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Pattern Activities Identification in the Framework of Medical Nursing Home Using Infrared Sensors

P. A. C. Aguilar[1], C. M. A. Carvalho[1], D. Istrate[2], J. Boudy[3], T. Guettari[2], P. Dore[4] and R. M. C. Andrade[1]

[1] The Group of Computer Networks, Software Engineering, and Systems (GREat)
Universidade Federal do Ceará (UFC)
Av. Mister Hull, s/n - Campus do Pici - Bloco 942-A, 60455-760, Fortaleza, Brasil

[2] Sorbonne University, Université de technologie de Compiègne, CNRS,
UMR 7338 Biomechanics and Bioengineering (BMBI),
Centre de recherche Royallieu - CS 60 319 - 60 203 Compiègne cedex

[3] Department of Electronic and Physic (EPH)
Institute Mines Télécom - Télécom SudParis (IMT-TSP),
9 rue Chales Fourier, 91011, Evry, France

[4]LEGRAND, DIST Research Departement,
128 Avenue Maréchal de Lattre de Tassigny 87000 Limoges, France

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Abstract. This work propose a remote healthcare monitoring system designed to derive elderly's activities of daily living and distress situation in Nursing Home environments through a set of pyroelectric infrared sensor placed in the rooms. We aim to infer from the nursing home environment information as the exits and entries in the room, presence of care-givers and activities as night rounds, sleeping, eating, care-giver intervention. Thank to the sensors emplacement in the present case is possible to extract patterns regarding paths performed inside the room. Based on these patterns, we propose in a first step, a finite state model that represents the behavior of only one person moving inside the room. Through accomplishing of this model, we can derive some information as resident tracking, presence of care-givers, entries and exits. In previous work we have used the Dempster-Shafer theory (DST) based on static and dynamic model called Evidential Networks [11] in order to take into account the imperfect information (uncertainty, precision and conflict) involved by the sensors data acquisition and also providing a framework allowing the fusion of multi-sensors data yielding richer and reliable information. To this aim, the imperfect information representation by DST was considered in the proposed model. Thus, degradation of the sensor signals can be considered, becoming our model most reliable. In a second step, DST can also be used to perform the data fusion of the infrared sensors with other sensors introduced in the environment [11]. The proposed algorithms were evaluated in the framework of real data recording made in a medical nursing home in France in the framework of EMonitor'age project.

1 INTRODUCTION

Patient telemonitoring is a good solution to help manage medical environments such as nursing homes and hospitals in daily tasks as well patients managing, health monitoring, abnormality and distress situations detection and activities of daily living recognition. It can increase the quality of care and the efficiency of services provided. Indeed, it should facilitate daily tasks of care-givers in the cases of casual and continuous monitoring of chronic patients, elderly and dependent people.

Several patient telemonitoring systems using different kind of sensors have been proposed in the literature. [1] presents a multi-camera motion capture system aiming to provide caregivers with timely access to the patient's health status through mobile communication devices. In [2], a Distress Sound Extraction System for Elder Care is proposed. [3] presents a fall detection system based on accelerometer sensors from smartphone based using machine learning classification algorithms. [4] describes a prototype developed for remote healthcare monitoring using a Wireless Sensor Network (WSN) Pulse Oximeters, environmental sensors and streaming video to monitor patients.

The greatest presented sensors, such as cameras, microphones, oximeters and pulse sensors could be intrusive for the most of monitored people. To this aim, telemonitoring systems have been giving increasing attention to the utilization of less intrusive sensors such as pyroelectric infrared movement sensors. In this context, [5] developed a monitoring system to monitor patient activities of daily living, such as mobility, agitation, repartitions of stays, and displacements. [6] proposed a new benchmarking for human activity recognition algorithms based on infrared sensors. [7] developed a soft tracking system using an infrared ceiling sensor network and proposes a novel algorithm for tracking multiple people.

In this work we proposed a remote healthcare monitoring system to derive elderly's activities of daily living and distress situation in Nursing Home environments through a set of pyroelectric infrared sensor placed in the rooms. In the first step of our researches we proposes, a finite state model that represents the behavior of only one person moving inside the room. Through accomplishing of this model, we can derive some information as resident tracking, presence of care givers, entries and exits in the room.

