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Telemonitoring of the elderly at home: Real-time pervasive follow-up of daily routine, automatic detection of outliers and drifts

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1. Introduction

Playing tennis or ski jumping in one's living room is fashionable. Being equipped with a self-regulated heating or light exposure system is convenient. Finding one's way in the middle of nowhere is reassuring. Smart devices have already flooded one's home, car, mobile phone, etc. Health Smart Home systems are not just trendy neither comfortable, they are necessary. Indeed, the worldwide population increases and ages. Moreover, lack of medical staff and suited infrastructures will become a real issue shortly. Aging in place should not be a request difficult to fulfill anymore. To meet this need, many studies have been led, these two last decades, on the development of biomedical devices which aim at improving the elderly quality of life, avoiding their entrance in dependence and thus in institution as much as possible (Cook *et al.* 2009, Chan *et al.* 2009). Telemonitoring is among the innovative technologies explored for the maintaining of elderly people at home. It consists in the follow-up of the subject behaviour, activities and more generally health state by means of ubiquitous smart sensors either placed in the environment (infrared or radar detectors, pressure sensors, video cameras, etc.) or embedded (GPS, accelerometers, etc.) (Chan *et al.* 2008).

This chapter discusses the ability to obtain reliable pervasive information at home from a network of localizing sensors allowing to follow the different activity-station at which a dependent (elderly or handicapped) person can be detected (Fouquet *et al.* 2009 a, b). The main idea is to watch the person at home in order to classify its activities of daily living, detect early its abnormal states or behaviour like perseveration, diagnosis and prolong its autonomy. Alzheimer or dementia related diseases are the first cause of autonomy loss and hence of entrance in institution (World Alzheimer report 2009). Detecting their onsets earlier is crucial for treatment effectiveness and to put the entry in dependence back. Following up the subject's sequence of locations may allow detecting spatial and temporal disorientation or abnormal behaviour. Has the subject got a clear goal or does he/she wander within his/her flat? Does he/she manage to perform daily living activities well? Questionnaires and scoring already exist (*e.g.* Katz basic Activities of daily living (ADL) scale, Katz *et al.*

1963, and the Lawton-Brody Instrumental Activities of Daily Living (IADL) scale, Lawton and Brody 1969). However, by fear of consequences or by shame, elderly people tend to lie to their doctor and do not admit their difficulties. Isolated consultations are not enough to detect this kind of symptoms whereas the monitoring of the subject in his/her owns environment may be a more accurate and reliable autonomy measurement tool. Perseveration may be a good indicator of autonomy loss beginnings (Miyoshi 2009, Joray *et al.* 2004, Sebastian *et al.* 2001, 2006).

The second section is a brief review of the Health Smart Home concept and techniques associated with. It includes the description of our platform of experiments located in Grenoble, France.

The data collection is described in the third section.

Then, in the fourth section, two approaches of perseveration modelling are introduced and a procedure to quantify their respective relevance is proposed. In the first approach, the succession of locations is interpreted as a sequence of coloured balls withdrawn from a generalized Pólya's urn. Each location corresponds to a given colour. Persistence is represented by adding balls of the last colour withdrawn. This model seems particularly pertinent for watching. In the second model, the succession of location is seen as a walk in a first order Markov chain. In this case, a location depends only on its predecessor. Persistence is interpreted as the probability to remain in the same activity-station. This approach has the advantage of being easily implemented.

The fifth section is dedicated to a location prediction procedure using a *n*-grams approach. It allows to determinate the order of the Markov chain which suits the most to predict the next location. Deviations from the predictions may be used as an indicator for alarm triggering.

Tools for decision-making are proposed in the sixth section.

Finally, numerical application of the processes introduced in the two last sections are presented in the seventh section and discussed in the eighth one.

2. Home Telehealth

2.1 Health Smart home concept

"Health Smart Home" (HIS in French) is a concept introduced during the last two decades (Cook *et al.* 2009, Chan *et al.* 2009), referring to the entrance of technologies dedicated to health into the household. These technologies are not limited to the monitoring of the inhabitant, they watch over him/her and act accordingly. The recent development of micro- and nanotechnologies allows the devising of ever more miniaturized sensors blended in the background, the clothes, everyday items, etc. These sensors acquire, in an automatic and unsupervised way, information about both the inhabitant and its surroundings. Three kinds of data may be distinguished: physiological (weight, skin temperature, blood pressure, cardiac and respiratory frequencies, blood glucose level, etc.), actimetric (posture, movements, walking trajectories) and environmental ones (ambient temperature, relative humidity of the air, noise level, luminosity, etc.). Recorded data are gathered and transmitted to a master computer which processes them while taking into account knowledge about the user. The software used must be able to fuse, analyse data from the sensor network, compare them to the user profile, update this profile according to what it learns from the data and trigger alarms if need be. All these actions must be fulfilled in a very short time to ensure the user's safety. Although both computers and data-processing

techniques (data fusion, data-mining) are more and more efficient, we believe that a too large amount of data may be counterproductive. Consequently, the choice of the sensors (type, number, data format, etc.) and the sample frequency must be done strategically. Two kinds of approaches emerge. Some prefer multiplying sensors (video, audio, sophisticated, etc.) without being concerned about the cost, the energy consumption, the limited data storage (Chan *et al.* 2009). The others favour as far as possible the use of simple sensors dispatched in relevant places. Anonymous, binary sensors are cost-effective in terms of treatment as well as investment. More sophisticated sensors are used for more specific or accurate monitoring (physiological data, prevention of bedsore formation, etc.). However that may be, a preliminary classification work is made to quantify the relevance of the sensors chosen (Fleury *et al.* 2008, Rammal *et al.* 2008).

