

A Methodology for Defining Smart Camera Surveillance Locations in Urban Settings

Rodrigo Tapia-McClung(✉) and Tania Gómez-Fernández

Centro de Investigación en Ciencias de Información Geoespacial, Contoy 137, Col. Lomas de Padierna, Tlalpan, 14240 Mexico City, Mexico
rtapia@centrogeo.edu.mx, gfe.tania@gmail.com

Abstract. In this paper we propose a methodology to solve the problem of locating a set of cameras in an uncontrolled open space, such as a city. For this purpose, the geometric approach of the problem is transformed towards the optimization of a surveillance service system in which a metaheuristic model is used to maximize the service capabilities of the set of cameras.

Keywords: Differential evolution · Surveillance · Crime prevention

1 Introduction

Insecurity situations in many cities have forced the authorities to find a way to bring harmonious coexistence and lead ideal behavior on citizens in such a way that everyone can feel their integrity and possessions are protected. In this continuous search to guarantee the population's well-being, it is valuable to incorporate the use of technology to facilitate the work of people assigned to public surveillance tasks. Among the most popular tools are video surveillance technologies such as closed circuit television (CCTV). Despite the opinions against video surveillance systems related to privacy issues [1], there is proof that CCTV can serve as a tool to prevent or reduce incidents related to criminal behavior [2].

The implementation of video surveillance systems in public spaces has many faces opened for discussion. In recent years, society has questioned the use of cameras as a tool to guarantee safety, although there are obvious advantages, it is often ethical and moral issues that generate acceptance or rejection of this method of surveillance, particularly when economic investment does not necessarily translate into greater security for society [3]. In relation to this problem, Scotland Yard promoted initiatives with the intention of improving the use of CCTV, which affected the way of how public surveillance cameras had been exploited until then, as the legal system vaguely allowed the images captured with this tool to be used as evidence in court [4]. Despite the disapproval, many authorities are still betting on this surveillance method and continuously assign a good part of the security budget to these projects [5], recognizing to a large

© Springer Nature Switzerland AG 2019
S. Misra et al. (Eds.): ICCSA 2019, LNCS 11621, pp. 505–520, 2019.
https://doi.org/10.1007/978-3-030-24302-9_36

extent that cameras are a very useful technology but are not the absolute solution to society's problems. The cost of these security alternatives is considerable for all the infrastructure and maintenance they require, so it is convenient to obtain the maximum benefit and optimize the use of this resource. In the end, CCTV is perceived as a necessary evil [6].

There are a number of applications that exploit CCTV capabilities for specific surveillance tasks [7–10]. Most of these applications require that the cameras are previously placed in the area that wants to be observed. This means that camera placement must be carefully studied.

An important part of the assembly of the surveillance is to determine the camera locations. Particularly when dealing with observing public space, the system could have many elements that can be scattered in very large and irregular areas. Camera placement becomes a critical step when their locations have a great influence on the performance and cost of the system, therefore a strategic positioning is preferred over an arbitrary one.

Location problems are studied extensively in combinatorial optimization [11] and use enumeration and search techniques to find the solution, but there exist NP-hard complexity problems where enumeration and search techniques have difficulties in recognizing optimal configurations when the worst case of the problem occurs. It is common that location models are subject to multiple conditions that compete with each other, so it becomes more difficult to find an exact solution to the problem. Although there are models that can find exact solutions, they are limited and not necessarily easy to implement [12]. Exhaustive methods are designed so that they guarantee finding an optimal solution in a finite amount of time. This "finite amount of time" increases exponentially respect to complexity and dimension of the problem. Heuristics do not guarantee this, and sometimes return solutions that are sub-optimal. But they usually find "good" solutions in a "reasonable" amount of time. Many heuristic algorithms are specific and very problem-dependent. In contrast, metaheuristics is a more sophisticated method and a problem-independent algorithmic framework that uses strategies to lead the search of the solution. For this reason, the use of a heuristic or metaheuristic model can be a more feasible approach. A heuristic solution can be developed specifically for the conditions of the problem, while a metaheuristic solution has a more independent structure and can be adapted for other instances of the same problem [13,14]. Since the cost and maintenance of CCTV systems is substantial, it is convenient to study the placement from an optimization perspective because it can suppose an improvement in the way the available resources are destined for the installation. CCTV is recognized as a useful tool that serves multiple purposes to meet the operational needs of a city and also reinforces the sense of security. The implementation of a methodology based on the analysis of spatial data and optimization by heuristic models can help establish the placement of the cameras of a CCTV network, which meet the specific surveillance needs to record significant activities in a given time and space. Even more, we want to incorporate the use of heuristic models as a tool geared towards obtaining a robust and acceptable solution for camera placement that is used specifically for urban street observation.

