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Coverage optimization to support security monitoring

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Abstract

The placement of sensors to support security monitoring is obviously critical as it will directly impact the efficacy of allocated resources and system performance. It is critical to be able to observe and monitor the greatest total area possible. In addition, it is necessary to be able to spatially track the movement of people and activities in support of security. It is shown that important aspects of the security sensor placement problem can be modeled using the maximal covering location problem (MCLP) and/or the backup coverage location problem (BCLP) combined with visibility analysis. Thus, an approach is detailed for supporting security monitoring. The approach is applied in the context of video sensor placement in an urban area, illustrating the various tradeoffs that can be identified using optimization-based techniques.

Keywords: Security monitoring; Visibility analysis; Location modeling

1. Introduction

In modern society security monitoring is a necessity. The increasing social demand for security leads to a growing need for surveillance activities in various environments, such as

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transport infrastructure and public places like banks, department stores and parking lots. As sensors are used in greater numbers to monitor large areas, the efficient deployment of such equipment becomes increasingly important as it can directly impact the efficiency of allocated resources as well as system performance.

The sensor placement problem is not simple. Identifying an optimal configuration of multiple sensors in order to observe the greatest total area with a given number of sensors is a combinatorial optimization problem. Further, such problems have been found to be NP-hard (Cole & Sharir, 1989). This means that simple enumeration and search techniques as well as developed general purpose algorithms will likely have great difficulty in identifying optimal placement configurations in the worst case.

While much work has been done related to the coverage of demand by facilities using optimization methods in 2 dimensions (e.g., evaluating the planar distance between a facility and a demand point), the placement problem of surveillance equipment, such as cameras, and fire and watch towers, in 3 dimensions is far less studied (see Church, 2002; Schilling, Vaidyanathan, & Barkhi, 1993). This problem requires visibility analysis across space in addition to configuration optimization. Visibility analysis is used to generate coverage or visible area of a sensor in 3 dimensions. This paper deals with a GIS-based approach for optimizing the spatial coverage of security monitoring equipment in an urban environment. This approach incorporates visibility analysis into spatial optimization. The purpose of this paper is to develop a procedure for finding the most efficient configuration of multiple sensors in order to cover as much area as possible in a 3D urban environment. The next section reviews the associated literature on this topic. Following this, sensor placement models are suggested. The next section develops a procedure for siting multiple sensors. Implementation details for this approach and application results are given. The paper ends with a summary and discussion.

2. Background

There are many areas of research contributing to security monitoring, particularly efficient sensor placement. The placement of surveillance equipment on a surface, like radar, telecommunication relay towers, and fire and watch towers, has been undertaken for art gallery guard placement and terrain viewshed assessment.

The art gallery problem, which has been extensively discussed in the computational geometry literature, is to find the minimum number of guards for a polygon such that every point in the polygon is visible by at least one guard. Chvátal (1975) first showed that in the worst case $\lfloor n/3 \rfloor$ such locations will suffice for any polygon of n sides. Fisk (1978) provided a concise and elegant proof of this worst case expectation using a three-coloring algorithm. Bose, Shermer, Toussaint, and Zhu (1997) and Marengoni, Draper, Hanson, and Sitaraman (2000) extended the art gallery problem to consider 3-dimensional terrain guarding problems. Cole and Sharir (1989) showed that the terrain guarding problem is NP-complete. Eidenbenz (2002) suggested approximation algorithms and heuristics for this problem.

The art galley problem has been the subject of much theoretical work with efficient algorithms proposed for its solution, and research continues to focus on this problem. Some work has been interested in addressing restricted guard visibility (Erdem & Sclaroff, 2004; Kazazakis & Argyros, 2002), but generally unrealistic guard capabilities are assumed, i.e., unlimited visibility. As a consequence, developed approaches for the art gallery problem may not be suitable for sensor placement under this assumption. In addition, there is no capability to account for budget constraints or heterogeneous area importance. In practice only a specified number of sensors can be sited because of costs and some areas are often more important to monitor than others.