2.2 Smart sensors

Smart sensors field has moved with the development of Micro-Electro-Mechanical Systems (MEMS), telecommunication (internet, wireless network) and data-processing techniques (Sammarco *et al.* 2007, Huijsing 2008). Smart means that the sensor does not content itself making measurements, it also includes a pre-treatment of the data (quantifying the data quality, self-test, etc.). The miniaturization of the sensors allows their placement wherever in the subject surroundings: in article of clothing, devices, furniture, wall, doors, etc. They become nearly transparent for the user. This feature is very important to ensure the user's comfort but also to make him/her forget the telemonitoring system. Indeed, the elderly are very sensitive to a modification of their environment. Thinking continuously to the sensors may lead them to change voluntary or not their behaviour. It is well-known that by fear, some elderly are able to lie about their state of health to avoid a hospitalization or a supplementary cure. To understand the situation the user is in (context-awareness: Das and Roy 2008) without watching him/her directly, many kinds of sensor have been developed. Motion sensors like PIR detectors or RFID (Radio Frequency Identification) tags may be placed on the wall to follow-up the localization of the inhabitant. Sensors located on everyday items (*e.g. fridge, kettle, under the chairs, the bed...)* allow quantifying the interaction the user has with these objects. They may provide enough information to determine what task the user is performing. Embedded sensors (*e.g.* sewed within a cloth) may provide physiological (ECG, respiratory frequency, skin temperature) or actimetric data (posture, fall *via* 3D-axis accelerometer). In many cases, using only one kind of sensors is insufficient to ensure the safety of the subject that is why different kinds of sensor are usually combined. Concerning health, no rough estimate is bearable but minimizing uncertainty has a cost. Both technical and economical constraints (limited processing power, communication bandwidth, energy resources…) are added to the equation limiting the amount of sensors used. This optimization issue is the stake of classification which develops algorithms able to assess the relevance of the different sensors according to what is observed.

2.3 Data-processing tools

Data collected from the sensor network are gathered together and sent to a central where they are analysed. In case of missing/censored data, a reconstruction phase may be included to estimate them. Completed data are then fused. Data fusion consists in combining data extracted from different sources to obtain better information. For instance

knowing that the subject is in the kitchen is not sufficient to claim that he/she is cooking. On the other hand, knowing that the subject is in the kitchen, the fridge door opened and the gas cooker switched on may be a good indicator of his/her activity. These preliminary steps are important for the reliability of the pervasive information. To detect abnormal behaviour, a "normal" profile of the user needs to be established. However, due to inherent inter-individual variability, it is not possible to create a general model. Therefore, the system has to be able to learn (*i.e.* deriving knowledge about) the user's behaviour from the data in an automatic and unsupervised way. Activity recognition is another expected feature of the system. It was very investigated the last ten years (Hong *et al.* 2009, Das and Roy 2009). To ensure the user's safety or to detect mild cognition impairment onsets, it may be useful to know if the daily living activities are well performed (occurrence, duration, accomplishment, etc.). Moreover, being able to predict the following activity could represent a real advantage. Deviations from the expected behaviour may become a supplementary tool revealing either a non-pathological change in the habits and then the necessity to update the user's profile or a suspicious change and then the necessity to trigger alarm.

2.4 The HIS and AILISA experimental platforms

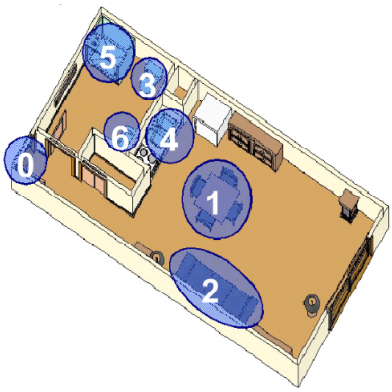

Fig. 1. Architecture of the experimental health smart home. Location sensors are placed at different places in the apartment, allowing the monitoring of individual's successive activity phases within his/her home environment: 0. Entry hall - 1. Living room - 2. Bedroom - 3. WC - 4. Kitchen - 5. Shower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