2 Background and Related Work

Nowadays the complexity involved in video surveillance systems applications demands for pretty fussy planning for camera locations, particularly when there are multiple cameras to be placed that must also be coordinated in order to accomplish a given task without compromising performance [8,15]. Planning becomes complex when multiple factors present in the space to be monitored and the capabilities of the devices that make up the system are taken into consideration.

We started by looking at surveillance systems applications, focusing on how the camera placement was solved before assigning tasks for the system. However, sometimes the placement depends on the space and the assigned task. For example, the placement will be different if the scene corresponds to a closed, open, private or public space, because it depends on many factors that may constrain or relax the placement conditions for the devices. Also, in the reviewed articles on the topic [9,16,17], the requirements of the devices are taken into account so they can perform the assigned task keeping continuity, accuracy, and quality on the records.

Initially, the *Art Gallery* problem [18] we consider as the first approach because it focuses on coverage and visibility analysis using space triangulations to find the minimum number of guards that keep watch over a full or specific objective. This problem considers the demand of surveillance to be uniform, unlike outdoors public surveillance systems that attend specific points while simultaneously try to watch all the space. With this in mind, we decided to look into covering models since they consider measures of spatial availability of services as a parameter to quantify the effectiveness of a location configuration. One definition of a measure of effectiveness in [19] is "how well a particular location configuration performs with respect to the overall purpose facilities are intended to serve".

The *Location Set-Covering Problem* (LSCP) [19] proposes to identify the location of the minimum set of facilities that satisfy all the demand points within a maximal service distance of a facility. Some authors consider the maximal service distance is not good for the performance of the system because eventually it will be economically unfeasible to satisfy all the demands with a limited set of facilities [11,19]. However, it may be impossible for a surveillance system to achieve a complete coverage of all the demand points because the devices' sensor distance is too short and this implies the need of a lot of facilities to cover all the objectives that require video surveillance. In the *Maximal Covering Location Problem* (MCLP) [11], the full coverage restriction of the LSCP is relieved. This model determines the locations that maximize the portion of demand served within a standard distance with a given number of facilities. Instead of maximal service distance, this model proposes a standard distance to satisfy the maximum request of service, which is similar to what surveillance cameras have to do. With the cameras capabilities we expect to cover the maximum proportion of the space or at least as many objectives as possible [20]. Even if the cameras have the best zooming capabilities and widest field of view, maximizing the surveillance service does not depend on these characteristics, but rather in the location of the facilities.

Analyzing criminal spatial displacement may offer relevant information that could be added to planning the location for surveillance facilities. If we were to consider predicting the occurrence of a crime, we would likely rely on statistical reports, but in fact it would be very difficult to actually get the right position and time of occurrence. In this sense, criminal incidence has a stochastic nature. Waples *et al.* [2] refer six types of displacements and conclude that spatial displacement of crime is a complex subject to explore, especially since no standardized method has been yet specified. Furthermore, CCTV by itself cannot displace crime frequently or uniformly across offence types or space, but careful management with realistic objectives could be an effective crime prevention measure. Bearing on the complexity of the criminal spatial displacement, we may consider investigations that incorporate stochastic nature of the demand-to-location modelling.

According to Hogan and ReVelle [11], coverage models which include stochastic demands and spatial availability are likely to be multi-objective. They may be viewed on a hierarchical or true multi-objective sense. We consider our location problem with a multi-objective hierarchical approach. Because we are focused on using a limited number of cameras, we try to maximize the coverage of the observed space together with the proportion of previously recorded crimes, as well as optimize the overlap between the observed spaces of different cameras. It is realized that in applications of surveillance systems target coverage must satisfy certain conditions of continuity on the camera records to reconstruct the displacement or recognition of an object between several cameras. This feature implies that overlap between camera records and the maximization of the observed space are opposed objectives, so a maximum threshold must be defined for the overlap and try not to exceed it.

As an extension of the MCLP, the *Backup Coverage Model* [11] suggests 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". Criminal displacement may vary from time and location [2], taking advantage of the blind spots and spaces without surveillance facilities. It would be helpful to have a principal coverage to maximize the observed surface and a secondary coverage to control the blind spots. Particularly, the *Backup Coverage Model 2* (BACOP2) [11] suggests the need of backup coverage to deal with areas of high demand where the probability of nearly simultaneous demand points is large. This problem allocates different levels of coverage with a fixed number of facilities. Also, the backup coverage will be provided when the principal coverage is already set.

