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Location Optimization in Heterogeneous Sensor Network Configuration for Security Monitoring

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보안 모니터링을 위한 이종 센서 네트워크 구성에서 입지 최적화 접근

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Abstract : In many security monitoring contexts, the performance or efficiency of surveillance sensors/networks based on a single sensor type may be limited by environmental conditions, like illumination change. It is well known that different modes of sensors can be complementary, compensating for failures or limitations of individual sensor types. From a location analysis and modeling perspective, a challenge is how to locate different modes of sensors to support security monitoring. A coverage-based optimization model is proposed as a way to simultaneously site *k* different sensor types. This model considers common coverage among different sensor types as well as overlapping coverage for individual sensor types. The developed model is used to site sensors in an urban area. Computational results show that common and overlapping coverage can be modeled simultaneously, and a rich set of solutions exists reflecting the tradeoff between common and overlapping coverage.

Key Words : security monitoring, location modeling, geographic information systems(GIS), coverage optimization, common coverage, overlapping coverage, multiple sensor type location problem

요약 : 안전과 보안이 현대사회의 중요한 관심사로 등장하고 있고 그 대상 영역이 실내 공간으로 넘어서 도시로 확대되고 있다. 도심 지역에 수 많은 감시 센서들이 설치 · 운영되고 있다. 많은 보안 모니터링 맥락에서 감시 센서/네트워크의 수행능력 혹은 효율성은 조명의 변화와 같은 환경 조건에 제약을 받는다. 서로 보완적인 상이한 유형의 센서를 설치함으로써 개별 유형의 센서의 고장 혹은 한계를 극복할 수 있다는 것은 익히 잘 알려진 사실이다. 입지 분석과 모델링의 관점에서 관심사는 어떻게 보완적인 상이한 유형의 센서들의 적절한 입지를 결정하여 보안기능을 강화할 수 있느냐 이다. 이 연구는 *k* 개의 상이한 유형의 감시 센서의 위치를 결정하는 커버리지 기반의 최적화 모델을 제시한다. 이 모델은 상이한 유형의 센서 사이의 공통 커버리지와 동일 유형의 센서 사이의 중복 커버지리를 동시에 고려한다. 개발된 모델은 도심 지역에 센서를 위치시키는데 적용된다. 연구 결과는 공통 및 중복 커버리지가 동시에 모델링 될 수 있으며, 두 유형의 커버지리 사이의 tradeoff를 보여주는 많은 해들이 있음을 보여준다.

주요어 : 보안 모니터링, 입지 모델링, 지리정보시스템(GIS), 커버리지 최적화, 공통 커버리지, 중복 커버리지, 다중 센서 유형 입지 문제

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1. Introduction

Security monitoring has become an important issue in modern society, particularly due to a series of terrorist attacks such as 9.11 (September 11, 2001) and the London bombings (July 7, 2005). Much surveillance equipment has been installed in urban areas in order to protect critical facilities or districts, like commercial, financial, and government districts (Valera and Velastin, 2005). For example, the City of London constructed a video camera surveillance system (the so-called "ring of steel") which encircles the center of London and monitors every entering driver and vehicle (McCahill and Norris, 2002). Similarly, the New York City Police Department is considering the construction of a surveillance network in order to control access to lower Manhattan, a world financial center and a target for terrorist attacks (Wall Street Journal, 25, Jan 2006). Surveillance has become a prevalent activity in urban areas.

How and where to site sensors is an important task in designing surveillance sensor networks as the location of sensors has an influence on the performance and the cost of a system. Too many sensors will increase processing time and algorithmic complexity, and require much storage space in addition to high installation costs. In contrast, too few sensors may not provide appropriate coverage for an entire area of interest to be monitored. As a result, efficiency and performance of surveillance sensor networks is dependent upon the location of sensors (Hu et al., 2004). Therefore, modeling approaches to support the appropriate location of surveillance sensors are appealing.

Several studies have demonstrated that siting surveillance equipment on terrain surfaces or in urban areas can be approached using coverage-based location models, such as the location set covering problem (LSCP), the maximal covering location problem (MCLP), or the backup coverage location problem (BCLP)(Goodchild and Lee, 1989; Lee, 1991; Kim et al., 2004; Murray et al., 2007). The objective of past research has been to locate the minimum number of surveillance facilities so as to cover an entire area, to locate a specified number of equipment so as to maximally cover an area, or to simultaneously maximize primary and backup coverage for a given number of surveillance facilities. These approaches focus on siting a single type of surveillance equipment, all with the same service characteristics.

However, the performance and robustness of surveillance systems or networks using a single type of sensor, specifically visible sensors only, may be limited by environmental conditions, such as presence of shadows, lack of night-time visibility, or sudden illumination change (Hu et al., 2004; Lipton et al., 2003; Torresan et al., 2004; Brown et al., 2005; Conaire et al., 2005; Chen and Wold, 2006; Conaire et al., 2006). These environmental conditions affect the quality of captured information, which influences the performance of object detection and tracking algorithms. As a result, environmental variation restricts the capabilities of surveillance systems (Brown et al., 2005). According to Lipton et al. (2003), the night-time performance of a surveillance system in an airport based only on visible sensors was limited due to low-level illumination. This implies that a surveillance system with only visible sensors may not enable 24/7 continuous monitoring, introducing vulnerability to terrorist attack or crime.

