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Use of Electrical Devices Reveals Our Well Being

N. Noury, *Senior Member, IEEE,* K-A Quach, M. Berenguer, H. Teyssier, M-J Bouzid, L. Goldstein, M. Giordani

Abstract— **We want to objectivize the level of activity of elderly persons living independently at home. Most existing monitoring systems are intrusive and/or require a large number of sensors. We hope the "ubiquitous computing" concept could find an application in this context. We proposed to monitor the use of electrical appliances. We built a unique "activity indicator" which integrates all the activities of the person. This was assessed during 6 months within 12 flats occupied by single elderly persons.**

Ubiquitous computing, Ambient Assisted Living, Activity monitoring, Multi perceptive systems, data Fusion

I. Introduction

Ubiquitous computing can find an unexpected application in helping elderly people to live independently at home.

Age-related diseases (cognitive impairments, Dementia, Alzheimer's disease) have frequently a direct impact on the performance of the daily activities [1]. It is expected that activity monitoring systems will produce interesting feedback to care providers and to the subject. Many experimental platforms were developed to follow up these activities. Most of them are very intrusive (invasive vision systems, large numbers of sensors or arrays of motion sensors [2-4]). Ubiquitous computing primarily aims at the development of inexpensive and easy to deploy sensing systems for context awareness applications in living environments.

We proposed to use a minimally invasive sensor which detects electrical activities via the residential power line [5,6]. It records the electrical impulses on the electrical power line caused by the on/off switching of identified electrical loads. It thus detects the spatio-temporal context of the subject (taking meals in the kitchen, sleeping in bedroom, etc.). Each electrical appliance becomes a sensor. Thus, the solution is both acceptable and cost effective.

The viability of the system relies on its acceptability to the professional team, in charge of the remote monitoring, who needs an efficient way of monitoring the person and of detecting abnormal situations. We therefore developed a unique index of activity based on the fusion of information from multiple sources. In this paper, we describe the materials and methods used and we report on the results of a field test performed with 12 senior citizens over a 6 months period.

N.Noury is with the University of Lyon, lab INL-INSA, Lyon, France (phone: +33472438986; e-mail: Norbert.Noury@insa-lyon.fr).
KA Quach, M Berenguer, H Teyssier, MJ Bouzid and M Giordani are with Orange Labs, 28 Chemin du vieux Chêne, 38243, Meylan, France
L. Goldstein is with Mondial Assistance, Paris, France.

II. Material and Methods

The MAPA [6,7] consists of a distributed information infrastructure, a in-home local system and algorithms to derive the index of activity.

A. The information Infrastructure

The MAPA information system is built on a data warehouse, a global communication network (ADSL, GPRS/3G, PSTN) and a in-home local sensor (Fig. 1). The information system is built on an Apache server hosting a MySQL data base with SQL requests developed under the PHP language.

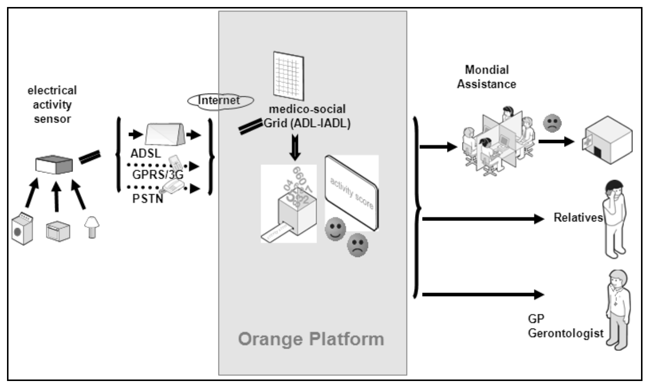

Figure 1. Synoptic of the information system MAPA

The communication uses the Internet with a private access line. The data server is located on the premises of Orange Labs in Grenoble. The home access point is a net box connected to the ADSL public line.
The data of interest is collected in each flat using a local sensor which tracks the electrical activities on the power line.

B. The detection of electrical activities on the power line

The sensor (WPC[1]) monitors the power consumption of each individual electrical appliance and the short impulses generated when a device is turned on or off. This unique short impulse is a "signature" for each device [7]. After a learning period, the WPC system produces instantaneous data on each electrical appliance (electrical consumption, active and reactive power, supply current).

[1] WPC15.4 is a trademark of the WATTECO company : http://www.watteco.fr

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A. Activities of Daily Living

The activities of daily living [1], concern "*all the things we normally do in daily living including any daily activity we should perform in full autonomy for our own self-care*" (such as feeding ourselves, bathing, dressing, and grooming).