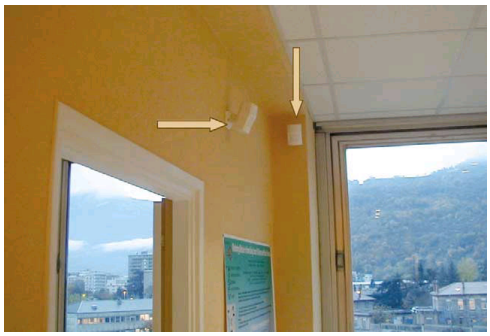

Fig. 2. Infrared (arrows) for localizing dependent people in a health smart home

The HIS platform has been developed for a decade (Rialle *et al.* 2002; Demongeot *et al.* 2002; Virone *et al.* 2002, Le 2008). It is an experimental flat of 30m² located in the Faculty of Medicine of Grenoble, used for technological and clinical evaluation. At first sight, this flat looks common but on closer examination it turns out this flat abounds with sensors capturing all the day long measurements about the inhabitant (localization *via* PIR sensors, mobility), and his/her surroundings (temperature, hygrometry). Data are collected and

transmitted *via* a controller area network (CAN) to a master PC placed in a dedicated room. Then, software analyzes automatically the data, compares them to the user's profile to detect abnormal trends and eventually trigger alarms. This system is passive *i.e.* it works automatically, without the inhabitant intervention. This feature is particularly important concerning the elderly who are not used to handle current technologies. Moreover, the use of anonymous sensors does not breach of the privacy of the followed person contrary to video cameras which must be used very carefully. Any private residence may be equipped with such a simple system. The HIS concept may be extended easily to other environments such as Hospital suites (LeBellego *et al.* 2006, Noury *et al.* 2008), office, public places, etc.

During the AILISA project (Noury 2005), the HIS platform was transposed in two real flats (Fig. 1) of the "Notre Dame" residence for the elderly in Grenoble (Fouquet *et al.* 2009 a, b). Passive IR sensors (DP8111X, ATRAL) were placed in each room (Fig.2) to follow-up automatically and continuously the localization of the inhabitant, an older woman, aged 80, within her own flat. Monitoring her localization in time provides a good approximation of her sequence of daily living activities. The aim of this experiment is to follow-up the sequence of daily routine of the inhabitant at home in order to detect a possible loss of autonomy or the emergence of a pathological behaviour such as perseveration. In particular, the present work focuses on the location modelling and prediction. Easy procedures are proposed to interpret surveillance at home data and to provide a perseveration index which may used to trigger alarms and counselling diagnosis search for cognition impairment (Miyoshi 2009, Joray *et al.* 2004, Sebastian *et al.* 2001, 2006). To reduce the complexity of the problem, a preliminary hypothesis is adopted. We only consider atomic *i.e.* elementary tasks. Therefore, we may identify a task and the room in which it is executed and talk about without distinction.

3. Experimental procedure

Recording time-stamped locations allows us to create a corpus for experiments. Timestamps are space separated numerals representing day of month, month, year, hour, minutes, seconds of the location captured (Table 1). The location itself is a code (Fig 1). The example cited in Table 1 means that the subject was in the kitchen the 3rd of August 2007 at 12:04'36''. Data were collected during 10 months from the 22nd of March 2005 until the 24th of January 2006 and 6 months from the 18th of July 2007 to the 15th of January 2008. The corpus has been cut into 80% for learning model, 20% for testing it.

Day	Month	Year	Hour	Minute	Second	Activity-Station Code	Corresponding corpus line
03	*08*	*2007*	*12*	*04*	*36*	*4*	*03 08 2007 12 04 36 4*

Table 1. A time-stamped location and its corresponding translation into the corpus.

To make these data easier to handle, they were reformatted as followed. A line of the "new" corpus is a sequence of length 86,402 which represents a day as a series of location captured at each second and separated by a space. For instance, "*s 2 2 2 ... 2 2 3 3 3 ... 3 3 4 4 4 ... e*" means: since "*s*" the start of day, the subject was in the bedroom (*2*) where he/she spent *x* seconds (*x* is the number of successive *2*), he/she passed in the toilet (*3*), then after y seconds (*y* is the number of successive *3*), he/she went to the kitchen (*4*), etc. The end of day is represented by "*e*".

4. Persistence modelling approaches

The easiest way to analyse location data and extract from them preliminary trends in daily routine consists in the establishment of presence curves (Fig 3.)(Virone, 2009). To go on further, more sophisticated random processes techniques may be used. Classical time series techniques, like Box-Jenkins auto-regressive processes, have already been tested for modelling location succession (Das and Roy 2008, Virone *et al.* 2002, 2003 a, b, c). Among the various possible approaches for modelling the actimetric data, two methods have been selected. The first one is based on a generalized Pólya's urns scheme (Fouquet *et al.* 2009 b) in which the observed activity at time t depends on the whole past (since a reset supposed to be made at the beginning of each day). The second one concerns a first order Markov chain approach in which the dependency of the future of $t+1$ lies only through the present time t. In both models, a persistence parameter is defined. To decide which method suits the most, a criteria based on the empirical mean E_i of remaining duration in a task i was proposed.