Furthermore, to better representing and processing the imperfect information in this model, Dempster-Shafer Theory [8,9] was considered. Thus, degradation of the sensor signals can be considered, becoming our model most reliable. The proposed finite state model is approximated by a *Markovian Prediction Framework* [10,11].

The proposed approach is validated through unannotated real dataset and tested by an annotated dataset performed in an isolated room where all sensors were installed reproducing the same architecture of the real dataset.

This paper is organized as follows: Section 2 further details the E-Monitor'Age Project where this work was inserted. Section 3 presents the proposed approach. In Section 4, we represented the proposed model by Dempter-Shafer theory. Section 5 presents the experiments and results of our approach. Finally, Section 6 presents conclusions and perspectives.

2 EMONITOR'AGE PROJECT

The EMonitor'age project is a National project which aims to help medical staff in a nursing home providing a report about the elderly people activities daily life. In the framework of this project several sensors are used: infrared sensors, sound sensor, environmental sensor and respiration sensor.

In the framework of EMonitor'age project [13], this work propose a remote healthcare monitoring system designed to derive elderly's activities of daily living and distress situation from a medical nursing home in France through a set of pyroelectric infrared sensor placed in the rooms.

We aim to infer from the nursing home environment:

- Tracking of residents inside their room;
- Identifying the presence of care givers inside the rooms;
- Identifying entries and exits of persons;
- Identifying some activities inside rooms: night rounds, sleeping, eating, care giver intervention (toilets, meals, etc.).

The proposed solution for each issue above will aid medical staff for:

- *Patient's Managing*: The hospital administration has a low quantity of employees such that we need optimize their schedules in order to assist all patients;
- *Abnormality and Distress Situations*: The identification of some kind of situations like falls, bathroom accidents, invasion or even if any caregiver forget your task to watch this room.
- *Activity Daily Life Identification*: The knowledge about the patient's habits will help hospital administration to manage better the employee's time schedule and identify some patient actions that could characterize a good recovery or a worsening of his clinical situation.

2.1. Medical Nursing Home of Ambazac

In order to perform the experiments of validation and evaluation, some rooms of the medical nursing home of Ambazac [14] in France was equipped with sensors as shown in the Figure 1. In a modern room configuration, each room is divided in three distinct zones: bedroom, bathroom and corridor. This architecture can be different in older configurations having separate toilets from the shower.

In order to monitor activities from residents in this environment, some rooms were equipped with domotic sensors, such as pyroelectric infrared, CO2, temperature and humidity sensors. In the first step of our approach it was only used pyroelectric infrared sensors. Sensor specifications and architecture of the proposed system is detailed as follow.

Figure 1: The medical nursing home of Ambazac.

2.2. Sensor specifications and architecture

In the proposed architecture, each room is equipped with a set of pyroelectric infrared sensors that detects the movement of a person that stay in its covered area. Sensors used are products from Legrand. It was used the references 78490 for the corridor and bedroom and 48823 (corner) or 48822 (ceiling) for the bathroom as described in Figure 2 and 3.

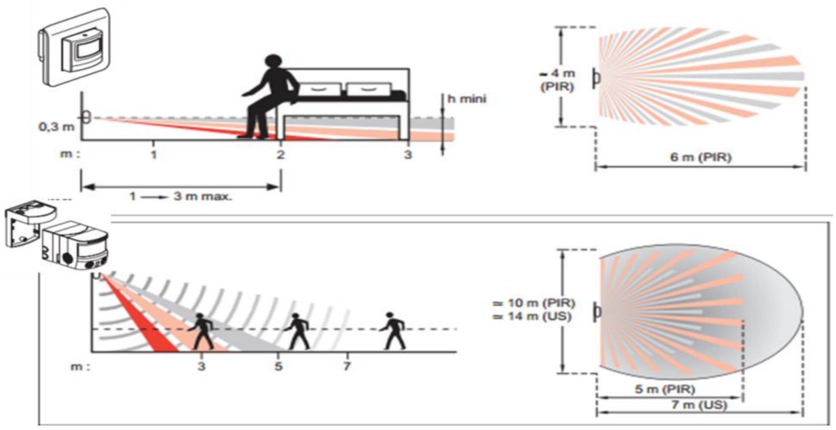

Figure 2: Characteristics of sensors used in the experiments: above 78490 and below 48823.

