Indoor Human/Robot Localization using Robust Multi-modal Data Fusion

Mohamed-Hédi Amri, Yasmina Becis, Didier Aubry, Nacim Ramdani

Abstract—Home automation is now implemented in many retirement homes in order to improve elderly’s autonomy and safety. Smart homes allow to monitor the activities of elderly persons using information coming from different sensors. The ADL (Activities of Daily Living) are used to evaluate the ability of a person to perform on their own a selection of the activities which are essential for independent living in everyday life. The ADL are then used to detect deviations in a person’s behaviour. Indoor localization based on the fusion of heterogeneous data from different sensors, is then essential for ADL characterization. For this purpose, a robust data fusion method is presented in this work through a multi-modal analysis to monitor the activities of elderly people (immobility, walking, etc) in a smart home. The paper describes the installation of sensors in a Living Lab and the preliminary experimental results using a set of Pyroelectric Infra Red (PIR) sensors, Radio Frequency Identification (RFID) distance measurement and the outcome of a noise analysis. Within a set-membership framework, our algorithm for robust localization employs a multi-modal data fusion approach dealing with faulty measurements.

I. INTRODUCTION

Recently, indoor location sensing systems have become a growing field of research involving theoretical and application challenges. These systems are used in several applications of sensor networks such as tracking and monitoring [1]. The design of an indoor positioning system depends on sensor’s technology.

The most common positioning systems are based on infrared (IR) technology. Such sensors are low-cost and non-wearable.

Pyroelectric infrared (PIR) sensors have been widely deployed in commercial applications, to detect human presence, to trigger alarms and to control lighting. PIR sensor network are now employed in several advanced applications such as to achieve coverage, assist surveillance as well as perform tracking [2].

Active Badge [3] was the first system designed and built for locating simple devices within a building. It uses diffused infrared technology to realize location sensing and exploits the natural limitation of infrared waves by walls as a delimiter for its location granularity. A badge periodically transmits a globally unique signal. In each room, at least one receiver detects the infrared signal sent by an active badge. The information from these sensors is stored on a central server which can be queried for the location of the tracked active badge [4], [5].

A wireless pyroelectric sensor system was presented in [6]. The system is composed of 3 modules: a sensing module, a synchronization and error rejection module, and a data fusion module. The sensing module consists of geometric sensors designed with a spatially modulated viewing using a Fresnel lens array. This configuration allows the PIR sensor to detect the angular displacement of a moving thermal target.

The same concept of geometric PIR sensor was used in [7]. The positioning system was proposed to deal with multiple human localization. The tracking scheme consists of event detection, object localization and motion filtering and prediction. This prototype system is combined by a Bayesian joint probabilistic data association scheme.

In [8] a pyroelectric infrared sensor-based indoor location aware system was proposed: an array of PIR sensors was installed on the ceiling of each room, which is regarded as a cell, in a smart home. PIR sensors attempt to detect the resident continuously and transmit its sensing information to a room terminal via the home network system. The sensor information received from all the sensors belonging to one cell are integrated by the room terminal which provides the resident’s location with sufficient accuracy. A Bayesian classifier was used as a location recognition algorithm. The output of the PIR sensors are characterized by the magnitude and variation of the observed voltage. These features are classified into three classes which are the inside, the boundary and the outside of the sensing area. The Bayesian classifier computes, then, the probability that a feature vector belongs to each class and select a class with the highest posterior probability.

In [2] dual pyroelectric infra-red sensors were employed to achieve the objective of human activity monitoring: the phase delay between the responses of the two PIR sensors is measured. This information is then used to provide an accurate direction detection and to estimate the speed of the moving object.

A set of wireless nodes equipped with PIR sensors was used in [9] to track people in hallway: several autonomous clusters of PIR sensors are used to cover the area of interest. A cluster is made of 2 PIR sensors, facing each other, able to detect the direction of movement and classify people position within three possible regions (close to one sensor, middle and close to the other). These features are sent to the cluster head node that uses a classifier to estimate locally the position of the person. The system manager, which receives, local position from each cluster, is able then to track people position in the environment.

However, indoor positioning systems using PIR sensors, have
some common disadvantages. In fact, IR signals have some limitations for sensing location, for example, interference from fluorescent light and sunlight are error-prone[4]. That is why, different sensing modalities have been integrated with each others to improve the accuracy of localization processing.