It is well known that different modes of sensors can be complementary, compensating for failures or limitations of individual sensor types (Torresan et al., 2004; Conaire et al., 2005; Conaire et al., 2006; Therrien et al., 1997). Specifically, infrared or thermal imagery is a complementary technology to visible imagery, as it relies on emitted energy rather than reflected. Given this, infrared imagery can detect objects in low lighting conditions. The fusion of visible and infrared information provides the potential for operating a surveillance system on a 24/7 basis, if integration is done correctly.

Collins et al. (2000) defined system architecture for integrating many different sensor modalities, like visible, thermal, mobile, etc. Therrien et al. (1997) described a system where infrared images are combined with visible images. Torrensan et al. (2004) presented a detection algorithm combining infrared and visible data and reported successful improvements in object detection and tracking compared with the use of only a single type of sensor. Conaire et al. (2005) showed an example of infrared/visible fusion for autonomous pedestrian detection. Conaire et al. (2006) evaluated the performance of a tracking algorithm through combining information from standard CCTV (Closed Circuit Television) and thermal infrared information. These studies empirically demonstrated that combining the information from multiple sources can provide more accurate and robust information for object detection and tracking. Furthermore, Cucchiara (2005) argues that multimedia surveillance systems integrating video technology with other media streams, such as audio and sensor signals, will become the fundamental infrastructure for new generations of surveillance systems.

While the main focus of previous research is on how to design system architectures and develop algorithms for fusing multiple sources, an overlooked issue is how to locate multiple sensor types in an efficient and complementary way. This paper presents a new location model for simultaneously siting multiple sensor types with different sensing ranges and characteristics to support surveillance functions such as object detection and tracking. The next section reviews literature related to locating multiple types of facilities (or sensors). The following section provides a covering location model for siting multiple sensor types. Finally, application results are presented and the paper ends with a summary and conclusion.

2. Literature Review and Theoretical Background

Locating multiple types of facilities (sensors in this study) has in fact been discussed in the location analysis and modeling literature, but with respect to hierarchical services (see Sahin and Süral, 2007). Recently, studies on wireless sensor networks also have examined the issue of siting different types of sensors with different sensing ranges and capacities (see Chakrabarty et al., 2002; Du and Lin, 2005; Su et al., 2005). This paper focuses on the literature primarily dealing with covering objectives, but a general review of hierarchical facility location models can be found in Narula (1986) and Sahin and Süral (2007).

In order to improve the scalability and performance of surveillance systems, Kulkarni et al. (2005a, 2005b) argued the necessity of surveillance systems consisting of multiple sensor types. Chakrabarty et al. (2002) presented an integer linear programming model for siting two sensor types with different sensing ranges, minimizing the number of both sensor types so as to completely cover all demand. This is similar to the work of Current and O'Kelly (1992) who formulated covering location models for siting two types of emergency warning sirens having different costs and covering radii. In Chakrabarty et al. (2002) and Current and O'Kelly (1992), the coverage of demand is accounted for only if demand is within the covering radius of a facility of any type. Du and Lin (2005) additionally considered difference in the coverage level for a demand area (i.e. more important areas have higher degrees of coverage requirements), and proposed an algorithm for maintaining differentiated coverage with two types of sensors. Su et al. (2005) developed a multiple coverage algorithm for heterogeneous sensor networks consisting of k different types of sensors with different sensing radii. While Chakrabarty et al. (2002) and Current and O'Kelly (1992) modeled single coverage by different types of facilities, Du and Lin (2005) and Su et al. (2005) modeled multiple coverage by different types of facilities.

Even though the studies mentioned thus far have dealt with multiple facility types, each type of facility provides the same kind of service. That is, there is no difference in the service provided by different types of facilities, other than range of service. However, in many planning applications, locating multiple facility types results in different service quality depending on the facility type. Thus, defining the relationship among different service levels is an important issue (Marianov and Serra, 2001). Based on the relationship among service levels, multiple facility type location problems can be categorized into inclusive and exclusive models (see Narula, 1984; Tien et al., 1983).

In the case of the inclusive models, a facility at a higher level provides services of facilities at lower levels and its own unique service. Moore and ReVelle (1982) proposed a hierarchical service location problem for locating two different types of facilities having different service coverage, maximizing demand that has access to all components of service. Mandell (1998) investigated a covering-type model for two types of services with different capabilities and also additionally considered server availability. Serra (1996) presented a coherent covering location model for siting two types of facilities such that coverage at each level is maximized and coherence is obtained. Here, the coherence means that all demand covered by a facility at level one also is covered by a facility at level two.

A facility at each level can provide only its own unique service, however. This implies that there is no intersection among the services offered by different types of facilities, i.e. exclusive relation. Berlin et al. (1976) considered the locations of both ambulances and hospitals relative to accident sites and showed that this location problem is separable into two traditional location-allocation problems. However, this separable approach for multiple facility types may produce a suboptimal solution, rather than a global optimum (Schilling et al., 1979). Schilling et al. (1979) suggested a Facility-Location Equipment-Emplacement Technique (FLEET) model, combining the location of fire stations with the allocation of primary and special service equipment to the selected stations.

While studies reviewed thus far have focused on relationships among different types of facilities, they have not considered the relationship among the same type of sensor. This paper explicitly considers not only the relationship among different types of sensors, but the relationship among sensors of the same mode, and formulates a multi-objective location model for siting k multiple sensor types in the context of surveillance sensor planning. Two modeling concerns in this paper are how to locate different types of sensors to enhance the performance of object detection algorithms and how to achieve overlapping coverage for each type of sensor in order to improve the performance of object tracking algorithms. The former allows coordination among different types of sensors and the latter allows collaboration within the same type of sensor. The second concern is usually required in automated surveillance systems for tracking moving objects in a large area (Murray et al., 2007). Both modeling concerns are explicitly considered in the formulated sensor siting model.

