Autonomous Determination of Locations for Observing Home Environment Using a Mobile Robot

Syed Atif Mehdi and Karsten Berns

Abstract The paper focuses on determining locations in a typical home environment for monitoring or observing the surroundings using an indoor mobile robot. Currently, these locations are manually selected for the robots. In the process of autonomously evaluating minimum number of key locations, the proposed methodology targets free spaces in the environment that may provide maximum observability to a mobile robot with limited range of sensor systems. The technique also ensures that these locations are at a distance from obstacles in the environment in order to guarantee sufficient space for robot navigation. The experiments have been performed both in real apartment using an autonomous mobile robot and in simulation with a variety of environments. The results demonstrate an area coverage of up to 96 % with minimal locations computed in fairly acceptable time. These locations can be used in various scenarios like monitoring an elderly person in the home environment.

Keywords Autonomous location determination · View points · Area coverage · Indoor mobile robot

1 Introduction

With the advancement in technology several methodologies have been developed for observing a home environment. Most of them are related to installing a dense network of sensors in the environment for monitoring purposes especially elderly people living alone in their homes. Such examples include *Aware Home* at Georgia Tech in Atlanta [1], *house_n* [2] at MIT, *Assisted Living Lab* in Kaiserslautern, Germany [3], *HomeLab* in Eindhoven, Netherlands, and Heracleia human-centered

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E. Menegatti et al. (eds.), *Intelligent Autonomous Systems 13*,
Advances in Intelligent Systems and Computing 302,
DOI 10.1007/978-3-319-08338-4_13

computing laboratory[1] in Arlington, Texas, USA [4] and many more, where a variety of sensors have been used to observe the environment. Installation of various sensor systems not only require manipulation in the environment but may also effect the privacy of the person living in the home.

According to World Robotics,[2] the number of mobile robots for providing services to inhabitants at home are continuously increasing in the world. These mobile robots can also be used for inquiring health conditions of an elderly person at home or observing area for identifying changes in the environment. The process of inspecting the environment can speed up if the robot has some knowledge about its environment in terms of locations which may provide maximum visibility and thus tremendously reducing overall navigation of the robot. Identification of such places is not an easy task as a normal home environment is usually cluttered with furniture which hinder the view of the robot and make locations inaccessible for the mobile robot.

Researchers have devised various methods for environment observation. One class of methods, e.g., "Art Gallery Problem", determine some specific points which provide maximum observability. It mainly focuses on installation of static sensors at those points. Other class calculates a shortest path for a mobile robot which ensures full observability of the environment, e.g., zoo-keeper problem. It seems that calculating a path is the best option for mobile robots, however, it greatly depends on the desired goal. In case, the robot has the task of finding the human in the home environment, performing the human detection process at specific locations will be more preferable due to their high computation cost. It will be unwise to perform the costly image processing task at every intermediate point of path of the robot.

This paper has been organized as follows. Section 2 provides a short summary of related work addressing determination of locations for observing environment. Section 3 explains the concept of *View Points* (*VPs*) and describes the developed methodology for autonomously evaluating *VPs* in a typical home environment using a mobile robot. The experiments and results are provided in Sect. 4 and conclusion and future work have been presented in Sect. 5.

2 Related Work

The problem of finding locations for optimally observing area using guards or sensor systems can be traced back to "Art Gallery Problem" in computational geometry. In 1973, Victor Klee posed the problem of determining minimum number of guards that may be required to fully cover the interior of an n-wall art gallery room. A variety of solutions have been proposed by many researchers for this problem. An in-depth theoretical analysis of the problem has been provided by [5, 6]. They have also shown that the optimal placement of the sensors or the guards in a polygon is an NP-hard problem. Exact solution and bounds to the general "Art Gallery Problem" has been

[1] http://heracleia.uta.edu/.

[2] http://www.ifr.org/service-robots/.

provided by [7]. Their strategy places an arbitrary number of guards randomly in a given polygon to cover the entire interior and afterwards computes a lower and upper bounds on the optimal number of guards. The process stops when an optimal solution is reached.

The NP-hard characteristic of the problem has lead many researchers to focus on suboptimal solutions based on heuristics depending on features of a given environment to determine places for sensor placement in adequate time.

