

An Approach for Spatial Optimization on Positioning Surveillance Cameras

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Abstract. Strategic crime monitoring, surveillance, and prevision in public security is a fundamental topic in public administration to efficiently control certain types of criminal behavior that affect citizens' integrity and quality of life. Technological advances in computer networks and video surveillance cameras allow improving monitoring coverage by installing closed circuit television network systems comprising several high-resolution panoramic cameras in public roads and streets. This is specially useful in cities with high density of population where, naturally, crime density is high in specific zones. One of the main problems is to decide where to locate the surveillance video-cameras. To address this problem, we present an optimization-based methodology that suggests where the surveillance cameras are more likely to observe more crimes. In order to implement the optimization methodology, we propose the use of the Criminal Visibility Index that evaluates how optimal the position of a video-camera is, given the historical reported geo-referenced criminal incidence. The definition of this index is fundamental to pursue the cost function that can be solved by means of optimization algorithms for non-convex problems. Our proposal focuses on the spatial aspects of the optimization problem and relies on the implementation of a greedy algorithm that has the advantage to find a near-global optimal solution for any number of surveillance cameras limited by the available computing memory.

Keywords: Spatial optimization · Coverage · Crime monitoring · Surveillance

1 Introduction

Crime monitoring, surveillance, and prevention have become important topics in studying and modeling urban settings and behaviors therein. Closed circuit

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television (CCTV) has been adopted as a popular tool to incorporate the use of technology in urban surveillance tasks. While there has been debate on whether surveillance cameras are actually useful in reducing crime, catching offenders, or are indeed helpful in creating the sense and perception of a more secure environment [2], they have proved to be useful in certain cases [19].

Deploying surveillance systems plays a pivotal role in ensuring public safety, securing critical infrastructure, and preventing unlawful activities. The effectiveness of these types of surveillance systems heavily relies on the strategic placement of cameras to help maximize coverage and minimize blind spots. In this sense, spatial optimization have become indispensable tools in achieving optimal camera placement, thereby enhancing the overall surveillance capabilities.

With this in mind, it then becomes important to study crime incidence events and critically observe where these devices have actually been useful and where cities and governments can profit from certain adjustments, given the possible budgetary constrains that they are typically subject to, the high percentage of security budgets that are assigned to these types of projects, and, at the same time, the fact that surveillance cameras may be useful, but are far from being the solution societies need [11,15].

In this sense, the spatio-temporal nature of crime incidence gains more relevance, as certain events are likely to detonate criminal behaviors and incidence, or may show seasonal trends. But careful and timely monitoring could reveal interesting shifts and changes that could prove useful for the authorities.

Different studies have tackled the problem of covering a certain area with surveillance cameras, where coverage can focus on incidents, area or a decent trade-off with a combination of both [3,7,9,13]. On the one hand, because these approaches are typically developed in a static setting, cameras are previously placed in or around the area to be monitored and, thus, placement plays a fundamental role. On the other hand, a static setting makes it difficult for surveillance to be easily modified or adapted after possible interventions or other events that may change the currently observed patterns of incidence in the area.

The optimal surveillance camera positioning is related with the classical set-covering problem. This problem is one case of combinatorial optimization and it has been proved that, due to its computational complexity, there are no algorithms able to efficiently find the exact solution in polynomial time. Nevertheless, greedy approximation algorithms can achieve a near optimal solution in polynomial time [5]. Also, there are approaches that look into finding the exact solution to the problem, but are typically difficult to implement and sometimes are not a real-life option [17]. Other methods have looked into exhausting the possibilities and find and optimal solution, but usually take a very long time demonstrating the no polynomial time complexity nature of the problem. Another approach has been the use of heuristics, which do guarantee a sufficiently good solution in a reasonable amount of time, but cannot ensure it is the optimal one or that it can be replicated [1,8,18].

An alternative to combinatorial, heuristic or meta-heuristic methods, are greedy algorithms. The greedy algorithms construct a solution incrementally

searching for the immediate best solution. This strategy ensure that, given certain conditions and simplifications, to achieve near-optimal or optimal solutions in the best case. One advantage is that greedy algorithms are deterministic and results can be replicated [5].

Selecting the place, installing, and providing maintenance to CCTV systems can be costly and, therefore, it is advisable to study the selection of the optimal placement as an optimization problem to better spend the allotted resources. Our goal is to first analyze the spatial data in a central portion of a Mexican city and propose an optimal placement of cameras, subject to budgetary constrains. In terms of optimization, we develop an index to measure aerial and incidence coverage and test all possible solutions and select the most useful ones.