3. Model Formulation

An approach for overcoming the limitations of surveillance systems being composed of a single sensor type is to combine information obtained from different modalities, like visible and thermal sensors (Torresan et al., 2004; Conaire et al., 2005; Conaire et al., 2006; Therrien et al., 1997). In this paper, the relationship among different types of sensors is assumed as "exclusive". Thus, different types of sensors provide different information about an object and/or area. For example, when siting visible and thermal sensors, each type of sensor detects a different part of the radiation spectrum and different characteristics of radiation, reflected and emitted radiation respectively. The sensor location problem with different sensor types can be modeled using the concept of coverage as the sensing range of each type of sensor is spatially bounded due to geographic features and the minimum resolution required for object detection.

A challenge is to derive the coverage of a sensor. This is not a simple task as geographic features as well as the capabilities of a sensor dictate resulting coverage. Fortunately, geographic information systems (GIS) provide computational geometry capabilities for deriving the coverage of sensors. Visibility (or viewshed) (see De Floriani and Magillo, 2003) is a spatial analysis tool in many GIS packages, enabling the derivation of a visible area from one or more points or lines. Visibility computation on a surface is typically based on line-of-sight. If a line between two points is not obstructed by the surface, then the two points are mutually visible (see Murray et al., 2007). The shape of coverage derived using visibility analysis may be regular, irregular or noncontiguous.

Given viewsheds (or coverage) for each sensor type at a potential location, a remaining challenge is to develop an optimization model for siting multiple sensor types. Different types of sensors interact with each other to provide surveillance. Demand is considered as observed only if it is covered by all k types of sensors. This paper utilizes the notation z_i to explicitly track common coverage by all types of sensors. If demand is observed for all types of sensors, then the decision variable is equal to 1. Common coverage is explicitly stated as an objective goal and is maximized for a given number of k sensor types. In addition, the concept of backup coverage (Hogan and ReVelle, 1986) can be utilized to introduce overlapping coverage in the context of multiple sensor type location modeling as done by Murray et al. (2007). An additional variable, u_i^k, is used to account for overlapping coverage for each sensor type. Overlapping coverage of demand is accounted for only if it is covered by more than one sensor of type k. Overlapping coverage also can be structured as an objective goal, maximizing overall overlapping coverage from all k sensor types. Therefore, a covering location problem that simultaneously considers common and overlapping coverage can be approached using multiple objectives. In order to mathematically state this optimization model, consider the following notation:

i=index of demand
j=index of potential sensor locations
k=index of sensor types

$$\lambda_{ij}^k=\begin{cases}1, \text{ if demand } i \text{ is covered by } k \text{ type of sensor sited at } j \\ 0, \text{ otherwise}\end{cases}$$

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

a_i=importance of demand i(weight of demand i)

p_k=number of k type of sensor to be sited

The decision variables for this planning problem are:

$$x_j^k=\begin{cases}1, \text{ if } k \text{ type of sensor sited at } j\\ 0, \text{ otherwise}\end{cases}$$

$$y_i^k=\begin{cases}1, \text{ if demand } i \text{ is covered by } k \text{ type of sensor}\\ 0, \text{ otherwise}\end{cases}$$

$$z_i=\begin{cases}1, \text{ if demand } i \text{ is covered by all type of sensor simultaneously}\\ 0, \text{ otherwise}\end{cases}$$

$$u_i^k=\begin{cases}1, \text{ if demand } i \text{ is covered by more than one } k \text{ type of sensor}\\ 0, \text{ otherwise}\end{cases}$$

Using this notation and decision variables, the multiple sensor type location problem (MSTLP) can be modeled as follows:

Multiple Sensor Type Location Problem (MSTLP)

$$\textit{Maximize } \Omega_1=\sum_i a_i z_i \quad (1)$$

$$\textit{Maximize } \Omega_2=\sum_i\sum_k a_i u_i^k \quad (2)$$

Subject to:

$$\sum_{j\in N_i^k} x_j^k-y_i^k-u_i^k \geq 0 \quad \forall i, k \quad (3)$$

$$u_i^k \leq y_i^k \quad \forall i, k \quad (4)$$

$$z_i \leq y_i^k \quad \forall i, k \quad (5)$$

$$\sum_j d_i^k = p_k \quad \forall k \quad (6)$$

$$x_j^k=\{0, 1\} \quad \forall j, k \quad (7)$$

$$y_i^k=\{0, 1\} \quad \forall i, k$$

$$u_i^k=\{0, 1\} \quad \forall i, k$$

$$z_i=\{0, 1\} \quad \forall i$$

The objectives, (1) and (2), maximize the amount of demand commonly covered by all k types of sensors and maximize overlapping coverage for each type of sensor, respectively. Constraints (3) and (4) track overlapping coverage of k type of sensors for each demand. Demand i receives overlapping coverage only when it is observable from two or more of k type of sensors. Constraints (4) ensure that overlapping coverage is achieved only after primary coverage is provided. Constraints (5) stipulate that the common coverage variable, z_i, can be equal to 1 only if demand i is covered by all types of sensors at the same time. Constraints (6) limit the total number of each sensor type to be sited. Finally, Constraints (7) state integer requirements on decision variables.

The MSTLP is a generalized version of the maximal covering location problem (MCLP, Church and ReVelle, 1974) and backup coverage location problem (BCLP, Hogan and ReVelle, 1986). If k is equal to 1, then this model becomes the original BCLP. Additionally, if objective (2) is ignored, the MSTLP becomes the MCLP. Thus, the MCLP and BCLP are special cases of the proposed MSTLP.

