



Optimal Sensor Deployment According to a New Approach for Target Tracking in Smart Homes

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PAPER'S TITLE

Optimal sensor deployment according to a new approach for target tracking in smart homes

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Optimal sensor deployment according to a new approach for target tracking in smart homes

Abstract – Ambient Assisted Living (AAL) aims to ease the activities of daily lives for elderly or disabled people living in smart homes. In these systems, the assisting services are provided by use of the sensors that detect the location of inhabitants. Even though the cost and performance efficiencies of sensor networks depend directly on the number of the deployed sensors as well as the approaches that are employed to track the location of inhabitants, these factors are separately considered in research studies. In this paper, we propose an approach to track a target in smart homes. We present a new Integer Linear Programming (ILP) model that i. optimizes the number of the deployed sensors according to our proposed target tracking approach, ii. determines the placement of sensors in the network while considering the layout of the Region of Interest (RoI), iii. proposes appropriate settings for the sensors' field of view and their orientation, and, iv. deploys sensors according to the satisfaction of a reliability level in the network. In order to validate the proposed model and show its applicability, we use two sets of data, including real data gathered from a living lab and randomly generated data, as well as a test scenario. We also present a user interface that employs the concepts, which are presented in this research. The interface helps to easily monitor the location, energy consumption and well-being factors of a target in an AAL environment.

1. Introduction

According to the statistics published by the World Health Organization [1], the number of people aged 60 and over will double by 2050. Consequently, a significant effort is required to develop solutions that ensure comfort and assistance in old ages. Ambient Assisted Living (AAL) refers to the systems that aim to increase the comfort and safety of people with physical or cognitive disabilities in their smart homes [2]. The AAL systems use a set of connected sensors and ICT (Information and Communication Technology) tools to extract the data from the environment and provide the services required. Examples of these services include remote counselling for patients, recognition of activities and monitoring of indoor locations of inhabitants.

PIR (Pyroelectric InfraRed) sensor networks are widely used for indoor target tracking [3,4,5]. Generally, in these networks, binary information is created to determine if targets have been observed by sensors. [6,7] use data mining approaches to track the location of the targets who are in smart areas. [8] deploys learning procedures and [9] uses Voronoi diagrams to present methods to track the location of the targets in smart zones. In [10], Lu et al. present space encoding and decoding techniques for multiple target tracking. Using the presented methods, a single identification may be associated to multiple spaces. In order to cope with this issue, the authors present the development of an extra distinguishing phase.

In the context of the optimal deployment of sensors, Li and Ouyang [11] propose a new sensor deployment method to maximize the profit. The term profit has been considered as a measure for both flow coverage (O-D flow estimation) and path coverage (travel time estimation). Guerriero et al [12] present several optimization models taking into account different objectives such as maximization of the sensors' lifetime, minimization of the residual energy and maximization of the number of sensor nodes whose residual energy is above a chosen threshold value. Pradhan and Panda [13] develop a multi objective optimization model to simultaneously maximize coverage and lifetime in sensor networks. Zhao et al [14] develop a Mixed Integer Linear Programming (MILP) model that aims to extend the network's lifetime by optimal placement of sensors. To validate the model, they develop heuristics and conduct a set of different experiments. Rebaï et al [15] propose a model to optimize the sensor placement in the network with the consideration of

connectivity between them. In Karabulut et al [16], a bi-level non-linear programming model is developed to deploy sensors. Ahmed et al [17], propose an integer linear programming model to maximize the network lifetime. They define the lifetime as a time interval that elapses until any active set of sensors fails to satisfy the required coverage. Sharma et al. propose an approach for optimal sensor placement regarding uncertainties due to occupancy and boundary fluxes of buildings [18]. A relaxation sequential algorithm is proposed for optimal sensor placement in [19]. In [20], the authors provide a survey on different approaches that are used to optimally place cameras for surveillance. Reviewing the literature, a large body of studies is carried out to deploy sensors optimally in regions of interest. In the context of deploying the sensors to track the targets, the performance and cost efficiencies of systems not only depend on the optimal placement of the sensors but also depend on the approaches that are implemented to track the targets. To the extent of our knowledge, the current literature presents a gap in addressing and dealing with this matter. Besides, in the sensor networks, it is probable that one or more sensors break down because of power failure, faulty materials, poor workmanship, etc. These failures may cause losses of information and data. The ability of a system to operate well even in failure situations is defined as the reliability [22]. The consideration, evaluation and analysis of the reliability in the sensors network regarding internal and external factors are discussed in [23, 24, 25]. In deployment of sensors, in order to track the location of the targets, establishment of a system that is both reliable and inexpensive is a significant need.

In this paper, we contribute to the existing literature in the following ways:

- We propose a novel target tracking method. Our method is constituted based on the optimal number of the sensors that are deployed in the network. It determines the real-time location of a target living in a smart home and helps to trace her/his movement path over time.
- We present a new integer linear programming model that optimizes the sensor deployment with regard to the proposed target tracking method.
- In order to find optimal places to locate sensors, we consider the layout of the RoI. Therefore, the solutions are determined according to the existing obstacles in the RoI, e.g. the walls, and the hidden zones as well as the surfaces which cannot be used for sensor deployments.
- Taking into account the failure rate of sensors, we consider the satisfaction of a minimum level of reliability in the sensor network.
- We present a user interface that uses the target tracking and sensor deployment approaches that are developed in this research. It helps the AAL service providers to easily monitor the real-time location, energy consumption and comfort of a target who lives in an AAL environment.