In the architecture of the Figure 3, we covered the three main areas of the room by five sensors: *Bed h* (Bed High position), *Bed w* (Bed Window positiondetect) and *Bed b* (Bed Bathroom) in the bedroom, *Bath* (Bathroom) and *Corr* (Corridor). They were described as follow.

- *Bed h*: Placed inverted on the bed wall at 1m45 from the floor. It only detects movements from people who are in standing position in the bedroom. It does not detect movements from people who are in the sitting and lying position (below the 1m45).
- *Bed w*: Placed on the window wall at 0m30 from the floor, it detects movements from people when they get out of the bed and putting their feet on the floor.
- *Bed b*: Placed on the bathroom wall at 0m30 from the floor, it detects movements from people when they get out of the bed and putting their feet on the floor.
- *Bath*: Placed upper to the bathroom door, it detects movements in the bathroom.
- *Corr*: Placed on the corridor wall at 1m45 from de floor in order to detect every people which enter/goes out from the room. It detects movements from people who pass in the corridor. We use this information to try to infer entries and exits from the room.

The sensor technology adopted in this work operates according the specific architecture described as follows in the section 2.3.

2.3. System architecture

Every sensor sends its information through a wireless network to fixed PLC (power line carrier) base. It receives the signals from Infrared sensors by radio frequency and sends them

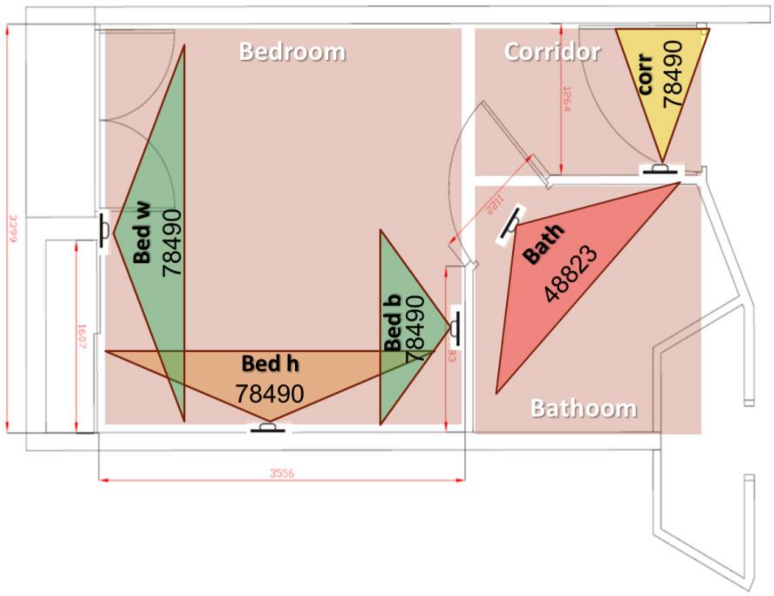

Figure 3: Sensor's architecture of Ambazac.

through the power line to another device responsible to take, decode and transmit them to PC by USB connection according protocol OpenWebNet as shown in Figure 4.

When the PC receives a signal, it uses a data base and the sensor identifier in order to obtain information about the sensor which generates this emission. The identifier is linked to the information about instant when the sensor was excited, and all information is stored in a table. The information about the time of activation is important to compute the elapsed time between two signals in the sequence. It could be useful afterward to cross with information about the daily service schedule in order to predict certain situations in each room.

Thus, starting from the presented sensor architecture, in the next section we detailed our first approach to derive some elderly's activities from the medical nursing home of Ambazac.

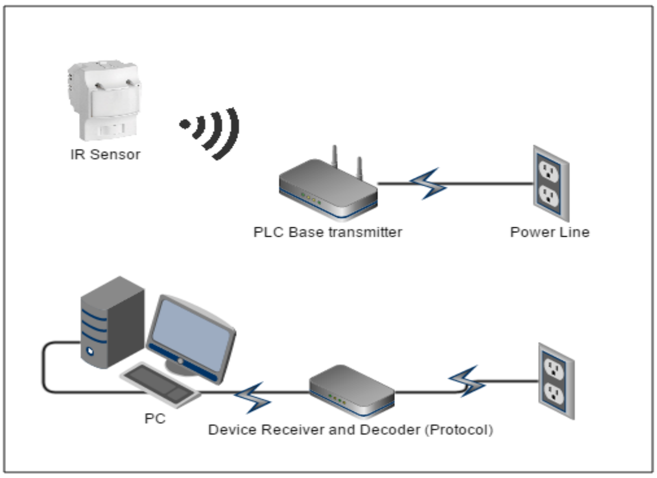

Figure 4: System Architecture.

