctions in rhythmicity are in most cases synonymous of health problems (*e.g.* diabetes or cardiac arrhythmia). Rhythmicity of the human being is also influenced by social rhythms inherent in one's daily life (*e.g.* work, transportation, regular social interaction) and way of living (*e.g.* culture, education). Indeed, activities of daily living (cooking, eating, sleeping, etc.) are strongly regulated by both biological and social rhythms [23] and then follow periodical variations (*e.g.* hunger is mediated by both hormones and activity). This phenomenon is particularly accurate whilst observing the daily routine of elderly people who are free of most of the social constraints.

With ageing, rhythms evolve, their characteristics (amplitude, period, *etc.*) may change sensitively but they maintain consistency (*e.g.* some hormone levels with menopause) [24,25]. For instance, sleep/wake disturbances are frequently observed in elderly people but are more pronounced in those with AD. In comparison, they show an increased nocturnal activity, a higher sleep fragmentation with daytime naps and decreased amplitude of the sleep/wake cycle. Moreover AD patients with sleep disorders have more rapid cognitive decline and those who engaged activities in nighttime such as eating, wandering, etc. are more likely to be institutionalized at one year [6]. In the same way, strong association of the activity profile with functioning and well-being in demented elderly has been demonstrated [5].

The activity monitoring of AD patients may provide complementary information on their progression in disease and entrance in dependency. It may allow to adapt in a better way non-pharmalogic strategies such as light therapy and other treatments that enhance daytime activity and may improve well-being [26]. Identifying the breakdown of the circadian control of daily routine may be critical for therapy effectiveness and successful management of the person at home.

Regarding recent works led on the monitoring of daily life rhythms through location data, Virone *et al.* (2008) have focused on pattern recognition and deviations from these patterns using a statistical analysis of the occupation rate of each room [23]. Cerny *et al.* (2009) have introduced technical solutions for representation of the resident's location based on RGB coding [27]. Their systems have not been implemented to deal with pathological patterns. This paper proposes a new tool for detecting pathological behaviors and hence loss of autonomy in home-dwelling AD patients.

3. Materiel and methods

3.1. The Health Smart Home

Within the HIS project, a common 50m^2 flat, located in the Faculty of Medicine of Grenoble, was equipped with different kind of sensors and used as an experimental platform for both technological development and clinical evaluation [28,29]. The main purpose of such an installation is to support the maintaining at home of elderly people as long as possible while ensuring their safety, autonomy, wellness and preserving their privacy. To come up to this last expectation, priority is given to anonymous sensors like the Passive InfraRed ones which are used to monitor the inhabitant's successive locations all the day long in this study. The follow-up of the life space occupation provides insights into the inhabitant daily routine. Important deviations from this routine may reveal pathological behavior such as perseveration in task [30,31], difficulties to perform everyday activities, temporal disorientation. They are all good indicators of a loss of autonomy.

3.2. Daily Routine Modelling

Within the framework of this study, the concept of HIS was transposed in a real flat of a residence for elderly in Grenoble [19,30,31]. A private apartment of an old woman, aged 80, at the Institution Notre-Dame (Grenoble, France) is equipped with a health integrated smart home (HsH) with a network of PIR motion sensors. In general, the underlying principle of the HsH consists in continuously collecting data regarding her individual activity within her home environment and sending them to a telemedicine center via electronic mails (SMTP). As illustrated in Fig. 4, our experimental health smart home includes 7 presence infra-red sensors (DP8111X, ATRAL), allowing the detection of the infrared radiations emitted by body surfaces (face, hands), and hence the monitoring of individuals successive activity phases within her home environment [32-35].