The remainder of the paper proceeds as follows. Section 2 provides a description of the problem as well as the proposed target tracking approach and presents the mathematical model that is formulated for optimal placement of sensors in ALL environments. The results of the application of the model on two sets of data, namely random data and real-world data, are shown in section 3. Furthermore, section 3 presents the data management system that is developed to outline different properties concerning the energy consumption, comfort and location of targets living in smart homes. Section 3 also represents a test scenario, which is employed to verify the theoretical approaches of this paper and show the visualization of outputs in the interface. And finally, section 4 gives a summary of the study and some perspectives for future works.

2. Problem statement and formulation

In this study, a three-dimensional AAL environment (region) is considered for sensor deployment. The region of interest is discretized into small blocks, according to a suitable scale, see Figure 1. Among

different sides of the blocks, a set of them are potential surfaces for sensor deployment. In Figure 1, these surfaces are represented by hatched areas. Nevertheless, due to some technical constraints such as the presence of the power wires and HVAC (Heat Ventilation and Air Conditioning) infrastructures, the others are unsuitable for the deployment of a sensor. In Figure 1, these surfaces are not hatched. Each sensor is identified by three aspects: the surface (p) on which it is deployed, the level of its field of view (l), and its orientation (o), see Figure 1. We present sets O, L and P to respectively determine the possible directions for the sensors' orientations, levels for the sensors' fields of view and potential surfaces for sensor deployment. Thereby, a set to determine all the sensors can read as $S = \{s \triangleq (o, l, p) : o \in O, l \in L, p \in P, 1 \leq s \leq |O| \cdot |L| \cdot |P|\}$. We suppose that a block is covered by a sensor if its centroid is seen by the sensor. In addition, we suppose that the deployed sensors on the surfaces are located at the centroid of the surface, see Figure 1.

Please, insert Figure 1 approximately here.

The target tracking scheme in this study associates a unique X -bit binary array (code) to each block. We note that in our approach the size of the array, i.e. the number of elements in the array, is equal to the optimal number of the sensors that are deployed in the network. The optimal number of deployed sensors and the assignment of the unique codes are defined throughout the resolution of the mathematical model. The digit 1 in the binary array for a given block indicates that a movement made by a given target in the block is detected by the corresponding deployed sensor, and, a 0 indicates that the sensor does not detect any movement in the block. Following the received data from the sensors (0/1 situations), the unique binary arrays enable the ALL service providers to find the real-time location of a target and trace her/his displacement path. The illustration of our proposed target tracking approach is given in Figure 2. In this figure, the region of interest is divided into nine blocks. Four sensors are optimally deployed in the region, which means that the optimized size of the binary arrays (codes) is equal to 4. Deployment of these four sensors assigns unique codes to every block. Following the data sent by each of the sensors concerning the detection of a movement in the blocks and considering the created unique codes, the location of the target at a given time can be recognized. Tracking the location of the target over time can lead to the constitution of a mobility trace.

It is worth noting that in the problem of this study every block is supposed to be covered by a minimum number of sensors with an *a priori* determined value. Considering the failure rate of the sensors, a reliability level must be satisfied in the network. The objective of the problem is to minimize the total cost of employment of sensors in the region of interest while meeting the previously mentioned requirements of the problem. We note that we use PIR sensors to establish the sensor network. Our approach for sensor deployment and target tracking is useable in any networks where binary data can be generated to report the presence and movement of a target living in AAL environments.

Please, insert Figure 2 approximately here.

The problem of this study is mathematically presented through an Integer Linear Programming model. The following notations are used to formulate the model.

Sets:

(I,J,K): set of blocks indexed by (i,j,k) .

S: set of sensors indexed by s .

Parameters:

$H_{(i,j,k)}$: minimum number of sensors required to cover block (i,j,k) .

$\Omega_{s,(i,j,k)}$: a binary matrix that presents the set of sensors, which cover block (i,j,k) , i.e. $\{s \mid d \leq R_s^{\text{sensing}}, CP \in \text{FoV}_s\}$, d is the Euclidian distance between the centroid of the surface where sensor s is located and the centroid of block (i,j,k) . R_s^{sensing} is the sensing range of sensor s . It is worth noting that a block is covered by sensor s , if its center point, CP , is in the field of view, FoV_s , of the sensor, i.e, $CP \in \text{FoV}_s$. If so, $\Omega_{s,(i,j,k)} = 1$. Otherwise, if for some reason, such as not being in the sensing range of sensor s or being covered by an obstacle or being in a hidden zone, the centroid of the block (i,j,k) is not covered by sensor s , $\Omega_{s,(i,j,k)} = 0$.

r : network reliability.

M : a large positive number.

C : fixed cost of deploying a sensor in the network.

q : failure rate of each sensor in the network.

Decision variables:

X_s : is equal to 1 if sensor s is deployed. 0, otherwise.

$Y_{(i,j,k),s}$: is equal to 1 if block (i,j,k) is covered by sensor s . 0, otherwise.

$V_{(i,j,k),(u,w,z),s}$: is equal to 1 if blocks (i,j,k) and (u,w,z) are covered by sensor s . 0, otherwise.