With our unique sensor, we studied 5 kinds of activities (feeding, hygiene, elimination, diurnal and nocturnal level of activity) within 4 time periods (night, morning, day, evening). This led to a combination of 10 activities (Fig.2).

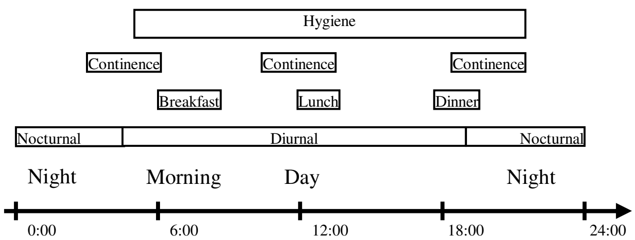

Figure 2. The set of activities selected in this study is a subset of the possible ADLs within the time periods.

B. Electrical activities versus daily activities

The daily activities are strongly associated with rooms and with the electrical activities detected (Table 1):

Table 1. Relationships between rooms, electrical appliances and ADLs

Room Location	Electrical Appliance	ADL
Kitchen	Light, fridge, furnace, boiler, dish-washer…	Feeding (or cooking)
Toilet (WC)	Light, heating	Continence
Bathroom	Light, hair-dryer, heating	Grooming
Other rooms	Light, heating	Other

As can be seen in Fig.3, the relationship between each ADL and individual electrical activities is not simple.

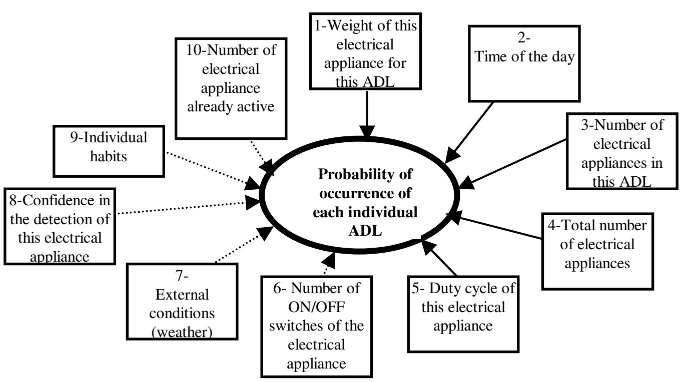

Figure 3. The factors influencing the decision on the weighting of an electrical appliance in the performance of an ADL

We therefore decided to associate a weighting factor, p_{ij} Є [0..3], for each electrical device (1),

$$
\begin{aligned}
p_{ij} &= 3 \text{ for a device « always used »} \\
&= 2 \text{ for a device « commonly used »} \\
&= 1 \text{ for a device « rarely used »} \\
&= 0 \text{ for a device « never used »}
\end{aligned} \qquad (1)
$$

p_{ij} is the weight of the electrical device n° i in the realisation of the daily activity n° *j*.

Thus, when we consider all possible ADLs and all the electrical devices, we obtain the matrix P=[p_{ij}] which depends on the habits of this person in his context (Table 2),

The weighing process can take into account the function of each electrical appliance. For a electrical device very representative of an activity, it will carry a heavy weigh in the activity. The coffee machine, frequently used in the morning will receive the weight '3' for « Breakfast », whereas the kitchen light will only receive '1' for its lower relationship to feeding activity.

Table 2. Matrix P=[p_{ij}] of weightings of electrical activities in ADLs

Device	ADL				
	Breakfast	Lunch	Dinner	Hygiene	WC
Kitchen light	Pij=1	1	2	0	0
Coffee machine	3	1	1	0	0
Bathroom light	0	0	0	3	0
WC light	0	0	0	0	3

Eventually, at a given time t_i, the classifier will elect the activity ADL_j which maximises the quantity

$$ADL_j(t_i) = Max\left\{\sum_{i=1}^{N} p_{ij}.r_i\right\} \qquad (2)$$

With r_i = 1 if the electrical activity occurred- or else 0.

C. Index of achievement of a day

To be representative of the global activity, our index must take into account each single activity detected but also the incompleteness of data on electrical activities. We therefore created a vector of features which integrates the average activity of the person. This referential is further compared to the data gathered during one day, in order to produce a current value which is in turn compared to the referential vector of features.

For each activity *j*, an index of achievement *Ij* is individually computed

$$I_j = Cr_j.a_j.D_j \qquad (3)$$

With a_j = weight of activity j and Cr_j = belief in the model of activity j.