Figure 1 depicts three potential MSTLP solutions in siting two sensor types with different sensing ranges and characteristics. In Figure 1a, the coverage of each sensor type is maximized, but common coverage is not maximized. The maximization of the common coverage objective in the MSTLP results in the configuration shown in Figure 1b, where demand is simultaneously monitored by two sensor types as much as possible. Obtained complementary information from the two sensor types can be used to facilitate and enhance object detection in security monitoring. However, from Figure 1a and 1b, it may not be possible to continually observe moving objects due to coverage gaps between sensors. For example, the three Type A sensors cannot track people or vehicles moving along the path lines in Figure 1a and 1b because they cannot cover the dash segments. This problem can be overcome by increasing the overlapping area for each sensor type. Overlapping coverage for each sensor type increases when greater emphasis is placed on the second objective of the MSTLP (Figure 1c). From Figure 1c, three type A

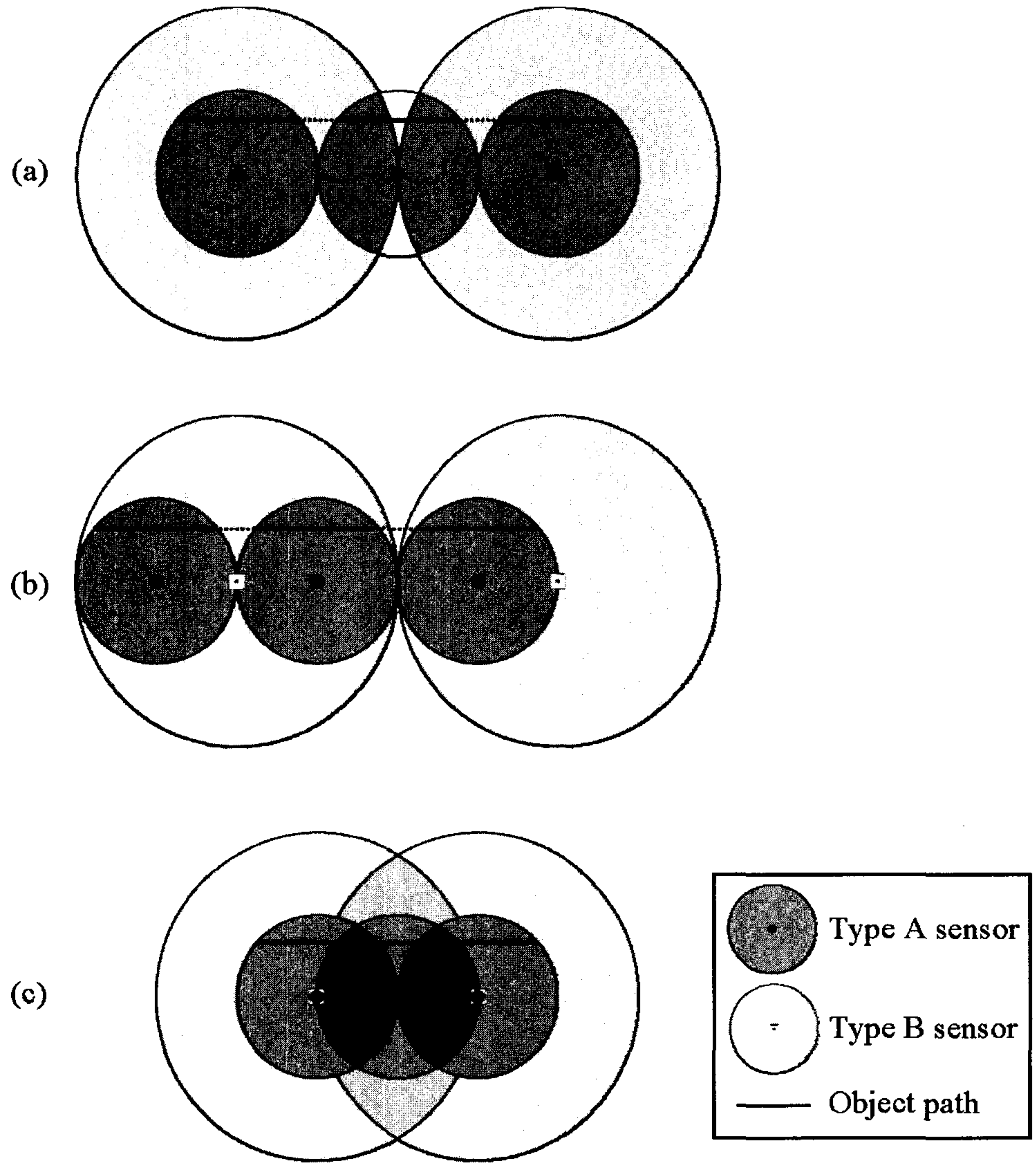

Figure 1. Common and overlapping coverage in the MSTLP

sensors now can follow movement along the path line without any gaps. Redundant information obtained from overlapping coverage not only can facilitate object tracking in a large area, but also can improve the performance of object detection approaches. Examining Figure 1b and 1c, it is clear that it is impossible to increase overlapping coverage without decreasing common coverage, and vise versa. This means that common and overlapping coverage compete with each other, so one type of coverage must be sacrificed in order to gain in the other type of coverage. The MSTLP explicitly accounts for overlapping coverage of each sensor type as well as common coverage among all k types of sensors using objectives (1) and (2).