Using these notations, the ILP formulation of the problem is described below:

Equation 1 presents the objective function. It aims to minimize the total cost of deploying the sensors in the region of interest. Since the deployment cost is equal for all the sensors, the objective function implicitly minimizes the total number of the deployed sensors in the network.

$$\text{Min } Z = \sum_s C X_s \quad (1)$$

The objective function of the model is optimized subject to the following constraints:

Coverage constraints: Constraints (2) guarantees that every block is covered at least by $H_{(i,j,k)}$ number of sensors.

$$\sum_s \Omega_{s,(i,j,k)} Y_{(i,j,k),s} \geq H_{(i,j,k)} \quad (2)$$

$\forall (i,j,k) \in (I,J,K)$

Constraints related to deployment of sensors according to the proposed target tracking method: Using the proposed target tracking approach, a unique and optimized-in-size code must be assigned to every block. In order to formulate this concept, constraints (3) and (4) state that if blocks (i,j,k) and (u,w,z) , $(i,j,k) \neq (u,w,z)$, are covered by same sensors, one of the blocks should be covered by at least another sensor that covers only that block and does not cover the other. On the contrary, if blocks (i,j,k) and (u,w,z) , $(i,j,k) \neq (u,w,z)$, are not covered by same sensors, there will be no need for an extra sensor deployment. We note that expression $\sum_{b \neq s} \max((\Omega_{b,(i,j,k)} - \Omega_{b,(u,w,z)}), 0) Y_{(i,j,k),b}$ searches for sensors that cover block (i,j,k) and do not cover block (u,w,z) . Similarly, expression $\sum_{b \neq s} \max((\Omega_{b,(u,w,z)} - \Omega_{b,(i,j,k)}), 0) Y_{(u,w,z),b}$ seeks to deploy sensors that cover block (u,w,z) while they do not cover block (i,j,k) .

$$Y_{(i,j,k),s} + Y_{(u,w,z),s} \leq 1 + M V_{(i,j,k),(u,w,z),s} \quad (3)$$

$\forall (i,j,k),(u,w,z) \in (I,J,K), (i,j,k) \neq (u,w,z)$

$$\begin{aligned}
& \forall s \in S \\
& \sum_{b \neq s} \max((\Omega_{b, (i,j,k)} - \Omega_{b, (u,w,z)}), 0) Y_{(i,j,k), b} + \sum_{b \neq s} \max((\Omega_{b, (u,w,z)} - \Omega_{b, (i,j,k)}), 0) Y_{(u,w,z), b} \geq \\
& 1 - M(1 - V_{(i,j,k),(u,w,z),s}) \\
& \forall (i,j,k),(u,w,z) \in (I,J,K), (i,j,k) \neq (u,w,z) \\
& \forall s \in S
\end{aligned} \tag{4}$$

Reliability-level satisfaction constraints: Network reliability is guaranteed by constraint (5). The term reliability presents a minimum level for the probability that at least one sensor is operating in the network. This constraint can be also rewritten as $\sum_s \Omega_{s, (i,j,k)} X_{(i,j,k), s} \geq \frac{\log(1-r)}{\log(q)}$. We note that, according to the magnitude of $\frac{\log(1-r)}{\log(q)}$ and $H_{(i,j,k)}$, one of the constraints (2) or (5) becomes redundant. In cases where the value of $\frac{\log(1-r)}{\log(q)}$ is greater than $H_{(i,j,k)}$, constraint (2) becomes redundant. On the contrary, when $H_{(i,j,k)} \geq \frac{\log(1-r)}{\log(q)}$, constraint (5) functions as the limiting expression.

$$\begin{aligned}
& 1 - q^{\sum_s \Omega_{s, (i,j,k)} X_s} \geq r \\
& \forall (i,j,k) \in (I,J,K)
\end{aligned} \tag{5}$$

Constraints concerning the relation between deployed sensors and covered blocks: Constraints (6) states that a deployed sensor covers blocks whose centroid are in the field of view of the sensor.

$$\begin{aligned}
& Y_{(i,j,k), s} = X_s \\
& \forall (i,j,k) \in (I,J,K) \\
& \forall s \in \Omega_{s, (i,j,k)}
\end{aligned} \tag{6}$$

Integrity constraints: Constraints (7), (8) and (9) show that the decision variables of the model are binary variables.

$$X_s \in \{0, 1\} \tag{7}$$

$$\forall s \in S \tag{8}$$

$$\begin{aligned}
& Y_{(i,j,k), s} \in \{0, 1\} \\
& \forall (i,j,k) \in (I,J,K)
\end{aligned} \tag{8}$$

$$\begin{aligned}
& \forall s \in S \\
& V_{(i,j,k),(u,w,z),s} \in \{0, 1\} \\
& \forall (i,j,k),(u,w,z) \in (I,J,K), (i,j,k) \neq (u,w,z) \\
& \forall s \in S
\end{aligned} \tag{9}$$

The proposed integer linear model includes $|S|(1+|(I,J,K)|+|(I,J,K)|^2)$ variables. In addition, the number of constraints in the model is equal to $|(I,J,K)|(|S|(|(I,J,K)|-1) + 2 + |S|)$, excluding constraints (7), (8) and (9).

3. Materials, methods and results

Aiming to match real situations and measure the real features of sensors, we perform different experiments to calibrate the sensors. Section 3.1 describes our approach to carry out the sensor calibration. In order to validate the proposed modeling framework and study its efficiency, we employ the real values that we

obtain from the calibration of sensors, and we use two sets of numeric instances. The first set of data is generated randomly and the second one is gathered from a real case. We describe the results from the application of the model to both of the data sets in section 3.2 and section 3.3. And finally, in section 3.4, we present a tool (user interface) that is developed to support the sensor deployment and target tracking approaches that are proposed in this research. Using a test scenario, in section 3.4, we prove the working mechanism of our model and show how the interface monitors the location and well-being of a target living in AAL systems.

3.1. Sensor calibration

The general features of PIR sensors like the range of detection and field of view are not precisely known or they may drift over time, due to temperature, pressure or change in ambient conditions. The calibration of the sensors makes the sensors function as accurately, or error free, as possible. Indeed, the sensors are calibrated to improve their performance and provide more accurate data for decision making. The nominal values of the sensing range of the PIR sensors, identified by reference number 048920 and manufactured by the company Legrand in France, are depicted in Figure 3.

