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Optimized Sensor Placement based on Route

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***Abstract* — This paper presents an optimized math model for a sensor placement problem for an indoor positioning system under constraints of the cost limitation and the complete coverage of a floor plan. A scenario based grid placement is used and the sensor placement problem is formulated as an optimization problem for minimizing the maximum distance error in a sensor field associated with the probability of a target frequently pass for a grid's cell during its positioning calculation. The proposed algorithm is based on the simulated approach. The experimental results reveal that indoor positioning systems increase accuracy and performance when they take in consideration the most demanded route when placing the positioning sensors. Utilization of Ultra-Wide Band – UWB in indoor navigation systems improves the acquisition and positioning algorithm even in environments with a high number of walls and obstacles.**

Index Terms—Sensor Placement, Indoor Positioning, UWB.

I. INTRODUCTION

Recently, positioning and location sensing systems have become very popular, especially those systems dedicated to detect the location of objects or even people in indoor environments like hospitals, airports, train stations, etc. For example, with appropriate positioning system and accuracy is possible to detect the location of a medical equipment or a health care professional in a hospital; the position of maintenance tools in a construction site or plant; or even a simple system to count the number of peoples visiting a museum or using a train station service.

To accomplish all those real-world positioning applications, accuracy is something very important. The accuracy of an indoor positioning system will define how good the system is in detect and distinct an object's position from others in the same area, for instance. As another example, take a group of robots in a same room. If the positioning system does not have sufficient accuracy to detect the positioning of each robot, separately; it will be very hard to associate a robot and its specific position during certain time.

To improve more accurate indoor sensing systems, a series of recent advances in technologies and algorithms based on Radio Frequency (RF) have been proposed. In general, those technologies take in consideration low cost utilization of wireless devices in industrial and commercial buildings, factories, universities, and association with optimized algorithm to find a better sensor position into those structures.

Between various methods used for indoor positioning using RF, a common method is to use the Received Signal Strength Indicator (RSSI) of the transmitters found in the structured sensor environment.

A relationship between the RSSI and the distance between be transmitter and receiver will provide an estimate about the current position and relative pose of the mobile platform. The main issue with these solutions are associated with implementation, maintenance costs, system configuration, and power source as described by [1], [2], and [3] including available commercial solutions provided by [4], [5] and [6].

Figure 1 shows an example an indoor navigation and positioning system based on RF active beacons spread around a building floor. The blue dots in the wall represent the beacons (active RF transmitters) and the red dot in the center of the figure represents the receiver. A geometric algorithm based on trilateration is performed to estimate the position of an unknown point based on three other known points. Different techniques are used to calculate accurately the distance between the points, like Time Of Arrival (TOA), Time Difference Of Arrival (TDOA), Round Trip Time Of Flight (RTOF) or RSSI [7] [8].

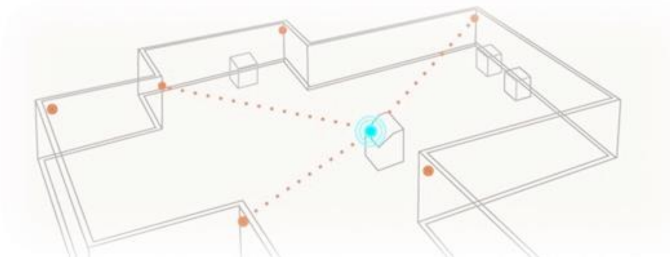

Figure 1. Indoor Navigation Positioning System. Source [7].

Another import point that also depends of the positioning system's accuracy is the tracing of a global and local path planning to be used by a robot or mobile platform to reach its destination point. Path planning represents an algorithm for autonomous systems that lets robots find the shortest or optimal path between two points. According with [9], a Global path planning consists of a path planning algorithm applied over the entire target environment (a map, a floor, a room, corridor, building, etc.) that, in general, demands more computational resources to calculate different alternatives and routes to be used by the mobile platform and managed by a central control system. A local path planning is the embedded algorithm used frequently and dynamically by a robot to avoid immediate obstacles that were not considered by the global path planning, but they are present in the same path way designed by the global path planning.

A key element to improve accuracy of positioning systems is how to cost-effectively place sensors to collect meaningful response data, so that the data well characterize fundamental navigational properties.

The general idea is develop an algorithm to minimize the number of sensors to cover the mapped area and, at the same time, maximize the distance covered by the signal transmitted for each sensor.

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Even recently, in most situations, the sensor placements are based purely on empirical judgment and experience of a technician or engineer [10]. In this regard, numerical sensor placement optimization has become a potential alternative and has been a research topic over last decades in the structural control, health-monitoring, and performance-modeling fields.

A variety of algorithms have been developed to facilitate sensor placement optimization. In [11], for instance, Handam and Nayfeh proposed a modal controllability and observability as metrics to instruct sensor placement determination. Worden and Burrows in [12] investigated fault detection and classification using neural networks. A Bayesian approach within a damage detection theory framework was proposed by Flynn and Todd in [13]. A few years ago, Yi et al. [14] applied a distributed algorithm for the optimal design of system sensor arrays. Zhang and Xu, in [15] used a Kalman filter framework with unknown excitation to conduct placement of different types of sensors. In [16], Papadopoulou et al. identified sensor configuration using sequential sensor placement algorithms.