2 Background and Related Work

Surveillance can be easily associated with "Big Brother watching" scenarios where everything and everyone is being watched. While, under some circumstances, this could be desirable, in reality it is far from feasible and attainable. Typically, a reasonable trade-off between coverage and performance must be attained [7,20] so that surveillance tasks can be accomplished.

Surveillance applications usually look into solving the problem of locating cameras, understanding the area of study, and taking into account what is going to be monitored. In this step, it is usually considered whether it is an open or closed space, private or public. Additionally, it is also important to take into consideration specific characteristics of the devices that will be used [9,10,21].

Because we are interested in studying and analyzing coverage and visibility, the "Art Gallery" problem was a source of inspiration [16], given the idea it puts forward of triangulating space to calculate the least number of guards one would need to visually cover a specific region of space. Because we are interested in covering both area and incidence, a natural second step was to look into coverage models that aim at maximizing effectiveness in the sense of Church and Meadows' proposed "Location Set-Covering Problem" of identifying "how well a particular location configuration performs with respect to the overall purpose facilities are intended to serve" [4] and trying to identify the least number of facilities that satisfy a particular demand within a certain given distance.

There are, however, improvements to this proposal like the "Maximal Covering Location Problem" [6] that aims at maximizing coverage with a given number of facilities or covering the maximum proportion of space as possible with a limited number of objectives [14]. Another improvement is the "Backup Coverage Model" [6] which states that "providing secondary, or backup coverage, to as much of the population as possible is an appealing method by which to protect coverage from varying with time or with unit availability". A further refinement is the "Backup Coverage Model 2" [6] that looks into the need and usefulness of having backup coverage in regions where there is a high density of incidence or where it is likely for a large number of simultaneous events to occur. It is important to note that, even if one were to use the best technical

capable surveillance cameras, maximizing their coverage is secondary to said characteristics, but rather depend on where they are located.

By taking into consideration the stochastic nature of crime occurrence and displacement in coverage models, Hogan and ReVelle [6] conclude that they must be multi-objective. For the case at hand, we consider a limited number of surveillance cameras, and realize we will only be able to cover a certain amount of incidences with the available resources. Additionally, while suitable, at this stage we do not consider overlaps between sensors to support backup coverage, especially in dense areas. We recognize that overlaps could prove useful when trying to reconstruct or follow certain observed events that my be of interest, but is beyond the scope of this paper.

Spatial displacement of crime incidence is a very interesting subject that could greatly benefit from predicting the spatio-temporal behavior of crime but, as identified by Waples et al. [19], it is a complex topic to address, given there are no standardized method yet and is beyond the scope of this paper.

Even though there are exhaustive methods to solve the problem, our focus turns to proposing a greedy algorithm able to select the immediate top performing locations. Again, unlike meta-heuristic approaches, these results can be replicated and guarantee that the same solution can be obtained, while improved with additional field work. [8].

In this study, we propose to address the problem of positioning Surveillance Cameras as an optimization approach using the novel Criminal Visibility Index I. We also propose a greedy algorithm to effectively optimize the index I by positioning strategically the surveillance cameras. By adopting a greedy approach, the research aims to address the inherent challenges in surveillance camera positioning of limited camera surveillance resources.

By identifying suitable camera placements through the index I and application of the greedy algorithm, this study seeks to provide valuable insights for security professionals, urban planners, and decision-makers involved in the design and implementation of surveillance infrastructures in the public policy realm.

We first introduce the proposed Criminal Visibility Index, then we detail the implementation of the algorithm to optimize the objective function based on the Criminal Visibility Index to produce a near-optimal solution. We then present a discussion of the results and, lastly, the conclusions where we summarize key findings and suggest avenues for future research in the dynamic field of spatial optimization for surveillance systems.

3 Study Area and Data

To test the usefulness of the proposed index, we study the Mexican city of Aguascalientes in the state of Aguascalientes, located in the central-northern region of the country, about 480 km northwest of Mexico City. Covering an area of about 5,470 km^2 (roughly 0.03% of the country), it is a very small state that contains 11 municipalities. The central municipality of the state of Aguascalientes is also

called Aguascalientes and houses an estimate of 76% of the state population. Furthermore, 85% of the criminal incidence in the state occurs in this central municipality.

