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Towards optimal sensor deployment for location tracking in smart home

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Abstract - Ambient Assisted Living (AAL) aims to ease the daily living and working environment for disabled/elderly people at home. AAL use information and communication technology based on sensors data. These sensors are generally placed randomly without taking into account the layout of buildings and rooms. In this paper, we develop a mathematical model for optimal sensor placement in order (i) to optimize the sensor number with regard to room features, (ii) to ensure a reliability level in sensor network considering a sensor failure rate. This placement ensures the target tracking in smart home since optimizing sensor placement allow us to distinguish different zones and consequently, to identify the target location, according to the activated sensors.

Keywords: Ambient assisted living, sensor PIR, target tracking, mathematical modelling.

I. INTRODUCTION

According to the statistics published by the World Health Organization [1], the number of people aged 60 and over will double in 2050. Consequently, a significant effort is required to develop Ambient Assisted Living (AAL) systems that ensure comfort and safety for elderly people in their smart homes [2]. AAL systems use a set of connected sensors and ICT (Information and Communication Technology) to treat sensor data in order to recognize activities of daily living or to assist elderly people.

PIR (Pyroelectric InfRared) sensor networks are widely used for indoor target tracking [3,4,5]. Binary data are studied and analyzed using data mining approaches [6,7] and learning procedure to track targets [8]. In the context of target tracking, computational geometry methods such as high order Voronoi diagram are also used by [9]. In [10], the authors present space encoding and decoding techniques for multiple target tracking. Using these methods, a single identification may be associated with multiple spaces. In order to cope with this issue, the development of an extra distinguishing phase is required. The size of the generated data depends on the number of deployed sensors in the network. Hence, developing an effective tracking scheme relying on a proper number of sensors will be of significant importance.

Sensors in buildings are used for a wide variety of applications such as monitoring air quality and indoor temperature. In the

context of the optimum 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] presents several optimization models taking into account different objectives such as maximization of the sensor life time, 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] develops a multi objective optimization model to simultaneously maximize coverage and life time in sensor networks. Zhao et al [14] develops a Mixed Integer Linear Programming (MILP) model to extend the network life time by optimal placement of sensors. To validate the model, the authors develop heuristics and conduct a set of different experiments. Rebaï et al [15] proposes a model to optimize the sensor placement in the network with the consideration of connectivity between sensors. In Karabulut et al [16], a bi-level non-linear programming model is developed to deploy sensors. Ahmed et al [17], proposes an integer linear programming model to maximize the network lifetime. The authors define the life time as an 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 with regard to uncertainties due to occupancy and boundaries fluxes of buildings [18]. A relaxation sequential algorithm is proposed for optimal sensor placement [19]. The optimal sensor placement is similar to the optimal camera placement problem [20].

The literature review prove that researches have focused on the optimal sensor placement for different topics such as mobile wireless networks, wearable activity recognition, etc. We propose a mathematical model based on linear programming. The proposed approach take into account room features and hidden zones where sensors cannot be placed. The approach is adapted to building layout. We propose the sensor placement for target tracking. Indeed, the sensor placement is calculated taking into account a unique sensors combination for each adjoining zone knowing that each zone is covered by several sensors. Theses combinations allows us to identify according to the activated sensors, the target location. Besides, in wireless sensor network, it is probable that one or more sensors breakdown 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 [21]. In sensor networks, deploying

a system that is both reliable and inexpensive is important. The consideration, evaluation and analysis of the reliability in the sensor networks regarding internal and external factors are discussed in [22, 23, 24]. The proposed approach takes into account a minimum level of reliability to be satisfied.

In section 2, we describe the proposed problem and the mathematical model. The results obtained on a real-world case are outlined in section 3. And finally, a summary of the study presenting the conclusion and perspective for the future works are provided in section 4.