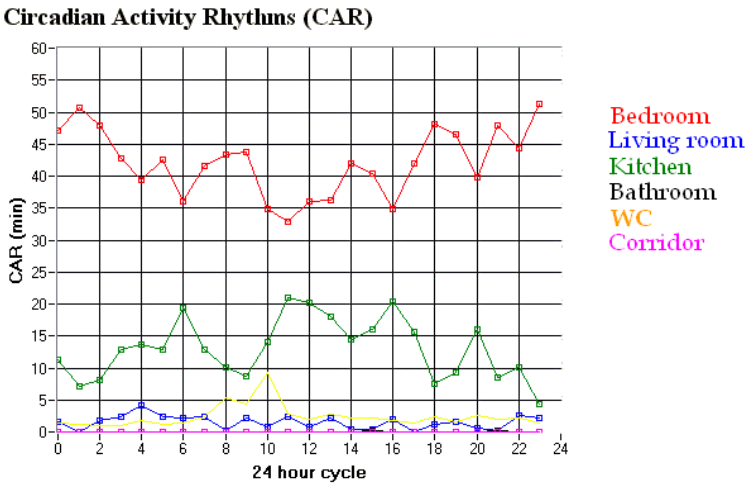

Fig. 3. Presence curves in different flat rooms

4.1 Pólya's urns model

Pólya's urns were used in 1923 by Eggenberger and Pólya to model the spread of contagious diseases. Since then, they were applied to various domains like climatology for the sequence of dry and wet days (Galloy *et al.* 1983). The success of the Pólya's urns scheme may be accounted by the fact that it is a visual mechanism easy to interpret in contrast with some abstract principles of probabilities (Kotz *et al.* 2000, Inoue and Aki 2001).

Regarding the scheme, a generalized Pólya's urn is an urn containing initially b_0 balls of N different colours split as follow: $a_0(i)$ balls of colour i, for i from 1 to N, with $b_0 = \sum_{i=1}^{N} a_0(i)$.

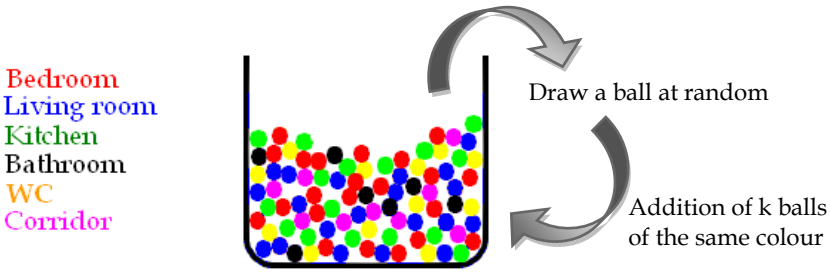

Fig 4. The generalized Pólya's urn scheme used for modelling location. Each colour represents a room of the flat. Persistence is taken into account by adding balls of the last colour drawn.

In our case, each colour corresponds to a location in the flat. At each step (*i.e.* each second here), a ball is withdrawn, its colour pointed out and the ball is put back in the urn along with additional balls of the same colour (Fig 4.). This last feature is precisely the way we chose to represent the persistence of an action/a location (Demongeot *et al.* 2008, Fouquet *et al.* 2009 a, b). In this approach, the persistence in task i parameter π_i(t) is the ratio between the number $k_i(t)$ of balls of colour i added after the withdrawing of a ball of colour i at time t and the initial total number of balls b_0 unknown *a priori*.

$$\pi_i(t) = \frac{k_i(t)}{b_0} \tag{1}$$

In case of no pathologic change (sudden due to a fall or chronic due to the entrance in a neuro-degenerative disease), $k_i(t)$ does not depend explicitly on the time t, but only on the activity/station-code i. On top of that, we suppose that k_i does not depend on i either by considering that each room has the same role. Then, we are able to estimate π_i from the empirical frequencies $f_i(t)$ to get a ball of colour i at the $(t+1)^{\text{th}}$ draw and the number $x_i(t)$ of times where the ball of colour i has been drawn from the urn at time t (estimated in a series of days supposed to be independent).

$$\bar{\pi}_i(t) = \frac{f_i(0) - f_i(M)}{M f_i(M) - x_i(M)} \tag{2}$$

where M is the total number of draws performed during a day *i.e.* 86,400 for a frequency sampling of one second.
Other assumptions on the $k_i(t)$ were further envisaged in (Fouquet *et al.* 2009 b).

To determine the domain of validity of this approach, we then estimate the expectation of the remaining duration in the task i denoted by E_i. The simplest estimator $\overline{E_{i,1}}$ is obtained by considering the empirical (*i.e.* on observed days) mean of the remaining duration in a day and given by:

$$\overline{E_{i,1}} = \frac{1}{M+1} \sum_{t=0}^{M} z_i(t) \tag{3}$$

where $z_i(t)$ is the length of the sequence of "drawing a ball of colour i" (possibly 0) since a draw at time t of a ball of colour i.
A more accurate estimator $\overline{E_{\iota,2}}$ may be calculated by approximating the probability $c_{i,m}(t)$ to have m consecutive draw(s) of a ball i from the tth draw. It is given by:

$$\overline{E_{\iota,2}} = \frac{\sum_{t=0}^{M}\sum_{m=0}^{M} m[(1-f_i(t+m+1))\prod_{j=0}^{m} f_i(t+j)]}{M+1} \tag{4}$$

Then the 95%-confidence interval of $\overline{E_{\iota,2}}$ may be calculated based on the f_i's one which is:

$$\left[f_i \pm 1.96\sqrt{\frac{f_i(1-f_i)}{M}}\right] \tag{5}$$

The null hypothesis H_0: "the persistence model is a Pólya's urn model" is rejected, if $\overline{E_{\iota,2}}$ does not belong to its interval. Otherwise, this model could be used to represent the persistence in task.