3 THE PROPOSED APPROACH

As we described before each room has three distinct zones: bedroom, bathroom and corridor. These zones were covered by five movement sensors (Bed h, Bed w, Bed b, Bath and Corr) as detailed in Table 1. There is also another zone that it was taken into account: the outside (out) of the room. These four zones are shown in Figure 5.

Table 1: **Relationship between the zones and sensors**

Sensors	Zones
Bed w, Bed h, Bed b	Bedroom
Corr	Corridor
Bath	Bathroom

Regarding the Figure 5 and some empirical considerations, we note that the all the movements performed by a person inside the room, must fulfil specific rules as follows:

a) There is no way to directly move from the bathroom to corridor (and vice-versa) without passing from the bedroom.
b) We can identify someone exiting the room if the last active sensor was in the corridor (Corr) followed by a long time of absence of sensor activity. We call “silence” the interval of time that there is no sensor activity. The threshold that determines if a “silence” is a high value is an adjustable parameter and we can tune it manually to best fit the model. The inverse treatment happens when we need to identify someone entering: a long “silence” followed by Corr activation.
c) The movement performed by a person, between two adjacent zones, should be continuous. If we move between two adjacent zones, the sensors could be activated.

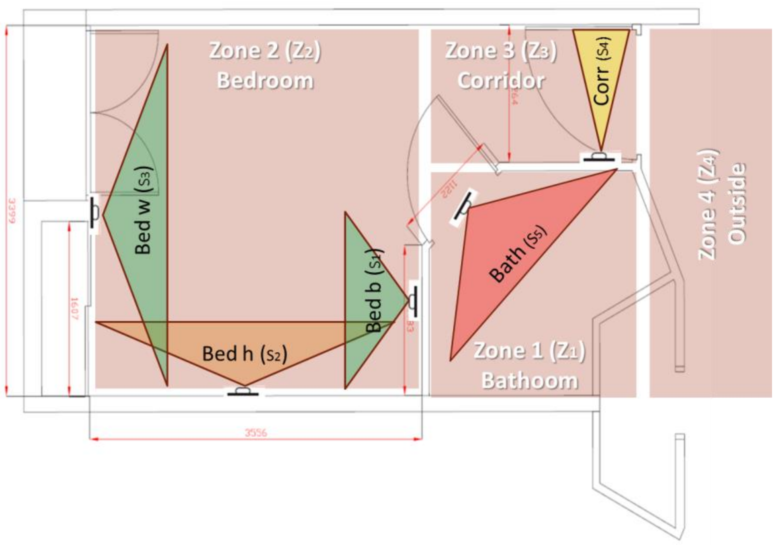

Figure 5: Zone Mapping.

Since the observed phenomena above, we proposed a finite state model that describes the behaviour of the path performed by only one person inside according to the Figure 6 below:

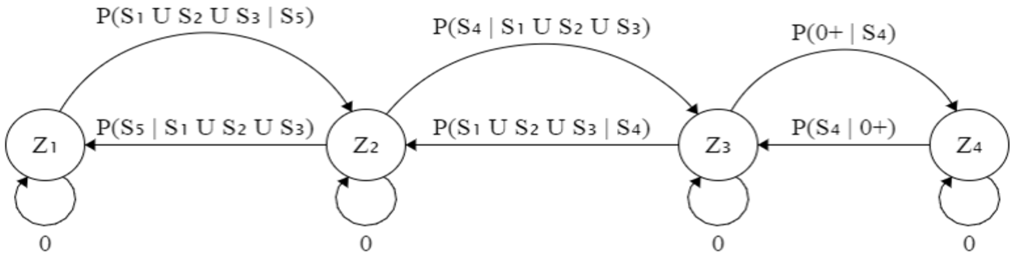

Figure 6: Finite State Model of a person's path.