Among these well-developed methods, the effective independence method first presented by Kammer, in [17], has been extensively applied in various sensor placement applications because of its simple concept and validated performance. In this method, a number of candidate sensor positions are eliminated or added in terms of their rankings evaluated by the determinant of a Fisher Information Matrix (FIM) [18]. On the other hand, because sensor measurement is unavoidably affected by ambient noise, the methods that take uncertainties into account become practically applicable. One potential method in this category, so-called information entropy, is widely adopted to address measurement uncertainty by finding the best match of structural testing that can minimize the negative consequence of uncertainty [19] [20] [21].

The process of sensor placement search and determination can be mathematically formulated as an optimization problem in which discrete variables represent the available sensor position in the structured system. The objective function, to be minimized or maximized, is defined to measure the performance of sensor configuration [22].

An exhaustive search for the optimal sensor configuration is computationally prohibitive, especially for large-scale structures with a huge number of rooms or levels. A different number of optimization schemes have been proposed to address the computational issue, such as simulated annealing in [23] and [24]. Genetic algorithms (GAs) was also introduced as a feasible approach by [25] and [26] where the authors improved the utilization of genetic algorithms to cope with the sensor location optimization problem by approximately solving the discrete optimization problem by exploring infinitesimal fractions over the entire sensor configuration space, allowing GAs to solve a wide range of problems with a global search function to reach optimal or near optimal solutions for engineering applications [27]. A drawback for the GA approach is the number of configurations and a final tuning process that still depend of a well experienced technician or engineer for the judgment for the final decision of sensor placement.

Currently, sensor placement analysis still requires repeated implementation to ensure result fidelity once the target indoor structure or the placement optimization metric changes. This research is conducted to address this issue by developing an optimized and dynamic sensor placement algorithm that take in consideration the most used route of a monitored specific agent or object (it could be a robot or a person for example).

The agent or object will provide statistical data that allow to calculate the most useful or common route in the indoor environment.

That statistical data or routes will be used as an input data for the sensor placement optimization algorithm, which will be taking in consideration the agent's path to minimize the sensors distance and maximize the signal transmission utilization.

The following sessions will present the methodology, mathematical modeling, and results obtaining by using this proposed sensor placement optimization approach.

II. METHODOLOGY

One of the first steps is how to represent properly a set of wireless network sensors. It can be done by two main different ways: with random placement or with grid-based placement. For unknown environments, random placement is the only choice and, sometimes, the alternative is to deploy sensors on a sensor field to guarantee a minimal and particular quality of service. The field is generally divided into grids and sensors are carefully deployed at the grid points like the one presented by Figure 2. A specific floor plan has its coordinates (x, y positions) related to a cell into the grid. This approach is called grid-based placement [28]. This paper focuses mainly on the utilization of this method.

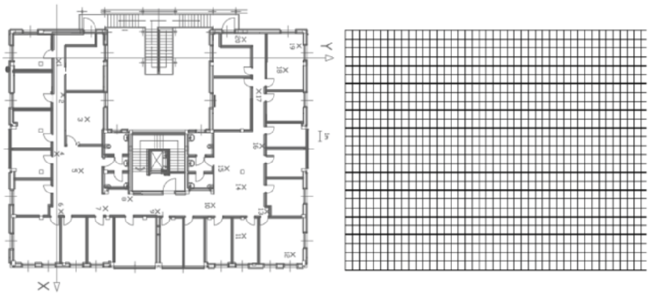

Figure 2. Example of floor plan divided into a grid. Source [28].

In [28] and [29] present a resource-bounded optimization framework for sensor resource management under the constraints of sufficient grid coverage of the sensor field while reference [30] details a sensor placement problem in terms of cost minimization under coverage constraints.

The sensor field is represented as a grid (two- or three-dimensional) of points. A target in the sensor field is therefore a logical object, which is represented by a set of sensors that see it. An irregular sensor field is modeled as a collection of grids. The optimization framework is however inherently probabilistic due to the uncertainty associated with sensor detections. The proposed algorithms for sensor placement address issues such as coverage optimization under constraints of imprecise detections and area properties.

In the proposed model, it is assumed that the probability of detection of a target by a sensor varies exponentially with the distance d between the target and the sensor. This model is illustrated in Figure 3. A target at distance d from a sensor is

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detected by that sensor with probability $e^{\beta d}$. Where the parameter β is used to model the quality of the sensor and the rate at which its detection probability diminishes according with the distance d. The detection probability is 1 if the target and the sensor are the same location in the grid. In a selected floor plan, divided into a respective grid, for every two grid points m and n in the sensor field, two probability values are associated: (1) $P_{\overrightarrow{mn}}$, which indicates the probability that a target at cell grid n is detected by a sensor at cell grid point m; (2) $P_{\overrightarrow{nm}}$, which denotes the probability that a target at cell grid m is detected by a sensor at cell grid n. Those values are equal when they are in direct line of sight and there are no obstacles between them, i.e. $P_{\overrightarrow{mn}} = P_{\overrightarrow{nm}}$. However, in general, those probabilities are not the same in the presence of obstacles.