Since de Floriani, Falcidieno, Pienovi, Allen, and Nagy (1986) showed that the determination of the minimal set of observation points is equivalent to the set covering problem, covering location models have seen greater application to visibility coverage problems. Goodchild and Lee (1989) and Lee (1991) investigated terrain coverage problems on topographic surfaces applying the location set covering and maximal covering location problems, solved them by using greedy approaches. Kim, Rana, and Wise (2004) explored these problems on a DEM (digital elevation model) and also solved them by using heuristic solution techniques. Kaučič and Žalik (2004) introduced the multiple terrain covering problem based on the set covering location problem and suggested heuristics for its solution. Terrain covering problems, given their equivalence and relationship to LSCP and MCLP, also belong to the set of NP-complete optimization problems. This means that computational challenges and difficulties can be expected when attempting to solve general application problems.

The placement of equipment like cameras also has been discussed in urban (indoor and outdoor) surveillance systems (see Erdem & Sclaroff, 2004; Pavlidis, Morellas, Tsiamyrtzia, & Harp, 2001). Surveillance systems with multiple sensors include various functionalities, such as object detection, recognition, tracking, activity analysis and data fusion, in addition to sensor placement (Fig. 1). Most surveillance system research has focused on the former (Collins, Lipton, Fujiyoshi, & Kanade, 2001; Foresti, Regazzoni, & Varshney, 2003; Remagnino, Jones, Paragios, & Regazzoni, 2002; Valera & Velastin, 2005) and has largely ignored the latter. An exception is the work of Pavlidis et al. (2001), who discussed the placement problem within a broader analysis system and placed equipment using an *ad hoc* heuristic. Erdem and Sclaroff (2004) considered capabilities of cameras, such as field of view, spatial resolution and depth of field, and cost constraints in camera placement. They obtained a solution to this problem using binary optimization as a discrete space problem.

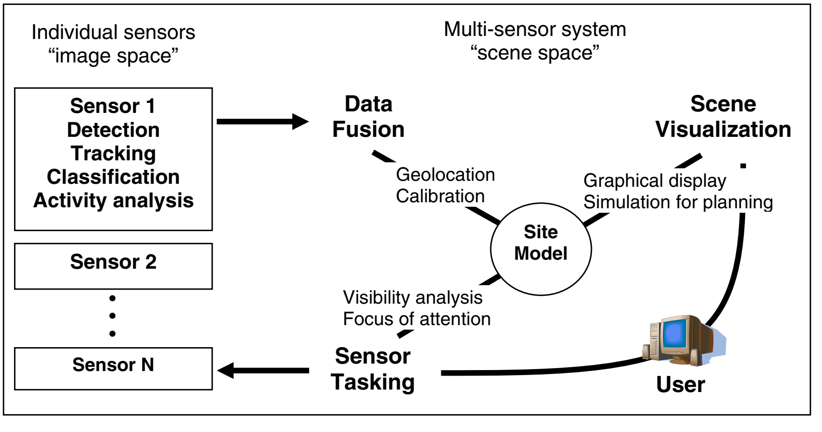

Fig. 1. Tasks of multi-sensor surveillance systems (Source: Collins et al., 2001).

There are a number of important considerations when locating security monitoring equipment, as suggested in the above reviewed literature. Here we focus on formalizing three fundamental concerns: area, budget and complementarities.

Optimizing the total area being monitored by located equipment is crucial, but it is also important to be able to differentiate the relative importance of spatial attributes. For example, monitoring a grassy area may not be as critical as viewing an entry/exit door path. Accounting for budget limitations is essential as only so much equipment is possible for siting. Complementary coverage is important because security monitoring necessarily involves tracking people across space. Equipment should be located to facilitate such tracking, taking into account the geographic limitations of sensors but also providing capabilities to observe a given area by multiple sensors. Sensors therefore need to be cooperatively sited to enable movement monitoring across a broad geographic area, data fusion, and sensor handoff. With these considerations in mind, we now formalize an approach for modeling the sensor placement problem.