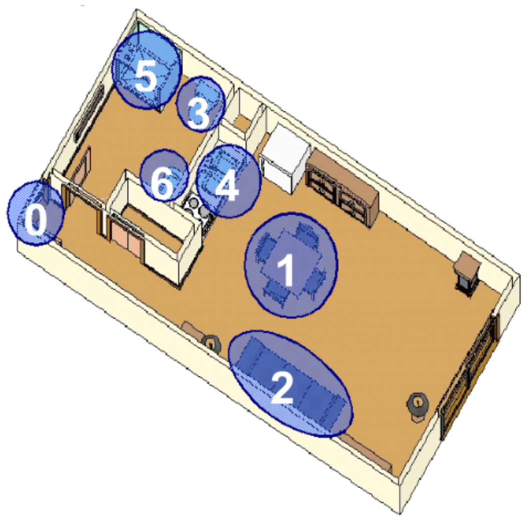

Fig. 4: Architecture of the experimental health smart home. Location sensors are placed at different places in the apartment, allowing the monitoring of individuals successive activity phases within their home environment: 0. Entry hall - 1. Living room - 2. Bedroom - 3. WC - 4. Kitchen - 5. Shower - 6. Washbasin.

Each room was fitted with at least one sensor (7 in total) and each activity station was numbered (Fig. 4). The detections by sensors are timestamped and stored in a database (SQL) and then daily transmitted by e-mail through an attached file (XML). They permit the continuous real-time surveillance on the screen of a dedicated workstation at the Hospital at Home (HaH) service which possesses nurses and doctors ready to visit the person at home in case of an acute pathologic problem or to transmit to a chronic disease service the information about the occurrence of a problematic change in the physiologic variables recorded at home (cf. Fig. 5).

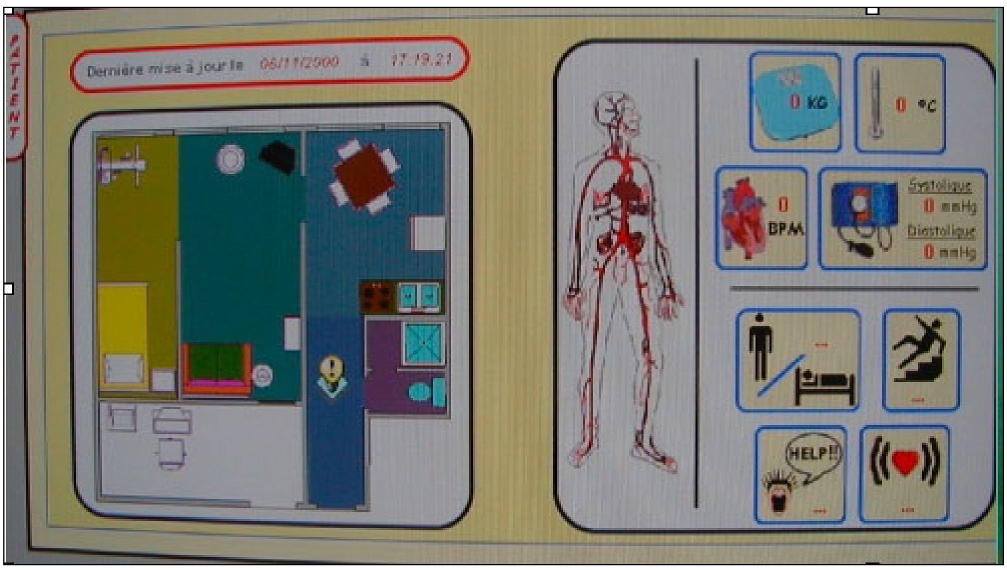

Fig. 5: Monitoring workstation at the Hospital at Home (HaH) service for the surveillance of dependent people at home, physiologic variables recorded at home.

3.3. Polya's urns for activity modelling

The data analysis of the records at home is primarily done through real-time updated descriptive statistics like presence histograms (Fig. 6) but it is also achieved by using more sophisticated random processes techniques like time series or Polya's urns.