For observing a defined critical region in the environment, [8] has proposed using multiple cameras to view from different locations. The use of multiple cameras to observe the same region helps in avoiding occlusion that may occur. Clearly, focus of the work is redundant coverage of a limited area from various positions.

A methodology for maximum area coverage has been presented in [9]. The main focus of the strategy is coverage of important areas in the environment rather than total area coverage. They have used liner programming for placing directional cameras in the environment. They have proposed a variety of heuristics for camera placement with different sensing ranges. The experiments have been performed in simple environments and show area coverage of some important areas in these environments.

Kazazakis and Argyros in [10] have proposed a divide and conquer approach to view a complete 2D workspace. The methodology assumes that the guards or autonomous mobile robots have a limited range of visibility and have 360 degrees field of view. The algorithm decomposes the workspace into polygons and subpolygons until it is visible by a single guard with the limited sensing range. This sometimes results in redundant or closely placed guards in some areas. Moreover, this placement is not workable with mobile robots as some locations are very close to obstacles and a mobile robot may not able to reach such locations due to obstacle avoidance mechanism.

A grid map-based approach for placement of camera system has been proposed by [11]. They have used Monte-Carlo simulations on $10\,\text{m} \times 10\,\text{m}$ area with a single obstacle in the environment. The approach assumes limited field of view of camera to determine locations in the environment. The experiments show 99 % area coverage with 11 cameras at different locations.

Similarly, [12] also describes the use of grid maps to represent the environment for finding locations for placement of cameras. They have used both directional and omni-directional cameras in their proposed approach. The experiment on 6×12 cell grid map with holes to represent obstacles, shows placement of cameras near to walls for full area coverage.

The solutions provided above are workable in scenarios where there is no concern about safety of guard and it can be placed close to obstacles or in case of cameras, on the walls. In situations where a mobile robot has to perform the task of surveillance, additional constraints like safe area for the robot, closeness to obstacles along with maximum observable area needs to be considered. Moreover, selecting corners for viewing is not feasible in many home environments as these already have furniture and other objects, thus cannot be reached by a mobile robot. Additionally, the methodologies described above assume an accurate description of the environment which is not possible in mobile robots due to imprecise sensor systems and localization errors induced during navigation.

An approach for full area coverage using multiple mobile robots have been presented by [13]. The environment has been represented as a polygon and it is assumed that a perfect sensor system is installed on the robots. The results show that some locations that are selected for viewing the environment are very close to obstacles and thus may endanger the robot. Similarly, some locations are very close to each other and are, thus, redundant.

In order to find a human in the home environment using a mobile robot, [14–16] have manually defined certain locations in the environment from where the robot should observe the person. The robot navigates to the user defined locations and tries to find the human from these locations.

Manually defining locations for viewing the environment or finding a person is fine for experimental purposes but for real-life scenarios it is not a workable solution. The location and position of the obstacles, placed in the environment, change more often and, thus, manually defining these locations every time is neither feasible nor practical. Therefore, a new methodology is required and is presented in this paper that can be used in indoor mobile robots to autonomously determine key locations in the environment which offer maximum observability despite the fact that furniture and obstacles will occlude the view of the robot.

3 Determination of *View Points*

There can be many locations from where an environment can be observed using an autonomous mobile robot. Some of these locations may be close to walls or furniture thus partially obstructing the view of the environment. Navigating to all these locations might not be feasible for the robot as it may get stuck at a place due to closeness of obstacles. Therefore, the most valuable are those few places which can be easily reached by a mobile robot and allow possibility to observe maximum area of the environment. The developed methodology is an elaborative explanation of *View Point* determination method coined in [17].

In this paper, following definitions are used to describe locations for observing the environment.

Definition 1 Locations in the environment from where a mobile robot can observe its surroundings using its sensors are called *View Points* (*VPs*).

Autonomous determination of *VPs* not only depends on the robot and its sensor systems but also on the working environment of the robot. The number of obstacles and their placement in the home environment will affect the number of *VPs* required for observation. In case, central region of a room is free from obstacles, only a few locations will be sufficient to observe the home environment. Consequently, distributed obstacles will require more number of *VPs*. Similarly, sensor system installed on the robot also affects the number of *VPs* in the environment. In case of short-range sensors, more *VPs* are required for maximum observability in the home environment. With long range sensors, the robot will be able to observe more of the environment requiring less number of *VPs*. An important aspect of determining *VPs* is to refrain from redundant *VPs* which are close to each other and observe the same area, a very prominent issue that can be seen in results of [10, 13].