Despite the existence of exhaustive methods to solve the problem, we will use a metaheuristic approach to solve it. A number of problems have incorporated metaheuristic approaches to solve spatial optimization problems [21,22]. Unlike exhaustive methods, metaheuristics may balance exploration and exploitation of the solutions space. This approach is fairly useful when resources are limited, so it is possible to get a robust solution that can be improved with additional field validation [14].

Differential evolution (DE) is a search method based on the global evolution of populations [23]. The DE method is similar to a Genetic Algorithm (GA) in that it allows each generation of solutions to evolve from the best qualities of the previous one. The differential evolution algorithm (DEA), derived from the concept of DE, is a bio-inspired algorithm that simulates the mechanism of natural evolution and can be used to solve real-valued problems, although good results have also been obtained in combinatorial problems [23]. Like the genetic algorithm, it uses crossing and mutation operators and the best solution must be chosen in each generation. In addition, it has few but high-impact parameters that control the convergence and quality of the solutions, takes less time, and is relatively easy to customize, unlike GA.

3 Proposed Approach

A method based on a differential evolution algorithm (DEA) to generate a robust solution to locate a set of cameras designed for street surveillance is presented. For this, a hierarchical approach will be used because we choose to maximize the proportion of recorded crimes over the other objectives to discriminate between alternate locations. Figure 1 shows the pseudo-code of the DEA used to develop the camera location methodology in this research. Figure 2 shows a schematic flow diagram of the methodology that was developed to solve the problem of locating cameras in urban settings with the restrictions that subject the fitness function.

The first two steps correspond to data preparation while the rest correspond to the algorithm implementation itself. On Step 1, raw crime incidence data are cleaned and layers for the study area are adjusted. In this work, city blocks are considered to be obstacles. Next, on Step 2, a spatially enabled data base (DB) is created and the adjusted layers are loaded. These layers serve as default inputs and auxiliary information during algorithm execution. In Step 3, `psycogp2` is used to connect Python and the DB so transactions can be executed and committed by the algorithm.

Before running the DEA, the parameters must be configured to our specific needs in Step 4. Parameters are separated into three groups: The first contains camera features, like field of view partition and sensor distance. The second contains differential evolution parameters like the stop criteria, size of population, cross rate and crossing factor. The third are the weights for the objective criteria. One needs to previously choose some criteria that are to be used as objectives to help evaluate the quality of the solutions. These criteria are quantified in the fitness function, so different weights are assigned depending on the properties of these criteria. Next, the DEA optimization method on Step 5 is executed. Figure 3 shows this execution in more detail and is explained below. As a result of this step, a list with the best solutions of the optimization process is obtained. Lastly, by using the `seaborn` and `folium` libraries, it is possible to create a chart of the performance and an interactive map that shows the evolution process of assigning locations together with the best solution obtained from the process.

Algorithm description for DE

1. **begin**
2. Set the generation counter $G = 0$. Randomly initialize a population of NP individuals X_i, with D attributes each. Initialize F and CR parameters.
3. Evaluate the fitness for each individual in P.
4. **while** stopping criteria not satisfied **do**
5. **for** $i = 1$ to NP **do**
6. randomly select $a \neq b \neq c \neq d \neq i$
7. **for** $j = 1$ to D **do**
8. $j_{rand} = \lfloor rand(0,1) * D \rfloor$
9. **if** $rand(0,1) \leq CR$ or $j = j_{rand}$ **then**
10. $u_{i,j} = x_{a,j} + F \times (x_{b,j} - x_{c,j})$
11. /* five mutation strategies */
12. **else**
13. $u_{i,j} = x_{i,j}$
14. **end if**
15. **end for**
16. **end for**
17. **for** $i = 1$ to NP **do**
18. Evaluate offspring u_i
19. **if** u_i is better than X_i **then**
20. $X_i = u_i$
21. **end if**
22. **end for**
23. Memorize best solution achieved so far
24. **end while**
25. **end**

Fig. 1. Pseudo-code for DEA. Adapted from [24]

As mentioned before, Fig. 3 stems from Step 5 of Fig. 2 and helps understand the proposed adaptation of the original DEA.

Step A. Sampling strategy. First, we need to identify the solution space. In order to position the cameras, all available public roads area considered as feasible candidates for installing devices. Then, a sampling strategy is used to generate initial random solutions that will serve as a starting point in the algorithm. When implementing a sampling strategy, it is possible to privilege certain zones in the street network that should have more devices due to the higher known criminal incidence in that area. At the same time, the solution space is reduced for exploration, leaving more chances for improving the final solution. For instance, by using random sampling, the initial solution has an equal chance of choosing locations inside all the street surface. In a stratified sampling, however, it is possible to partition the surface according to the density of incidents per square kilometer. The partition is then used to choose a different proportion of random positions in each fraction of the partition.