Please, insert Figure 3 approximately here.

Please, insert Figure 4 approximately here.

The features that we measure in our experiments are the detection distances in front and on the sides. A trolley equipped with sensors and cameras is used to verify the results, see Figure 4. The results show a difference between the obtained values from the experiments and the values that are documented in the manufacturer’s catalogue. According to the experiments, the detection width is guaranteed to be up to 5.7 meters in 100% of experiments, and in 60% of cases it is over 6.6 meters. Besides, in 100% of cases the width of the longitudinal detection is satisfactory up to an average distance of 2.3 meters. Furthermore, the detection length is up to 12 meters in 100% of cases and the longitudinal detection length is satisfactory up to an average distance of 3.3 meters. These results help us to employ real values to optimize the placement of the sensors and track the location of a target who is present in an AAL environment.

3.2. Random data generation and results

In order to verify the efficiency of the proposed model, different random instances are generated. Table 1 shows the pattern that is used to generate data for the different parameters of the model. To initialize the parameters in each of the instances, a random value is generated using the statistical distributions that are presented in Table 1. As represented in Table 1, the employed distributions are the bounded discrete uniform and bounded continuous uniform distributions. The values for the bounds of the statistical distributions are estimated by experts in the AAL systems. The model is solved for each of the instances using the LINGO 11.0 optimization solver. The tests are executed on a computer with Pentium Core i5, 2.70 GHz processor and 16.0 GB memory.

Please, insert Table 1 approximately here.

As depicted in the first column of Table 2, six different instances ranging from small to large sizes are considered. In the second column of Table 2, the first line represents the size of the instance, i.e. the number

of blocks by the number of sensor IDs, $|(I,J,K)|*|S|$. The second and third lines in the second column of Table 2 outline respectively the number of decision variables and the number of constraints in each of the instances. The expressions $|S|(1+|(I,J,K)|+|(I,J,K)|^2)$ and $|(I,J,K)|(|S|(|(I,J,K)|-1) + 2 + |S|)$, which are presented in Section 2, are used to determine respectively the number of decision variables and the number of constraints of the instances. The third column of Table 2 represents the total number of sensors that is required for deployment. The fourth column reports the value of the objective function. It represents the total cost of deployment of sensors in each of the instances. And finally, the fifth column represents the elapsed time by the solver to read the data from a excel file, solve the model and save the results in the same excel file.

The performance and efficiency of the model are analyzed with regard to the resolution time in different sizes of the instances. As presented in the fifth column of Table 2, the resolution time of the model increase with the augmentation in the size of the model. However, it is short enough in small and medium sizes of the instances. The short resolution time of the model makes it more applicable and shows the efficiency of the proposed mathematical model.

Regarding the results presented in the third column, it is worth noting that the number of the deployed sensors directly depends on $\Omega_{s,(i,j,k)}$. If each of the sensors covers large number of blocks, the model will employ more sensors in order to differentiate the codes and create unique arrays. Inversely, if the intersection of the blocks covered by sensors is not much, the model will deploy fewer sensors. In instance 7, because of the low intersection between the blocks that are covered by same sensors, the model employs fewer sensors. It must be mentioned that in this study, we discretize the region of interest according to desirable scaling. In large sizes of the instances, we suppose that the region of interest is large enough. We also assume that there are no major limitations in the number of deployed sensors or complexities in the installation of the sensors.

Please, insert Table 2 approximately here.
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3.3.Real data collection and results

To study the applicability of the proposed theoretical framework, we apply the model to a set of real data derived from an AAL lab that is called GIS MADONAH and located in Bourges, a city in France. The lab is a housing alternative to give assistance to people who cannot perform some activities of daily living independently. Possessing automation facilities, specific furniture, sensors networks and computers, the lab provides means to study the safety and well-being of inhabitants in smart homes. The total space of the lab is partitioned into five different parts, consisting of a bedroom (18 m²), a living room (22.5 m²), a corridor (9 m²), a kitchen (9 m²) and a bathroom (11 m²) with 2.7 meters of ceiling height. Photos of the lab are given in Figure 5. Considering hidden zones and using a suitable scale, the area is further discretized into smaller zones (blocks). The PIR sensors manufactured by the Company Legrand are used in the lab for target tracking. Three levels of the field of view, including level 1=60°, level 2 =120° and level 3=180°, and one orientation, i.e. to forward, are considered for the sensors. The sensing range and deployment cost of a single sensor in the network are respectively equal to 12 meters and 160 euros. Regarding the different causes leading to failures in the network and using expert assessments, the failure rate of the sensors and the network reliability are presumed to be respectively 25% and 98%. Since different parts in the lab are separated by walls, they are independent of each other. Therefore, the sensor placement is separately optimized in each part.

Please, insert Figure 5 approximately here.