The city of Aguascalientes is located in this central municipality and is host to the annual San Marcos Fair, considered to be the most important one in the country [12]. The Fair attracts millions of visitors during its the three-week duration. Because of the large number of visitors the city welcomes during the Fair, it is of interest to study the behavior of criminal incidence during this time. Additionally, most of the activities occur in the central region for the city, inside the first ring. Thus, only consider this region to test our methodology in this paper. The ring-shaped road "Aguascalientes Convention of 1914" bounds the area of interest, distributes transportation both north-to-south and east-to-west, and the downtown area is contained inside it. Figure 1 depicts the locations of the state, city, and municipality of Aguascalientes, along with the border of the first ring considered for this study.

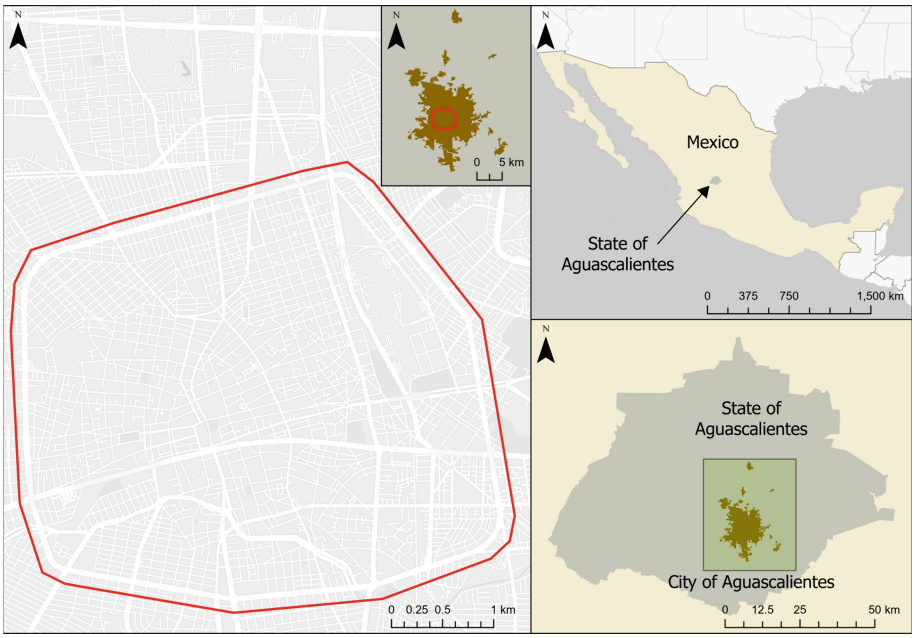


Fig. 1. Area of study: The location of the state, city, and municipality of Aguascalientes and the First Ring.

Data for this study is obtained from two official sources. On the one hand, city blocks and streets of the state and city of Aguascalientes are from the National Institute of Statistics and Geography (Instituto Nacional de Estadística

y Geografía - INEGI). On the other, geo-referenced criminal incidence records from the state's General Attorney's office for thefts that occurred in 2018 in the whole state. For the rest of the study, however, we only consider incidence that occurred in the public space, in particular on the streets inside the first ring of the city. Therefore, for those cases in which they are registered as occurring on parks or inside buildings, their original locations have been slightly modified so they can be accounted for in the visible surface of the space solution. Overall we have little over 1300 data points.

The first ring of the city, housing many of the Fair's activities, experiences an increase both in the number of visitors and the demand for services like lodging, food, transportation, and banking. The nature of the activities during the 3-week duration of the Fair makes it more likely for three main different types of theft to occur: pedestrian, vehicle, and auto parts, which are depicted in Fig. 2.