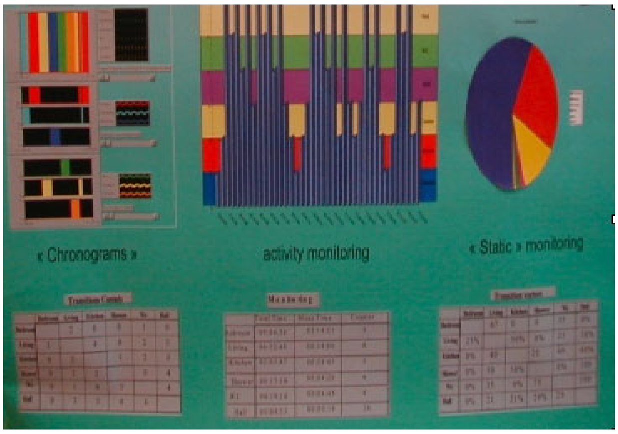

Fig. 6: Monitoring workstation at the Hospital at Home (HaH) service for the surveillance of dependent people at home, updated descriptive statistics.

The random processes made of the succession of the recorded localization data have been indeed already modelled by using classical time series techniques like Box-Jenkins auto-regressive processes to extract the entropy [17] or the coefficients of the linear auto-regression [29,36-39]. In this paper, the information to be treated is reduced at the minimum and the only thing retained is the succession of the activity-station -codes corresponding to the successive locations of the elderly people at home. An important feature to extract from the random process made of the succession of these activity-station-codes is the breaking times at which a specific model of Polya's urn is no more available, obliging to change the values of the parameters $n(k(i))$'s corresponding to the (algebraic, possibly negative) number of balls which must be added after obtaining a ball of color $k(i)$ at time i. It is supposed that if there is no pathologic change either sudden due to a fall or chronic due to the entrance in a neuro-degenerative disease, $n(k(i))$ is not depending explicitely on the time i, but only on the activity-station-code $k(i)$.

The first use of Polya's urns to represent persistence in a succession of qualitative data has been done since 25 years by climatologists for the sequence of dry and wet days [40,41], and a lot of fundamental [42-44], or more applied [45-47], papers have been after published for studying the theoretical properties of the corresponding random process, or for estimating its parameters or its thermodynamical variables (like the entropy of its stationary distribution).

The Polya's urn scheme is a Markov chain in which the balls are sequentially drawn from an urn initially containing a given number $a_0(j)$ of balls of the j-th color, j=l,...N, and after each draw the ball is returned into the urn together with $n(j)$ new balls of the same color j. It is assumed that we observe at time i the $a_j(k)$'s (corresponding to the number of balls of color k drawn from the Polya's urn at time i) and $b_i=\Sigma a_i(k)$ balls and that we estimate the parameters $n(1),...,n(N)$ supposed to be positive, by observing the frequencies in m trials of occurrence of balls of corresponding colors. For processing the estimation of $n(j)$'s, we consider the integer-valued random vector denoted

$a_i=(a_i(1),...a_i(N))$ and distributed, if $n(j)\geq 0$, in the set:

$$K_N=\{k=(k_1,\ldots,k_N):k_i / s=\sum k_i \geq b_0=\sum a_0(k)\}$$

according to:

$\forall i\in\{1,...,m\}$,

$$P(\{a_i=k\}a_{i-1})=\begin{cases}\dfrac{a_{i-1}(j)}{b_{i-1}}, & \text{if } k_j=a_{i-1}(j)+n_i(j) \text{ and} \forall r\neq j, k_r=a_{i-1}(r)\\ 0, & \text{if not,}\end{cases}$$

$$P(\{a_i=k\}a_{i-1})=\begin{cases}\dfrac{a_{i-1}(j)}{b_{i-1}}, & \text{if } k_j=a_{i-1}(j)+n_i(j) \text{ and} \forall r\neq j, k_r=a_{i-1}(r)\\ 0, & \text{if not,}\end{cases}$$

where $n_i(j)$ is the number of balls of color j added at time i. Let us denote $n_i=\Sigma n_i(k)$ and suppose that $n_i=Np>0$, where p is the mean persistence rate (supposed to be independent of the time). When the n_i's are equal, the probability above reduces to:

$$\forall i\in\{1,\ldots,m\}, P(\{a_i=k\}a_{i-1})=\frac{a_{i-2}(j)+p}{b_{i-2}+p},$$

where j is the index in $\{1,...,N\}$ for which we have: $k_j=a_{i-1}(j)+p$ and $\forall r\neq j, k_r=a_{i-1}(r)$.