3. Coverage optimization to support security monitoring

3.1. Visibility analysis

The area covered by or visible from a sensor relates to research known as visibility analysis. The observable area of a sensor is restricted by geographical features, like buildings and trees, as well as the characteristics of a sensor. Such characteristics include relative elevation, vertical distance from a surface and sensor capabilities, like horizontal and vertical angle limits. The observable area of a sensor is similar to the concept of the range in central place theory (Christaller, 1966), where visibility is limited to a maximum effective distance. Geographic Information Systems (GIS) are useful for delineating the visible area from a sensor given their computational geometry capabilities.

A viewshed is the visible area from a specified point v with coordinates (x, y, z). A viewshed $\Phi(v)$ can be defined as the set of points or cells on the surface D that are visible from v extending out to some maximum distance r from the viewpoint (de Floriani & Magillo, 2003). Formally,

$$\text{Viewshed } \Phi(v) = f(v, D, r) = \{\delta \in D \mid d(v, \delta) \leqslant r \text{ and } \delta \text{ visible from } v\}$$

Visibility computation on the surface is typically based on line-of-sight. If the line segment connecting two points is explicitly above the surface, then the two points are mutually visible. For example, in Fig. 2, δ_2 is visible from δ_1 but not visible from δ_3. This is because line segment $\overline{\delta_1\delta_2}$ is above the surface, but $\overline{\delta_3\delta_2}$ is blocked by the surface.

Polyhedral Terrain Models (PTM) and Regular Square Grids (RSG) are generally used to represent a terrain or topographic surface in visibility analysis (de Floriani & Magillo, 1994). While PTM subdivides a domain into straight-line planes and interpolates them with linear functions, RSG subdivides a surface into regular rectangular (or square) regions induced by a regular grid. Triangulated irregular networks (TIN), which are a special class of PTM and are characterized by a set of continuous, none-overlapping triangles, have been preferred in visibility analysis because they are efficient for representing a 3D surface. Strictly speaking, visibility analysis based on the RSG or TIN is 2.5 dimensional rather than 3 dimensional in that current GIS functionality cannot effectively deal with overhangs, archways, tunnels, etc. Computer graphics work does provide for 3D capabil-

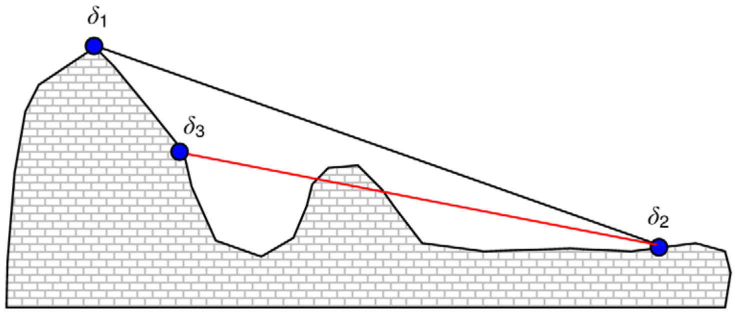

Fig. 2. Line of sight and visibility.

ities in visibility analysis (see Bittner & Wonka, 2003). The focus here, however, is sensor coverage optimization, assuming that visibility analysis is possible. The optimization approaches that follow are sufficiently general for 3D, 2.5D or 2D application.