$Z_{1,2,3,4}$ is the set of zones covered by sensors as described before in Figure 5. The arcs between the zone states indicate which paths are permitted between each one. $S_{1,2,3}$ are the sensors of the bedroom, S_4 is the sensor of the corridor and S_5 is the bathroom sensor. $P(S_I|S_j)$ points the activation conditional probability of sensor S_i given the activation sensor S_j before.

This model reproduces the normal path behaviour of an alone resident as well as his entries and exits of the room. However, the rupture of this model could indicate the presence of a care-giver or a third person inside the room. This information is very important for us. Thus, the primary goal of this model is to derive this information: resident tracking, presence of care givers, entries and exits in the room.

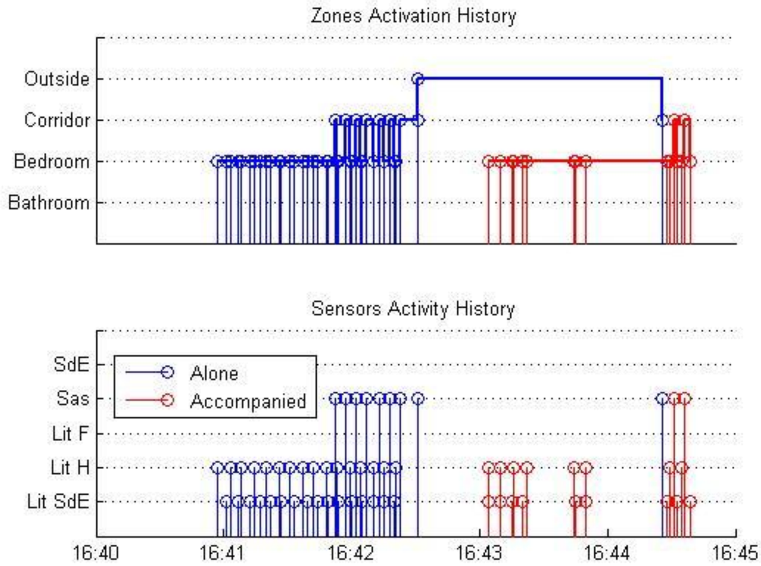

Figure 7: Rules-based algorithm implemented in Matlab.

Regarding the established rules, we developed a simple algorithm in order to verify how these rules can help to solve the proposed problems and identify some situations as indicated before. This algorithm was implemented in MATLAB in order to perform reliability tests with real non-annotated dataset (Ambazac nursing home recordings) and experimental annotated dataset (laboratory recordings) as shown Figure 7.

4 DEMPSTER-SHAFER'S REPRESENTATION

Sensors never are completely reliable; they may present some kind of failure. Then, we must consider the imperfections from sensor's observations. In order to take into account the imperfect information (uncertainty, precision and conflict) involved by the sensors data acquisition in the proposed model, a framework using the uncertainty theory of Dempster-Shafer [8,9] is presented. In this section we modelled the proposed finite state model by Dempster-Shafer's representation [11]. Firstly we give some preliminary mathematical definitions.

The *frame of discernment* Θ represents a finite set containing mutually exclusive and exhaustive events about the knowledge of our problem. In this problem we have four possible zones: bedroom (bedr), bathroom (bath), corridor (corr) and ouside (out). Thus we have a frame of discernment containing four possible events:

$$\Theta = \{bedr, bath, corr, out\} \tag{1}$$

The power set 2^{Θ} of Θ contain the set of the subsets of Θ. It contains $2^{|\Theta|}$ elements, called *focal elements*. Thus we have,

$$2^{\Theta} = \begin{bmatrix} \{bedr\}, \{bath\}, \{corr\}, \{out\}, \{bedr, bath\}, \{bedr, corr\}, \{bedr, out\} \\ \{bath, corr\}, \{bath, out\}, \{corr, out\}, \{bedr, bath, corr\}, \{bedr, corr, out\}, \\ \{bedr, bath, out\}, \{bath, corr, out\}, \{bedr, bath, corr, out\}, \{\emptyset\} \end{bmatrix} \tag{2}$$

In our previous model, we assumed in the inference process that each sensor is completely reliable (1 for excited and 0 for a non-excited sensor). A *belief mass function* $m(\cdot)$ allow us to assign a *belief degree* to the sensor's observations within the range [0 1].