The environment, in the proposed methodology, has been represented as an occupancy grid map as it is the most common type of map used in indoor mobile robots for mapping the environment. The procedure for generating the grid map for the current work has been explained in [18, 19]. The proposed methodology considers range of the sensors and free space required by the mobile robot for safe navigation in computing *VPs*. These parameters are adjustable according to application scenarios and are defined as follows.

Definition 2 The distance viewable by the sensors of the robot to observe an environment or to detect an object or a human is called *Sensing Range* (SR) and is measured from kinematic center of the mobile robot.

Definition 3 The distance between kinematic center of a mobile robot and its surrounding obstacles required to safely navigate in an environment is called *Inner Circle* (IC).

Only those locations in the home environment are considered for being a *VP* which have a circular region of radius IC free from obstacles. This ensures that a mobile robot has sufficient place for navigation at that *VP*. From the definition of IC; SZ can be defined as

Definition 4 The absolute minimum distance between kinematic center of a mobile robot and obstacles in its surroundings is called *Safety Zone* (SZ).

Any distance less than SZ may result in a collision between the robot and the obstacles. The relationship between SZ, IC, and SR, can be defined by (1).

$$SZ \leq IC \leq SR \tag{1}$$

The proposed methodology can be used to determine *VPs* at multiple levels.

Definition 5 The *VPs* determined at the first level offer maximum area coverage and are called *Primary View Points* (*PVPs*).

Definition 6 The *VPs* determined at the second level to observe remaining area are called *Secondary View Points* (*SVPs*).

The *PVPs* are locations that are farthest away from the obstacles and thus offers maximum observability besides being easily reachable by a mobile robot. The area coverage by *PVPs* is exclusive and no two *PVPs* observe the same area. This results in some distributed areas in the home environment that are not being observed by any *PVP*.

For observing the remaining area, *SVPs* are evaluated. These locations are relatively closer to the obstacles in the environment, thus offers limited visibility. The

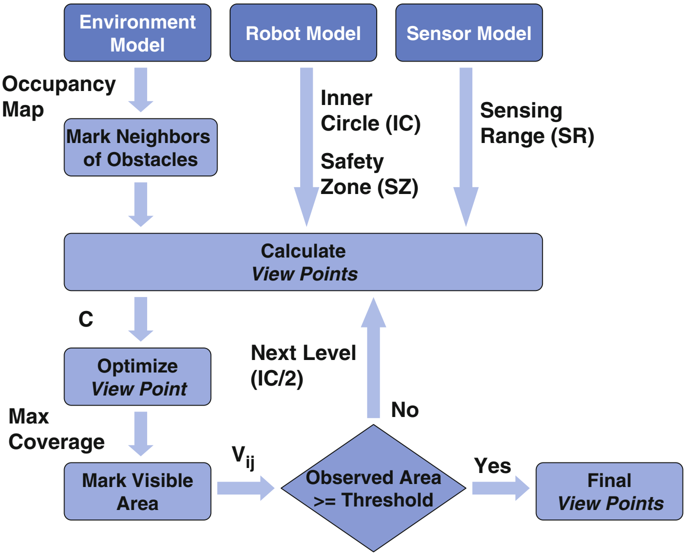

Fig. 1 Overview of methodology for determining *VPs* in a grid map of an environment. The process takes occupancy grid map of the environment, range of sensors on the mobile robot and dimensions of the robot to calculate *VPs*

SVPs share the area coverage among themselves and also with the *PVPs*. The advantage of determining *VPs* in different levels becomes more prominent in situations where prioritized area coverage is required and only *PVPs* may suffice the need.

An overview of the methodology for determining *VPs* in a home environment is presented in Fig. 1. The goal of the algorithm is to maximize area observability with minimum number of *VPs* making it a typical optimization problem. As has been discussed in Sect. 2, an optimal solution will be NP-hard, therefore, a greedy approach has been adopted for selecting *VPs*. The use of greedy approach generates a suboptimal solution which is acceptable for observing or finding a person in a typical home environment.