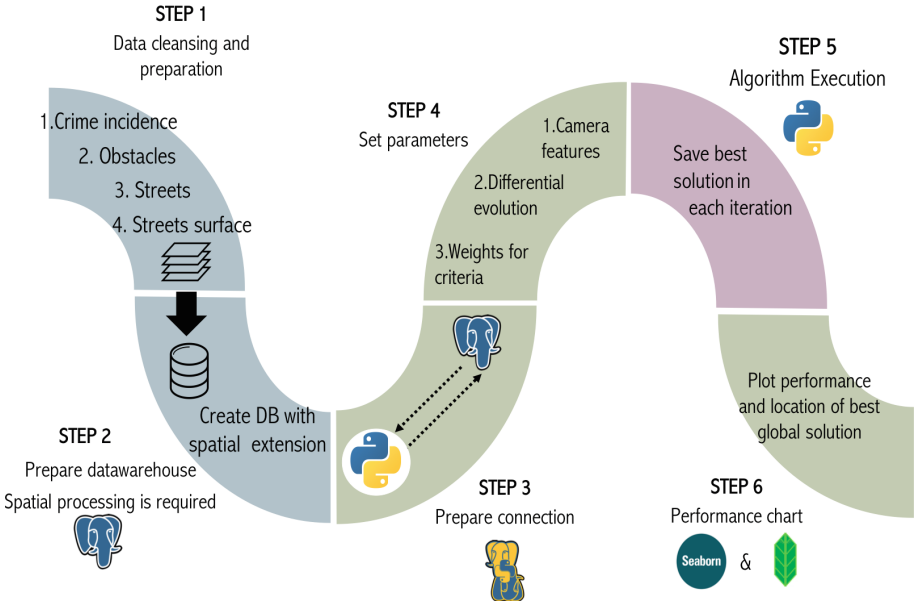

Fig. 2. Schematic flow diagram of the methodology that was developed to solve the problem of locating cameras in urban settings

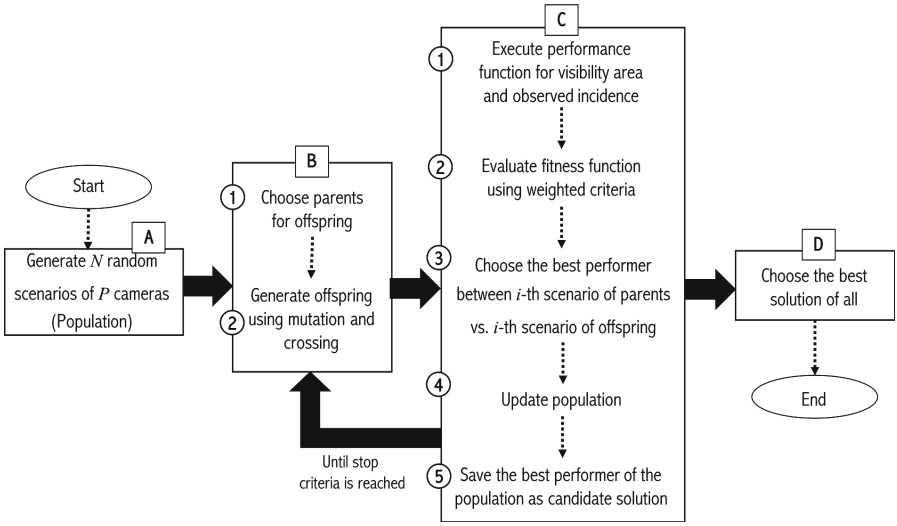

Fig. 3. Schematic diagram explaining the execution of the DEA

Step B. Generating solutions. New scenarios are generated using the DEA crossing and mutation rules. Also, a function that randomly chooses three different scenarios (x_a, x_b, x_c) from the population and recombines them according to the DEA conditions and the rule $x_a + F \times (x_b - x_c)$ to obtain a new scenario is defined.