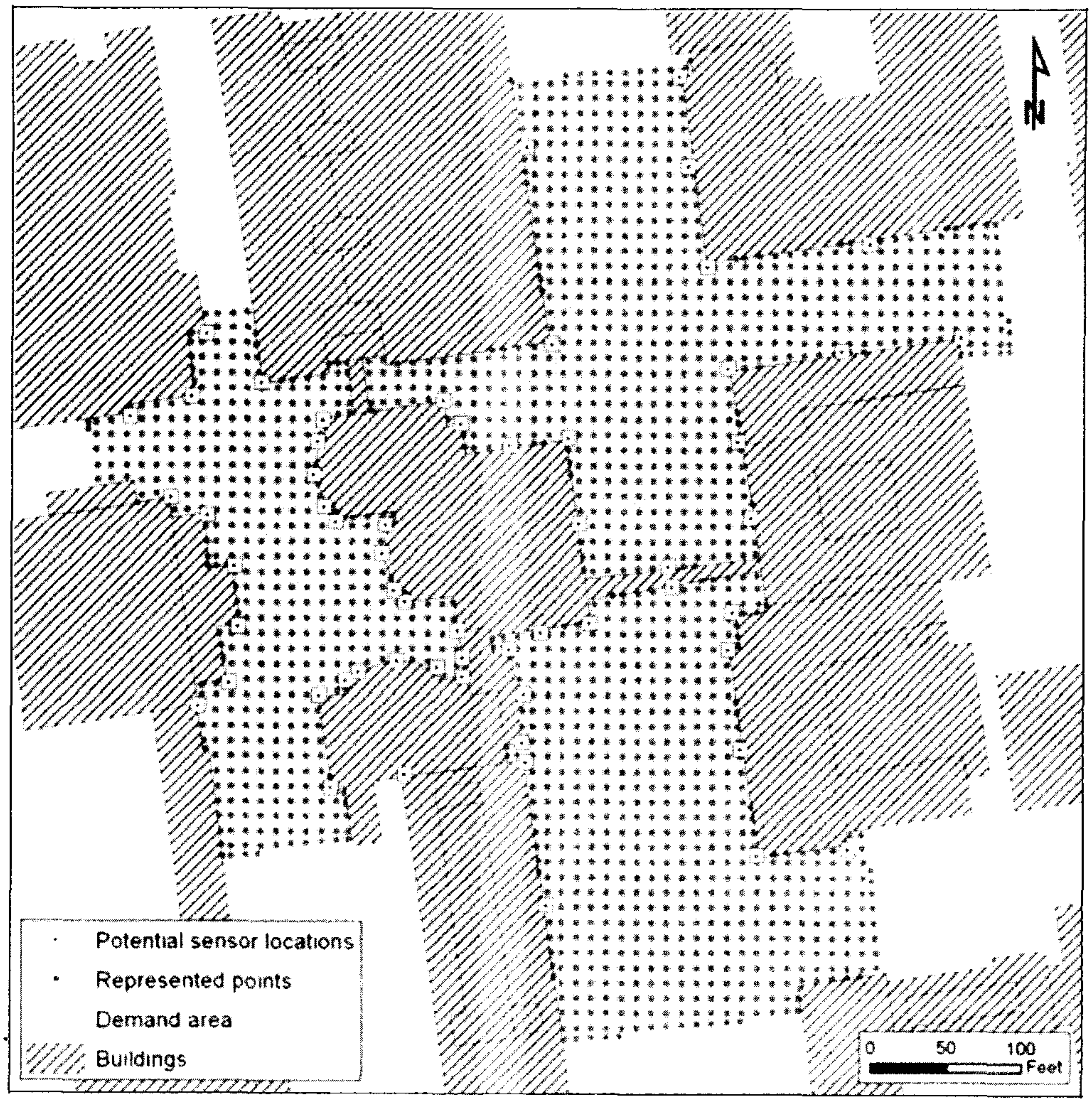

Figure 2. Study area and potential sensor locations

4. Application Results

The MSTLP was applied to a planning application siting two types of sensors, i.e. visible and thermal, in an urban area. It is assumed that both sensor types have 360° pan movement and vertical tilt from 0° to 90° and the value of vertical tilt is limited by the minimum resolution required for object detection. Maximum observation range is a function of vertical tilt, θ, and vertical height, h, for both visible and thermal sensors, that is, $h \times \tan\theta$. Figure 2 shows the study area, which is a portion of The Ohio State University campus. The demand area (144,924 ft^2) was partitioned into a regular square grid 10×10 ft in size and each polygon was represented as a point (centroid). The number of demand points totals 1683. The squares shown in Figure 2 indicate potential sensor locations, totaling 59 being on the middle or corner of buildings' roof. It is assumed that the potential sensor locations are given. The coverage of visible and thermal sensors at each potential location was derived using GIS. When deriving coverage, sensor

Table 1. Computational results of the MSTLP (p_1=5, p_2=3)

No.	w	Common Coverage Ω_1(%)	Overlapping Coverage Ω_2(%)			Time (sec)	Iterations	Branches	Gap (%)
			Total	Visible	Thermal				
1	0.0	39.9	47.2	42.4	52.1	171.3	304,477	6,478	0.0
2*	0.2	53.4	46.9	42.1	51.7	4,778.0	1,821,482	536,736	11.7
3*	0.3	56.8	44.3	37.0	51.6	4,540.3	1,780,601	502,761	13.6
4*	0.4	58.6	45.0	38.4	51.6	4,317.8	1,787,114	485,126	8.9
5*	0.6	58.7	45.1	38.4	51.7	5,098.1	3,072,882	485,793	6.4
6*	0.7	77.6	29.1	28.4	29.8	5,275.7	3,202,996	550,889	1.8
7	0.8	79.0	26.6	23.4	29.8	22.9	20,137	374	0.0
8	1.0	80.6	20.8	19.6	22.0	0.5	1,122	0	0.0

* Optimality not guaranteed in these cases due to solver limitations.