Since the environment is described as uniform sized cells in the grid map, the methodology for finding the *VPs* is discrete in nature. A location selected as a *VP* corresponds to center of a cell. Similarly, a cell is considered viewable from a *VP* if and only if it is fully observable from that *VP* which is a strict constraint and as a consequence partially observed cells are treated as unobserved. The obstacles in a grid map of dimension $m \times n$ are marked as follows

$$\vec{M} = \begin{cases} 1 & \text{if there is an obstacle} \\ -1 & \text{else if it is free} \\ 0 & \text{else if it is not observed}\,, \end{cases} \tag{2}$$

where $\overrightarrow{M}$ is a cell in the map. Thus, a set of obstacles O can be defined as

$$O = \{O_k : \overrightarrow{M_i} = 1\}\,. \tag{3}$$

All the cells that are free and do not have an obstacle can be a *VP* and, therefore, need to be evaluated for maximum observability. A filter of $IC \times IC$ is used to extract cells which have free neighbors in their surroundings. Equation 4 describes the condition for a cell $\overrightarrow{M_i}$ to be a candidate for being a *VP* if the distance of the cell from any obstacles in the environment is greater than the IC. Thus, from constrained defined in (1), it is clear that there is no obstacle within the SZ of the cell.

$$||\overrightarrow{M_i} - O|| > IC\,. \tag{4}$$

Thus, a candidate *VP* (Cvp) can be described by (5)

$$Cvp \in \{\overrightarrow{M_i} : \overrightarrow{M_i} = -1 \text{ and } ||\overrightarrow{M_i} - O|| > IC\}\,. \tag{5}$$

A cell is viewable from a *VP* if and only if there is no obstacle between the cell and the *VP* within the SR. In case an obstacle is present, all cells behind the obstacles are not observable from the *VP* as the sensors cannot see through the obstacles. The set of cells that is viewable from a *VP* can be described as

$$\begin{aligned} Vc_{Cvp_n} = &\{\overrightarrow{M_i} : ||\overrightarrow{M_i} - Cvp_n|| < SR \\ &\text{and all cells between } Cvp_n \text{ and } \overrightarrow{M_i} \text{ are free}\}\,. \end{aligned} \tag{6}$$

After evaluating the number of cells visible from the selected candidate *VP*, the neighboring cells are examined for selecting a cell from where more number of cells may be visible. Finally, only the cell with maximum visibility is selected as the *VP*. In order to speed up the process of determining next *VP*, all cells in the range of SR of the previously evaluated *VP* are skipped. This also ensures maximum coverage with minimum number of *VPs* and avoid redundancy.

The strict constraints in *PVPs* results in several distributed areas in the environment that are reachable by the robot at a reduced speed due to closeness to the obstacles. To observe such areas, *SVPs* are evaluated by reducing the IC while maintaining the condition mentioned in (1). The selection criteria of a *SVP* includes that a candidate *SVP* must be a free cell and is not observed by any other *VP*. Moreover, all cells within IC of the *SVP* must not contain any obstacles but they may be visible from other *VPs*.

4 Experiments and Results

Several experiments have been conducted both in real environment and in simulation to validate the developed methodology. In real-world scenario, ARTOS (see Fig. 2a) has been used in an Assisted Living Lab at IESE, Fraunhofer in Kaiserslautern,