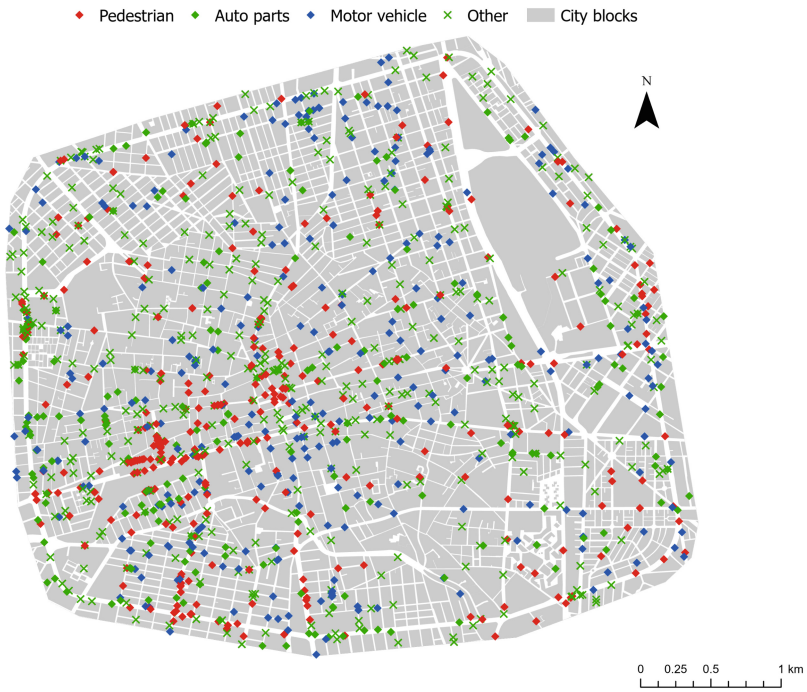


Fig. 2. Spatial distribution of different types of theft inside the first ring of the city of Aguascalientes.

4 The Criminal Visibility Index for Surveillance Cameras

This section describes the Criminal Visibility Index I. This is a measure to estimate the ability to detect criminal theft events given a set of cameras positioned in the region of interest. To use this index we make the assumption that the distribution of events remains roughly the same throughout the years. This assumption is adequate given the nature of the city and the Fair.

Formally speaking, the camera positions are represented by the set $\mathbf{p}$, where $\mathbf{p} = \{p_i | p_i = (x_i, y_i), \text{for } i \in \{0, 1, \ldots, n\}\}$ contains the positions (x_i, y_i) for each camera p_i.

We associate attributes of interest at each camera p_i. First, we associate the proposed Criminal Detection Sensitivity Map $R(p_i)$. This map describes the detectability of a crime at a certain distance from a camera positioned at coordinate p_i.

As an example, Fig. 3 shows the Criminal Detection Sensitivity Map $R(p_i)$ for a camera positioned at matrix coordinates $p_i = (2836, 1394)$, and the Local Criminal Detection Sensitivity Map $R_i^{\Omega}(p_i)$ enclosed by the red square.

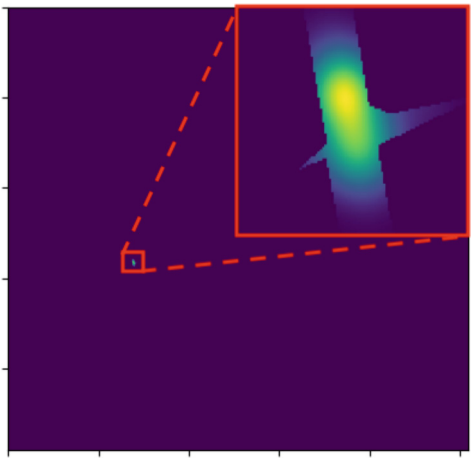


Fig. 3. Example of the Criminal Detection Sensitivity Map $R(p_i)$, for a given camera position in the Cartesian plane $p_i = (2836, 1394)$ and its Local Criminal Detection Sensitivity Map $R^{\Omega}(p_i)$.

Here, the Global Criminal Detection Sensitivity Map $R(p_i)$ represents the entire region for p_i, but only the neighborhood around p_i can have values if and only if the isovist detects criminal activity.

$R(p_i)$ is a sparse matrix where only the cells inside the area bounded by a radius r from the position (x_i, y_i) would present a level of Criminal Detection Sensitivity. The circular region is inside a square with side length of $M' = 2r + 1$ for matrix operation convenience.

The Crime Density Map D represents the criminal activity required to calculate the Criminal Visibility Index I for each position. The Criminal Visibility Index for each camera p_i depends on the following three spatial variables:

1. The closeness to the camera position described by a Gaussian kernel represented by the matrix $K \in \mathbb{R}^{M' \times M'}$.
2. The Criminal Theft Density map $D_i \in \mathbb{R}^{M \times N}$ that is the result of applying a Gaussian kernel to the raster image of geo-referenced crimes.
3. The visible range of camera p_i described by its isovist, $V_i \in \mathbb{R}^{M \times N}$, which is a binary map.

Therefore, $R(p_i)$ is a sparse matrix where only the cells inside the area bounded by a square of side M' with the camera in the center (x_i, y_i) would have a level of crime detectability, since the cameras have a limited range. An example of these variables is presented in Fig. 4. The map $R(p_i)$ only has values in its neighborhood $R^{\Omega}(p_i)$ and is the result of applying the element-wise matrix operation $R(p_i) = V(p_i) \circ D(p_i) \circ K$.