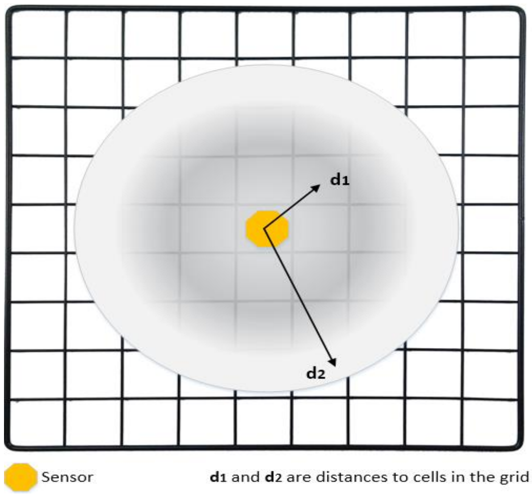

Figure 3. Sensors and probability detection model.

In an indoor environment, it is possible to establish a comparison about its mobility patterns with highway traffic with open or closed routes, conjunctions, and routes with more or less intensive traveled flow [31]. Considering that there are restrictions and limitations on the full coverage of sensors in a specific area, a natural solution would be to place the sensors to cover the most traveled area. By placing the sensors in those most traveled areas also take in consideration the relevance to calculate the positioning accuracy in those areas than the others in the rest of indoor space [32]. Following that natural solution, this research addresses an optimizing sensor placement algorithm with respect to how frequently a vehicle, robot or mobile agent crosses a specific region in an indoor environment.

An indoor environment, at the begging, does not provide any information about its mobility pattern and attempts to collect or generate such data becomes unfeasible [33].

Because of that, the proposed algorithm takes in consideration initial knowledge of the structural environment associated to the indoor space; the algorithm considers the floor plan and all contextual information associated to the positions of static objects (walls, doors, stairs, etc.) and dynamic objects (like furniture, etc.) inserted in the indoor environment.

Figure 4 considers the floor plan of a simplified hospital's room and assuming that a mobile agent like a doctor or a health care assistant, for example has a daily set of tasks that consists of a number of short path segments between random number of objects described in the floor plan (for example: table → couch → door → large table). Areas and objects related to those frequent tasks are then identified and augmented to describe the structural environment and their relevance during the task execution and path planning.

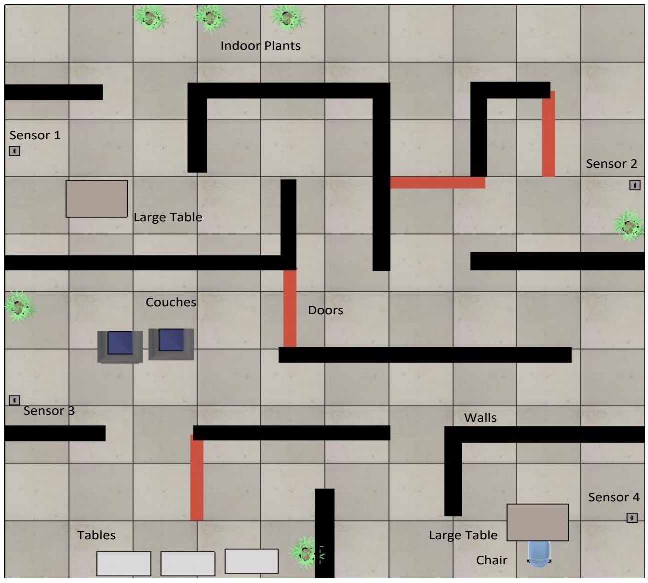

Figure 4. Floor Plan Model.

Figure 4 shows the result of the procedure and contains different number and types of objects: 1) walls; 2) doors and doorways; 3) Obstacle with constant position like walls and large tables; 4) obstacles with dynamic positions like chairs or couches; and 5) points of interest related to the set of tasks frequently executed. A detailed view of the floor plan and the description of some types and objects is presented in Figure 5.

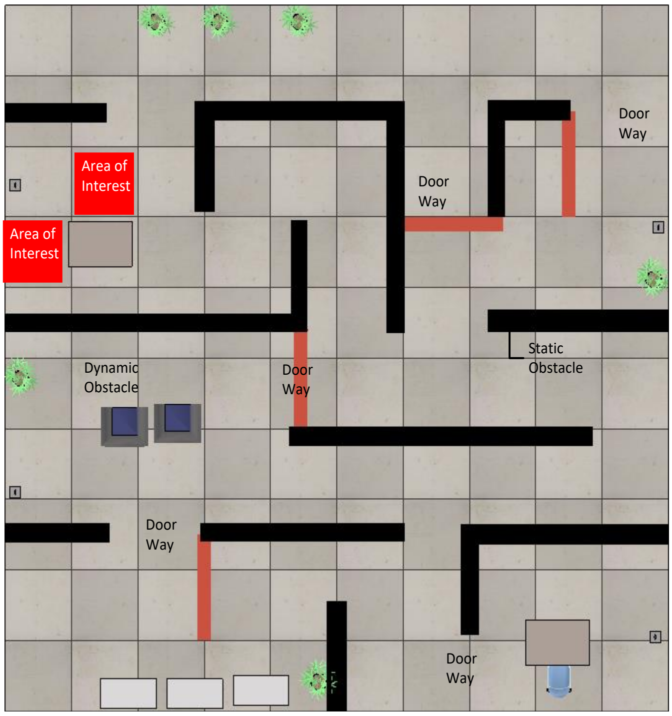

Figure 5. Detailed Floor Plan Model.