3.2. Spatial analysis and modeling

Even though visibility analysis provides information about the visibility structure for a given point, it does not say anything about the optimal combination of sensors and where they should be located. A model is needed to support this location decision problem. The location set covering problem (LSCP), maximal covering location problem (MCLP) and art galley problem have been used for siting surveillance equipment in previous work. The LSCP (Toregas, ReVelle, Swain, & Bergman, 1971) aims to locate the minimum number of facilities in such a way that all demand is covered within a specified distance standard. While it is ideal to cover all demand, this is sometimes economically infeasible. That is, this may require excessive resources not available to service providers. The art gallery problem (O'Rourke, 1987), noted previously as determining the minimum number of guards required to cover a polygon, generally assumes unlimited guard visibility so that this is not suitable for locating equipment with a limited viewing range. In addition, the number of identified guards depends on polygon structure. This means that guarding a polygon with complex shape may necessarily require excessive resources, irrespective of planning concerns or resources.

Given the limitations of the LSCP and art gallery problem approaches, the focus here will be on the MCLP as it relaxes the rigid requirement of complete coverage of all demand in the LSCP and the unrealistic assumptions of the art gallery problem. We will see that the MCLP can easily be extended in order to satisfy surveillance requirements. Goodchild and Lee (1989), Kim et al. (2004) and Lee (1991) used the MCLP to locate facilities on topographic surfaces. The MCLP supports decision making associated with service demand points or areas. The orientation of the MCLP is to maximize total demand covered within a stated service distance or time by a given number of facilities. A demand point is considered 'covered' if it is within a critical distance (time) from at least one facility. In contrast to the LSCP, this model incorporates a budget constraint to limit the number of facilities located, which means that all demand points may not necessarily be covered. The MCLP was originally introduced by Church and ReVelle (1974). Notation for stating the problem formally is as follows:

i = index of demand areas, $i = 1$ to n

j = index of potential sensor placement locations, $j = 1$ to m

$$\lambda_{ij} = \begin{cases} 1 \text{ if demand } i \text{ is covered by a potential sensor } j \\ 0 \text{ otherwise} \end{cases}$$

$N_i = \{j \mid \lambda_{ij} = 1\}$

a_i = importance of demand i

p = number of sensors to locate

The decision variables for this planning problem are:

$$x_j = \begin{cases} 1 \text{ if potential sensor } j \text{ is located} \\ 0 \text{ otherwise} \end{cases}$$

$$y_i = \begin{cases} 1 \text{ if a demand } i \text{ is covered} \\ 0 \text{ otherwise} \end{cases}$$

Thus, one set of variables tracks sensor placement and the other tracks coverage.

Maximal covering location problem (MCLP)

$$\text{Maximize } Z = \sum_i a_i y_i \tag{1}$$

$$\text{Subject to} \sum_{j \in N_i} x_j - y_i \geqslant 0 \quad \forall i \tag{2}$$

$$\sum_j x_j = p \tag{3}$$

$$x_j = (0, 1) \quad \forall j \tag{4}$$

$$y_i = (0, 1) \quad \forall i \tag{5}$$

The objective (1) is to maximize covered demand. Constraints (2) allow a demand point i to be covered ($y_i = 1$) only if one or more sensors are sited at locations in the set N_i. Constraint (3) requires exactly p sensors to be located. Constraints (4) and (5) specify integer requirements on decision variables.

In surveillance monitoring it is not only important to deploy sensors to maximally cover an area, but also ensure sensor coverage overlap (Pavlidis et al., 2001). Thus, coverage overlap is a reification of spatial complementarities. This is necessary for spatially tracking the movement of people and activities. These two goals compete with each other, however. Pavlidis et al. (2001) informally dealt with coverage overlap. Their algorithm places cameras such that their fields of view should be overlapped at least 25%. The MCLP can model the first goal but does not address coverage overlap (spatial complementarities between sensors).