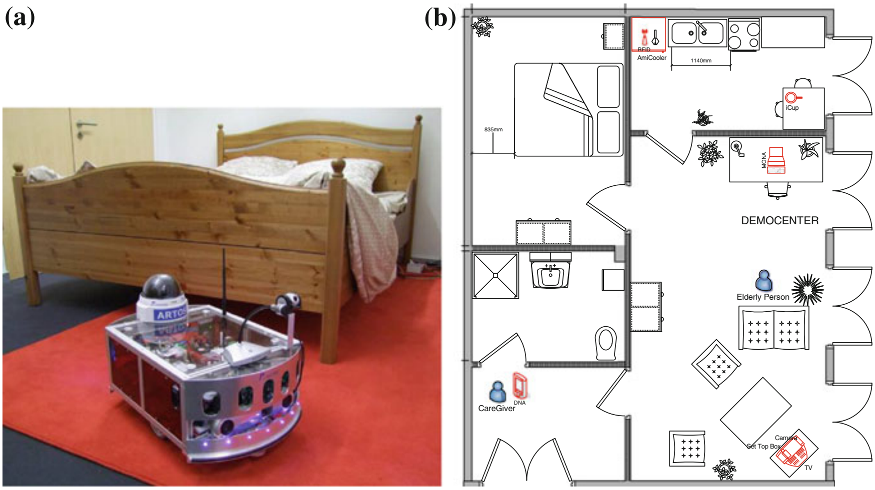

Fig. 2 **a** Autonomous Robot for Transport and Service, (ARTOS) in bedroom of Assisted Living Lab. **b** Overview of Assisted Living Lab at IESE Fraunhofer

Germany, see Fig. 2b. The robot ARTOS is equipped with laser scanner, pan-tilt-zoom camera, sonar sensors, and bumper sensors to perceive the environment. The lab has an area of about 7 m × 9 m and contains all the necessary furniture that is usually required in a living apartment.

In order to obtain an occupancy grid map of the environment, the robot has been driven in the environment. The neighboring area to the obstacles is traversable but should be avoided in order to maintain a safe distance from the obstacles. Therefore, both the obstacles and the neighbors are registered in the grid map. Figure 3 shows the grid map generated using laser scanner of the robot. During mapping process, some artifacts have also been introduced and can be seen as white cells outside the living area. These have been generated mainly due to inaccurate sensor measurements and localization errors during navigation.

Each cell in the grid map corresponds to an area of 10 cm × 10 cm. For consistency, all discussion in the following will be carried out in terms of cells rather than distances. The sensing range of the laser scanner on ARTOS is about 40 cells (400 cm). Since, the accuracy of measurement decreases with the increase in distance, therefore, SR is set to 10 cells. Based on the dimension of ARTOS, SZ is set to 4 cells which is the minimum distance required by the robot for safe navigation in the environment and IC is set to 8 cells.

At first, *PVPs* are determined based on the above-mentioned parameters, see Fig. 3a. As can be seen, only a few cells have been selected as *VPs* and small distributed free spaces are not visible from these *PVPs*. The second level is proceeded by reducing IC by half while keeping other parameters unchanged. Figure 3b shows the combination of *PVPs* and *SVPs* from where about 88 % of the environment is observable.

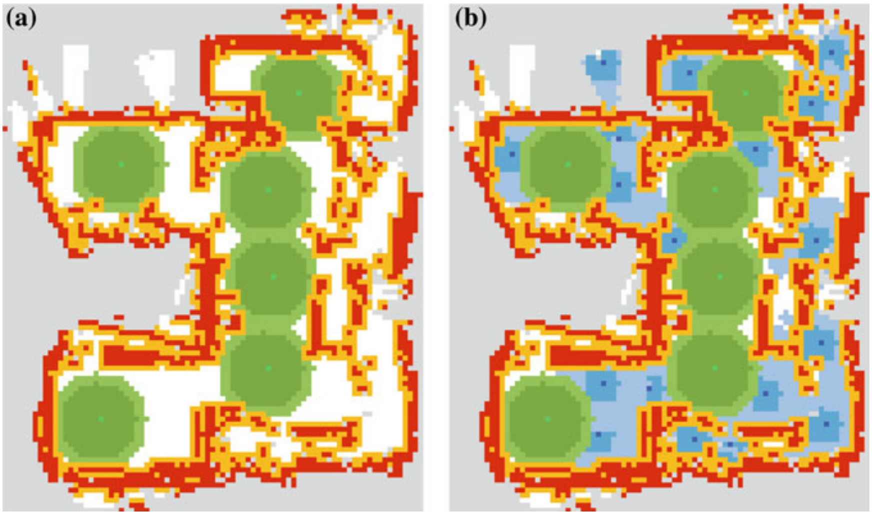

Fig. 3 Experiments with ARTOS in lab at IESE for determining *VPs* in the home environment. *Gray* cells are unseen and *white* cells have been seen by the robot. *Red* cells represents the obstacles and *Orange* cells are neighbors to the obstacles. *Inner Circle* and *Sensing Range* are represented in *darker shade* and *lighter shade* ,respectively. **a** *PVPs* shown in *green* have been determined at level 1 and cells within SR around them are observable from these *VPs*. **b** Shows the complete observability from *PVPs* (*green*) and *SVPs* (*blue*) after level 2