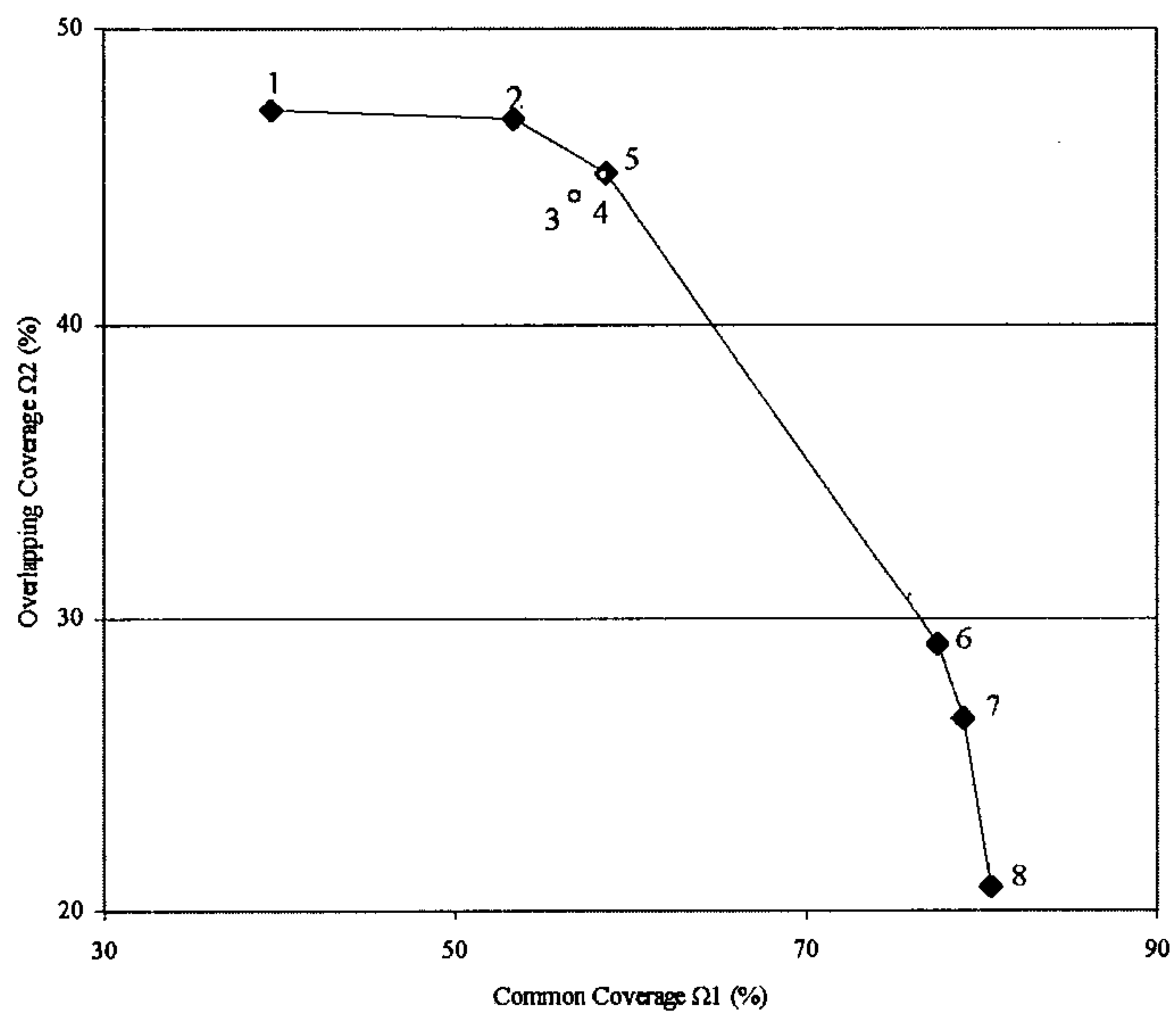

Figure 3. Tradeoff curve for common and overlapping coverage

installation characteristics, such as vertical and horizontal search limits, offset values of sensors and demand points on the surface, and elevation of the potential senor location were explicitly considered. This paper assumed that thermal sensors have low resolution, a large sensing range and are relatively expensive in comparison to visible sensors.

The analysis was carried out on a Dual Intel Xeon 3.2 GHz workstation running Windows XP with 3 GB RAM using a commercial optimization package, ILOG CPLEX[1)] version 10.1. The MSTLP having multiple objectives was solved using the weighting method. Specifically, a weight w, where $w \in [0, 1]$, is used to combine the two objective functions as follows:

$$Maximize\ \Omega = w\sum_i a_i z_i + (1-w)\sum_i\sum_k a_i u_i^k \qquad (8)$$

Figure 4. Visible sensor location and coverage

ESRI ArcGIS 9.0 was utilized for delineating the coverage of sensors and for generating optimization problem instances for the MSTLP as well as visualizing solution results.