Overlapping visible area is similar to the backup coverage concept in facility location. The backup coverage location problem (BCLP) was originally used in siting emergency services (Daskin & Stern, 1981; Eaton, Sánchez, Lantigua, & Morgan, 1986; Hogan & ReVelle, 1986), and more recently applied to select reserves for protecting rare species (Malcolm & ReVelle, 2005). The backup coverage approach is an extension of the MCLP, and is mathematically formulated as follows (Hogan & ReVelle, 1986):

Backup coverage location problem (BCLP)

$$\text{Obj1}: \text{ Maximize } Z_1 = \sum_i a_i y_i \tag{6}$$

$$\text{Obj2}: \text{ Maximize } Z_2 = \sum_i a_i u_i \tag{7}$$

Subject to:

$$\sum_{j \in N_i} x_j - y_i - u_i \geqslant 0 \quad \forall i \tag{8}$$

$$u_i - y_i \leqslant 0 \quad \forall i \tag{9}$$

$$\sum_j x_j = p \tag{10}$$

$$x_j = (0,1) \quad \forall j \tag{11}$$

$$y_i, u_i = (0,1) \quad \forall i \tag{12}$$

where u_i is used to track multiple coverage as follows:

$$u_i = \begin{cases} 1, & \text{if demand } i \text{ is covered more than once} \\ 0, & \text{otherwise} \end{cases}$$

The first objective maximizes primary coverage and the second objective maximizes backup (or overlapping) coverage. Constraints (8) and (9) determine which areas have backup coverage. Area i receives backup coverage only when two or more sensors can view it. Constraints (9) ensure that backup coverage is provided only when primary coverage is also provided. The number of sensors covering an area is tracked by constraint (10). Constraints (11) and (12) indicate integer requirements.

The two objectives of the BCLP can be reduced to a single objective using the weighted sum method,[1] and can be solved using a commercial optimization package. The two objectives, (6) and (7) can be restated as follows:

$$\text{Maximize } Z = w \sum_i a_i y_i + (1-w) \sum_i a_i u_i \tag{13}$$

where w is a weight varying between zero and one.

4. Multiple sensor placement

In support of sensor placement to ensure good spatial coverage, we detail an approach that incorporates the broad concerns to be addressed. This approach explicitly incorporates visibility analysis in coverage optimization. Fig. 3 summarizes the main components of this approach.

Spatial information, such as a DEM (digital elevation model) and urban features like buildings, is needed to support this analysis as input data in Fig. 3. In order to perform visibility analysis and apply coverage optimization models, discretization of continuous space is required (second step in Fig. 3). A regular square grid (RSG) is chosen as a discrete representation of space, as it sufficiently accounts for areas in need of monitoring.

[1] Other multi-objective methods are available, but are not discussed here. See Cohon (1978) for more details.

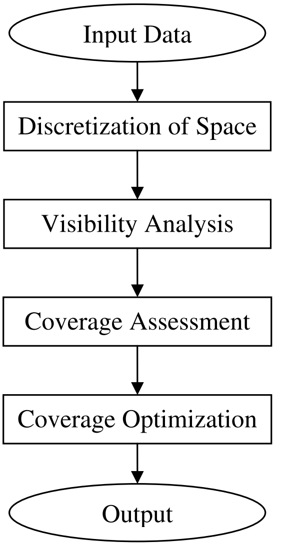

Fig. 3. Multiple sensor placement approach.

The RSG is generated from a building layer, with height as an attribute, and a DEM. Thus, each cell in the RSG has an associated height value. A new grid in which each cell is assigned a weight reflecting the relative importance of cells is also created. The weight is calculated based on two criteria: landuse and distance from entry/exit doors. Roads and sidewalks have higher values than grassy areas. Cells close to an entrance also have higher weights, reflecting greater security importance.