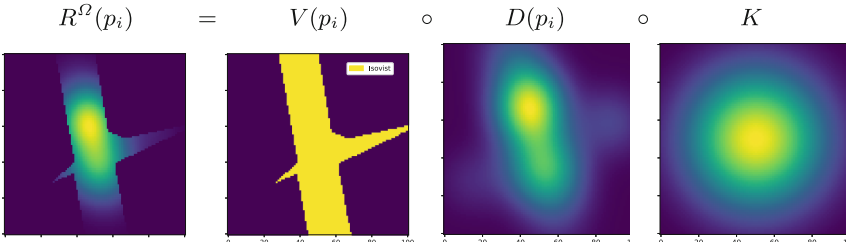


Fig. 4. Example of the three spatial variables at position $p_i = (2836, 1394)$ required to evaluate the surveillance camera suitability.

Formally, the Global Criminal Detection Sensitivity Map $R(p_i)$ is defined in Eq. 1 as follows:

$$R(p_i)[m,n] = \begin{cases} 0 \text{ if } \sqrt{(m-x_i)^2 + (n-y_i)^2} > r \\ V_i(x_i, y_i) \cdot D_i(x_i, y_i) \cdot K_i(x_i - m - r, y_i - n - r) \text{ otherwise} \end{cases}, \tag{1}$$

where (m, n) are the values of all the possible coordinates in the horizontal and vertical axes. The matrix has zero values in case (m, n) is out of range with respect to the position (x_i, y_i).

With the expression for $R(p_i)$ established, we now define the Criminal Visibility Index I for surveillance cameras in Eq. 2.

$$I(\mathbf{p}) = \sum_{x \in M} \sum_{y \in N} \max_i R(p_i)[x, y]\,, \tag{2}$$

where $R(p_i)[x, y]$ is the value of a matrix coordinate (x, y) of the Global Criminal Detection Sensitivity Map of camera p_i. The max operator seeks the camera that produces the maximum value in a coordinate (x, y). Then, the maximum values are added-up to produce the Criminal Visibility Index I of solution $\mathbf{p}$.

Lastly, we define the cost function for I in Eq. 3 that indicates we want to find the set of positions $\mathbf{q}$ that maximizes the index I.

$$\begin{aligned} \mathbf{p}^* = & \arg\max_{\mathbf{p}} I(\mathbf{p}) \\ \text{subject to: } & \{(p_i, p_j) | \text{Distance}(p_i, p_j) \geq r, \forall (i, j) \in [0, \ldots, |\mathbf{p}| - 1]\} \\ & \text{and} \\ & |\mathbf{p}| = s\,, \end{aligned} \tag{3}$$

where all the possible pairs (p_i, p_j) must have an Euclidean distance of at least a radius of r, and s is the constraint for the number of sensors.

The cost function is useful to compare several different solutions and decide which one is the best. While this function can be solved in different ways, one of the most basic strategies is to test several random solutions and select the best one. Another one is to implement optimization algorithms, like evolutionary or gradient-based algorithms. Yet another one is to use greedy algorithms, which is the approach we follow.

5 A Greedy Algorithm to Approximate the Solution for Optimal Camera Placement

We propose the implementation of an easy but powerful algorithm to find the near-optimal solution to the camera placement problem.

A greedy algorithm is one that is used to approximate the global solution for a wide variety of problems in a reasonable amount of time. In some cases, it can lead to an exact global solution of an optimization problem [5]. One characteristic of a greedy algorithm is that the solution is constructed by selecting the best immediate solution without considering any consequences.

In this case, if we add the constraint that two or more cameras cannot be located inside a radius r of another, then the greedy algorithm produces a near-optimal global solution by positioning cameras in regions not already covered with the highest criminal density.

Algorithm 1 shows the proposal for finding a near-optimal global solution for locating cameras. The central component that allows to implement the greedy algorithm, is the sorted camera positions in decreasing order according to their individual Criminal Visibility Index, $I(p_i)$. These sorted positions are in the list $\mathbf{p}^{\text{sort}}$. The radius r is a constraint that allows finding a near-optimal solution restricting one camera inside a circle with respect to position p_i.

Algorithm 1 requires the sorted list of positions in $\mathbf{p}^{\text{sort}}$ and the desired number of cameras s to allocate. The algorithm returns the solution in $\mathbf{p}^*$.