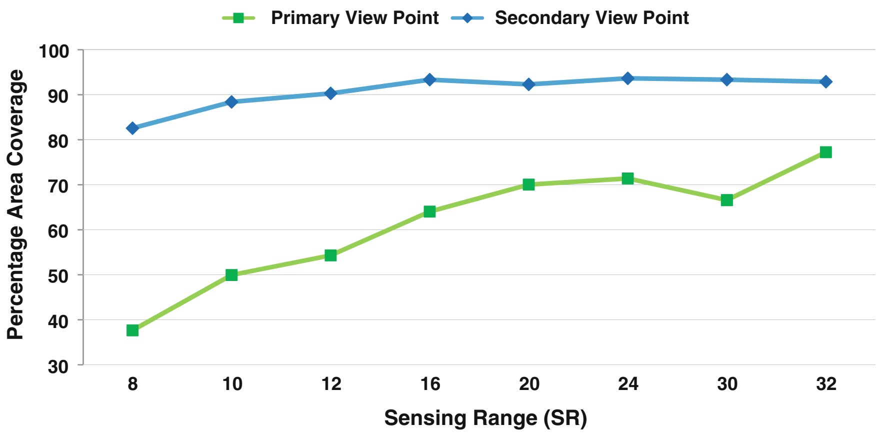

Fig. 4 Effect of varying SR on total area coverage in map of lab at IESE after determination of *PVPs* and *SVPs*

Several other experiments have been performed in the real environment with varying SR to see the relation between area coverage and *VPs*. Figure 4 shows the result of total area coverage after determining *PVPs* and *SVPs*. It can be seen that by increasing SR, more area is observable from *VPs*. Similarly, Fig. 5 shows the number

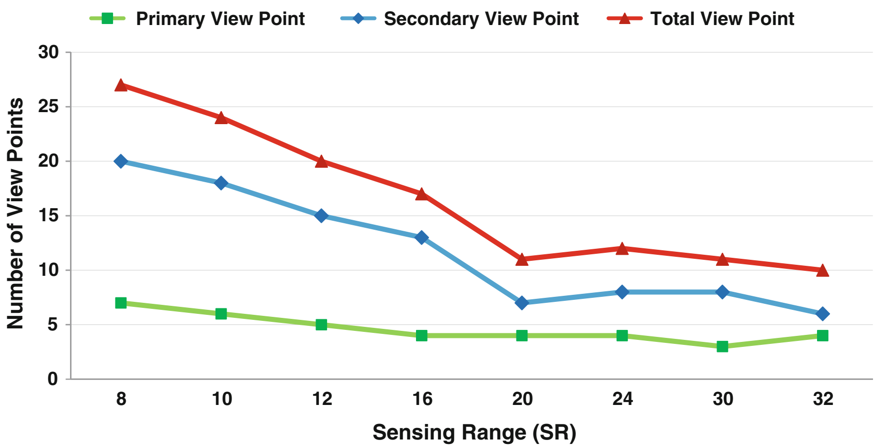

Fig. 5 Effect of varying SR on the number of *VPs* in map of lab at IESE

of *VPs* decreases as the SR increases. Considering a moderate SR of 20 cells, only 4 *PVPs* are required to observe about 70 % of the home environment. With an extra 7 *SVPs* more than 90 % of total area coverage is achieved showing the validity of the developed methodology for observing maximum area with minimum number of *VPs*.

In order to validate the applicability of the developed approach in different scenarios, several experiments have been conducted in simulation with various environments. The parameters for these experiments were the same as for real environment, i.e., SR, IC and SZ are 10, 8, and 4, respectively.