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In general, to improve results, certain sensors require a target to stay in their line of sight. Obstacles can cause occlusion and make such sensors unfeasible for detection. The sensor model considers a set of sensors less vulnerable to those limitations and it can even detect some targets by passing signals through some specific materials, like Ultra-WideBand (UWB) sensors for example.

The placement algorithm requires a previous knowledge of the floor plan prior to sensor placement. Existent obstacles are then modeled by updating their detection probabilities for specific cell grids. For instance, if an object such as a wall is present in the line of sight from cell grid m to cell grid n, then the probability is set to zero: $P_{\overline{mn}} = 0$ (see Figure 6). Partial occlusion can also be modeled by setting the detection probability to a small value different of zero. In all that scenario is assumed that the obstacles are considered static obstacles, since it is not considered sensor placement or grid coverage as a function of time yet; but this could be a future improvement buy merging different sensors and patterns recognition algorithms for example.

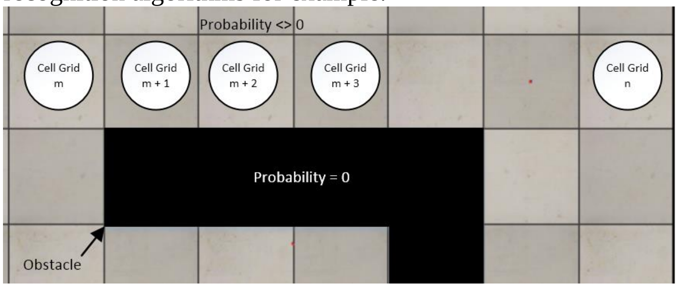

Figure 6. Obstacles (ex.: walls) in Floor Plan Model.

According with [34], dynamic objects in the floor plan is very interesting to provide the idea of context where tasks will be performed. To prepare the placement algorithm, it is assumed that those dynamic objects remain in certain cell grids, but may occasionally be moved to arbitrary locations. To model that dynamic behavior, it is assumed an area in the floor plan to limit their displacement, and then estimate all possible locations within that area that satisfy the size and dimensions of those dynamic objects. Figure 7 shows the limited area where the dynamic objects can be placed (Figure 7a), and estimated cell grids occupied for those objects according with their dimensions into the limited area (Figure 7b and Figure 7c, respectively.). Green areas in the picture identify estimated positions to place the dynamic objects (couches in that case).

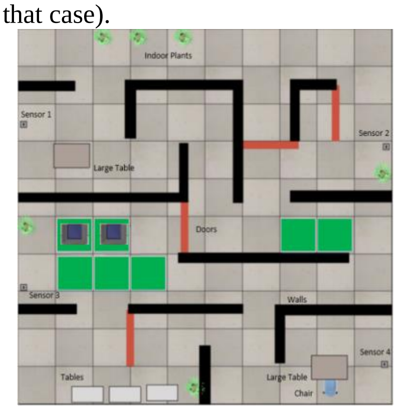

Figure 7a. Dynamic objects limited area.

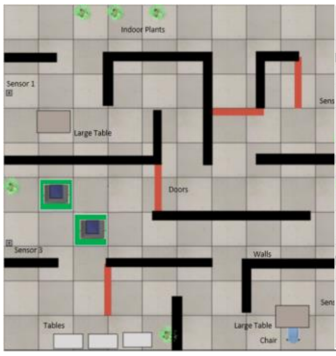

Figure 7b. Estimated position of dynamic objects in the limited area

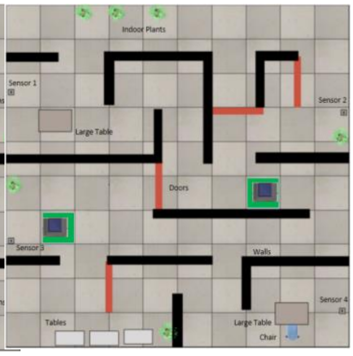

Figure 7c. Another estimated position of dynamic objects.

After defined the main objects in floor plan (static obstacles, dynamic obstacles, areas of interest, etc.), the new expanded floor plan will be transformed in a uniform matrix of cell grids (with configurable grid step size) separating corresponding data structures to each previously specified object. Figure 8 shows the new representation of the floor plan with respective cell grids.

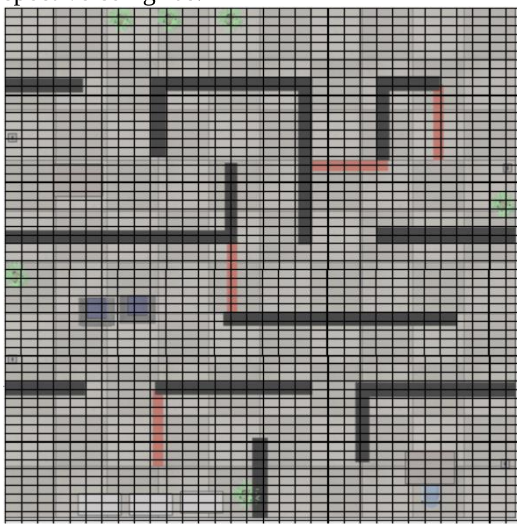

Figure 8. Floor plan formatted as a matrix of cell grids.