Solution information related to the MSTLP for siting five visible (p_1=5) and three thermal (p_2=3) sensors is summarized in Table 1. By varying the weight w from 0 to 1, eight unique solutions were found. The percentage of area receiving common, Ω_1, and overlapping, Ω_2, is shown for each weight w. As expected, the amount of common coverage increases but the percentage of overlapping coverage decreases as the value of w increases or rather increased emphasis is placed on the overlapping coverage objective. Figure 3 shows the tradeoff between common and overlapping coverage, empirically demonstrating that two objectives of the MSTLP

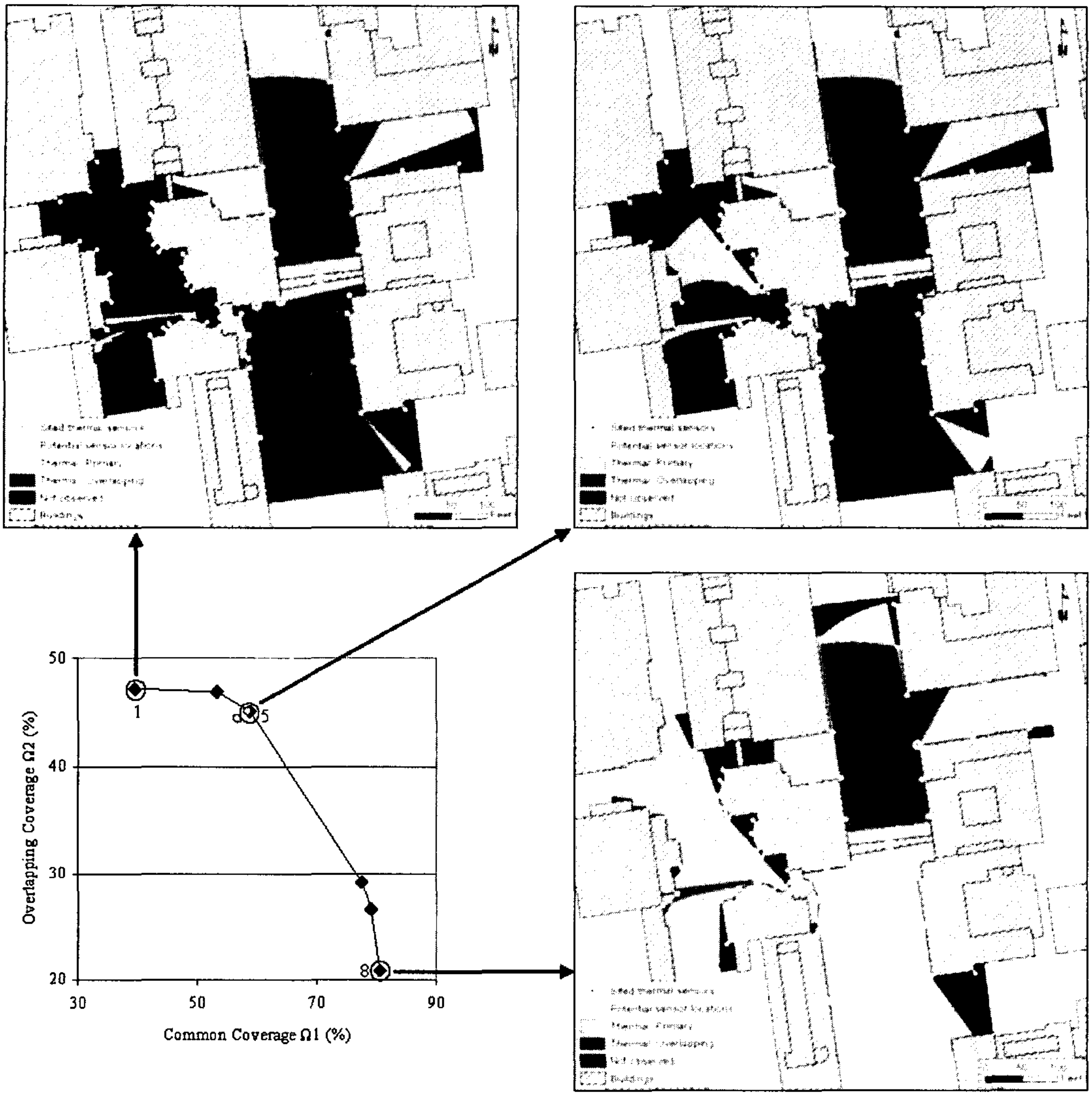

Figure 5. Thermal sensor location and coverage

compete with each other. For example, when comparing solution 6 to solution 5 in Table 1, 16.0% of overlapping coverage is sacrificed in order to improve common coverage to 18.9%.

This tradeoff between common and overlapping coverage makes the problem instances of the MSTLP difficult to solve using exact branch and bound methods which are a variety of adaptive partition strategies for solving discrete and combinatorial optimization models. That is, the tradeoff usually increases solution time, number of iterations and branches (Table 1). Table 1 reflects the computational difficulty of the MSTLP. When the problem instances of the MSTLP have some weight for both common and overlapping coverage, their solution process was terminated with an optimality gap due to solver limitations. For example, the problem instance with a weight of 0.3 for common coverage required 1,780,601 iterations, 502,761 branches,