II. PROBLEM DESCRIPTION

We suppose that a three-dimensional environment is covered by PIR sensors. The area is discretized into small blocks with different sides (Figure 1). Sides are the surface where we can deploy sensor or not (due to technical constraints). Each sensor is identified by three features: the surface (side) on which it is deployed, the level of its Field Of View (FOV), and its orientation. Sensors are assumed to be deployed in the center of the surface. Furthermore, we suppose that a block can be covered by a sensor if its centroid is observed by this sensor.

The target tracking scheme in the proposed model associates an array of binary numbers to each block. The array size is equal to the optimum number of sensors needed to cover the block. This number is defined by the solution of the mathematical model. The main aim in the proposed target tracking method is to cover each block by a unique binary code (array) which allow us to identify the target location. Following the received data of the sensors deployed in the network, these unique binary arrays give ability to identify the target location and trace his path (see Figure 2).

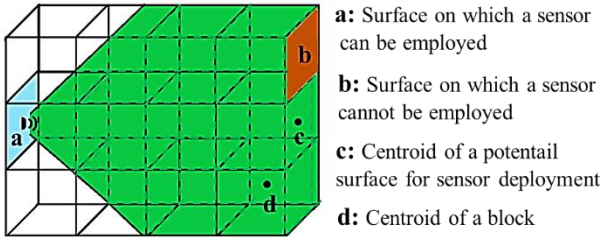


Figure 1. Area discretization and sensor deployment

Every block is supposed to be covered by a minimum number of sensors with a pre-determined value in order to guarantee the target tracking and the reliability level for the sensor network. The objective of the model is to minimize the total cost of deployed sensors in the region of interest while meeting the problem constraints.

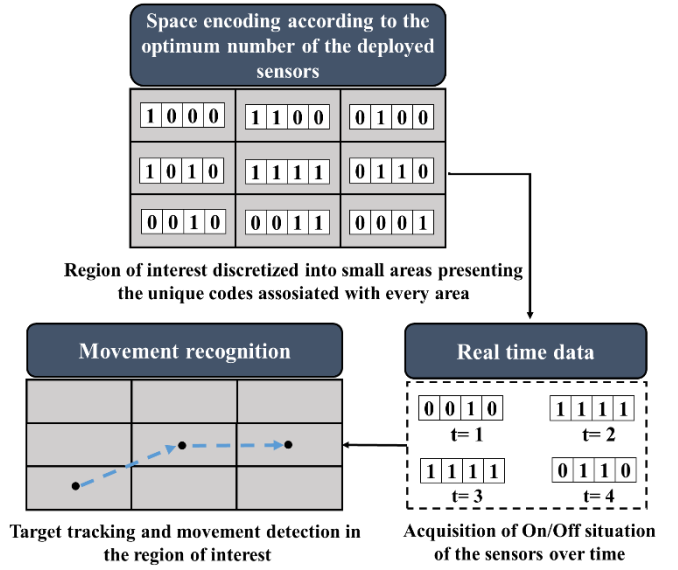


Figure 2 Example of target tracking with optimal sensor deployment.

The following notations are used to present the mathematical 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 a block (i, j, k) .

$\Omega_{s,(i,j,k)}$: a binary matrix that indicates for each block (i, j, k) , the set of sensors that cover it, i.e. $\{s \mid d \leq R_s^{\text{sensing}}, CP \in \text{FoV}_s\}$, where d is the Euclidian distance from the centroid of the surface where sensor s is located to centroid of the block (i, j, k) . R_s^{sensing} is the sensing range of sensor s . Besides, to have a coverage in a block, the center point of the block needs to be in the sensor's field of view, $CP \in \text{FoV}_s$.

r : network reliability

M : A large positive number

C_s : cost of deploying sensor s in the network.

q : failure rate of sensors in the network.

Decision variables:

$X_s = 1$ if sensor s is deployed. 0, otherwise.

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

$V_{(i,j,k),(u,w,z),s}$: auxiliary binary decision variable.

The mathematical model of the problem is described below. The objective function (1) minimizes the total cost of deploying sensors in the region of interest.