The *Basic Belief Assignment* (BBA) is defined for each binary sensor providing a *belief distribution* which is created from the belief mass functions shown in Fig. 8.

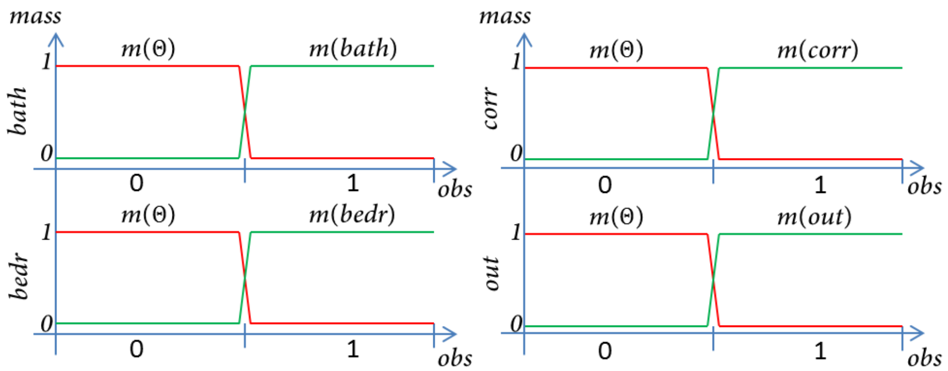

Figure 8: Basic Belief Assignment (BBA) defined for each binary sensor.

For each observation a *belief distribution* containing a belief mass function related for the available evidences (known focal elements) is produced as shown below,

$$\begin{aligned} m^{\Theta^{bedr}} &= [m(\{bedr\}), m(\{bedr, bath, corr, out\})] \\ m^{\Theta^{bath}} &= [m(\{bath\}), m(\{bedr, bath, corr, out\})] \end{aligned} \tag{3}$$

$$m^{\Theta^{corr}} = [m(\{corr\}), m(\{bedr, bath, corr, out\})]$$
$$m^{\Theta^{out}} = [m(\{out\}), m(\{bedr, bath, corr, out\})]$$

After computing the belief distribution from each sensor observations according to the basic belief assignment, the *Smets operator* [12] is used to perform the fusion of these belief distributions in order to obtain a consensus. The Smets operator is particularly well adapted to isolate the resulting conflict from the data fusion of these belief distributions. Thus we have,

$$m^{\Theta^1\Theta^2}(C) = \sum_{A\cap B=C} m^{\Theta^1}(A) \cdot m^{\Theta^2}(B) \tag{4}$$

and the conflicting value is achieved as follows

$$m^{\Theta^1\Theta^2}(\emptyset) = \sum_{A\cap B=\emptyset} m^{\Theta^1}(A) \cdot m^{\Theta^2}(B) \tag{5}$$

As shown in [10], we can represent the proposed finite state model within a *Markovian Prediction Framework*. A Markovian prediction of a probabilistic observation in the time *t* + 1 is produced given a probabilistic observation in the time *t* and a *transition matrix* denoted T:

$$P^{t+1}_{prediction} = P^{t}_{observation} \cdot T \tag{6}$$

where the transition matrix can be fixed according to experimental considerations:

$$T = \begin{array}{c} \\ bath \\ bedr \\ corr \\ out \end{array} \begin{array}{c} \begin{array}{cccc} bath & bedr & corr & out \end{array} \\ \begin{bmatrix} 1/2 & 1/2 & 0 & 0 \\ 1/3 & 1/3 & 1/3 & 0 \\ 0 & 1/3 & 1/3 & 1/3 \\ 0 & 0 & 1/2 & 1/2 \end{bmatrix} \end{array} \tag{7}$$

The *pignistic transformation* is used to convert the set of masses $m^{t}_{observation}$ into a probability set $P^{t}_{observation}$

$$BetP(A) = \sum_{A\subset\Theta} \frac{1}{|\Theta|} m(\Theta) \tag{8}$$

After obtaining a Markovian prediction, the predicted set of probabilities $P^{t+1}_{prediction}$ must be converted into a predicted set of masses $m^{t+1}_{prediction}$ in order to be able to carry out an evidential fusion between the predicted and the observed set of masses using the Smets operator.