4.2 First order Markov chain model

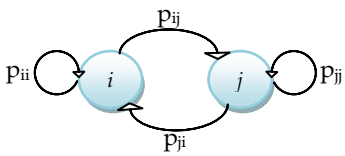

Fig. 5. The Markov chain obtained for two rooms i, j

In a first order Markov chain approach, the location at time t depends only on its predecessor (Fouquet *et al.* 2009 a). Each location is represented by a node (N nodes altogether) fitted with the probabilities of transitions from it to another one as illustrated in Fig 5. The succession of locations is seen as a walk in the Markov chain. Let us denote by p_{ij} the probability, supposed to be constant (*i.e.* each room has the same role), to draw a ball of colour j after a ball of colour i. Then, p_{ii} may be seen as the persistence in task i parameter and easily estimated by the corresponding empirical frequency f_{ii}. The probability p_j to draw a ball of colour j is obtained by adding the probabilities of transitions encountered on each arrow which points to the node j *i.e.*by considering all the ways leading to j:

$$p_j = \sum_{i=1}^{N} p_{ij} \tag{6}$$

In this approach, the variable z_i above-mentioned is easy to interpret:

$$P(z_i = 0) = 1 - p_i \tag{7}$$

$$P(z_i = l) = p_i(1-p_i){p_{ii}}^{l-1} \quad \text{for } l \in [\![1, N]\!] \tag{8}$$

Thus, E_i may be estimated by:

$$\overline{E_{\iota,3}} = \sum_{l=0}^{M} \frac{l+1}{2} f_i(1-f_i) {f_{ii}}^{l-1} \tag{9}$$

The 95%-confidence interval of $\overline{E_{\iota,3}}$ may be calculated based on the f_i's and f_{ii}'s ones which are respectively:

$$\left[f_i \pm 1.96\sqrt{\frac{f_i(1-f_i)}{M}}\right]; \quad \left[f_{ii} \pm 1.96\sqrt{\frac{f_{ii}(1-f_{ii})}{M}}\right] \tag{10}$$

The null-hypothesis H_0: "the persistence model is a first order Markov chain model" is rejected, if $\overline{E_{\iota,3}}$ does not belong to its interval. Otherwise, this model could be used to represent the persistence in task.

At the end of the hypothesis testing, in case of acceptation for both models, the Markovian model will be chosen because of its simplicity and its handiness. If both tests conclude to the rejection of the null-hypothesis, the model having the closest distance between $\overline{E_{\iota,1}}$ and the confidence interval of $\overline{E_{\iota,j}}$ (j=2, 3) will be retained.

We will focus now on the description of the first order Markov chain model and its generalization by the n-grams approach proposed. The latter aims at providing the best order of the Markov chain *i.e.* the rank of the last data on the historic of locations needed to determine the present location.

	Pólya's urns model	**First order Markov chain model**
Estimator of the persistence in the ith task parameter	$\bar{\pi}_i(t) = \frac{f_i(0) - f_i(M)}{M f_i(M) - x_i(M)}$	f_{ii}
Estimator of the ith task remaining duration	$\overline{E_{\iota,1}} = \frac{1}{M+1}\sum_{t=0}^{M} z_i(t)$ $\overline{E_{\iota,2}} = \frac{\sum_{t=0}^{M}\sum_{m=0}^{M} m[(1-f_i(t+m+1))\prod_{j=0}^{m} f_i(t+j)]}{M+1}$	$\overline{E_{\iota,3}} = \sum_{l=0}^{M} \frac{l+1}{2} f_i(1-f_i){f_{ii}}^{l-1}$

Table 2. A time-stamped location and its corresponding translation into the corpus.

5. Statistical location prediction: *n*-grams model

5.1 Fundamental basement

Predicting one's activities during the day seems *a priori* a very difficult task. One may perform the same activities every day but not necessary in the same order. One's daily

routine may also be disturbed by tiredness, visits, etc. Actually, as well as the human being's processes and physiological variables (blood sugar level, hormone level, temperature, cardiac rhythm, muscular strength, etc.) are regulated by biological internal rhythms and are well-organized in time, activities of daily living also follow periodical variations adapted, in this case, to both ones biological and social rhythms (Reinberg 1998, Virone *et al.* 2002, Demongeot *et al.* 2002). The elderly are less sensitive to the clocks of society and their way of living is slower. Hence, the observation of their daily routine is easier and is less subjected to the unexpected. Indeed, with aging, the everyday procedure becomes more and more stable allowing the establishment of an activity prediction procedure. Important and unexpected deviations from the behaviour expected may be a good indicator for triggering alarms. The development of such a procedure is difficult because of individual variability. Each person has his/her own habits and even for the same person, depending the day of the week, the season, etc. or also fatigue state, the sequence of activities may be different. In the speech recognition domain, this problem is encountered for word prediction. Statistical approaches based on *n*-grams theory are often used to overcome these kinds of difficulty (Shannon 1948, Rosenfeld 1996, Fouquet 2004). The following experiment aims at applying the *n*-grams theory to location modelling problem. The model used is a generalisation of the first order Markov chain model.