III. EXPERIMENTS AND RESULTS

$$\text{MIN } Z = \sum_s C_s X_s \quad (1)$$

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

$$\sum_s \Omega_{s,(i,j,k)} Y_{(i,j,k),s} \geq H_{i,j,k} \quad \forall (i,j,k) \in (I,J,K) \quad (2)$$

Constraints (3) and (4) guarantees that block (i,j,k) and (u,w,z) are covered by two different combination of sensors in order to distinguish zones and to identify target location. These constraints ensure the unique sensors combination for each zone.

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

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

$$\sum_{b \neq s} \max((\Omega_{b,(i,j,k)} - \Omega_{b,(u,w,z)}), 0) Y_{(i,j,k),b} + \sum_{b \neq s} \max((\Omega_{b,(u,w,z)} - \Omega_{b,(i,j,k)}), 0) Y_{(u,w,z),b} \geq 1 - M(1 - V_{(i,j,k),(u,w,z),s}) \quad (4)$$

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

Network reliability is guaranteed by constraints (5). Supposing that the failure rate of the sensors are identical and independent probability values, $q^{\sum_s \Omega_{s,(i,j,k)} X_s}$ is the probability in which all the sensors that can cover block (i,j,k) are down. This value subtracted from one, states the probability that one or more sensors are operational. Therefrom, the constraint (5) guarantees the reliability level in which at least one sensor is operational to monitor the area. These constraints can be also equivalently identified by the following linear expression:

$$\sum_s \Omega_{s,(i,j,k)} X_s \geq \frac{\text{LOG}(1-R)}{\text{LOG}(q)}$$

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

Constraints 6 determines the relation between decision variable X_s and $Y_{(i,j,k),s}$.

$$\max(\Omega_{s,(i,j,k)}, 0) Y_{(i,j,k),s} = \max(\Omega_{s,(i,j,k)}, 0) X_s \quad (6)$$

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

$$X_s \in \{0, 1\}, \forall s \in S \quad (7)$$

$$Y_{(i,j,k),s} \in \{0, 1\}, \forall (i,j,k) \in (I,J,K); \forall s \in S \quad (8)$$

$$V_{(i,j,k),(u,w,z),s} \in \{0, 1\} \quad (9)$$

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

Constraints 7, 8 and 9 are the integrity constraints.

Different random instances and experiments are generated in order to assess the efficiency of the proposed mathematical model. To validate the applicability of the proposed theoretical framework, data from a real case is used. The model is coded in LINGO 11.0 optimization software and the tests are performed on a notebook with Pentium Core i5, 2.70 GHz Processor and 16.0 GB Memory.

TABLE 1 -RESULTS OBTAINED FROM MODEL FOR DIFFERENT SIZES OF THE PROBLEMS

Test N°	Dimension (I,J,K) * S No. of variables No. of constraints *	Objective function value (€)	CPU time (s)
1	6 * 25 1 075 912	810.000	1
2	14 * 37 7 807 7 280	1 141.000	2
3	28 * 52 42 276 40 824	3 423.000	14
4	48 * 97 228 241 223 584	7 498.000	43
5	62 * 185 722 795 711 264	9 780.000	258
6	70 * 210 1 043 910 1 029 140	11 410.000	433

Table 1 shows the results obtained from six different instances ranging from a small size to a large one. Tests differ from each other in the parameter setting, decision variables and constraints number. The performance of the obtained results is analyzed regarding to resolution time and objective function value.

To illustrate the model applicability, the proposed theoretical framework is applied on a set of real data derived from an AAL lab¹ located at Bourges city in France. 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 (9m²), a kitchen (9 m²) and a bathroom (11 m²) with 2.7 meters of ceiling height. Considering the regions that are not allowed to sensor deployment, and also using a suitable scale, the parts are further discretized into smaller areas. Three levels for sensors' field of view, level 1=60°, level 2 =120° and level 3=180° are defined. We consider only one direction for sensor orientation, i.e. forward. The sensing range and unit cost of sensors is defined according to the values mentioned by the sensors' manufacturer, being respectively equal to 12 meters and 160 euros. Regarding the different causes leading to failures in the network and using the expert assessments, the failure rate of the sensors and the network reliability are presumed to be respectively 25% and 98%.