The weight a_j of the individual activity *j* is given the value 0.1 as each 10 activities are of equal importance. The additional "belief" parameter Cr_j is given the value 1 if the model was built on 15 consecutive days of full data. If a number (n) of days of data were missing (i.e. no electrical events due to the absence of the person), the belief Cr_j is reduced in proportion

$$Cr_j = \frac{15-n}{15} \qquad (4)$$

Eventually, the 10 individual I_j are summed up to give a global index of achievement I_{day} which will equal to 0 if the current day is close to the model. As it is easier to work with a global index which is maximal in this case, we used the complement to the maximum value (1 or 100%),

$$I_{day} = 1 - \sum_j Cr_j . a_j . D_j$$

$$\text{with} \quad a_j = \frac{1}{\text{number of activities}} = \frac{1}{10} \qquad (5)$$

$$\text{and} \quad Cr_j = \text{belief}$$

When current day had no electrical activities, we set I_{day}=0.

D. *Chronograms of ADLs*

From equation (2) we can derive the chronogram signal $ADL_j(t)$ for each activity j. The visualization of the chronograms of the electrical ADLs shows a specific time repartition for each single activity. As an example, the electrical events related to the $ADL_{Feeding}$ mostly happen during daytime and are localised in 3 main periods of the day.

During a preliminary experiment (13 persons monitored during 9 months [6]), we observed two kinds of distribution of the electrical activity, one limited to daytime and one spread over the complete 24 hours period (Fig.4).

Events are considered to belong to the same activity if they are closer to each other than a given proportion of the mean temporal distance between all the electrical events.

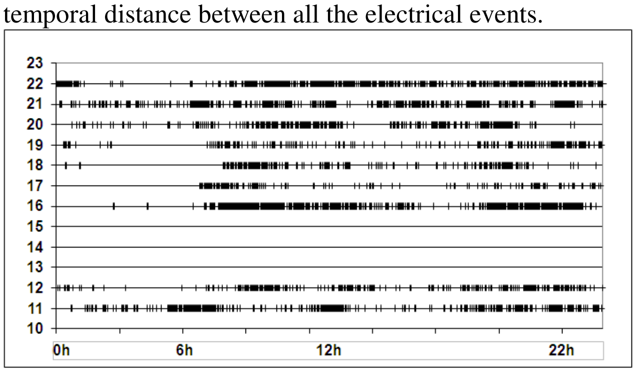

Figure 4.The global dispersion of electrical events, over the 24 hours period, for13 persons during a 9 months preliminary experiment. We can clearly distinguish 2 kinds of distribution, one is limited to the day time (ID16,17,18,19) the second is continuously spread over the time (ID11,12, 20, 21, 22).

We consider the vector [t_0…., t_i, t_{i+1},….], made up of all the electrical events in a same activity, we can compute the mean distance M_e between the events of a same activity and σ_e the standard deviation

$$M_e = \frac{1}{n} . \sum_{i=0}^{n} |t_{i+1} - t_i| \qquad (6)$$

We then decide that the events belong to the same activity if,

$$|t_i - t_{i-1}| < a^* \, \sigma_e \qquad (7)$$

If the activity is continuous the parameter 'a' is equal to 1, when it is discontinuous it is given the value 3.

We use this algorithm on the learning data set to determine the time slots for each activity (start/end times) and for each individual person/flat. We then build the unique model of the activities of the person. Eventually we evaluate the "level of achievement" of each activity from the distance of the current "daily" model (built on a one day data) to the "average" model (built on 15 days).

The index I_{day} in eq. 5, decreases in both cases of over-and under-activity. This also eliminates the risk of masking the decrease of an activity by the increase of another activity (cancelation effect).

III. Experiments

A. *Protocol of investigation*

The experiments involved 12 senior citizens (age = 80.5±3.2) recruited in the local community. The inclusion criteria were: (i) aged above 75, (ii) single persons living alone, (iii) a good level of autonomy. The subjects signed informed consent forms and were made aware that they could discontinue participation at any time. Each subject was assigned a unique, non consecutive, identifier (IDxx) to preserve the privacy. The data collected through a private network was then secured in a data warehouse.

During the experiments, a professional team of social workers, from the local council in charge of the elderly (CLIC[2] and CCAS[3]), was on the field and could provide feed backs from their direct observation.

The experiments lasted 6 months but the following preliminary results are related to only 90 consecutive days of data.

B. *The spatio-temporal diagrams*

The spatio-temporal diagrams represent the time succession of activities for successive days. For clarity, each activity is given a different color. A first result of this real world experiment is to observe that the spatio-temporal diagram is different for each of the 12 subjects. Moreover, this diagram is mostly stable for each individual. In other words, the spatio-temporal diagram is very specific to each subject and thus can be taken as a "biometric signature" (Fig.5).