Step C. Fitness function. Because the goal is to maximize both the visible surface and the observed thefts, it is important to quantify the quality of the solutions. To do this, a function $v(x, y, d, g)$ is defined to measure the visible surface of each camera in each scenario. Here, x and y are the camera coordinates, d is the sensor distance, and g is the field of view partition. Another function, $c(x, y, v)$, is used to count the thefts inside the visible surface of each camera. To determine the visible surface of the solution, the following procedure to find an *isovist* is constructed (see Fig. 4): For each camera location in the solution, k rays of length d are built, where k is the number of partitions from 0 to 360 degrees by g degrees. Each ray is truncated when it first intersects a city block, a vertex is added at the intersection and the segment closest to the camera location is kept. The rest of the ray is discarded from the solution. If the ray does not intersect with anything, it is kept as is. When all rays have been analyzed, the k vertices are joined to form a closed polygon that represents the estimated visible surface for each camera in the solution. The total visible surface $V(\bar{x}, \bar{y})$ of the scenario is obtained by joining the polygons $v(x, y, d, g)$ for all the cameras in each scenario. The global surface is the union of all the polygons in the solution. The theft count $C(\bar{x}, \bar{y})$ is obtained by taking into account all thefts contained in the polygon of the visible surface of the solution $V(\bar{x}, \bar{y})$. This is carried out locally for each camera's polygon and globally for the whole solution, thus making it is possible to know the performance of each element and the overall solution. The results of $V(\bar{x}, \bar{y})$ and $C(\bar{x}, \bar{y})$ are not enough to choose the best option for the camera locations. Therefore, a fitness or objective function is defined in order to measure the quality of each scenario:

$$f(\bar{x}, \bar{y}) = \alpha_1 \frac{V(\bar{x}, \bar{y})}{\mathcal{V}} + \alpha_2 \frac{C(\bar{x}, \bar{y})}{\mathcal{C}},$$

where $\mathcal{V}$ is the area of all the street surface, $\mathcal{C}$ is the total number of thefts in the surface, α_1 and α_2 are the weights for each criteria that satisfy $0 \leq \alpha_1, \alpha_2 \leq 1$ and $\alpha_1 + \alpha_2 = 1$. Using the $f(\bar{x}, \bar{y})$ function it is possible to rank the solutions by their quality. Fitness values are compared between parents and offspring for each element in the current population, keeping only the winner of each comparison. Then, the population is updated with the winners and the best solution of the iteration is kept.

Step D. The final solution. When the stop criteria is reached, the best solution of all is kept. This scenario is the best result obtained during the execution of the algorithm, not necessarily the optimal solution of the whole solution space.

Model Constraints. There are some restrictions and limitations to our problem and approach. First, we assume there are no cameras installed on the surface

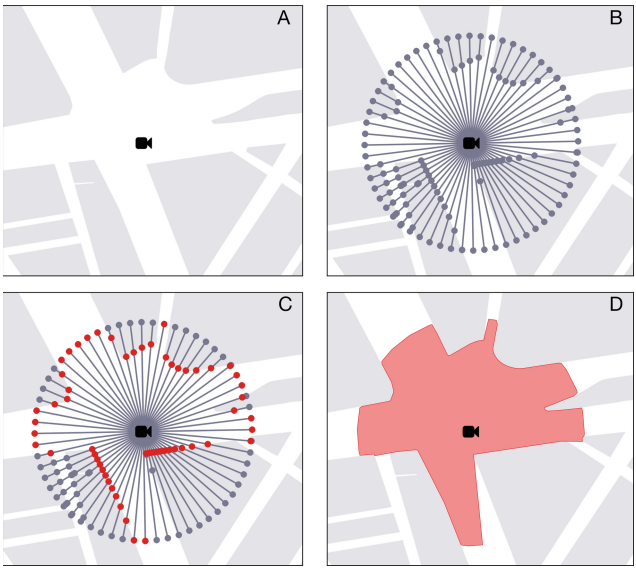

Fig. 4. Construction of isovists for individual cameras

we want to monitor. Second, that it is possible to place surveillance cameras anywhere on the perimeter or inside the surface. In addition, the number of available cameras is fixed and all have the same operating properties. In particular, and for the sake of simplicity, it is assumed they all have a viewing angle of $\theta = 360°$ and the maximum distance of the sensor d is the same for all devices. At this stage, we do not account for overlaps between the visibility polygons of each camera.

Algorithm Tuning. To improve the obtained results, some parameters can be modified depending on what wants to be attained. The DEA parameters can be tuned when some problems are identified during the algorithm execution. However, before modifying the parameters, some patterns must be recognized. For example, if the crossing factor is very large, cameras accumulate in the outer limits of the valid surface. This means that cameras were located outside the valid surface, but the algorithm relocates them in a position closest to the valid surface. To correct this, the crossing factor is reduced and one must recall that camera displacement depends on the measurement reference system. Displacement is different for geometries and geographies (degrees vs. meters). On the other hand, if the performance for scenarios is seen to be stuck from the beginning, then the crossing rate is modified. This parameter controls the number of cameras reassigned by each scenario. When the crossing rate is low, few cameras will be reassigned; if it is high, then almost all cameras will be reassigned and the algorithm behaves as the random search case. It is important to consider that population size also influences the obtained results. For example, if a small population is generated (*e.g.* 4 scenarios), each offspring will be a redundant

case of the parents because of the lack of variability. It is preferable to use larger population sizes to get more configurations of parents. If we want to improve the choice of the best scenario, then we can modify the initial conditions of the general algorithm. By adding more camera features like height or different camera types, and including obstacles on the surface like threes, lighting structures, buildings height, etc., we will achieve more realistic locations for the cameras. Furthermore, if we consider other decision criteria and modify the weights, we upgrade the fitness function to choose an elite of solutions. With this, the quality of the final solution will be improved.