The next step in Fig. 3 involves visibility analysis, or more precisely the computation of viewsheds. The computational complexity of visibility analysis between every cell and every other cell is $O(n^2)$, where n is the number of cells in a RSG (Kim et al., 2004). This means that the visibility calculation for a RSG with a large number of cells may be computationally prohibitive. To mitigate time complexity, 'reduced targets strategies' (Franklin & Ray, 1994; Rana, 2003) and 'reduced observers strategies' (Kim et al., 2004; Lee, 1994; Rana & Morley, 2002) are employed. As a sensor, or camera in particular, has a limited field of view, its visibility range is restricted. When calculating a viewshed, only cells within a given range are considered. There are practical constraints imposed by the topography of an area under surveillance, limiting feasible potential sensor locations. It is assumed that a sensor can be sited on the edges or corners of building rooftops. Each potential sensor location has the following attributes: elevation of a sensor, vertical distance of sensors and targets in surface, horizontal angle limits, vertical angle limits and search distance limits. These attributes are determined by sensor settings and location characteristics.

Using a GIS, a viewshed for each potential sensor location is calculated. A cell is visible if the center is viewable from the observation point. A visibility function typically requires three input parameters: input raster data (RSG with height values), observation point data (potential sensor locations), and visibility characteristics. Such analysis returns a grid consisting of binary-encoded values: visible being 1 or not visible equaling 0.

Once visibility analysis has been conducted, it is possible to undertake coverage assessment in Fig. 3. Specifically all cells are evaluated for potential coverage by sensors. Such an assessment involves determining N_i for each cell i. The set N_i represents those potential sensors that can monitor cell i.

These individual components enable one to undertake the modeling effort of identifying the best sensor locations. As noted previously, the MCLP and BCLP are used to support to this sensor placement problem (final step in Fig. 3). The two models are solved using a commercial optimization package.

5. Application

The approach described in the previous section was applied for siting sensors on part of the Ohio State University campus in Columbus, Ohio. The objective is to find the optimal configuration of visual surveillance cameras and their locations in order to maximize viewable area, and also maximize overlapping coverage by a given number of cameras. The study area is subdivided into grid cells of 3 by 3 feet in size. The number of possible cells to be monitored is 16,087 and the number of potential camera locations is 59 (points shown in Fig. 4). The Spectra III^{TM} SE camera with horizontal resolution of 470 TV lines and 3.6–82.8 mm f/1.6 lens is the equipment to be utilized here. It has 360° pan movement and vertical tilt from +2° to −92°.

Visibility analysis and coverage assessment are performed using ESRI ArcGIS 9.0 and procedures are coded using ArcObjects in ArcGIS (Visual Basic Editor). The problem instances for the MCLP and BCLP are produced using ArcGIS and solved using CPLEX