To model real life paths that take in consideration the most frequent ways used to reach areas of interest in the floor plan, once the floor plan is transformed into a square grid, each area of interest becomes a cell grid. The method to build a path between a start point and a goal point into the floor plan is called path finding algorithm. There are different types of path finding algorithms, including the classical implementation of A* [35] and improved and fast approach like the one described by [36].

All cell grid in the floor plan, except static and dynamic obstacles, are navigable; in other words, a mobile agent can freely cross those cells and a path finding algorithm can be developed to use those cells. Figure 9 shows an example of an automatically generated path between a mobile agent and its area of interest in the floor plan. On the top of Figure 8 is presented a small robot (mobile agent) that follow a path (line) crossing the floor plan until reach its first goal (circle with number one inside). .

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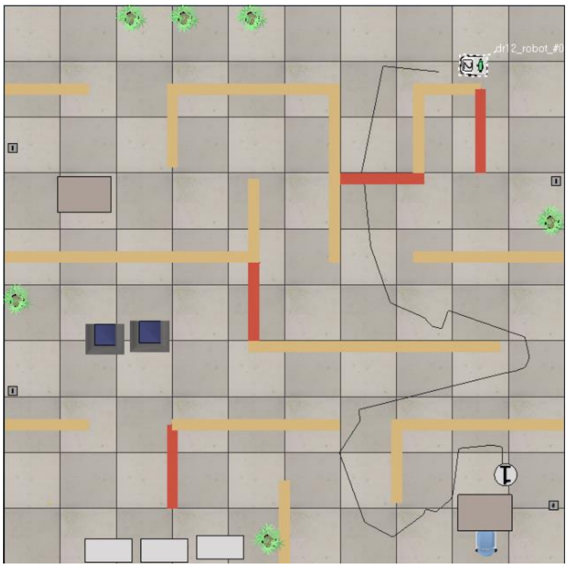

Figure 9. Example of Path Planning.

Considering that an adopted path planning algorithm always produces the shortest path between two points, in the proposed algorithm is added some criteria to the path planning to consider the probability to have dynamic obstacles during the path between the mobile agent and its goal, and also the most frequent paths and probabilities when trying to accomplish similar tasks.

To obtain a general overview of mobility patterns in the floor plan, the algorithm is simulated multiple times to generate a degree of importance over a specific path.

The importance over a specific path is represented by an increased probability in a specific cell grid. The path planning algorithm then will be using that data as a weight to choose the most appropriated path next time it runs.

A heat map can be used to represent the resulting mobility map that considers the frequency or number of times that the mobile agent uses a specific path or cell grid. Figure 10 shows an example of a heat map generated by the previous path plan when different simulated scenarios are attempted to reach the same goal. The hot areas (darkest blue ones) can point to a place that could be monitored by a sensor or, in some cases, a bottleneck due the floor plan layout that can be improved in the future.

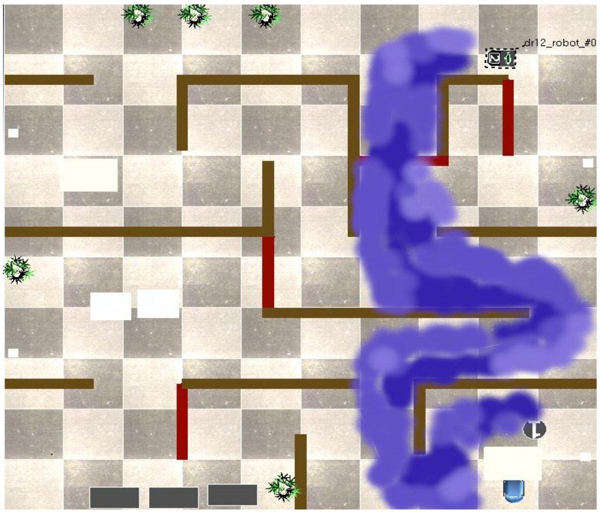

Figure 10. Heat map of path patterns.

In that case, the mobility model in the floor plan can be defined in the following way: Let N the maximum number of navigable cell grids, and P_i the probability (heat score or visiting frequency) of the ith cell grid. The mobility model is represented by the set of values $\{P_1 \quad P_2 \quad \dots \quad P_N\}$.

Associating the mobility model and the sensor coverage model, both can be used to formulate the optimization problem for the sensor placement based on route.

The optimization problem is, therefore, defined as the following min-max model:

Let:

A = {1, 2, 3…, m) the index set of the sensors candidate locations;

B = {1, 2, 3 …, n} the index set of the locations in the sensor field, m ≤ n.

r_k = the detection radius of the sensor located at k, $k \in A$.

d_{ij}= Euclidean distance between location i and j, where $i, j \in B$.

c_k = The cost of the sensor allocated at location k, $k \in A$.

G = Total cost limitation.

C is an arbitrarily large number.

$$y_k \begin{cases} 1 \text{ if a sensor is allocated at location } k \ (k \in A) \\ \qquad\qquad 0 \text{ otherwise} \end{cases}$$

$v_i = (v_{i1}, v_{i2}, \dots, v_{ik})$ = The power vector of location i, where v_{ik} is 1 if the target at location i can be detected by the sensor at location k and 0 otherwise, where $i \in B$, $k \in A$.