In [10], [11], a model which combines PIR and RF (Radio Frequency) localization system was developed to enhance the accuracy information of humans and robots location and to deal with multiple targets. The system was installed in the ceiling of the area of interest. The fused information was performed through RSS (Received Signal Strength) technology and pyroelectric sensors. A dynamic triangulation approach was proposed to reduce the error of RF based triangulation method. The Cramér-Rao bound (CRB) function was used to obtain the probable region of target.

In [12], infrared sensors were combined with a wearable kinematic sensor (Actimometer) to monitor the activities of elderly people in a smart home. These two types of information allow to localize the person and to detect walking events. The data fusion process was based on a Bayesian approach.

In [13], location tracking was performed by binary sensors such as motion detectors, door barrier sensors and sensors delivering a signal that can be interpreted as binary using a threshold such as electricity consumption, water flow or pressure sensor. Indoor location tracking algorithm is based on the construction of a state estimator to estimate in real time the current location of a single inhabitant into his instrumented home.

Our work falls within the same framework of [10], [11]. The aim is to estimate a state corresponding to an indoor location zone, using several modalities of sensing. Generally, process knowledge and measurements coming from sensors are prone to indeterminable noise. In our work, we suppose that these errors are unknown but bounded. The unknown but bounded error (UBB) is used within a set-membership state estimation framework. We will show how to solve the estimation issue using set-membership computations techniques. Our method makes it possible to compute uncertainty domain for the reconstructed localization. This approach will be defined later in the paper.

The remainder of the paper is organized as follows. Section 2 describes the hardware configuration of our system. In section 3, the problem is formulated within the framework of set-membership theory. Then, a robust data fusion using an interval analysis method is developed. Finally, a scenario and preliminary results dealing with indoor localization are provided to show the performance of our data fusion strategy.

II. HARDWARE CONFIGURATION

A. The Living Lab

Our Living Lab, named ‘GIS MADONAH’, is an actual apartment of 40 m² inside the retirement home Bellevue at Bourges (France). The apartment was partially used so that the Living Lab will be close to a conventional room of any nursing home. It is composed of a bedroom, a hallway and a bathroom.

To locate the person inside the room, the Living Lab was equipped by five binary PIR sensors. The range of each sensor is $6m \times 4m$ and the detection area depends on the position chosen for the sensor as shown in Fig. 1.

![Fig. 1. Technical characteristics of the PIR sensor](image1)

The repartition of sensors, as depicted in Fig. 2, allows us to track the person throughout the room and to monitor his daily activities.

![Fig. 2. Sensors installation in the Living Lab](image2)

Since sensors range is too large, Fresnel lenses have been partially masked so that a zoning of the area is obtained. Each zone is covered in a discriminate way by a set of sensors, Fig. 3.

![Fig. 3. Repartition of sensors and definition of zoning areas A→G](image3)

Generally, the sensors required in the smart-home are supposed non-wearable and non-intrusive. Hence, the use of PIR detectors in this work as binary sensors. We are also equipping the Living Lab with new sound and Radio Frequency Identification (RFID) sensors. An experimental data collection, using PIR sensors, will be provided to perform our algorithm. A partial theoretical observation
based on sound and RFID will be added to the experimental collection of data, in order to enhance the efficiency of the algorithm. Therefore, RFID sensors allow us to have the distance between their positions and the person in motion. This information will be used to refine our results.

The sound sensor is designed to provide a class of sounds depending on many events. Each event is referred to a class number. In our work, classes 1, 2, 3 and 4 stand respectively for cough, Shaver, door slam and water flow.

**B. Data acquisition and communication protocol**

The data collected by all these sensors are expanded and acquired using KNX communication protocol for building automation, which has been standardized internationally as ISO/IEC 14543-3 Home Electronic Systems. KNX is used in the field of home automation and commercial building automation as well. In a KNX network, sensors and actuators are assigned to a set of communication objects. A communication object represents a value of a given type, for instance a temperature, a switch state, or a set point. The communication objects communicate via group addresses.

Network integration in a KNX system is accomplished by a software installation tool based on a database (ETS Engineering Tool Software). At each time step, we acquire measurements during one second.