Then we can calculate the probability $P(\{a_i=k\})$, when $k_j=a_0(j)+s_jp$, by using the formula:

$\forall i\in\{1,...,m\}$,

$$P(\{a_i=k\})=C_i^{k_1,\ldots,k_N}\frac{[\prod_{j=1}^{N}\prod_{s_j=0}^{\frac{k(j)-1}{p}}(a_0(j)+s_jp)]}{\prod_{s=0}^{i-1}(N+sp)},$$

where the k_i's verify: $k_i\geq 0$ and $\Sigma k_c=i$.

Let us now consider possible strategies of estimating the persistence p and the initial distribution a_0:

1) If we know the initial distribution of balls a_0, observing the empirical frequency $f(\{a_i=k\})$, we can estimate p by calculating the likelihood function and using the maximum likelihood estimator

2) If we do not know the initial distribution nor the persistence, we can:
- either estimate it by deciding that b_0 is fixed to a multiple of the number of activity-stations (*e.g.* twice this number) and by using a procedure similar to those proposed in [45], by supposing p known, and after deriving this initial estimation as function of p, finally trying to fix p at the integer value maximizing the likelihood function.
- or, if the attempt above is not successful, to assume the uniformity of the initial distribution (*i.e.* decide that the initial number of balls was the same for each color/activity-station).

In the case where: $\forall j\in\{1,...,N\}, a_0(j)=1$, the probability of having the balls vector equal to k at time i becomes:

$\forall i\in\{1,...,m\}$,

$$P(\{a_i=k\})=C_i^{k_1,\ldots,k_N}\frac{[\prod_{j=1}^{N}(\prod_{s=0}^{\frac{k(j)-1}{p}}(1+sp))]}{\prod_{s=0}^{i-1}(N+sp)},$$

where the k_i's verify: $k_i\geq 0$ and $\Sigma k_c=i$.

Then by replacing $P(\{a_i=k\})$ by $f(\{a_i=k\})$, we can estimate p. The empirical frequency $f(\{a_i=k\})$ is calculated from observations done at different days supposed to be independent (the initial distribution a_0 is supposed to remain the same at the beginning of each day and the days are supposed to be independent). If there are 2 persistence parameters to estimate, *e.g.* p for the living (activity-station number 1) and p' for the other activity-stations, we can use a sequential probability ratio test (SPRT) procedure [48] by considering that there are only 2 super activity- stations codes, 1 for the living and 2 for the other activity-stations and by trying to estimate the best sampling size threshold allowing a significant decision in testing the hypothesis $H_0 \equiv \{p=p'\}$ (*i.e.* the persistence is the same in the two super activity-stations) against $H_1 \equiv \{p \neq p'\}$ (*i.e.* the persistence is different in the two super activity-stations).

3) If we have no information about the initial distribution of balls a_0 (even concerning the initial total number of balls b_0), but if we suppose that there is the same persistence in each activity-station, we can follow during a sufficient time the activity of the dependent person at home and estimate the conditional probability:

$$P(\{a_{i+1}(j) - a_i(j) = 1\}\{a_i(j) = k\}) = \frac{a_0(j) + kp}{b_0 + ip}$$

By replacing the conditional probability above by the corresponding conditional empirical frequency (estimated from series of independent activity days for different activity-stations), we can get an estimation of p. We can also perform a test of $H_0 \equiv \{p=1\}$ against $H_1 \equiv \{p>1\}$, by comparing the empirical frequency of the event $\{d_{i+1}(j)=1\} \cap \{d_i(j)=1\}$ (*i.e.* the frequency to have consecutively the same color j, if $d_i(j)$ is the number (0 or 1) of balls of color j drawn from the Polyas's urn at time i) to its theoretical probability, which is binomial under H_0, with the probability to draw a ball j at time i equal to $a_0(j)/b_0$. When i increases, the estimation of $a_0(j)/b_0$ becomes rapidly very precise and allows the use of a classical test of comparison between an empirical and a theoretical frequency.