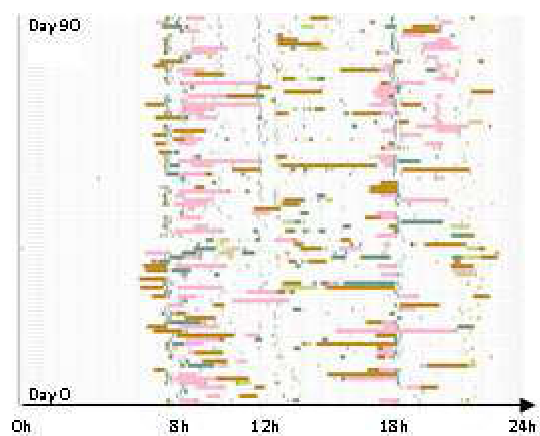

Figure 5. The spatio-temporal diagrams are a "signature" of the electrical activity of each individual (90 days). The electrical activities of the person (ID22) show regular and reproducible patterns.

[2] Conseil Local d'Information et Conseils (local council for information)
[3] Centre communal d'Action Sociale (local centre for social actions)

C. Results on the Index of Activity

The highest level of refinement is given by the index of achievement I_{day}. As it results from a data fusion (barycenter) of each individual index of activity, its absolute value holds little information. It proved to remain mostly stable for significant periods of time, showing little variability. Its trends hold more interesting information. In some cases I_{day} shows important variability, for example subject ID11 in (Fig.9) suffering from mild dementia.

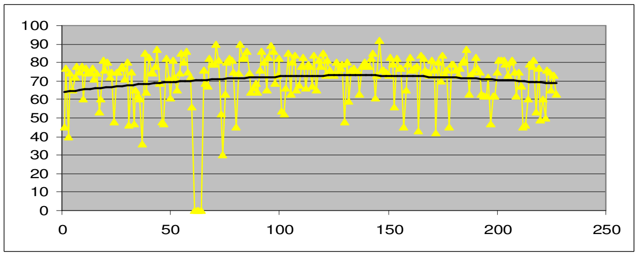

Figure 2. The chronogram of the index of achievment Iday shows a significant variability for this subject (ID11) suffering from mild dementia

D. Usage

1) Acceptability

Acceptability was evaluated with questionnaires on recipients and social workers (at middle and end of stay). They reported no disagreement. The system perceived as unobtrusive. Recipients assumed the utility of the service, even if they could not fully understand its operation. Eventually, most recipients were disappointed when their system was removed at the end of the experiments.

The experiments proved that the follow-up of the recipients by a remote assistance platform based on a single unique index was sufficiently reliable. The professionals easily monitored this unique index and its trends. The professionals at the remote assistance centers quickly get used to the index and trusted the variations of the index rather than the absolute values. The social workers appreciated the decision-making tool, helping to better manage the dynamic resources, enabling better assistance to residents.

2) Needs for Education

The professionals in charge of the technical installation of the system requested a special training to help them at installation when in direct contact with end users.

The social workers also had to build a closer relationship with end users. They asked for more education on the interpretation of the index of ADLs which they were not familiar with.

3) Intuitive tools and expertise

The social workers appreciated the information was intuitive and informative. They adopted rapidly the chronograms of the index of achievement and asked for a plot of the last 7 days of the index which they could intuitively interpret.

4) Improving the collaborative network

One of the main findings is that the tool contributed to strengthen the collaboration between the remote center and the social workers on the field. Actually, the social services were less interested in the day to day follow up of the person, but more in the possibility of evaluating the efficiency of their workers in the field.

IV. Discussions and Conclusions

Our objective is to detect some scenarios of activities of daily living (sleeping, toileting, taking meals…). We proposed a non-intrusive system which turns all electrical appliances into sensor. The experiment on a group of 12 elderly persons, on a 6 months period, demonstrated that most daily activities are detected. The results are encouraging on a reduced group and short duration. Although, the method requires several assumptions, among which the person using the electrical appliance is indeed the subject monitored.

We can improve the training for our classification process by taking into account the declarations of the patient about his daily habits. But in most cases the answers are not precise and cautious.

The ultimate goal of this work is to interpret the trends of the electrical activities to establish a relationship with a low health status. For this, we lack continuous and precise feedback information.

A limitation to the deployment is the time needed for the learning of electrical appliances. We currently study an automatic learning of the electrical appliances.

The method however has several benefits, such as low cost, scalability, together with non intrusive monitoring, privacy and ubiquity.

Acknowledgements

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