¹ The lab, called [GIS MADONAH](#), is a housing alternative to give assistance to people who cannot perform some activities of daily living independently. Using automation facilities, specific furniture, sensors networks and computers, the lab aims to increase safety and well-being of inhabitants in smart homes.

Figure 3 shows the results of the model when $H_{(i,j,k)} = 1$. It is noteworthy that the model produce the same results for $H_{(i,j,k)} = 2$ and $H_{(i,j,k)} = 3$, since each zone is covered by at least three sensors in $H_{(i,j,k)} = 1$. The model covers every zone by more than one sensor. This fact originates from constraints (3), (4) and (5) which satisfy the reliability level in the system and guarantee the unique codes that should be assigned to each zone in order to identify the target location.

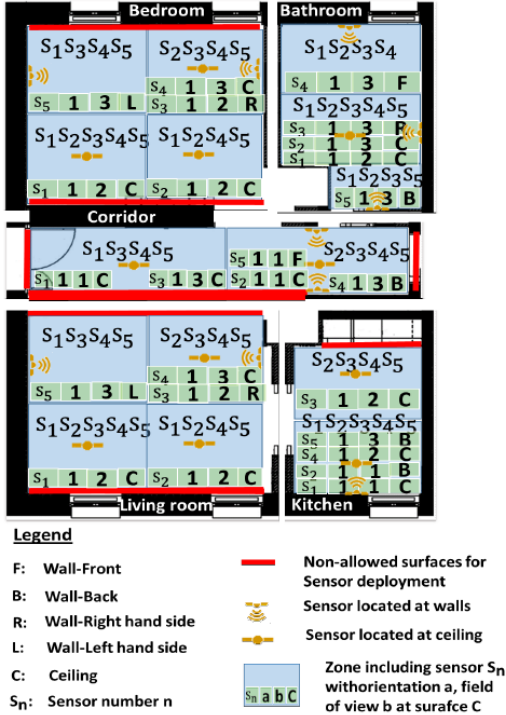


Figure 3- Optimal sensor deployment solution

Sensitivity analyses are conducted to observe how the deployed sensors number changes regarding to variations in the network reliability level and its failure rate. Since different parts in the lab are separated by walls, they are considered to be independent. Hence, the sensor placement is optimized in each part. The results of the analysis are outlined in table 2. The number of deployed sensors increases with an increase in reliability level and failure rate of the sensors. According to the results outlined in table 2, by transition from 85% to 90% of the reliability level, there is no change in the sensor number deployed. By increasing the failure rate from 20% to 40%, the difference between the number of the deployed sensors increases from 20 to 30.

TABLE 2 -NUMBER OF DEPLOYED SENSORS IN THE LIVING LAB ACCORDING TO THE RELIABILITY LEVEL AND FAILURE RATE.

Reliability level	Number of deployed sensors
1	15
0.98	15
0.95	15
0.9	20
0.85	20
0.8	43

Failure rate	Number of deployed sensors
0.4	30
0.35	25
0.3	25
0.25	20
0.2	20
0.15	20

IV. CONCLUSION AND FUTURE RESEARCHES

Being a newly observed domain, the optimal sensor deployment shows major requirements for developing the schemes that ensure optimality, efficiency and reliability of sensor network. This paper develops a new mathematical model to optimize the placement of wireless binary sensor in smart homes. Considering the constraints related to buildings' in a 3D environment, the presented model proposes an optimal sensors' placement with regard to sensor features such as orientation and field of view. In order to track target's location, the model take into account the constraint of covering each zone by a different sensor combination in order to identify the target location using sensors data. Since sensors are subjected to failures, the theoretical framework assumes to guarantee of a reliability level in the system. We show the efficiency of the proposed approach with tests and real data.

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