Figure 6 shows the results of the application of the model in the GISMADONAH lab. In the figure, the surfaces, which are forbidden for sensor deployment, are shown by bold red lines. A deployed sensor is identified by a quadruple $[S_n][a][b][c]$, where n presents the ID number of the sensor, a shows the orientation (since we suppose only one orientation, i.e., towards forward, to deploy a sensor, a is always equal to 1), b is the level of the field of view, and c presents the surface on which sensor S_n is placed. Different parts of the living lab are partitioned into small blocks. Both the bedroom and living room are divided into 4 blocks. The bathroom, corridor and kitchen are respectively partitioned into 3, 2 and 2 blocks. The case is solved when $H_{(i,j,k)} = 1$, where we suppose that each block is covered by at least one sensor. It is noteworthy that the model produces the same results for $H_{(i,j,k)} = 2$ and $H_{(i,j,k)} = 3$. This matter can be justified by the fact that each of the blocks in different parts of the lab is covered by at least three sensors when $H_{(i,j,k)} = 1$. In order to provide the area coverage and track the target's location at 98% level of reliability, the model covers every block with more than one sensor. Five sensors are employed in the bedroom, including one sensor placed on the wall-left hand side with 180° of field of view, one sensor on the wall-right hand side with 120° of FoV, two sensors on the ceiling with 120° FoV and one sensor that is placed on the ceiling with 180° of FoV. The constituent blocks of the bedroom are covered by $(S_1 S_3 S_4 S_5)$, $(S_2 S_3 S_4 S_5)$, $(S_1 S_2 S_3 S_4 S_5)$ and $(S_1 S_2 S_4 S_5)$ sets of sensors. As can be seen, these sensor deployments assign unique codes to each block that help to distinguish the location of the target who is present in the lab. The quadruple $[S_1][1][2][C]$ in Figure 6 shows that sensor S_1 is oriented towards forward, set on the second level of field of view (level 2 = 120°) and placed on the ceiling. To find the placement of the sensors in the other partitions of the lab, please see Figure 6.

Please, insert Figure 6 approximately here.

Please, insert Table 3 approximately here.

In order to validate the proposed mathematical model, we perform sensitivity analysis. For this purpose, we study the variation in the total number of the deployed sensors in different parts of the lab when there are variations in the network reliability levels and sensor failure rates. In order to study the change in the total number of deployed sensors according to the changes in the reliability level of the network, we suppose that the failure rate of the sensors is equal to 25%. We also assume that the network reliability level varies from 80% to 100%. On the other hand, when studying the variation in the total number of deployed sensors with sensor failure rate, we suppose that the network reliability level is fixed at 98% and the failure rate varies between 15% and 40%. We note that the above-mentioned values (fixed and changing values) are determined according to expert assessments. Furthermore, to carry out the sensitivity analysis, we presume that the deployment cost of a sensor in the network (C) and $H_{(i,j,k)}$ are respectively equal to 160 euros and 1. Table 3 outlines the obtained results from the sensitivity analysis. We expect that the total number of the deployed sensors increases with an increase in the network reliability level as well as the sensor failure rate. The results outlined in Table 3 justify this expectation. In our case, by transition from 85% to 90% of the reliability, no change in the number of the deployed sensors is found. This states that the model is only sensitive to the reliability levels which are greater than 90%. Furthermore, concerning the failure rate of the sensors, one can see that the model is more sensitive to the different variations in the value of this parameter. Using the results obtained from the sensitivity analysis for the network reliability level, an alternative that satisfies the decision makers more can be selected as a proposition to establish the sensor network. Considering that the failure rate of sensors in our case is equal to 25%, fixing the network reliability level at 98% (establishment of a sensor network with 98% of reliability level) is a satisfying proposition.

3.4. Interface for data display

In this section, we present the graphical interface that is developed using the theoretical approach of this paper. The interface employs the data that is collected by the deployed sensors and reports the real-time location of a target in the GIS MADONAH lab. In addition, it outlines the values that are measured to show some properties related to the environmental quality of the lab, such as the humidity and noise level. The measurement of these properties allows the AAL service providers to control the well-being and comfort of an inhabitant in the lab. Figure 7 depicts the different parts of the developed interface. It presents on:

- The left-hand side, the plan of the GIS MADONAH lab,
- The right-hand side, different indicators that are used to control different factors in the lab. They include:
 - The energy consumption indicator, which calculates the electrical energy consumed by TV, electrical doors, lights and HVAC system as well as the electrical energy consumed in the kitchen.
 - The comfort indicator that measures the temperature, humidity, volatile organic compound emissions, CO₂ emissions and noise level in the lab.
 - The presence indicator that shows the real time location of the target in different parts of the lab.

Please, insert Figure 7 approximately here.

Please, insert Figure 8 approximately here.

A single scenario is defined and played once to verify the real-time location of a single target in the lab. It describes a person that enters the corridor from the outside, then, goes to the living room to watch TV, then, prepares a meal in the kitchen. Thereafter, she/he goes to the living room to dine, while watching TV, and finally, goes to the bedroom to sleep. The data collected by the sensors is imported into the interface and processed to provide the results. Figure 8 summarizes the results. The figure presents the recognition of different activities that are performed by the target according to the scenario. Figure 8 (a) shows that the target is in the corridor (the door icon is to show an entrance into the corridor of the home). Figure 8 (b) depicts that the second location of the target is in the living room in the zone where the sofa is located (the sofa icon presents a part of the living room where sofas are placed). In Figure 8 (c), the target is in the kitchen. Figure 8 (d) shows that the target is in the living room and in the zone where the dining table is located. And, Figure 8 (e) shows that the target is in bed. As can be seen, the interface provides the results that correspond well the defined scenario. These results prove that the sensor placement is efficient and recognize the real-time location of the target in the lab. The developed interface presents a graphical tool that eases the monitoring of the location and comfort of the target in the lab. The efficient target tracking and comfort monitoring system help to provide real-time services, such remote counselling or nursing services, and boost the capability and functionality of the lab.