5.2 *N*-grams model

For the location prediction, a statistical method has been implemented to predict the next location on the basis of the location history (Reithinger & Maier 1995). Currently, *n*-grams location probabilities are used to compute the most likely follow-up location. To predict the ith location a_i, the *n-1* previously uttered locations are used and the most probable location is determined by computing:

$$a_i = \arg\max_{a} P(a|a_{i-1}, a_{i-2}, \dots, a_{i-n+1}) \tag{11}$$

To estimate this probability the standard estimations using relative frequency techniques are used. Otherwise, our corpus is a real-collection and, like in many real-situations, it was not possible to collect a large amount of data to properly estimate the statistics. This implies that it is not reasonable to use classical smoothing techniques. We need a solution for the two following problems:

1) unexpected input: the location model based on *n*-grams location sequences cannot be used in case unexpected input occurs,

2) lack of training data: the *n*-grams model predicts several locations with the same probability.

The treatment of these cases consists in using the *(n-1)*-grams model, recursively.

6. Decision-making tool

If and as soon as deviations from the expected behavior occurred, a smart home system must 'decide' to alert caregivers. The decision-making process is based on the information extracted from a Bayesian network. The advantage of using such a representation is that it allows us to combine both *a priori* knowledge (e.g. from the doctor) and collected data. Besides, it was recently used to mimic the brain decision-making process (Knill *et al.* 2004,

Koerding *et al.* 2004) in which both *a priori* distribution (knowledge about the environment) and observed random variables (metrological sensors) are taken into account. Another application of such a data fusion may be encounter in postural control correction in which the action consists in preventing the subject in case of bad position of the body. It is generally agreed that maintaining an upright stance or seated posture involves the integration (fusion) of sensory information from multiple natural sensors including visual (variable X_1), somatosensory (variable X_2) and vestibular (variable X_3) systems. The main idea is to provide supplementary sensory information to complete/improve the existing one. Along this line, innovative health technologies have been recently developed for pressure sores or fall prevention in older and/or disabled adults by the means of artificial sensors placed beneath the buttock or the feet, *via* an alternative sensory modality (electrotactile stimulation of the tongue, variable X_4) (Vuillerme *et al.* 2007 a, b). At this point, an effective fusion of natural (variables X_1, X_2 and X_3) and artificial - more reliable and accurate than the natural one's - sensory information (variable X_4) is crucial to enable individuals with spinal cord injuries, or with somatosensory loss in the feet from diabetic peripheral neuropathy to become aware of a localized excess of pressure at the skin/seat interface and/or postural orientation and thus to make adaptive postural corrections.

In this kind of multisensory contexts, by denoting X_i (for i from 1 to n) the n observed random variables, the conditional probability to execute a task A knowing the values of X_i's is given by:

$$P(A|\cap_{i=1}^{n}\{X_i = k_i\}) = P(A \cap \cap_{i=1}^{n}\{X_i = k_i\})/P(\cap_{i=1}^{n}\{X_i = k_i\}) \tag{12}$$

The calculation of such a probability requires the ability to estimate joint probabilities of the n observations. The Lancaster-Zentgraf estimator defined in the seventies was proposed to estimate of the joint probability of order n knowing the marginal and joint probabilities of order 2 as follow:

$$P_{Lan}\left(\bigcap_{i=1}^{n} A_i\right) = \sum_{\substack{i,j,k_1,\dots,k_{n-2}\in\{1,n\},\\ i\neq j\neq k_1\neq\dots\neq k_{n-2}}} \left(P(A_i \cap A_j)P(A_{k_1})\dots P(A_{k_{n-2}})\right) - \binom{n}{2}\prod_{i=1}^{n} P(A_i)$$

where $A_i = \{X_i = k_i\}$. (13)

For n=3, the equation becomes:

$$\begin{aligned} P_{Lan}(A \cap B \cap C) = {} & P(A \cap B)P(C) + P(A \cap C)P(B) \\ & + P(B \cap C)P(A) - 2P(A)P(B)P(C) \end{aligned} \tag{14}$$

However, it happens that this approach provides negative estimates (*e.g.* A, B, C disjoint). To alleviate this issue, we introduce a new joint probabilities estimation P_{New} based on the local equipartition of the amount of uncertainty (in a local maximal entropy approach) (Demongeot *et al.* 2008). The proposed formula is established to deal with dependencies characterized by strong incompatibilities, circumstances not well taken into account by the Lancaster-Zentgraf formula:

$$P_{New}\left(\bigcap_{i=1}^{n} A_i\right) = \frac{1}{n}\sum_{j=1}^{n} P_{New}\left(\bigcap_{i\neq j} A_i\right)P(A_j) \qquad \text{for } n>2 \tag{15}$$

For the intersection of any 3 events from a set of n events, this equation becomes:

$$P_{New}(A \cap B \cap C) = \frac{1}{3}\big(P(A \cap B)P(C) + P(A \cap C)P(B) + P(B \cap C)P(A)\big) \tag{16}$$

In practice, the calculation of P_{New} is done recursively from the calculation of P_{New} on the triplets of events involved in $\bigcap_{i=1}^{n} A_i$, that involves as for the Lancaster-Zentgraf estimator the knowledge of the marginal and order 2 intersection probabilities. Finally, we have:

$$P_{New}\left(\bigcap_{i=1}^{n} A_i\right) = \frac{1}{\binom{n}{2}} \sum_{i<j} P(A_i \cap A_j) \prod_{k \neq i,j} P(A_k) \tag{17}$$

7. Results

7.1 Pólya *vs.* Markov

The corpus of experiment was used to calculate the empirical means $\overline{E_{i,j}}$ (j=1,2,3) of remaining duration in task i. To achieve this calculation, Tables 3 and 4 show the empirical frequencies f_i and f_{ij} respectively, calculated from the 20% learning part of the corpus. As above-mentioned, M is the number of locations recorded during a day at a sampling frequency of 1 second (*i.e.* $M = 60 \times 60 \times 24 = 86400$).