In the present case of persistence in activity-stations, we can assume that after a series of presence in an activity-station equal to or more than 2 recording intervals, if the activity-station changes, that involves a reset and we return to the distribution a_0.

Then, we can use the following sequential procedure for tests :

- initially as above $H_0 \equiv \{p=1\}$ against $H_1 \equiv \{p>1\}$,
- if H_0 is rejected, $H_1 \equiv \{p=2\}$ against $H_2 \equiv \{p>2\}$,
- if H_1 is rejected, $H_2 \equiv \{p=3\}$ against $H_3 \equiv \{p>3\}$, $\cdots$

until we reach, with the value of $p=k$ at the step k, a probability of activity-station changing (rejection of H_{k-1}) in k steps more than the threshold value 0.95.

4. Data and Results

The files treated bring together the data recorded in the flat of the elderly people in a period of 8 months from the 24th of March 2005 until the 25th of November 2005. The file follows the structure presented in Table 1.

Table 1: Samples of records of times and location.

Day	Month	Year	Hour	Minute	Second	activity-station-code
24	03	2005	17	37	36	1
24	03	2005	17	37	37	2
24	03	2005	17	37	38	2
24	03	2005	17	37	40	1
24	03	2005	17	37	48	1
24	03	2005	17	37	49	4
24	03	2005	17	37	50	4
24	03	2005	17	37	51	4
24	03	2005	17	37	55	4
24	03	2005	17	37	56	4

Each line suits as a sensor's detection. The columns represent successively the time (with the day of month, month, year, hour, minutes and seconds of the recording) and the activity-station-code corresponding to the location of the watched person at this time. For instance, the "13 10 2005 18 35 48 4" sequence means "the 13th October 2005 at 18:35'48, the elderly was detected in the kitchen".

From these records, we have tested different hypotheses about the persistence following the procedure given in the previous Section. We will give below a short example sketching our testing strategy. 200 records of time and location were used to perform the two following times:

i)

- we calculated the empirical frequency

$$\frac{a_0(1)}{b_0} = \frac{58}{200} = 0.29$$

- we use it for testing H_0 against H_1. The probability to observe 2 consecutive stays in the living (activity-station 1) is equal, under the hypothesis H_0 to $0.29\times0.29=0.084\pm006$. The variance of an empirical frequency observed on a records sample of size i being estimated by $f(1-f)/i$. Then the hypothesis H_0 is rejected with a significance level less than 1/1000: large deviations (with probability less than 1/1000) of the number of pairs of consecutive stays in living start at the record 29, and there are 31 such pairs in the records .

ii) by pursuing the sequence of tests, we found that p=3 is the best estimation of the parameter of persistence in the living, because it is the first integer giving probabilities 6/10, 6/13, 6/16, 6/19 and 6/22 of exiting from the living room after respectively 1, 2,$\cdots$, 6 stages in this activity-station. These probabilities have been estimated by the corresponding empirical frequencies of exit from the living room after 1, 2, $\cdots$, 6 stages. These empirical frequencies were respectively equal to 14/24±0.06, 4/9±0.06, ..., 1/3±0.07 in the experimental records of 200 sampling times.

5. Discussion

People use to settle in daily routines following a circadian rhythm. Barely awake, they go up, prepare the coffee, wash, take the coffee, go to the toilet and so on. Each person as its own procedure. When people become more aged or more dependent, their procedure is more and more important. Activity prediction for the monitoring of a person in a Health Smart Home system could be helpful in order to detect variations in their behavior which could be abnormal and need further medical assistance. Such variations are symptomatic of decline in dementia-related diseases and must be detected as soon as possible for the treatment effectiveness as it could lead to the entrance in institution.