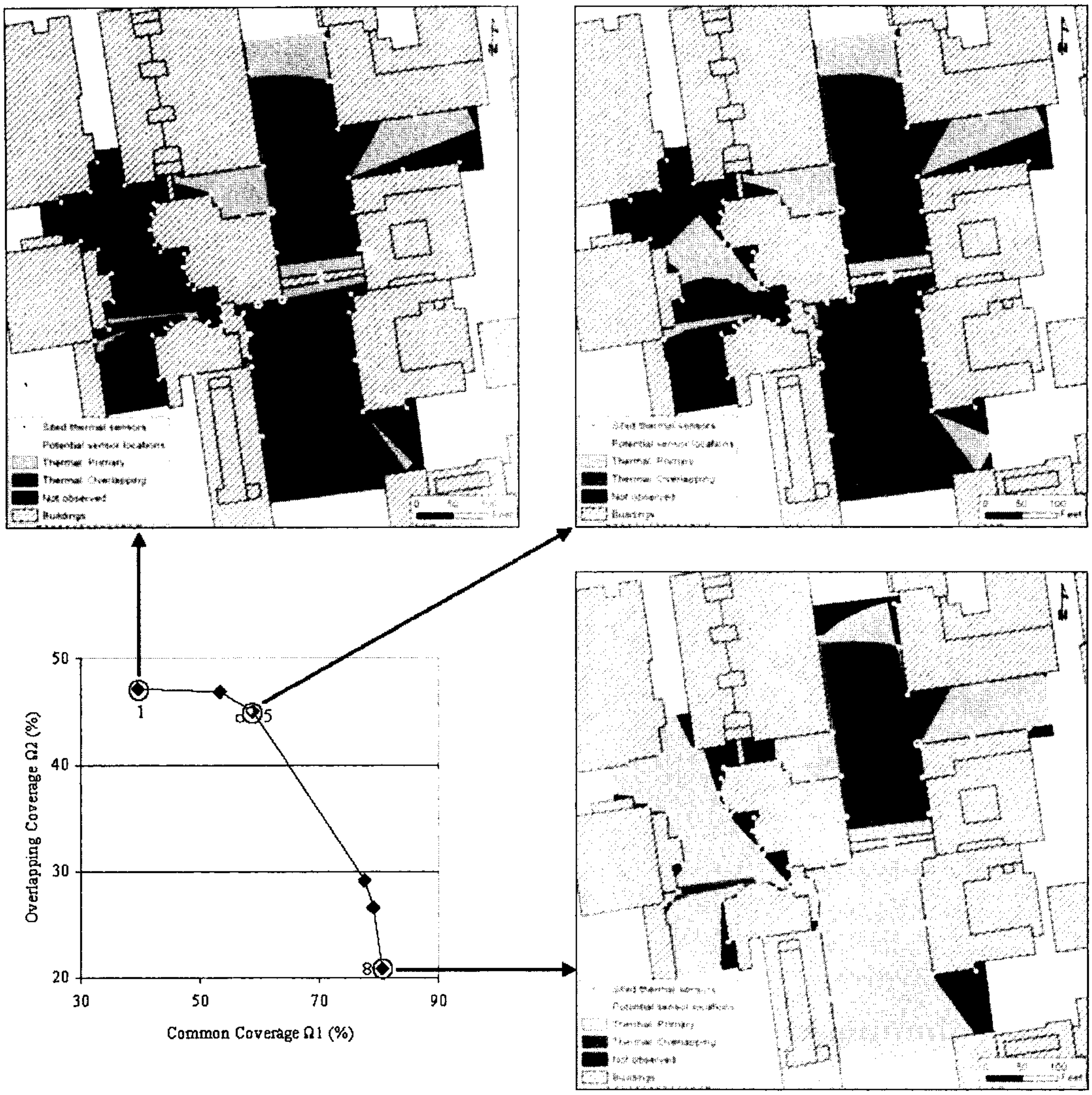

Figure 6. Spatial distribution of common coverage

and 1.26 hours of computational effort, but the optimality gap exceeds 13%.

Figure 4, 5 and 6 show selected sensor locations and primary, overlapping, and common coverage for the indicated tradeoff alternatives. When emphasizing overlapping coverage (solution 1 in Table 1 and Figure 3), 42.4 % and 52.1% of the total demand area can be observed from at least two visible sensors and two thermal sensors respectively, but only 39.9% of demand is simultaneously covered by visible and thermal sensors. On the other hand, when emphasizing common coverage (solution 8 in Table 1 and Figure 3), only 19.6% and 22.0% of demand receive visible and thermal overlapping coverage respectively, but 80.6% of demand area is observed by two sensor types simultaneously. A coverage tradeoff is reflected by solution 5 in Table 1 (and Figure 3). Common coverage is 58.7% and overlapping coverage is 45.1%. The differences in coverage for these three tradeoffs are highlighted in Figure 4, 5, and 6 shown visible sensor, thermal sensor, and common coverage, respectively.

5. Conclusions

This paper discussed the need for siting multiple sensor types simultaneously and reviewed related literature. As a way to overcome limitation in security monitoring based on a single sensor type, combining different modalities that are complementary is appealing. A challenge was how to locate multiple sensor types to support security monitoring. The multiple sensor type location problem (MSTLP) was proposed as a way to simultaneously site k different sensor types. This model considers common coverage among different sensor types as well as overlapping coverage for individual sensor types. The MSTLP is a generalized formulation of the maximal covering location problem (MCLP) and backup coverage location problem (BCLP).

The computational results demonstrated that common and overlapping coverage could be modeled simultaneously and there could be various alternative solutions due to tradeoffs between common and overlapping coverage. The MSTLP facilitates such analysis and can be utilized to enhance object detection in support of object tracking. On the other land, the computational results based on an exact solution method showed that it is computationally difficult to find optimal solutions of the MSTLP which belongs to the class of NP-hard combinatorial optimization problems and has multiple objectives. Beyond this, common and overlapping coverage which are competing with each other actually bring about confounding problem instances for exact branch and bound methods. Given this, in future research, heuristic and alternative solution approaches are required to be studied.

Notes

1) ILOG CPLEX is the most popular and well-known optimization tool and provides the highest-performance optimizers for linear programming (http://www.ilog.com).

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