4. Conclusion

Ambient Assisted Living (AAL) aims to develop the services that support the independent life of the older or disabled people living in ambient assisted environments. A typical AAL system consists of a user target, wireless sensor networks, computers and programs. In these systems, the collected data from the sensors is used to provide the assistance services to user targets. Being a newly observed domain, the AAL systems show major requirements for affording optimal and efficient solutions for the deployment of sensors and

tracking the location of targets. In the AAL systems, the cost and performance efficiencies of sensor networks depend directly on the number of deployed sensors as well as the approaches that are employed to track the location of the targets. For this reason, proposition of an optimal and efficient solution is only possible with simultaneous consideration of these two factors. In this paper, we propose an approach to track a target in an AAL environment, and we contribute to the literature by presenting a new Integer Linear Programming model that optimizes the deployment of sensors according to the proposed target tracking approach. Considering the layout of the AAL environment, its obstacles and hidden zones, the model presented in this paper determines appropriate areas to deploy the monitoring sensors. It also proposes proper configurations for the orientation and field of view of the sensors. Furthermore, since the sensors in the network are subjected to failures, the mathematical model of this paper guarantees a minimum level of reliability for the AAL system operation.

To show the efficiency of the proposed model, we use a set of randomly generated data. The short resolution time of the model proves its efficiency. In order to validate the model, we perform the sensitivity analysis using a set of real data that is gathered from an ambient assisted living lab. In addition, we determine a test scenario and run it in the same lab. The results of the implementation of the scenario prove our theoretical framework. We also develop a user interface that employs the approaches that are proposed in this paper. The interface helps the AAL service providers to visualize the recognition of the location, movements and activities of a target who is present in an ambient assisting environment. It also facilitates the monitoring of the comfort of the user target as well as the total consumed electrical energy in the AAL environment.

For future research, the study can be investigated by considering the uncertainty of different parameters of the model, such as the failure rate of the sensors and/or their deployment costs. To model the uncertainties, the robust optimization and fuzzy programming approaches could be of interest. Furthermore, the problem can be extended by adding more criteria for optimization, such the maximization of the network lifetime and/or maximization of the coverage quality.

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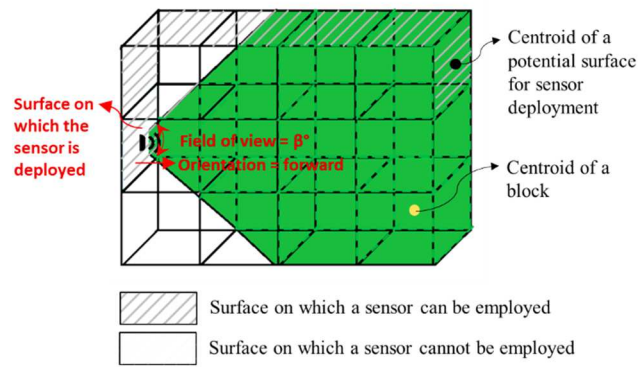


Figure 1. Presentation of a typical sensor deployed in a region of interest that is discretized into small blocks.

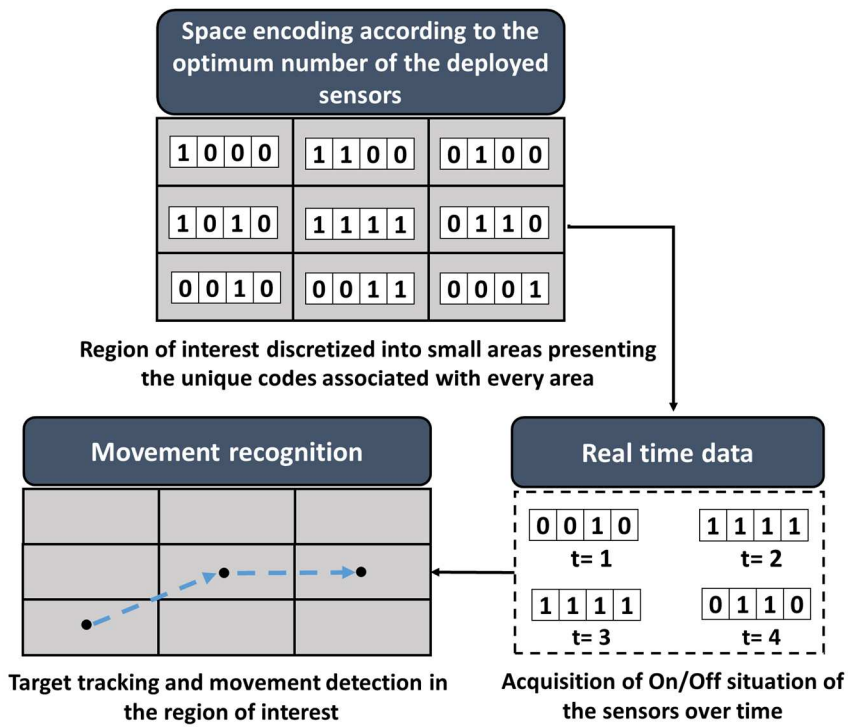


Figure 2. Illustration of the approach presented to track the targets according to the optimal number of deployed sensors.

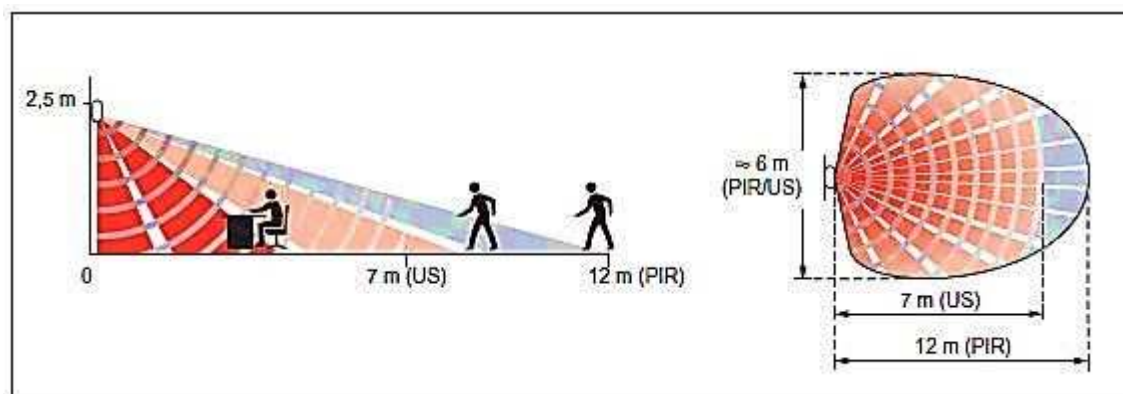


Figure 3. Documentation of different features of PIR sensors determined by the company Legrand.