The calculation of $\overline{E_{i,1}}$ consists in counting for each day the time remaining in task i divided by the number of times observed (which is equal to $M+1$ if the observation starts from 0 to M). It expresses persistence in task i, but it is not equal to the mean of past time in i (it should be half the preceding one). One can now distinguish two particular cases:

- If i was never observed: $\overline{E_{i,1}} = 0$
- If i was always observed: $\overline{E_{i,1}} = \frac{\frac{(M+1)(M+2)}{2}}{M+1} = \frac{M+1}{2} = 43{,}200.50$

For the other cases, further works have to be done now to calculate $\overline{E_{i,1}}$.

In the other hand, E_i can be easily estimated by the Markovian estimator $\overline{E_{i,3}}$ which values are shown in Table 5 for each location i.

i	0	1	2	3	4	5	6	9	e
f_i (%)	10.27	21.2	53.18	1.29	6.13	1.67	5.13	1.12	0.01

Table 3. Empirical frequencies f_i to draw a ball of colour i (%). Note that the *9* is an error.

j \ i	0	1	2	3	4	5	6	9	e
0	**99.64**	0.12	0.04	0.01	0.03	0.10	0.06	0.00	0.00
1	0.07	**97.48**	0.19	0.01	2.20	0.03	0.02	0.00	0.00
2	0.01	0.08	**99.89**	0.00	0.00	0.01	0.00	0.00	0.00
3	0.17	0.14	0.08	**81.29**	0.06	3.00	15.26	0.00	0.00
4	0.05	7.62	0.03	0.01	**92.24**	0.03	0.01	0.01	0.00
5	0.56	0.54	0.054	1.84	0.13	**86.50**	9.10	0.79	0.00
6	0.07	0.02	0.02	4.02	0.01	2.81	**90.63**	2.42	0.00
9	0.06	0.04	0.01	0.00	0.07	1.51	10.74	**87.57**	0.00
s	0.19	0.58	9.24	0.19	0.13	0.06	0.45	0.26	**88.89**

Table 4. Empirical frequencies f_{ij} to draw a ball of colour j after a ball of colour i (%).

The confidence intervals are shown in Table 6 for f_i and f_{ij}, respectively. They are necessary to derive the confidence interval of each estimator $\overline{E_{i,j}}$ (j=1, 2, 3) and to quantify their relevance.

i	0	1	2	3	4	5	6	9	e
$\overline{E_{i,3}}$	3,596.89	133.15	102,829.88	0.20	4.97	0.48	2.91	0.38	0.01

Table 5. Estimator $\overline{E_{i,3}}$ of the ith task remaining duration using the first order Markov Model.

	i	0	1	2	3	4	5	6	9	e
f_i	a	0.101	0.209	0.528	0.012	0.060	0.016	0.050	0.010	$0.3e^{-4}$
	b	0.105	0.215	0.535	0.014	0.063	0.018	0.053	0.012	$1.6e^{-4}$
f_{ii}	a	0.996	0.974	0.9987	0.812	0.921	0.864	0.905	0.875	0.888
	b	0.997	0.975	0.9990	0.814	0.923	0.866	0.907	0.877	0.890

Table 6. Confidence interval [a,b] for f_i and f_{ii} respectively.

7.2 Location prediction

	Global corpus (2,011,554)		Sunday (300,105)		Monday (267,983)	
n	Number of correct predictions	Good prediction rate	Number of correct predictions	Good prediction rate	Number of correct predictions	Good prediction rate
1	983,209	48.88 %	154,846	51.60%	126,858	47.34%
2	**1,958,535**	**97.36 %**	291,248	97.05%	261,253	97.49%
3	1,958,535	97.36 %	291,250	97.05%	**261,254**	**97.49%**
4	1,958,524	97.36 %	291,244	97.05%	261,252	97.49%
5	1,958,481	97.36 %	**291,258**	**97.05%**	261,222	97.48%
6	1,958,380	97.36 %	291,190	97.03%	261,212	97.47%
7	1,958,297	97.35 %	291,192	97.03%	261,181	97.46%
8	1,958,221	97.35 %	291,143	97.01%	261,148	97.45%
9	1,958,062	97.34 %	291,121	97.01%	261,113	97.44%
10	1,957,773	97.33 %	291,043	96.98%	261,057	97.42%

	Tuesday (289,876)		Wednesday (427,006)		Thursday (232,471)	
n	Number of correct predictions	Good prediction rate	Number of correct predictions	Good prediction rate	Number of correct predictions	Good prediction rate
1	123,530	42.61%	197,499	46.25%	136,005	58.50%
2	**284,163**	**98.03%**	416,983	97.65%	**226,140**	**97.28%**
3	284,162	98.03%	**416,984**	**97.65%**	226,129	97.27%
4	284,156	98.03%	416,980	97.65%	226,106	97.26%
5	284,129	98.02%	416,953	97.65%	226,099	97.26%
6	284,105	98.01%	416,909	97.64%	226,085	97.25%
7	284,089	98.00%	416,889	97.63%	226,070	97.25%
8	284,057	97.99%	416,841	97.62%	226,047	97.24%

9	284,002	97.97%	416,759	97.60%	226,024	97.23%
10	283,950	97.96%	416,687	97.58%	225,961	97.20%

Table 7a. Prediction results for the global corpus in one hand, for each day of the week in the other hand (the number to predict is in parenthesis).