**III. SET-MEMBERSHIP APPROACH FOR DATA FUSION**

**A. Set-membership state estimation**

In this work, indoor localization is addressed as state estimation problem. State estimation problems are usually solved by Bayesian estimators or the conventional or the extended Kalman filters. These methods estimate the dynamical system state from a series of incomplete and noisy measurements. However, such approaches are limited in real applications because the process knowledge and sensors noise cannot be determined a priori, which makes the condition of Gaussian distribution difficult to achieve. In addition, the nonlinear behaviour of some systems may degrade the proper functioning of these filters.

Unlike probabilistic approaches, set-membership filtering assumes only that the measurement and process errors are unknown but bounded (UBB). In the framework of Set-Membership Filtering (SMF) an iterative prediction update method is used to obtain a set that contains the feasible state values consistent with the measurement, the error bounds and system model.

Taking into account the condition of unknown but bounded error, SMF enables to enclose the actual system state in a compact shape, such as ellipsoids [14], [15], [16], [17], interval boxes [18], [19], parallelepipeds or zonotopes. In this paper we will use interval boxes.

**B. Problem formulation**

It is assumed in this paper that the system model can be described as follows:

\[
\begin{align*}
    x_{k+1} &= (p \land (f_1(x_k) + \omega_{1k})) \lor (-p \land (f_2(x_k) + \omega_{2k})) \\
    y_{k+1} &= h(x_k) + v_{k+1}
\end{align*}
\]  

where \( x_k \in \mathbb{R}^n \) \( (x_0 \in X_0) \) and \( y_{k+1} \in Y_k \subset \mathbb{R}^m \) are respectively the state and measurement vectors, \( i \in \{1, 2\} \), \( f_i(\cdot) \) and \( h(\cdot) \) are nonlinear functions, \( \omega_{i,k} \in W_k \subset \mathbb{R}^n \) and \( v_{k+1} \in V_k \subset \mathbb{R}^m \) are respectively the process and measurement noise, \( (X_0, W_k) \) and \( (Y_k, V_k) \) are bounded compact sets of \( \mathbb{R}^n \) and \( \mathbb{R}^m \) respectively, \( p \in \{0, 1\} \), \( \land, \lor \) are logical operators standing respectively for and, or and not. This is a class of switched dynamical systems.

The interest of this model will be addressed later in the paper. In the set-membership framework, the prediction step employs the previous state estimate to provide the predicted state using the dynamic model of the system. The predicted state is defined as:

\[
    X_k^+ = (p \land (f_1(X_{k-1}^+))) \lor (-p \land f_2(X_{k-1}^+)) + W_k
\]  

During the correction step, the current measurements are used to update the predicted state:

\[
    X_k^- = h^{-1}(Y_k)
\]

The feasible set \( X_k \) depicting the estimated set is consistent with the prediction model, the actual data and the error bounds. Hence, \( X_k \) is defined by the intersection of sets \( X_k^+ \) and \( X_k^- \):

\[
    X_k = X_k^+ \cap X_k^-
\]  

During the correction step, the intersection between the predicted set and the observations may be empty. This can be due to several causes such as inappropriate choice of system model, the initial set \( X_0 \) or bounds for noise sets \( V_k \) and \( W_k \). The purpose in this paper is to deal with the presence of faulty measurements in order to obtain a robust feasible set. For doing so, we propose the use of a *q-relaxed intersection* which is suitable for outliers detection [20], [21], [22], described here after.

**C. The q-relaxed intersection**

The robust feasible set may be computed considering the assumption below [20]:

**Minimal Number of Outliers (MNO) assumption:**

Outliers may exist for the outputs but within any time window of \( \ell \) time steps, we never have more than \( q \) outliers.

A robust method can be used which is the *q-relaxed intersection* to overcome faulty data [20]. This method consists in tolerating a given number \( q \) of outliers out of \( m \) measurements, and the solution set is then the set compatible with \( m - q \) measurements.