Algorithm 1. Greedy algorithm for finding a near-optimal global solution for camera positioning

Require: $\mathbf{p}^{\text{sort}}$
Require: s ▷ Number of sensors
Ensure: $\mathbf{p}^{*}$ ▷ Solution
1: $\mathbf{p}^{*} \leftarrow \{p^{\text{sort}}_{\text{first}}\}$
2: $\mathbf{p}^{\text{candidate}} \leftarrow \{p^{\text{sort}}_{i} | \text{Distance}(p^{\text{sort}}_{\text{first}}, p^{\text{sort}}_{i}) > r, \forall i, (i \neq \text{first})\}$ ▷ Euclidean Distance
3: $\mathbf{p}^{\text{sort}} \leftarrow \mathbf{p}^{\text{candidate}}$
4: **while** $(\mathbf{p}^{\text{sort}} \neq \{\emptyset\})$ and $|\mathbf{p}^{*}| < s$ **do**
5: $\quad \mathbf{p}^{*} \leftarrow \{\mathbf{p}^{*} \cup \text{first}(\mathbf{p}^{\text{sort}})\}$
6: $\quad \mathbf{p}^{\text{candidate}} \leftarrow \{p^{\text{sort}}_{i} | \text{Distance}(p^{\text{sort}}_{\text{first}}, p^{\text{sort}}_{i}) > r, \forall i, (i \neq \text{first})\}$
7: $\quad \mathbf{p}^{\text{sort}} \leftarrow \mathbf{p}^{\text{candidate}}$
8: **end while**

In Line 1, we initialize the set $\mathbf{p}^{*}$ with the first position in the list $\mathbf{p}^{\text{sort}}$ that contains the position with the highest index I.

In Line 2, we retrieve only the position candidates that are outside the circular region of radius r with a center in the position with the highest Individual Criminality Index $p^{\text{sort}}_{\text{first}}$. We discard other positions inside the radius.

In Line 3 we update the $\mathbf{p}^{\text{sort}}$ list. In this step, we reduce the candidates by discarding the positions inside the circle of the currently best position.

We repeat the process inside the loop in lines 4–8 while there are still candidate positions to select and the number of sensors to position has not been satisfied. Inside this loop, in Line 5, we append the next best position to $\mathbf{p}^{*}$. In Line 6, the list of candidates outside the current best position in $\mathbf{p}^{\text{sort}}$ is updated. Line 7 deals with updating $\mathbf{p}^{\text{sort}}$ by reducing the possible number of candidates available for selection during the next iteration.

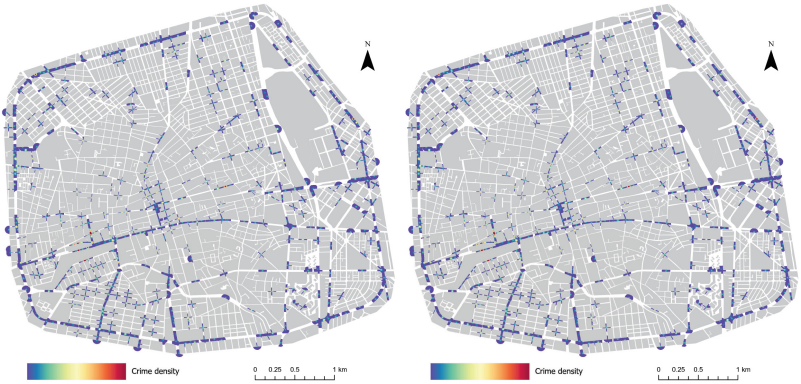
6 Experiments and Results

As mentioned before, we consider thefts occurring inside the first ring of the city of Aguascalientes for 2018. All maps have a 1 m pixel resolution. The Crime Density Map D, is produced in GRASS GIS using the `v.kernel` function with default parameters but with radius $r = 50$ and a Gaussian kernel window.

Our approach is to find a suitable solution that can leverage the cost associated with implementing a surveillance system considering the trade-offs between the cost and the benefit of increasing the Criminal Visibility Index while incrementing the number of cameras. Once we run the algorithm, we obtain a solution $\mathbf{p}^{*}$ with the list of coordinates sorted in descending order by their associated index I. One can decide on the particular number of cameras before running the algorithm.