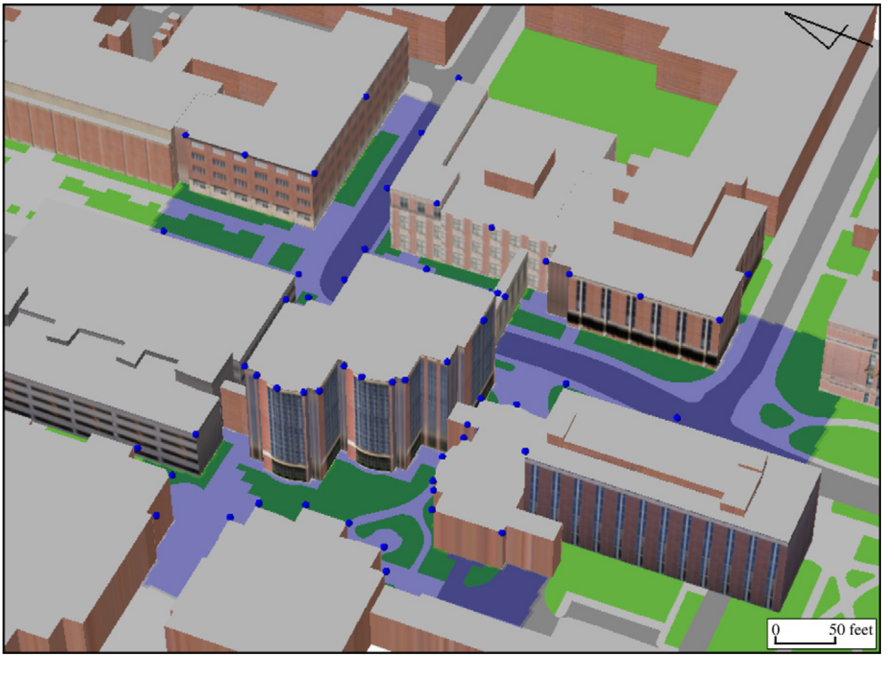

Fig. 4. Ohio State University study area.

8.1, a commercial optimization software package, on a Dual Intel Pentium III Xeon 733 MHz Window NT server with 1 GB RAM.

The MCLP for siting multiple sensors was assessed for a range of potential cameras, from 1 to 8. Table 1 summarizes computational results and Fig. 5 shows the tradeoff curve for the number of cameras and the amount of covered area. As shown in Table 1, approximately 94% of the study area can be monitored with just 4 cameras and nearly 98% with 8 cameras. The curve in Fig. 5 exhibits decreasing marginal coverage with each additional camera purchased. In other words, the additional coverage obtained by adding the kth camera is generally less than the additional coverage that is obtained by adding the $(k-1)$th camera. To cover more area, an additional camera is needed. The decision making issue is at what point is marginal coverage simply too expensive. In this case, the study area is not fully covered even with 20 cameras. The spatial distribution of coverage for siting five cameras is shown in Fig. 6.

Cameras in Fig. 6 (and Table 1) were deployed in order to maximally cover the study area using the MCLP. If complementarities between cameras are considered for monitoring activities across a broader area in order to track individuals using multiple cameras, this is beyond the structured intent of the MCLP. The BCLP, however, does address coverage overlap. Solutions for the BCLP are acquired by solving Eq. (13), varying the weight on multiple coverage from 0 to 1. If w is set to 1, then Eq. (13) is equivalent to the MCLP.

Table 1
Computational results for the MCLP

Cameras (p)	Covered cells	Area (%)	Iterations	Branches	Time (s)
1	8109	50.4	19,715	0	234.30
2	11,655	72.5	12,668	0	121.60
3	14,567	90.6	5495	0	55.22
4	15,030	93.4	9617	16	541.30
5	15,492	96.3	6028	39	385.10
6	15,646	97.3	3274	15	326.60
7	15,768	98.0	3119	17	226.80
8	15,876	98.7	1337	4	81.31

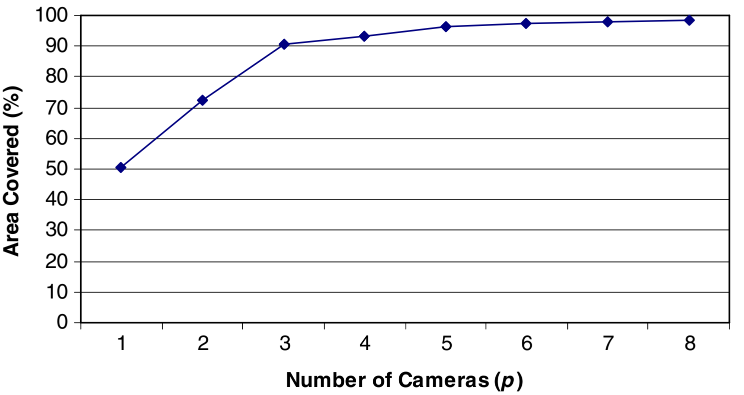

Fig. 5. Tradeoff curve for area covered by specified number of cameras.

Fig. 6. Coverage for five cameras ($p = 5$).

Alternatively, if w equals 0, then maximization of multiple coverage is only considered in sensor siting. When tradeoff weights are considered for these competing objectives, compromise solutions/alternatives are identified, if they exist.