The *q-relaxed intersection* of \( m \) sets \( X_1, \ldots, X_m \) of \( \mathbb{R}^n \) is denoted by \( X^{\{q\}} = \bigcap_{i=1}^{m} X_i \). Thereby, if a measurement is inconsistent with the other measurements, it will be identified as an outlier, and is excluded from the solution set. This definition is illustrated by Fig. 4.
Fig. 4. $q$-relaxed intersection of four sets for $q \in \{0, 1, 2\}$

D. Outliers impact on the feasible set consistency

In this section, a probabilistic approach is used to discuss the impact of the relaxation in the $q$-relaxed intersection [23], [24], [25]. Consider an error $v_k$ occurring on the measurement vector $y_k$:

$$y_k = h(x_k) + v_k$$

(5)

where $v_k \in V_k$. Thereby, $y_k$ can be represented by the set:

$$Y_k = y_k - V_k$$

(6)

The $i$th component of $y_k$ is said to be inlier if $y_{ki} \in Y_{ki}$, otherwise it is considered as an outlier.

The prior probability of $y_k$ to be inlier is assumed to be: $\pi = \Pr(y_{ki} \in Y_{ki})$. We shall assume that all components of $v_k$ are independent and equally distributed. Thus, the prior probability for every measurement interval to be consistent is the same and equal to $\pi$. Let us consider $m$ measurements and denote $n_c$ the number of inliers. The probability of having $m$ consistent measurements is:

$$\Pr(n_c = m) = \pi^m$$

(7)

In the framework of the $q$-relaxed intersection, we can obtain a solution set containing the true value even in the presence of outliers.

**Theorem 1**: [23], [24], [25] A lower bound on the prior probability of the feasible set $X$ to contain the true value can be provided by:

$$\Pr(x \in X) \geq \sum_{k=m-q}^{m} \frac{m!}{k!(m-k)!} \pi^k (1-\pi)^{m-k}$$

(8)

**Proof**: [23], [24], [25] The number $k$ of inliers follows a binomial distribution $n_c = \beta(k, m, \pi)$. Thus, the probability to have exactly $k$ consistent measurements among $m$ is:

$$\Pr(n_c = k) = \beta(k, m, \pi) = \frac{m!}{k!(m-k)!} \pi^k (1-\pi)^{m-k}$$

(9)

The probability of having at least $m - q$ inliers is obtained by adding all $k$ terms from $m - q$ to $m$ in Eq. 9:

$$\Pr(n_c \geq m - q) = \sum_{k=m-q}^{m} \beta(k, m, \pi)$$

(10)

As a consequence, the probability that the feasible set will contain the true parameter is:

$$\Pr(x \in X) \geq \Pr(n_c \geq m - q) \geq \sum_{k=m-q}^{m} \beta(k, m, \pi)$$

(11)

The table below provides a lower bound for $\Pr(x \in X)$ if we have 10 measurements. The lower bound is more important when the number of measurements considered as outliers is greater.

<table>
<thead>
<tr>
<th>$q$</th>
<th>$\pi = 0.2$</th>
<th>$\pi = 0.5$</th>
<th>$\pi = 0.8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.510^{-9}</td>
<td>0.006</td>
<td>0.21</td>
</tr>
<tr>
<td>3</td>
<td>0.26</td>
<td>0.73</td>
<td>0.94</td>
</tr>
<tr>
<td>5</td>
<td>0.78</td>
<td>0.99</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Computing the $q$-relaxed intersection of $m$ sets has an exponential complexity. Using interval analysis the complexity becomes polynomial [20]. That is why we choose state estimation based on interval analysis.

E. Set-membership based on interval analysis and constraint propagation

Interval analysis [19] is based on the use of real intervals and interval vectors. An interval $[x]$ is a connected set of real numbers between a lower bound and an upper bound denoted $\underline{x}$ and $\overline{x}$ respectively.

$$[x] = [\underline{x}, \overline{x}] = \{x \in \mathbb{R} | \underline{x} \leq x \leq \overline{x} \}$$

(12)

An interval vector, or a box, $[x]$ is a subset of $\mathbb{R}^n$ that can be defined as the Cartesian product of $n$ intervals. It is written as:

$$[x] = [x_1] \times \ldots \times [x_n] = [\underline{x}_1, \overline{x}_1] \times \ldots \times [\underline{x}_n, \overline{x}_n]$$

(13)