A simulation of Assisted Living Lab, closely resembling the real environment, has been used to perform a variety of experiments. Details of the simulation can be found in [17]. In this simulation, with all furniture as in the real environment, 66.45 % of area coverage is achieved with only 10 *PVPs*. This increases to 95.7 % coverage with additional 17 *SVPs*. As it has been mentioned in Sect. 2, that placement of furniture can change in the environment and new locations need to be determined autonomously. Therefore, position of furniture in simulation has been changed to determine the effect. With the changed environment, 9 *PVPs* were evaluated that covers about 57.4 % of the simulated environment. Total area coverage of 94.3 % is achieved with additional 22 *SVPs*. It is important to note that the number of *PVPs* have been changed in both the experiments reflecting the change in position of furniture in the environment.

The experiments with simulation of Assisted Living Lab proved to be successful in terms of area coverage by the evaluated *VPs*. But in order to ensure that the developed methodology is workable in larger environments, a simulation of RRLAB at University of Kaiserslautern was used to determine *VPs* in an office environment. A total of more than 96 % area coverage with 190 *VPs* was obtained. Further details of these experiments have been presented in Table 1.

Table 1 Overview of *VP* results in different environments with *SR* set to 10 cells (100 cm)

Map of location	Free area (m^2)	Total number of *VPs*	Area coverage (%)	Time taken (ms)
Assisted Living Lab at IESE	30.55	24	88.38	331.47
Simulation of IESE	38.84	27	95.7	436.13
Simulation with changed furniture	40.70	31	94.32	435.61
Simulation without furniture	49.51	35	96.83	802.19
RRLAB simulation	297.47	190	96.57	4587.96

Due to large number of obstacles in the environment and erroneous data from sensors, area coverage is less in real environment (Assisted Living Lab at IESE)

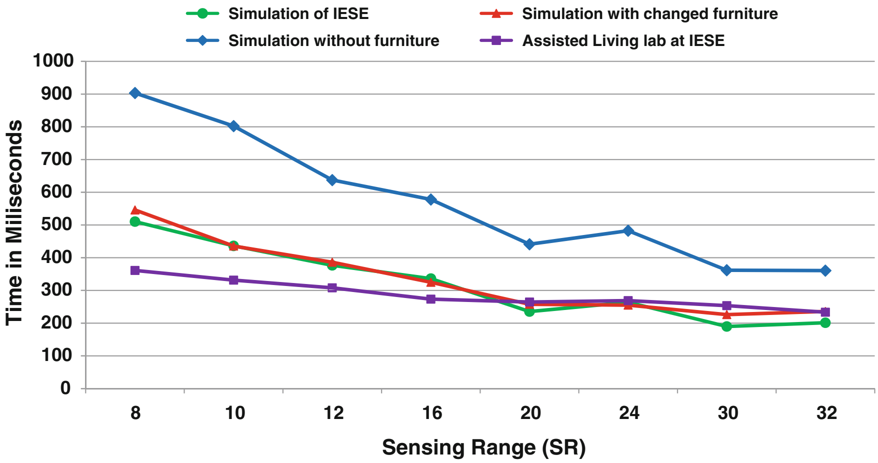

Fig. 6 Time required to calculate *VPs* in different environments with varying *SR*

Figure 6 provides an overview of total time required to compute both *PVPs* and *SVPs* in different environments with various *SR*. The algorithm developed by [11] takes minimum 1.90 s to evaluate 10 locations for camera placement in the environment. The maximum time reported is 10.01 s for calculating 9 locations. In both of these situations, the computational time is much higher than required to compute *VPs* by methodology explained in this paper. A running time of less then 10 ms has been reported by [10]. Despite extremely low computational time, their algorithm generates locations which are redundant and certain portions are left unobserved thus not workable in home environments. The proposed grid map-based algorithm for *VP* determination usually takes under 500 ms in a typical home environment. The running time can increase in case of small *SR* or in situations where there are less obstacles in the environment.

5 Conclusion and Future Work

Experiments performed in real-home environment at IESE and various simulated environments proved to be quite successful and demonstrates the usability and effectiveness of grid map based approach for autonomously determining *VPs* in home environment using a mobile robot. The parameters can be easily adjusted to suffice the need of the robotic platform and environmental setup. The lower run time of the developed methodology ensures usability in home environments.

The future work includes extending the developed methodology for 3D maps of the environment. This will require enhancements to the developed methodology to incorporate height of the robot to determine *VPs* in the environment. Furthermore, reachability from one *VP* to another has not been addressed in this paper and will be developed in future.

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