4 Case Study: The City of Aguascalientes, Mexico

As a case study, the Mexican city of Aguascalientes in the state of Aguascalientes is considered. The city hosts the annual San Marcos Fair, which attracts an average of 8 million visitors during the three-week period that the Fair lasts [25]. The Fair is considered to be the most important one in the country and has several types of events such as concerts of both international and national artists, bullfighting events, charrería, and the largest livestock exhibition in Latin America [26].

The state of Aguascalientes is located in the central-northern region of the country, 480 km northwest of Mexico City. It is a very small state, covering an area of approximately 5,470 km^2 (about 0.03% of the country), and is subdivided into 11 municipalities. The central municipality of the state of Aguascalientes, also called Aguascalientes, contains about 76% of the state population and accounts for around 85% of the criminal incidence in the state. Furthermore, because there is a large number of incoming visitors during the Fair, it makes sense to focus on criminal incidence around it. In order to study what happens in and around the Fair grounds, this research methodology only focuses on the first ring of the city. Figure 5 shows the location of the state and city of Aguascalientes together with the limit of the first ring that is used in this study.

The first ring is bounded by the road circuit named "Aguascalientes Convention of 1914", also known as "Primer Anillo". This ring-shaped road structure contains the downtown area and distributes transport services from north to south and from west to east using only this road.

The San Marcos Fair has been held annually during April and May since 1828 and lasts for about of 24 days [26]. During the festivities, various fairgrounds located to the southwest of the city are used to distribute all scheduled events. Due to this organizational structure, it is possible to recognize the increase in the number of visitors in that part of the city and, consequently, the demand for other tourist services such as lodging, food, transportation, and banking services also increase. For this case study, we use official data from the National Institute of Statistics and Geography (Instituto Nacional de Estadística y Geografía - INEGI) of city blocks and streets of the state of Aguascalientes. Geo-referenced crime data records were obtained from the state's General Attorney's office for thefts between January 2011 and May 2018 in the whole state. Because some

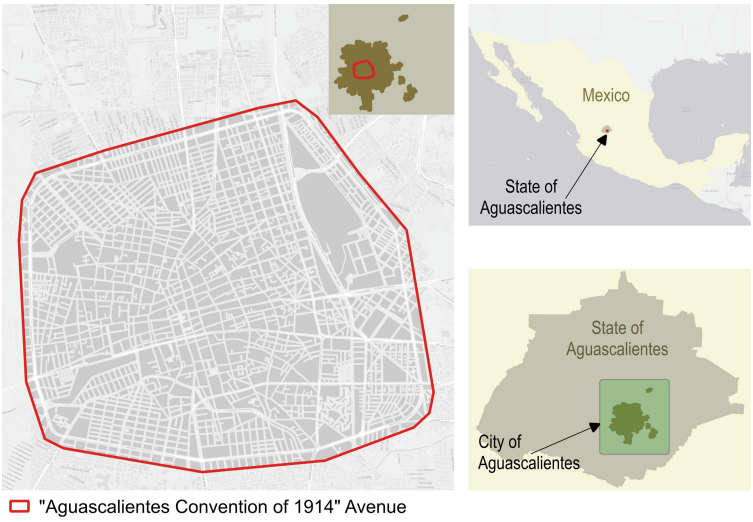

Fig. 5. The location of the state and city of Aguascalientes together with the boundary of the first ring

crime incidents are reported to occur on parks and inside buildings, for the purpose of this methodology, such crime locations were modified so they are accounted for on the street network and in the visible surface of the solution described above. We also consider 10 scenarios of 50 cameras that have a sensor distance of 100 m and partition the field of view with a 1° resolution. For this case, the stop criteria is the number of iterations set to 30.

According to official records, the first ring experiences three main types of theft: pedestrian, vehicle, and auto parts. Together, these three types of crime represent 67% of the recorded incidence between January 2011 and May 2018 (24%, 24%, and 19%, respectively). The temporal change of these crime types inside the first ring also shows that during the Fair the number of visitors concentrated in and around the fairgrounds create conditions ripe for theft exposure. Figure 6 shows the distribution of theft incidences during the Fair and their temporal behavior. Even though the city of Aguascalientes has low theft counts compared to other cities in the country, this distribution shows a significant increase during the Fair. By considering the spatial distribution of the three most common types of thefts together with the city infrastructure and services, it is found that pedestrian incidence is more pervasive around certain facilities, such as banks and, particularly, the fairgrounds. Figure 7 shows the spatial distribution of these incidences. The fairgrounds are located just to the left of the map center and to the southwest. When the temporal nature of the data is taken into consideration, it is found that 33% of the crime incidence corresponds to pedestrian thefts that took place in April, 30% in May, and then drops to the monthly average of 23%.