The classical operations of real arithmetic and set-membership, namely addition (+), subtraction (-), multiplication (×), division (/), intersection (∩) and union (∪) can be extended to intervals. For any operator, $\circ \in \{+,-,\times,\div\}$, we have:

$$[x] \circ [y] = \{x \circ y \in \mathbb{R} | x \in [x], y \in [y] \}$$

(14)

Elementary functions such as $\exp$, $\tan$, $\sin$, $\cos$, … can be extended to intervals:

$$[f](\{x\}) = \{[f(x)], x \in [x] \}$$

(15)

Let $f$ be a function, $x = (x_1, \ldots, x_n)^T$ a vector and the prior domain for $x$ as $[x] = [x_1] \times \ldots \times [x_n]$. Consider the equation: $f(x) = 0$. This corresponds to a constraint propagation problem (CSP) $\mathcal{H}$, which can be formulated as:

$$\mathcal{H} : f(x) = 0, x \in [x]$$

(16)
The forward-backward contractor $C_{↓↑}$ is based on constraint propagation. This contractor allows to contract the domains of the CSP $H: \{(f(x) = 0, x \in [x])\}$ by taking into account all the $n$ constraints separately.

F. Computing the $q$-relaxed intersection

The minimal number of outliers $q$ is determined by GOMNE (Guaranteed Outlier Minimal Number Estimator) [26]. This algorithm computes a solution by increasing $q$ beginning from 0. Once a non-empty solution during the intersection is achieved, $q_{\text{min}}$ will be returned as the minimal number of outliers. The example below is provided to show how to compute the $q$-relaxed intersection between $m = 3$ boxes.

- First, the corners of each box are projected on the $x$ and $y$ axis.
- Second, a paving is built using each two consecutive points on $x$-axis and two consecutive points on $y$-axis. The obtained paving consists of $(2m - 1)^2 = 25$ boxes.
- Third, a midpoint is affected to each box.
- Then, an inclusion test is made. The test consists in searching the midpoint belonging to $m - q$ boxes. Increasing $q$, here, we obtain a non-empty solution for $q = 1$. The box containing this midpoint is the $q$-relaxed solution.
- Finally, the set which does not contain the solution set is considered as an outlier unlike the others which are inliers.

![Fig. 5. Computing the $q$-relaxed intersection [20]](image)

IV. ROBUST SET-MEMBERSHIP DATA FUSION FOR INDOOR LOCALIZATION

A. Mobility model

Several mobility models have been proposed [27] in the literature to describe the motion of mobile entities. In our work, we aim to use a basic mobility model such that the algorithm remains general and applicable to as many situations as possible. A simple mobility model with minimum assumptions is the random walk model [27], in which, an entity moves from its current location to a new one by randomly choosing a direction and speed. The speed, $v$, and direction are both chosen from pre-defined ranges $[\text{speed}_{\text{min}}, \text{speed}_{\text{max}}]$ and $[0, 2\pi]$ respectively. It assumes that only the maximal velocity $v_{\text{max}}$ of entities is known. Between two time steps, the entity is able to move in any direction with a velocity less than $v_{\text{max}}$. Hence, the mobility equation is formulated as follows:

$$(x(t) - x(t - 1))^2 + (y(t) - y(t - 1))^2 \leq (\Delta t v_{\text{max}})^2$$

where $x(t)$ and $y(t)$ are the coordinates of the considered mobile entity at time $t$. Knowing the point position for the considered mobile entity at time $t - 1$, the mobility constraint given (17) is a disk equation whose radius is $v_{\text{max}}$. The mobility model can also be described by the following system:

$$\begin{cases}
  x(t) = x(t - 1) + \Delta t v(t) \cos(\theta) \\
  y(t) = y(t - 1) + \Delta t v(t) \sin(\theta)
\end{cases}$$

(18)

When using PIR sensors we can detect that the mobile entity speed is close to zero since PIR sensors do not yield any measurement where the entity is standing still. In other words, using our measurements we can check if $p$ or $-p$ is true. If the speed of the mobile entity $v(t) = 0$ then the mobility model switches to:

$$\begin{cases}
  x(t) = x(t - 1) \\
  y(t) = y(t - 1)
\end{cases}$$

(19)

This mobility model is equivalent to the state equation in (1). It switches from (18) to (19) depending on the speed $v$:

- $v(t) \neq 0 \Rightarrow p = 1$:
  $$(18) \iff x_{k+1} = f_1(x_k) + \omega_{1k}$$

- $v(t) = 0 \Rightarrow p = 0$:
  $$(19) \iff x_{k+1} = f_2(x_k) + \omega_{2k}$$

Any additional informations on entities’ mobility could be added to refine the model. The problem is solved using interval analysis in [28], [29].