The fusion of the predicted mass function $m^{t+1}_{prediction}$ and the observed mass function $m^{t+1}_{observation}$, is achieved through the Smets' operator '$\cap$' to separate the conflict resulting from the fusion:

$$m^{t+1}_{fusion} = P^{t+1}_{prediction} \cap m^{t+1}_{observation} \tag{9}$$

and the conflict

$$m^{t+1}_{fusion}(\emptyset) = \sum_{A\cap B=\emptyset} P^{t+1}_{prediction}(A) \cdot m^{t+1}_{observation}(B) \tag{10}$$

The conflict measure from this fusion represents a rupture model, i.e., a forbidden transition between the zones indicating a care-givers presence.

5 EXPERIMENTS AND RESULTS

In the beginning of the project, a dataset composed by a 4 subsets was available in order to be used in tests and validation of the algorithm. Each subset contains data for one whole day patient activity detected by infrared sensors. Each subset was composed by 2 attributes: activated sensor and time stamp for the activation. However, there was no annotated data. Thus, the outputs of the algorithm cannot be evaluated because the use of this data was a blind process.

In order to get new annotated data, some scenarios were composed taking care to represent the main situations that the algorithm seeks to treat. In this time, the dataset was built add 2 more attributes: person label (alone or accompanied) and transition label (inside, entrance or exit). Person label indicates whether the person, at the moment of movement detection is alone or accompanied. Transition label points whether the person movement was performed inside of room or whether that movement represents an entrance or exit.

For this purpose, a software was developed to deal with the data acquisition and communication tasks between PLC decoder and computer. That software includes a graphical interface, built in GUIDE tool of Matlab software, in order manage the experiment (select acquisition mode: sensor registering and data acquisition) and import and export data.

All experiments were performed in an isolated room and all sensors were installed reproducing the same architecture of Ambazac rooms. These experiments were performed in 10 days with 2 volunteers as actors and one manager to guide the scenario evolution. The main interest of these experiments is to verify the accuracy and tune the model to track the resident and identify the situations of care-givers presence and entries and exits. Each scenario has 5 minutes duration. These scenarios are short time because we just want capture the special situations as mentioned above.

After experiment realization, all data was processed by the rule-based algorithm. We annotate each scenario with the label AL (scenario which person is alone) and AC (scenario which person is accompanied by one or more people). The algorithm analyzes the whole data and assigns one of these labels for the analyzed dataset. We evaluated the results of algorithm comparing the real label annotated before with label assigned by the algorithm. All comparison results were summarized in the confusion matrix presented in Table 2 below:

Table 2: **Confusion matrix**

		PREDICTED CLASS	
		ALONE	ACCOMP
ACTUAL CLASS	ALONE	4	1
	ACCOMP	1	13

The actual approach has sensibility 80% and specificity 92%. Though there is an unbalance in dataset, which is major composed by scenarios of caregiver intervention, alone scenarios are easily detected by the algorithm, since no sensor presents any failure. Thus, we should give more attention to accompanied scenarios which its detection is main interest of our algorithm.

When we were performing the experiments, we check two phenomena that could mislead the algorithm to wrong decision: phantom signals and the sensor delay. Phantom signals are signals that randomly appears replicating a past signal, usually signals 5 seconds in past. When it appears, it could be misinterpreted by some rules, thus detecting a situation (exiting or third-party presence) when it not happen in fact.

The sensor presents a delay of 6 seconds, meaning that it can't activate again before past 6 seconds after the current activation. This high delay imposes some restrictions in development of time based rules of third-party detection as detection of discontinuities and simultaneous movements, when there are more than one person inside of room and various activations happens due the movements performed by these people.

6 CONCLUSIONS

The present work sought introduces a rule based algorithm to detect a presence of another person inside in a room. All rules were empirically developed regarding the disposition of the sensors inside the room and observing all possible transitions between zones. These observations resulted in a set of rules which depend of information about localization of sensor activated, instant of activation and certain times of inactivity.

Though these rules were empirically built, the result of algorithm seems to be promising. It shows that is possible to extract high-level information about resident and the people inside the room based on low level information as binary sensors activation.