Objective Function:

$$J = \min_{v} \max_{(i,j)} \frac{d_{ij}}{1+C\sum_{k=1}^{m}(v_{ik}-v_{jk})^2} \qquad (1)$$

Subject to:

$$v_{ik} d_{ik} \leq y_k r_k \quad , \forall k \in A, i \in B, i \neq k \qquad (2)$$

$$\frac{d_{ik}}{r_k} > y_k - v_{ik} \quad , \forall k \in A, i \in B, i \neq k \qquad (3)$$

$$v_{ik} = y_k \qquad , \forall k \in A, i \in B, i \neq k \qquad (4)$$

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$$\sum_{k=1}^{m} c_k y_k \leq G \qquad (5)$$

$$\sum_{k=1}^{m} v_{ik} \geq 1 \qquad , \forall i \in B \qquad (6)$$

$$v_{ik}, y_k = 0 \text{ or } 1 \qquad , \forall k \in A, i \in B \qquad (7)$$

Constraints (2), (3), and (4) require the relationship between sensor detection radius r_k and detection distance d_{ik} . If a target appears at grid point i and the grid is inside the coverage of sensor k, the sensor can detect the target if sensor k is available. Constraint (5) requires that the total deployment cost of sensors be limited by cost G. Constraint (6) is the complete coverage limitation. Constraint (7) is an integer constraint.

III. RESULTS

Intensive simulation experiments were prepared to evaluate the accuracy of the proposed optimized algorithm for sensor placement based on most frequent routes. Simulations allowed the generation of realistic traces that represent the most frequent routes of a mobile agent into a floor plan. For example, Figure 11 shows seven possible placements with a maximum of 4 sensors.

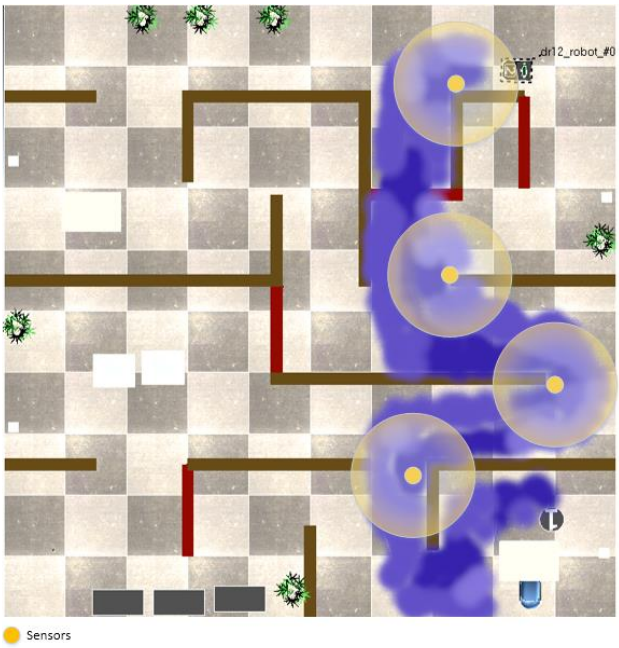

Figure 11. Example of placement area for 4 sensors.

In the following scenarios, there are a comparison between three diferent placement strategies: Placements generated by optimized algorithm; placements built manually; and random placements.

The location accuracy of optimized placements depends on the maximum number of coverage areas and the number of sensors into the floor plan. By observing the Figure 12, when the number of sensors are between 5 and 8, the optimized algorithm performs similarly as the manual method, but much better when in comparison to a random method. When its considered 9 to 20 sensors, the optimized algorithm performs better than manual and random methods by minimizing the location errors. After the number of 20 sensors, the optimized algorithm starts to saturate, covering to much areas with high probability and much less other areas.

The manual placement, in general, is represented by an expert agent that tries to maximize the covered area of the floor plan, but not taking in consideration existent dynamic obstacle into the floor plan. The sensors distribution in the environment is tipically uniform and based on previous experience, trying to cover the maximum area as possible. Figure 13 highliths the comparison between optimized and manual methods, pointing that after simulate 20 sensors, the manual method starts to show less positioning errors.

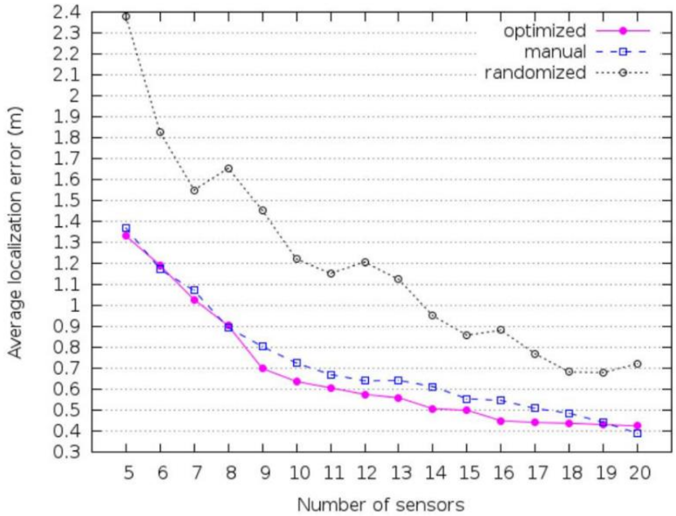

Figure 12. Positioning errors of optimized, manual, and random placement based on most frequent route.