B. Observation model

The measurements consist in boxes representing the coverage sensing of PIR sensors. When a PIR is activated, the box representing its coverage is activated. At each time step, a list of boxes is provided. This list consists of the predicted box as given by the mobility model (18) and the measurement boxes. The location zone is obtained by intersecting using the $q$-relaxed intersection of these boxes. A challenging task was to synchronize data coming from sensors. In our work, we acquire data during at a one second time step.

Moreover, three RFID antennas are employed. Each antenna provides a distance depending on the strength of the received signal. Conventionally, the position of a person is obtained through a triangulation algorithm. This method computes the position by intersecting three circles according to the three distances. Our algorithm, take into account a bounded error of $\pm 0.25m$ on each distance measured. Then,
triangulation method considers three rings. The position is then enclosed by a box, Fig. 6. Finding this box is performed by combining a constraint propagation (CSP) using the forward-backward contractor \( C_{t+1} \) and the \( q \)-relaxed intersection.

![Fig. 6. Result of an intersection of three rings](image)

**C. Proposed algorithm using interval analysis**

The problem consists in finding the zone in which the person is located. In our method, every variable is replaced by a box. In particular, the point location coordinates \( p(t) = (x(t), y(t)) \) defined in Eq. 17 will be taken as a box: \( [p](t) = [x](t) \times [y](t) \). The two-dimensional box \( [p](t) \) is computed through two phases:

1) **Propagation phase:** Assume that \( [p](t-1) \) is the subpaving obtained at time \( t-1 \). Computing the predicted set \( [p]_{estim}(t) \) may be achieved using Eq. 18 or Eq. 19 and interval framework [24], [25]. This box will be contracted using measurements during the correction phase.

2) **Correction phase:** During this phase, the predicted set \( [p]_{estim}(t) \) will be refined using \( q \)-relaxed intersection with measurements. Every measurement will be considered as a constraint during the contraction. The propagation and the correction phase are illustrated by Fig. 7.

![Fig. 7. Computing the Correction phase](image)

During the correction phase different situations may turn out to be possible: No outlier is detected which corresponds to non-empty solution between all sets, or outliers are detected and identified, or outliers are detected but not identified. These scenarios will be presented in the next section.

V. **EXPERIMENTAL EVALUATION**

A. **Possible solutions of the \( q \)-relaxed intersection**

The outliers detection using the \( q \)-relaxed intersection consists in checking if the solution set is consistent with all the measurements and the predicted set. Nevertheless, the identification procedure is more difficult. Indeed, we can obtain more than one box. In this case, the different boxes can not simultaneously contain all the measurements and the predicted set. In general, we can have three possible situations:

- No outlier: in this case, all the measurements and the predicted set are consistent, Fig. 8a.
- Outlier detection and identification: at least \( q \) sets do not belong to the solution set in Fig. 8b we have \( q = 1 \).
- Outlier non identification: the solution set is an union of two non-connected boxes. In Fig. 8c, the algorithm of \( q \)-relaxed intersection stops when \( q = 2 \). The measurement and predicted sets are not all compatible with the two boxes independently. This ambiguous situation emphasizes the case of different possible positions of a person indoor localization. This case may be used, also, to track multiple residents.

B. **Experimental results**

An actual motion for a resident is performed to illustrate the practical efficiency of the proposed algorithm. The initial location zone is provided by the first measurements. The scenario includes different activities such as crossing the bedroom or the hallway, immobility, sleeping and going to the bathroom. The video attached provides an online location zone based on the proposed algorithm.

In Fig. 9, a part of the scenario is presented: a resident is going from the bathroom to the bed crossing zones G, E, C, A and D. The location zones obtained by our algorithm contain real position at time steps 20s, 28s, 45s, 57s and 109s. It can be noted that the reconstructed location zones contain the true position. Real trajectory was already recorded when moving. We note also that at time step \( t = 28s \) we had two reconstructed location zones. This ambiguity can be removed using RFID sensors.