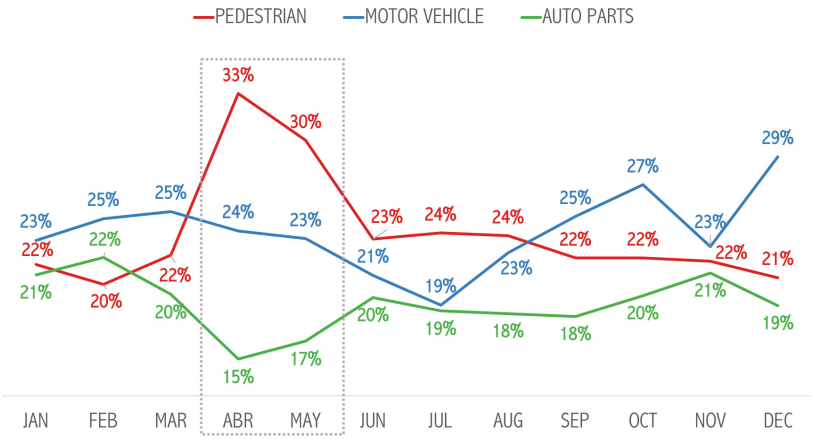

Fig. 6. Distribution of theft incidences inside the first ring of the city of Aguascalientes between January 2011 and May 2018. Dates spanning the San Marcos Fair are indicated

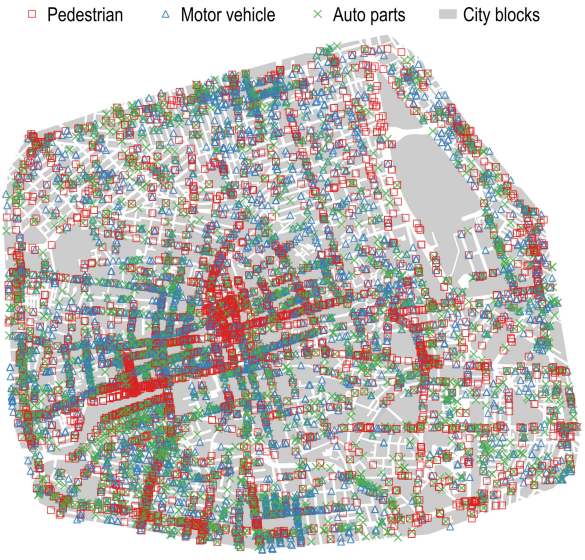

Fig. 7. Spatial distribution of the three main types of theft inside the first ring of the city of Aguascalientes

5 Results and Discussion

The cross and mutation parameters, CR and F, have a significant impact on the obtained solution and should be consider as a threshold. The use of high values for these two parameters results in the case of a random search. Conversely, low values produce a stagnation for the obtained solutions. For the specific case studied here, the effect that F has on the displacement of camera locations needs

to be taken into account due to the measurement units for the cartographic representation. As such, an F value of 0.5 (that corresponds to an approximate shifting distance of ∼50 km) produces unacceptable camera locations as it places them beyond the observable surface of road networks under consideration and a reassigning process needs to be triggered. For the case study presented here, F has a value of 0.001, which roughly represents a shifting distance of 100 m.

The parameters α_1 and α_2 also have an influence on the obtained solution. Depending on their value, they can make one criterion be preferred over the other. That is, either the number of observed incidences or the observed area is preferred. For this case study, both of the proposed criteria for the objective function are opposed: forcing the system to obtain the maximum amount of observed incidences can compact camera locations to specific points, thus leaving areas of the city unprotected without surveillance. On the other hand, if the system must maximize the observed area, then camera locations would be selected on broad streets and street corners that may not necessarily have high criminal incidence. Likewise, the algorithm is adaptable and could incorporate a way for the values of both α_1 and α_2 to be optimized.

The inclusion of the performance function that considers obstacles or intersections, such as city blocks, allows for a better understanding and exploitation of camera locations. The performance function could be further improved by adding more contextual information about the area under study coupled with camera characteristics. Thus, the performance function would provide results that would be a better match to reality and would therefore improve the quality of the solution.