	Friday (260,158)		Saturday (199,767)	
n	Number of correct predictions	Good prediction rate	Number of correct predictions	Good prediction rate
1	137,179	52.73%	91,473	45.79%
2	**252,605**	**97.10%**	**194,207**	**97.22%**
3	252,597	97.09%	194,207	97.22%
4	252,596	97.09%	194,200	97.21%
5	252,594	97.09%	194,194	97.21%
6	252,550	97.08%	194,192	97.21%
7	252,519	97.06%	194,174	97.20%
8	252,445	97.04%	194,126	97.18%
9	252,386	97.01%	194,121	97.17%
10	252,325	96.99%	194,085	97.16%

Table 7b. Prediction results for the global corpus in one hand, for each day of the week in the other hand. The number above each day represents the number to predict.

A first test (Table 7a.) was made on the whole corpus without time distinction (day of week, day of month, month, hour of journey, etc.). It turns out that the best prediction is reached with n=2. Indeed, nearly the same performance is obtained with n>2 (with two digits after the decimal point). Accurate performance decreases while n increases. Hence, n does not need to be bigger than 2, suggesting that the last second location is sufficient to predict the next one. Finally, this first result seems to indicate that watching too far in the past is not a good way to predict the future location of a person. It is in favour of a first order Markov approach.

Even if results from the global corpus are promising, better accuracy may be obtained by distinguishing day of the week (Table 7a, b.). Indeed, activity of an elderly person during the weekend is likely to differ from the rest of the week (time spent with family, Church service, etc.). Concerning household chores, the flat is not cleaned up from top to bottom every day.

On Sunday, the best prediction rate corresponds with n=5 which means that the last four locations are needed to predict the next one). On Monday and Wednesday, it is necessary to date back to the last three ones two ones. Finally on Tuesday, Thursday and Friday, only the previous location is needed to have a good prediction rate.

In both cases, n=2 provides the best prediction rate with two digits after the decimal point. Results of good prediction vary from 97.05% on Sunday up to 98.03% on Tuesday.

8. Discussion and Conclusion

The monitoring of elderly people in their home by location sensors provides the recording of their walk trajectories within their own flat giving some insights into their daily routine. These space/time data are then used to establish an individual specific profile concerning the time serie which corresponds to the successive locations of the person. The detection of large deviations from the profile may be used to trigger alarms at the level of the family (to make the family member more careful) or at the level of the Hospital at Home service (for an emergency). The present article proposes two different mathematical approaches for location modelling. The first calculations point out the simplicity of the Markovian model. This feature makes it more cost-effective in terms of calculation and response time and thus more interesting for implementation. Further works are necessary to explore the Pólya's urns model deeper. If the choice is available, however, priority will be given to the other. The Pólya's urns model will only be used if the Markovian one is no longer available.
For the validation of each model, a procedure based on the calculation of the mean of remaining duration in task is proposed. At this point, it is important to mention that this parameter differs from the mean of the time passed the task considered (it should be by a factor of 0.5). For deciding between the two methods proposed, further works should be performed using the statistics equal to the empirical mean E of a task remaining duration and their confidence interval.

The *n*-grams model used to predict the next location is also in favour of a first order Markov chain approach. Other models need to be improved more deeply. Indeed, first results offer promising results with n=2 and a degradation of performances with n increasing up to 10. For the confirmation of this trend, experiment should be applied for $n=60$, watching for the whole last minute in order to predict the 60th second. For the time being, the best model offers up to 98.03% of good prediction location, considering only the last second of location *i.e.* using the first order Markov chain model, but distinguishing days of week. Indeed, taking day of the week into account offers better performance (97.36% by working directly on the whole corpus). Performance seems to differ for each day of week. This factor of variability should be taken into account when designing a system using a location model. To go further, future experiments may be done for other refinements among which providing the possibility of distinguishing the time in the day to take into account the circadian rhythm (Virone *et al.* 2002, Cerny *et al.* 2009). Each day of the month could affect activity: some days, as 1st of the month for example, are particular. The comparison between each month may show seasonal effects, and so on (Fouquet *et al.* 2009 b). It could then be interesting to develop a new model with a continuum approach considering estimations (interpolation) between data observed.

Our procedure may be extended later to more complex task (named composite task in Das *et al.* 2008) recognition by means of a multi-sensors network. The multidimensional data collection obtained with such a system will be fused and mined using the data processing techniques above introduced.
Concerning the detection of progressive stereotyped behaviour for the early diagnosis of neuro-degenerative diseases, actimetric data may be completed by physiological ones to quantify the state of anxiety of the subject particularly at nightfall or a possible shift in his/her activity circadian rhythm which are behaviour commonly observed in the first stages of these pathologies (Monk 2005, Hofman and Swaab 2006).

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