In Fig. 10, a second part of the scenario is presented: the sound sensor is used. In fact, when the resident is in the bathroom, PIR sensors can not provide any information according to the instrumentation in the Living Lab. Therefore, water flow, which activates class 4 of the sound sensor, can be interpreted as an information on the location zone. Thus, any activities as well as their durations are reconstructed. Sleeping (from 440s to 480s) and having a wash (from 249s to 349s) are detected. A contribution of the proposed algorithm is then to perform an indoor localization even when we have heterogeneous measurements. It can be noted also that location zones still contain the true position.

In order to refine the location zones obtained previously, data coming from RFID sensors are used. In Fig. 11, it can be noted that location zones are more refined when using RFID as an additional modality of sensing.

The reconstructed location zones allow us to characterize the ADL, Table II. We are able to reconstruct the activities and their duration.

Our algorithm implemented with Matlab on a PC Intel(R) Core i7-3540M requires approx. 500 seconds CPU time i.e: 1s CPU time per 1s measurement time step. This result is promising for online operation.
There is no outlier.

The outlier is detected and identified as $Y_1$.

The outliers are detected but not identified.

Fig. 8. $q$-relaxed intersection: possible solutions

Fig. 9. Part 1 of the scenario: The resident is walking from the bathroom to the bed crossing zones G, E, C, A and D. The location zones obtained by our algorithm contain real position at time steps 20s, 28s, 45s, 57s and 109s.

Fig. 10. Part 2 of the scenario: Many activities as well as their durations are reconstructed. Sleeping (from 440s to 480s) and having a wash (from 249s to 349s) are detected.

Fig. 11. Impact of the use of RFID sensors: Location zones are more refined compared to part 1 of the scenario at time steps 20s and 57s, ambiguity is removed at time step 28s. Top: PIR only, bottom: PIR and RFID.
TABLE II
ADL CHARACTERISATION

<table>
<thead>
<tr>
<th>Time</th>
<th>Zones</th>
<th>Duration</th>
<th>ADL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1s</td>
<td>E-G</td>
<td>25s</td>
<td>Walking in the hallway</td>
</tr>
<tr>
<td>20s</td>
<td>E</td>
<td>5s</td>
<td>Walking in the left side of the hallway</td>
</tr>
<tr>
<td>31s</td>
<td>A-C-E</td>
<td>70s</td>
<td>Walking in the left side of the bedroom</td>
</tr>
<tr>
<td>102s</td>
<td>B-D</td>
<td>12s</td>
<td>Walking in the right side of the bedroom</td>
</tr>
<tr>
<td>121s</td>
<td>E</td>
<td>5s</td>
<td>Immobility</td>
</tr>
<tr>
<td>186s</td>
<td>F-D</td>
<td>20s</td>
<td>Walking in the left side of the hallway</td>
</tr>
<tr>
<td>201s</td>
<td>E</td>
<td>30s</td>
<td>Walking in the right side of the hallway</td>
</tr>
<tr>
<td>132s</td>
<td>G</td>
<td>17s</td>
<td>Walking in front of the bathroom</td>
</tr>
<tr>
<td>249s</td>
<td></td>
<td>100s</td>
<td>Having a wash</td>
</tr>
<tr>
<td>426s</td>
<td>C-E</td>
<td>20s</td>
<td>Walking in the left side of the bedroom</td>
</tr>
<tr>
<td>440s</td>
<td>A-B-C-D</td>
<td>40s</td>
<td>Lying on the bed</td>
</tr>
<tr>
<td>480s</td>
<td>B-D-F</td>
<td>20s</td>
<td>Walking in the right side of the bedroom</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

In this paper, we proposed a multi-modal data fusion method based on set-membership approach for indoor localization. The algorithm uses \( q \)-relaxed intersection to deal with faulty measurements. An online indoor zone location was obtained to track a person in his home or a robot in a sensor network. The efficiency of our method was evaluated through experimental scenario in a Living Lab. Preliminary results were satisfactory. They were obtained via computation times consistent with an online implementation. We will further this work considering other sensing modalities.

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