In this study, we focus on the persistence parameter through a Polya's urns based approach. We have assumed in the previous calculations 5 important hypothesis we can now discuss:

1) the activity is homogeneous in time and space inside a day, *i.e.* we have the same persistence for each activity-station sojourn and a reset of the persistence memory at the end of a sojourn.

We have surely a persistence more important in activity-stations in which several tasks can be done involving a long time investment, compared to stereotyped and standardized tasks done in other activity-stations.

2) the activity records sequence is a Markovian process, for which the future depends on the past only through the present.

There are surely some breaks of the Markovian character, specially during activities asking for more attention (like cooking or reading), in which a time series approach would be more convenient than the Polya's urn modelling (the classical time series treatment involves the extraction of a tendency through a mobile time window, and then the calculation of a time linear regression order [17]).

3) the role of the activity-stations is symmetrical, *i.e.* each activity-station generates the same initial conditions in the initial distribution of balls (representing activity-stations) in the Polya's urn.

Because of many differences of surface, functionality, illumination, the activity-stations are not playing the same role and have different weights after resetting, depending on the time in a day (certain tasks being executed only once at a fixed hour of the morning or afternoon).

4) the persistence do not depend on time

In fact, there are nycthemeral variations of activity ([29,36,38]) as well as seasonal effects (for instance, activity is reduced during winter and increased during summer thanks to length of the daytime) we have to take into account to improve the precision of the statistical structure of the persistence. A remanence of the persistence surely exists, especially at the end of day where the level of awakeness and attentiveness is diminished.

5) successive days can participate to the same independent identically distributed (iid) sampling.

In fact, there is certainly a dependency linked to the position of the days in the week (Saturday being for example used for recapitulating the working days activity and for anticipating the leisure organization of Sunday).

This preliminary work requires further refinements but these first results have already provided relevant insights into the daily routine of the monitored elderly woman. It permits to represent habits of a person and its perseveration. It should be tested on a longer period of time and on a wider population including demented and non-demented elderly. It would also be interested to test and validate it in a less variable environment such as an hospital suite where activities are regulated by the medical staff and therefore are easier to follow.

6. Conclusion

The monitoring of dependent people at home allows the recording of their activity. The study of the activity-station changing sequences is very useful to detect deviances with respect to their normal behavior. Polya's urns derived models seems to be a good approach for representing the perseveration of a person in a task, but we should also consider other approaches like n-grams derived ones [30]. The detection of large deviations from the “normal” individual distribution of the random process retained for the ordinary walking of a dependent person inside his flat, permits to detect early dementia onsets but also to anticipate the fall, whose risk is high and renders it ineluctable a day, after 80 years. The fixed or embarked localizing sensors give sufficient indications to trigger an alarm at the level of the patient or at the level of the Hospital at Home service (for an emergency sending to nurses or doctors, depending on the gravity of the detected dysfunctioning). The body sensors are incorporated in ordinary clothes rendering the surveillance ergonomically acceptable. We are now developping techniques for studying (like for a drug), the “toxicity” of the monitoring system, toxic here meaning unaesthetic, intrusive, invasive and/or pathogenic, the level of toxicity depending on the “compliance” of the recorded subject. We will hence develop further psycho-physic studies for the determination of the liminal level of sensitivity/specificity and of the level of rejection, necessary for quantifying the degree of acceptability of the sensors network studied in this paper.

Knowing its habits, a new person centered domotics could rule the temperature, hydratation and luminosity sensors through a control based on (or slaved by) a physiologic information feedback coming from the flat inhabitant. This person centered domotics could take the major part of its information from sensors located on smart flats and clothes recently developped for the medical surveillance at home [49,50].

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