As indicated before, we have some challenges to face as the problem of phantom signals and sensor delay, which are hardware issue and others that deal with the behavior of occupants of room like the simultaneous movements. To deal with behavioral issue, is mandatory to develop a statistical model that could formalize mathematically better our model, in order to get highest level information as number of people inside a room, tracking each person and try to identify through movements patterns presented, and thus, identify some performed activities.

Another good tool to be used is the analysis of resident agitation as proposed by [5]. We can create profile for person alone and person accompanied, and analyzes it in real time.

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REFERENCES

[1] Yun Ye; Song Ci; Katsaggelos, A.K.; Yanwei Liu, "A multi-camera motion capture system for remote healthcare monitoring," Multimedia and Expo (ICME), 2013 IEEE International Conference on, vol., no., pp.1,6, 15-19 July 2013.

[2] Istrate, D.; Vacher, M.; Serignat, J.F., "Generic Implementation of a Distress Sound Extraction System for Elder Care," Engineering in Medicine and Biology Society, 2006. EMBS '06. 28th Annual International Conference of the IEEE, vol., no., pp.3309, 3312, Aug. 30 2006-Sept. 3 2006.

[3] Aguiar, B.; Rocha, T.; Silva, J.; Sousa, I., "Accelerometer-based fall detection for

smartphones," *Medical Measurements and Applications (MeMeA), 2014 IEEE International Symposium on* , vol., no., pp.1,6, 11-12 June 2014.

[4] Fischer, M.; Yen Yang Lim; Lawrence, E.; Ganguli, L.K., "ReMoteCare: Health Monitoring with Streaming Video," *Mobile Business, 2008. ICMB '08. 7th International Conference on* , vol., no., pp.280,286, 7-8 July 2008.

[5] LeBellego, G.; Noury, N.; Virone, G.; Mousseau, M.; Demongeot, J., "A model for the measurement of patient activity in a hospital suite," *Information Technology in Biomedicine, IEEE Transactions on* , vol.10, no.1, pp.92,99, Jan. 2006.

[6] Noury, N.; Hadidi, T., "Simulation of human activity in a Health Smart Home with HMM," *e-Health Networking, Applications & Services (Healthcom), 2013 IEEE 15th International Conference on* , vol., no., pp.125,129, 9-12 Oct. 2013.

[7] Tao, S.; Kudo, M.; Pei, B.-N.; Nonaka, H.; Toyama, J., "Multiperson Locating and Their Soft Tracking in a Binary Infrared Sensor Network," *Human-Machine Systems, IEEE Transactions on* , vol.PP, no.99, pp.1,12.

[8] A. P. Dempster, “Upper and lower probabilities induced by multivalued mapping,”*Ann. Math. Statis.*, vol. 38, no. 2, pp. 325–339, 1967..

[9] G. Shafer, *A Mathematical Theory of Evidence*. vol. 1, Princeton, NJ, USA: Princeton Univ. Press, 1976.

[10] B. Marhic, L. Delahoche, C. Solau, A. M. Jolly-Desodt, and V. Ricquebourg, “An evidential approach for detection of abnormal behaviour in the presence of unreliable sensors,”*Inf. Fusion*, vol. 13, no. 2, pp. 146–160, 2012.

[11] Cavalcante Aguilar, P.A.; Boudy, J.; Istrate, D.; Dorizzi, B.; Moura Mota, J.C., "A Dynamic Evidential Network for Fall Detection," *Biomedical and Health Informatics, IEEE Journal of* , vol.18, no.4, pp.1103,1113, July 2014

[12] P. Smets and R. Kennes, “The transferable belief model,” *Artif. Intell.*, vol. 66, no. 2, pp. 191–234, 1994.

[13] Yves PARMANTIER, How can a nursing room become safer, AALFORUM 2014, Side-Event From Actimetry to ADL, in the framework of remote medical monitoring of elderly from living labs to the nursing home, September 9-12th, 2014

[14] N. Cislo, S. Arbaoui, Y. Becis-Aubry, D. Aubry, Y. Parmantier, P. Doré, T. Guettari , N. Ramdani, A System for Monitoring Elderly and Dependent People in Nursing Homes: the E-monitor’age Concept, Studia Informatica Universalis, Vol.11 n°2, 2014, pp. 30-33.