Figure 4. Trolley equipped with cameras and sensors.



Figure 5. Different parts in the GIS MADONAH AAL lab: (a) living room, (b) kitchen and (c) bathroom.

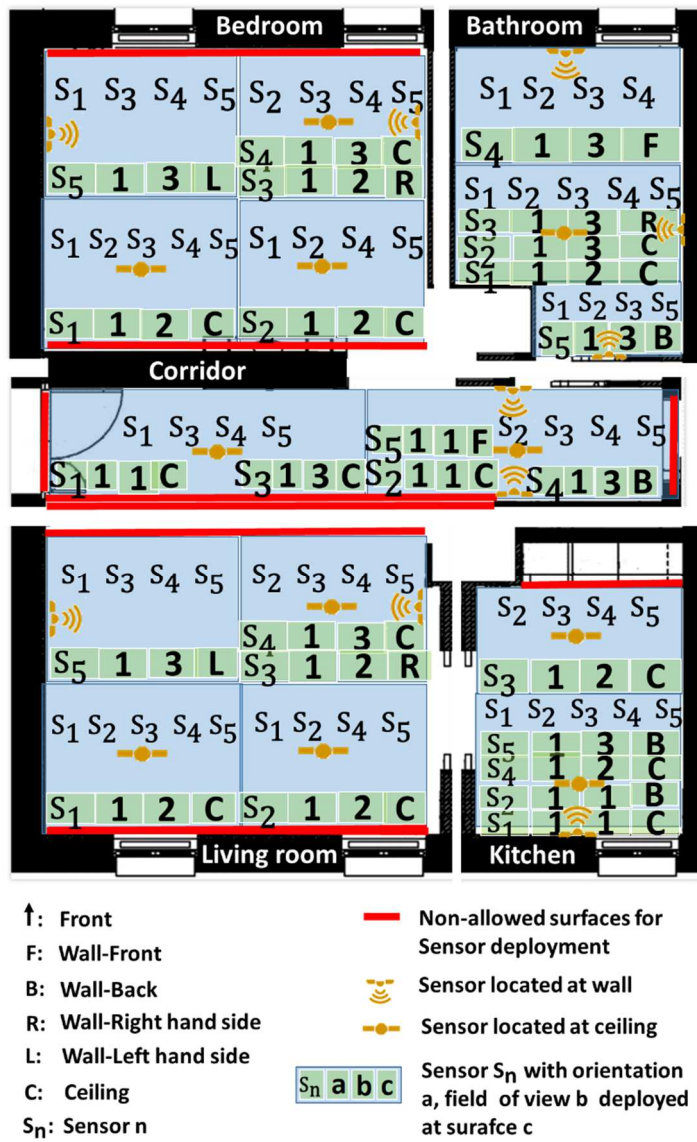
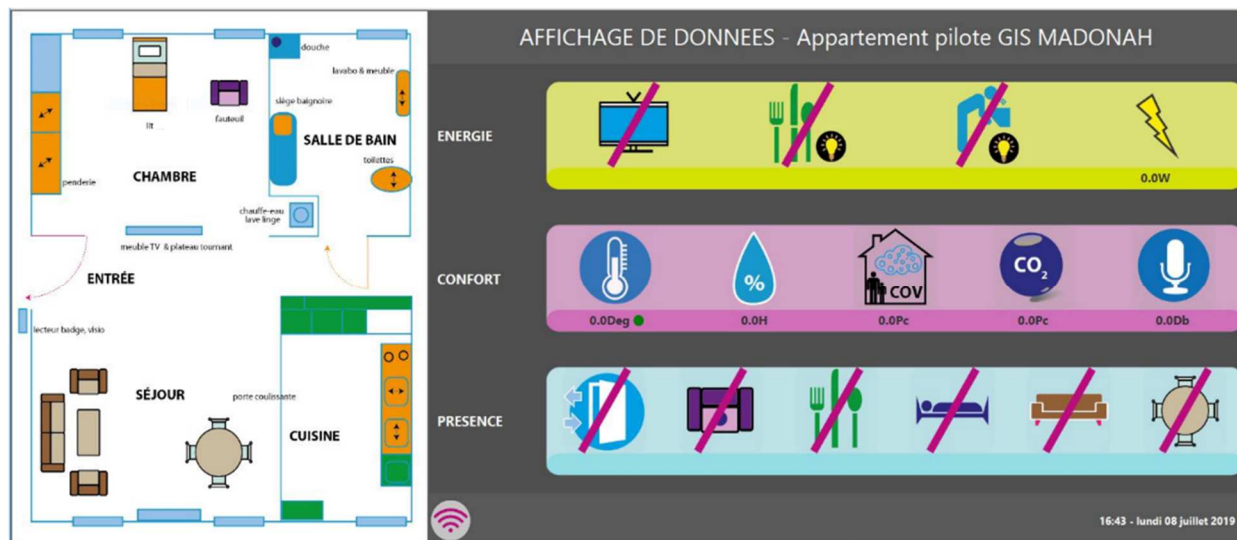
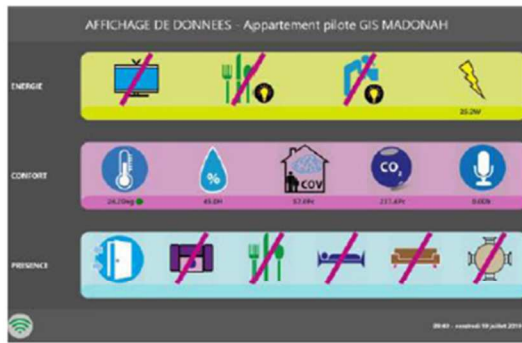