Solution information related to the BCLP for siting five cameras is summarized in Table 2. This table shows the relationship between primary and multiple coverage, and also provides CPLEX solution characteristics. As the importance on multiple coverage

Table 2
Computational results for the BCLP ($p = 5$)

Weights on multiple coverage	# of primary covered cells	# of multiple covered cells	% of primary covered cells	% of multiple covered cells	Iterations	Branches	Time (s)	Gap (%)
0.0	15,492	3573	96.30	22.21	6028	39	385.06	0
0.1	15,411	9106	95.80	56.60	24,581	16	540.94	0
0.2	15,084	11,070	93.77	68.81	139,554	1421	2,089.39	0
0.8[a]	14,971	11,103	93.06	69.02	839,351	235,293	49,636.86	9.37
0.9[a]	14,663	11,150	91.15	69.31	461,195	208,400	42,313.56	12.56

[a] Optimality not guaranteed in this case due to solver limitations.

increases, the number of cells covered by two or more cameras also increases, as intended. The relationship between primary and multiple coverage is depicted in Fig. 7. In this figure, the points indicate the *noninferior* set for $p = 5$. Point A is the same as that for the MCLP, the maximum number of cells that can be monitored by five cameras. This solution has a weight of one on primary coverage and a weight of zero on multiple coverage.

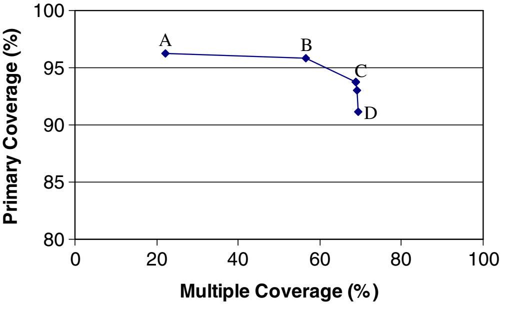

Fig. 7. Tradeoff curve for primary and multiple coverage ($p = 5$).

Fig. 8. Spatial distribution of primary and multiple coverage ($p = 5$, $w = 0.2$).

Point B is obtained by setting $w = 0.1$ for multiple coverage. With a decline in primary coverage of only 0.5%, an increase in multiple coverage of 34.39% is achieved. Point C shows that 93.8% of the cells may be covered once while simultaneously 68.8% of the cells two or more times. Lastly, point D, which corresponds to a weight of 0.9 for multiple coverage, covers 91.1% of the cells once and 69.3% two or more times.

Fig. 8 shows the spatial distribution of primary and multiple coverage when $w = 0.2$ for multiple coverage. In comparing Fig. 8 with Fig. 6 (MCLP result for siting five cameras, the same as the result obtained using $w = 0$ for multiple coverage), we can see that multiple coverage obviously increases by relocating cameras, with only a slight decrease in visible area. With a decrease in primary coverage of only 2.53%, an increase in multiple coverage of 46.6% is achieved (Table 2). This means that a high degree of multiple coverage is possible with little impact on primary coverage.

6. Conclusions

This paper has shown that sensor placement for supporting security monitoring in 3D urban environments can be approached using coverage optimization combined with visibility analysis. Visibility analysis was utilized for calculating coverage for each potential camera location. The optimal combination of cameras and their locations were modeled by the maximal covering location problem (MCLP) and the backup coverage location problem (BCLP).

The MCLP results show that the marginal coverage of adding sensors reaches a point where further investment is not economically feasible. The results of the BCLP reveal that substantial gains in multiple coverage can be achieved without substantial sacrifice in primary coverage. This model no doubt contributes to capabilities to track the movement of people and activities across space in the context of security monitoring. Consequently, these results demonstrate that security sensor placement problems, which have been ignored or implicitly studied in surveillance systems research, can be mathematically modeled using coverage location problems. These model-based sensor placement approaches can improve the performance of surveillance systems as well as the efficiency of allocated resources.

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