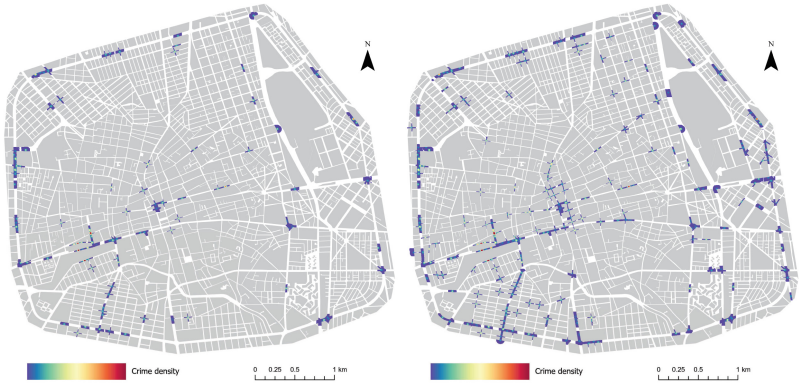
Figures 5a to 5f show the resulting optimal locations for 25, 50, 100, 250, 500, and 1000 cameras, respectively.

Our results indicate that including a larger number of cameras increases the value of the proposed index. This is expected since, intuitively, more cameras



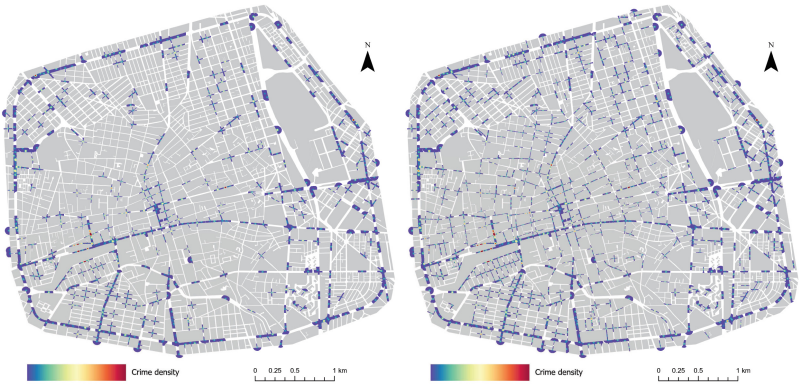
(a) 25 surveillance cameras; $I(\mathbf{p}^*) = 0.04153$.

(b) 50 surveillance cameras; $I(\mathbf{p}^*) = 0.06246$.



(c) 100 surveillance cameras; $I(\mathbf{p}^*) = 0.10188$.

(d) 250 surveillance cameras; $I(\mathbf{p}^*) = 0.17084$.



(e) 500 surveillance cameras; $I(\mathbf{p}^*) = 0.25129$.

(f) 1000 surveillance cameras; $I(\mathbf{p}^*) = 0.33097$.

Fig. 5. Solutions obtained with the proposed algorithm for different numbers of surveillance cameras and their associated Criminal Visibility Index values.

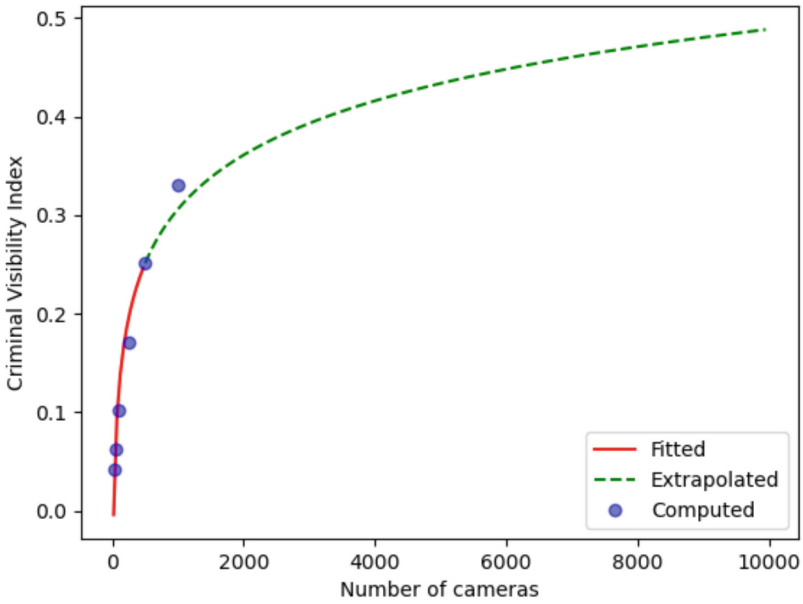


Fig. 6. Computed and expected values of the proposed index as a function of the desired number of cameras.

correspond to more locations on the streets and, thus, more possibilities to monitor. At the same time, more cameras mean more individual contributions to the overall value of the index.