Figure 6. Optimal solution for sensor deployment in the GIS MADONAH lab.

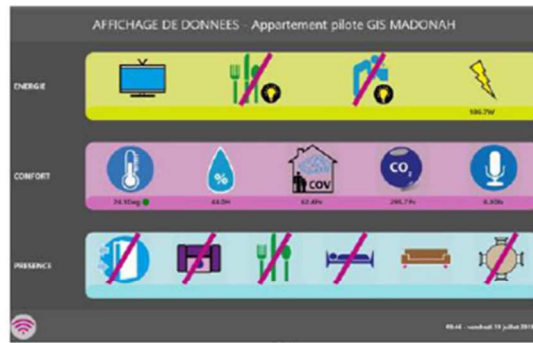


French terms	English equivalent	French terms	English equivalent	French terms	English equivalent
Affichage de données	Data display	Energie	Energy	Meuble TV & plateau tournant	TV stand & turntable
Appartement pilote	Flat	Entrée	Entrance	Penderie	Wardrobe
Chambre	Room	Fauteuil	Armchair	Porte coulissante	Sliding door
Chauffe-eau	Water heater	Lavabo et meuble	Sink and cabinet	Presence	Presence
Confort	Confort	Lave ligne	Washing machine	Séjour	Living room
Cuisine	Kitchen	Lecteur badge, visio	Badge reader, visio	Siège baignoire	Bath seat
Douche	Shower	Lit	Bed	Toilette	Toilet

Figure 7. Screen shot of the developed interface. The figure includes the translation of French terms to their English equivalents.



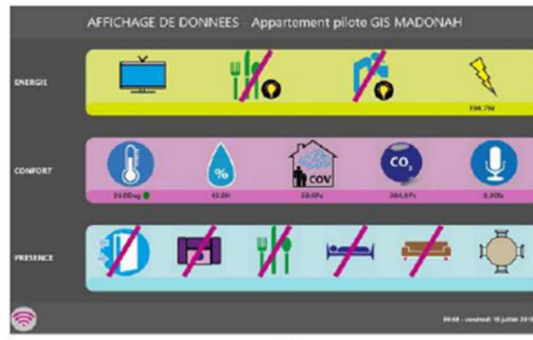
(a)



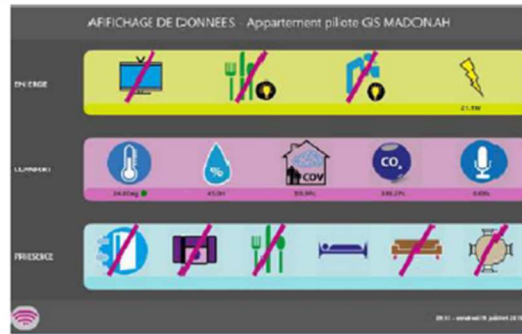
(b)



(c)



(d)



(e)

French terms	English equivalent
Affichage de données	Data display
Appartement pilote	Flat
Confort	Confort
Energie	Energy
Presence	Presence

Figure 8. Screen shot to present the recognition of different activities performed by a target in the lab. The figure includes the translation of French terms to their English equivalents.

Table 1- Test problem generation.

Parameter	Corresponding statistical distribution
$H_{(i,j,k)}$	~ Discrete uniform (1, 3)
C	~ Continuous uniform (150, 200)
$\Omega_{s, (i,j,k)}$	~ Discrete uniform (0,1)
r	~ Continuous uniform (0.5, 1)
q	~ Continuous uniform (0,1)

Table 2- Results of the model for different sizes of instances.

Test	Dimension (I,J,K) * S Number of the decision variables Number of the constraints	Number of deployed sensors	Value of the objective function (€)	Resolution time (s)
1	6 * 25 1 075 912	5	810.000	1
2	14 * 37 7 807 7 280	7	1 141.000	2
3	28 * 52 42 276 40 824	21	3 423.000	14
4	48 * 97 228 241 223 584	46	7 498.000	43
5	62 * 185 722 795 711 264	185	9 780.000	258
6	70 * 210 1 043 910 1 029 140	70	11 410.000	433

Table 3- Number of deployed sensors in the living lab according to the reliability levels and failure rates.

Reliability Level	Bedroom	Living Room	Corridor	Bathroom	Kitchen	Total	Failure Rate	Bedroom	Living Room	Corridor	Bathroom	Kitchen	Total
1	8	8	9	10	8	43	0.4	6	6	6	6	6	30
0.98	4	4	4	4	4	20	0.35	5	5	5	5	5	25
0.95	4	4	4	4	4	20	0.3	5	5	5	5	5	25
0.9	3	3	3	3	3	15	0.25	4	4	4	4	4	20
0.85	3	3	3	3	3	15	0.2	4	4	4	4	4	20
0.8	3	3	3	3	3	15	0.15	3	3	4	4	4	20

Graphical Abstract