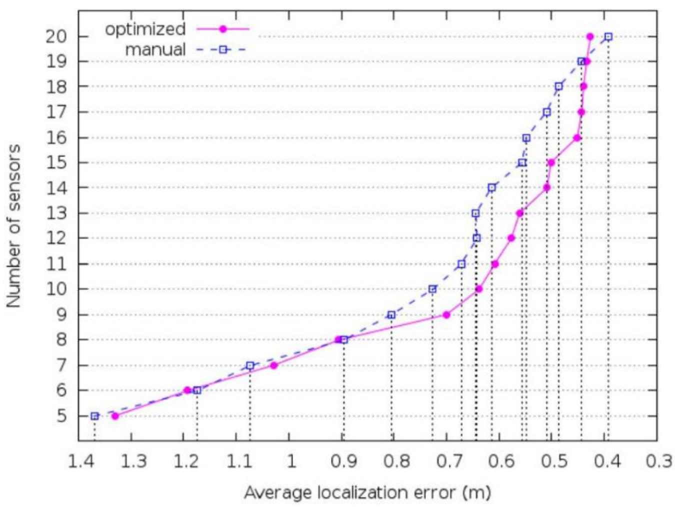

Figure 13. Detailed comparison between optimized and manual placement method.

The difference in average positioning errors for all considered methods is presented in Figure 14.

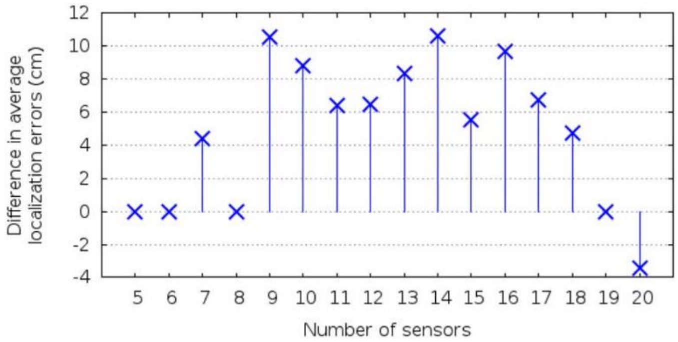

Figure 14. Difference in average positioning errors.

IV. SUMMARY AND CONCLUSION

Positioning accuracy depends on the sensor placement, which is commonly manually built for each new deployment and whose quality foar localization purposes depends on the designer's experience. The research presented in this paper evaluates the problem of optimizing sensor placement for positioning systems in indoor environment. Specially, an optimization problem is formulated considering constraint in the number of sensors to achieve the objective of maximum coverage area. The optimized sensor placement algorithm taking in consideration the most frequent routes used by a mobile agent in indoor environment significantly outperformed all random placement algorithms and also performed better than the manual methods in most of scenarios. The proposed algorithm and methodology can automatically eliminate the time consuming task of manually search and choose the best sensor placement strategy for indoor positioning systems.

Improvements in fault tolerance can be made and also evaluation on real-world scenarios too, making comparisons between positioning accuracy of estimated sensor placement against the accuracy achieved in the real world implementation.

Considering fusion with other types of sensors (vision, for instance) can improve accuracy and development of better path planning algorithms, especially when trying to identify or avoid dynamic obstacles in a specific route. As well, utilization of improved UWB sensors with at least 3 cm of accuracy and RFID tags can be further investigated and deployed in the path planning and positioning system.