Upon closer inspection, the corresponding values of the proposed index for the different number of cameras tested do not hold a linear relationship. A twofold increase in the number of cameras does not translate into a doubling of the obtained index, which is expected. By fitting a log-like function to the computed values and extrapolating their behavior for a large number of cameras (see Fig. 6), we can see that there seems to be an asymptotic behavior that tends to an index value of approximately 0.5. This means that, eventually, the cost of adding more cameras will not provide much value observing the space under scrutiny, hence using this plot as a tool would prevent the unnecessary use of public resources.

The experimental upper bound of the index is obtained by summing all the possible contributions of the pixels in the feasible geographic space. Each pixel contributes a very small amount, mainly given by $\max(K) \cdot D(x_i, y_i)$, where $\max(K)$ is the maximum value of the Gaussian kernel. In this case we use a Gaussian kernel with $\sigma = 4$. The maximum value for I is 0.62847 and we can thus measure the relative improvement of each of our experiments as a function of the number of cameras considered. Table 1 shows these results.

Table 1. Index values and percent of total for the different number of cameras considered.

Number of cameras	$I(\mathbf{p}^*)$	Percent of total
25	0.04153	7%
50	0.06246	10%
100	0.10188	16%
250	0.17084	27%
500	0.25129	40%
1000	0.33097	53%

7 Conclusions and Future Work

A methodology to define the best set of locations to obtain the optimal cover of criminal incidents, measured by the Criminal Visibility Index, was proposed. The greedy algorithm that was considered delivers good results in terms of finding optimal locations for surveillance cameras subject to the restriction of one surveillance camera in a fixed radius. In contrast to an exhaustive algorithm that searches for possible solutions, this approach explores the construction of the solution using a sorted list of positions in decreasing order by the index I of all the possible cameras and iterating to take the best immediate solution until the sorted list is empty.

Applying this methodology to the first ring of the city of Aguascalientes made it possible to test the suitability of using this approach with only considering geo-referenced theft incidence, the street network, and the geometry of city blocks. With this approach, it is possible to develop in-house solutions for city planners and decision-makers in terms of identifying the best locations to set up surveillance cameras. Of course, this approach does not replace field visits and confirmation of the suitable locations, but is certainly faster, more efficient, and provides a way to reduce costs.

It is, however, important to note that this is a data-driven solution. Perception or other subjective variables are not taken into account. As such, if citizens feel that placing a surveillance camera in a specific location would make them *feel safer*, it is not possible to refute or support that claim. Nevertheless, we propose an index that is useful for complementing other studies.

In terms of the solutions, we are, naturally, interested in those that perform better, and can easily select the best locations, map them, and compute the overall performance of the solution. Figure 5 shows the increase in area coverage together with a higher index value by considering more cameras.

It is important to note that Fig. 6 is obtained by using very few data points from our experiments. While it could be argued they are not enough to ensure a log-like fitting function is appropriate, we report our current findings and realize the need for more experiments and data points to compute a better fit.

Additionally, we realize it should be possible to execute parts of the algorithm in parallel and leverage the use of several cores to improve computation time.

We consider the results of the greedy algorithm to be the best solution, albeit expensive, that can be obtained. As such, it represents our benchmark or baseline for how solutions obtained using alternative methods and algorithms should perform. A natural next step is to compare these results with those obtained using other methods and spatial optimization strategies and test the efficiency of the proposed approach.

Additionally, while only considering incidents for 2018, we still need to test our approach with data from different cities, particularly ones that either have frequent crime incidence data updates or real-time data available. These tests could possibly expose some unidentified weaknesses of our approach and would provide grounds to develop a more robust one. Of course, it would be important to improve the current camera characterization and incorporate field of view or other more realistic coverage geometries.

Should we have better cadastral and urban data, like crowd-sourced building heights, tree locations, street stands, etc., it would be beneficial to incorporate them to better model and take into account elements that could hinder camera visibility. It would also be useful to consider parks and other potential surfaces as visible areas from the streets, so we could dispense with slightly adjusting the geometries of some data points to be located on the streets.

While the computed values of the proposed index seem relatively small, they are more easily understood when expressed as a percentage of the maximum value the index can have. This understanding could, however, be enhanced by comparing the performance of the existing cameras inside the first ring in 2018 to the experiments. Only after computing the value of the index for these cameras we will be able to better rank the solutions in these experiments and compare the spatial locations of both the existing and the proposed sets of cameras.

While the constraint regarding the number of camera inside a radius r simplifies the optimization problem, it would be interesting to explore other variations for solutions oriented to criminal traceability producing surveillance corridors in important or crowded streets.

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