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REFERENCES

[1] Bahl, P.; Padmanabhan, V. (2000). Radar: An In-Building RF-based User Location and Tracking System. In Proceedings of Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies, volume 2.
[2] Youssef, M.; Agrawala, A. (2005). The Horus WLAN Location Determination System. In Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services, MobiSys '05. ACM.
[3] Chintalapudi, K.; Padmanabha Iyer, A.; Padmanabhan, V. N. (2010). Indoor Localization without the Pain. In Proceedings of the Sixteenth Annual International Conference on Mobile Computing and Networking, MobiCom '10. New York, NY, USA. ACM.
[4] Ekahau (2017). Ekahau Wireles Solutions. Website: http://www.ekahau.com/. Accessed in October, 2017.
[5] SkyHook (2017). Skyhook Location Service. Website. http://www.skyhookwireless.com/. Accessed in October, 2017.
[6] Google Maps (2017). Google Maps - Indoor maps. Website. https://www.google.com/maps/about/partners/indoormaps/. Accessed October, 2017.
[7] Miah, S.; Gueaieb, W. (2014). Mobile robot trajectory tracking using noisy RSSI measurements: An RFID approach. ISA Transactions: The Journal of Automation.
[8] Dong, Q.; Dargie, W. (2012). Evaluation of the reliability of RSSI for indoor localization. In International Conference on Wireless Communications in Underground and Confined Areas.
[9] Zhang, T.; Chong, Z.; Qin, B.; Fu, J.; Pendleton, S.; Ang, M. (2014) Sensor fusion for localization, mapping and navigation in an indoor environment. Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM).
[10] Fontanini, A. D., Vaidya, U., and Ganapathysubramanian, B. (2016). "A methodology for optimal placement of sensors in enclosed environments: A dynamical systems approach."
[11] Hamdan, A. M. A., and Nayfeh, A. H. (1989). "Measures of modal controllability and observability for first- and second-order linear systems." JGCD – Guidance, Control, Dynamics. Volume 12, Number 3.
[12] Worden, K., and Burrows, A. P. (2001). "Optimal sensor placement for fault detection." Engineer Structures - Volume 23, Issue 8.
[13] Flynn, E. B., and Todd, M. D. (2010). "A Bayesian approach to optimal sensor placement for structural health monitoring with application to active sensing." Mech. Syst. Sig. Process.
[14] Yi, T. H., Li, H. N., and Zhang, X. D. (2015). "Sensor placement optimization in structural health monitoring using distributed algorithm." Smart Structured Systems.
[15] Zhang, C. D., and Xu, Y. L. (2016). "Optimal multi-type sensor placement for response and excitation reconstruction." Journal: Sound Vibration.
[16] Papadopoulou, M., Raphael, B., Smith, I. F. C., and Sekhar, C. (2016). "Optimal sensor placement for time-dependent systems: Application to wind studies around buildings." Journal of Computational Civil Engineer.
[17] Kammer, D. C. (1991). "Sensor placement for on-orbit modal identification and correlation of large space structures." Journal of Guidance, Control, Dynamics 14, Vol. 2.
[18] Kirkegaard, P. H., and Brincker, R. (1994). "On the optimal location of sensors for parametric identification of linear structural systems." Mechanical Systems Signal Processing 8. Vol. 6.
[19] Papadimitriou, C., and Lombaert, G. (2012). "The effect of prediction error correlation on optimal sensor placement in structural dynamics." Mechanical Systems Signal Processing 28.
[20] Papadimitriou, C. (2004). "Optimal sensor placement methodology for parametric identification of structural systems." J. Sound Vibrations 278. Vol. 4.
[21] Papadimitriou, C., Beck, J. L., and Au, S. K. (2000). "Entropy-based optimal sensor location for structural model updating." J. Vibration Control, 203. Vol. 6.
[22] Sun, H., and Büyüköztürk, O. (2015). "Optimal sensor placement in structural health monitoring using discrete optimization." Smart Material Structure 24.
[23] Chen, G.-S., Bruno, R. J., and Salama, M. (1991). "Optimal placement of active/passive members in truss structures using simulated annealing." AIAA Journal.

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[24] Lau, S., Eichardt, R., Di Rienzo, L., and Haueisen, J. (2008). "Tabu search optimization of magnetic sensor systems for magneto-cardiograph." IEEE Trans.

[25] Han, J. H., and Lee, I. (1999). "Optimal placement of piezoelectric sensors and actuators for vibration control of a composite plate using genetic algorithms." Smart Materials Structure, 8.

[26] Wu, Z. Y., et al. (2013). "Optimizing sensor placement and dynamic measurement of Verrazano narrows bridge span." 6th Int. Conf. on Structural Health Monitoring of Intelligent Infrastructure, International Society of Structural Health Monitoring for Intelligent Infrastructure, Hong Kong.

[27] Wu, Z. Y., Wang, Q., Butala, S., and Mi, T. (2011). "Generalized framework for high performance infrastructure system optimization." Computing and control for the water industry, Computer Control for Water Industry, Exeter, U.K

[28] Pobil, A. (2014). The need of Benchmarks in Robotics Research. European Robotics Network.

[29] Miah, S.; Gueaieb, W. (2015). RFID-based mobile robot trajectory tracking and point stabilization through on-line neighboring optimal control. Journal of Intelligent and Robotic Systems.

[30] Furey, E.; Curran, K.; McKevitt, P. (2012). HABITS: a bayesian filter approach to indoor tracking and location. International Journal of Bio-Inspired Computation (IJBIC).

[31] LaMarca, A.; Chawathe, Y.; Consolvo, S.; Hightower, J.; Smith, I. (2006). Place Lab: Device Positioning Using Radio Beacons in the Wild. Intel Research Seattle.

[32] Norrby, S; Curran, K. (2009). RFID-enabled location determination within indoor environments. International Journal of Ambient Computing and Intelligence.

[33] Muthukrishnan, K.; Lijding, M.; Havinga, P. (2005). Towards smart surroundings: enabling techniques and technologies for localization. Proceedings of the First International Workshop on Location and Context-Awareness (LoCA), Springer-Verlag.

[34] Webster, P.; Harter, A.; Hopper, A.; Steggles, P.; Ward, A. (2002). The anatomy of a context-aware application. Wireless Networks.

[35] Hart, P.; Nilsson, N.; Raphael, B.; (1968). "A formal basis for the heuristic determination of minimum cost paths," IEEE Trans. Syst. Sci. Cybernetic. Vol. 4, no. 2, pp. 100–107.

[36] Soovadeep, B.; Zeyu, Y.; Dongmei, C.; Qiang, Q.; Yinan, C. (2018). "A Fast Algorithm on Minimum Time Schedule of an Autonomous Ground Vehicle Using a Traveling Salesman Framework." ASME Trans. Journal of Dynamics Systems, Measurements and Control. Vol. 140. December, 2018