An improvement is observed from the starting solution by shifting from a uniform to a stratified sampling scheme. Incidence saturation on the surface indicates that there are areas more prone to theft than others. With this idea in mind, the street surface was fragmented into five categories according to the amount of criminal incidence. With this, the stratified sampling is used to proportionately distribute the number of cameras between the strata.

The final solution for this case study is shown in Fig. 8. The graphs on the right show the performance of the solution for different iterations. In the performance graphs, the variations in each decision criterion show they are competing while searching for the solution. Then, the algorithm should find a solution that maximizes both criteria simultaneously. For this case, in order to maximize both criteria, the DEA results in a decrease of the percentage of observed crimes in favor of an increase of the visible surface. By the end of the simulation, it can be seen that the percentage of observed crimes has decreased about 0.5%, while the visible surface increases approximately 0.8% from their initial values. The map shows the distribution of cameras and their isovists that represent the observable area for each camera. Upon visual inspection, a good match is observed on many locations when comparing the incidence map (Fig. 7) and the density of crimes added to the final solution. Regarding Fig. 7, there are some regions that seem to have high incidence and very few cameras. This apparent discrepancy can be explained because the incidence map only shows three types of crimes,

while the final solution uses all crime types on the study area. Also, even though the observed area drops, after inspecting the map it is found that cameras are located in small but conflicting streets.

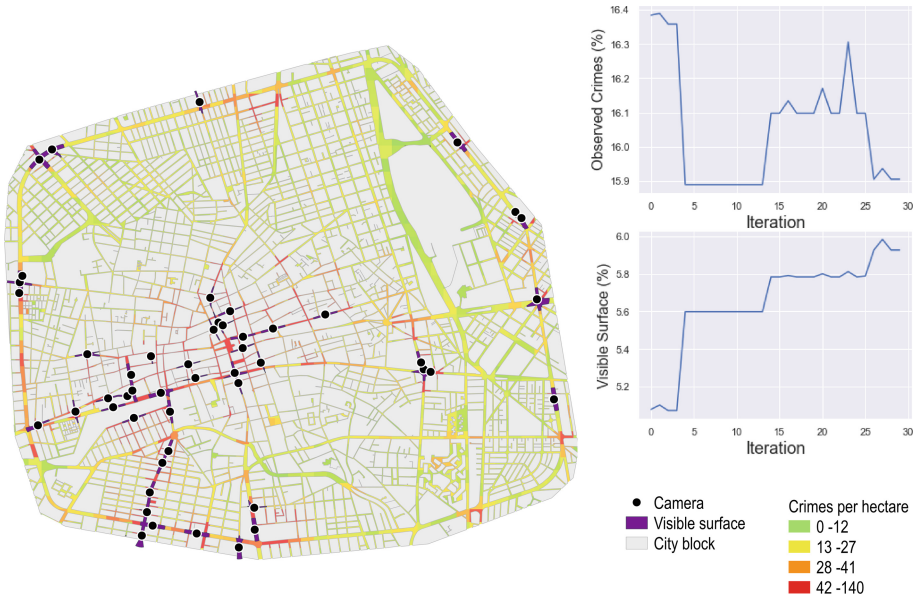

Fig. 8. Map depicting the proposed solution for camera locations on top of the spatial density of all crime types per hectare and graphs that show the performance of the algorithm

6 Conclusions and Future Work

A methodology to locate a set of surveillance cameras in an urban setting by using a metaheuristic model was proposed. This methodology improves the surveillance coverage thanks to the competition and selection structures in the DE algorithm. The case study proved it is possible to automate the location selection for surveillance cameras with very few available inputs. Furthermore, by simulating possible solutions it is possible to cut down costs for decision-makers and they have a flexible tool that can be adapted for specific needs.

With the existence of detailed information such as protruding facades, trees, lamp posts, or other types of obstacles, the obtained solutions would be far more realistic since there would be precise knowledge of the environment under study. If camera attributes such as field of view or detection and zoom capabilities are considered, together with the tasks the system would have to work on such as object recognition or tracking, it would be possible to have more control over the solution space and obtained results would be more attached to what the

system would do in reality. Additionally, the stop criteria was set to an upper limit to the number of allowable iterations but could include a tolerance threshold for the dissimilarity of the fitness function for the latest solutions from the best generations, stopping the execution when there are no significant changes between the performance of the best scenarios. For the tolerance threshold to work, however, it is required that decision criteria are good enough to rank the solutions and prevent ties.

This research used a DE algorithm based on the intuitive idea of natural evolution. However, there are other metaheuristic models that could be included, like Genetic Algorithm, Particle Swarm Optimization or Ant Colony Optimization, which have also been used with good results in finding camera locations [9,13,16,17]. It could even be possible to consider an adaptive model that uses previous knowledge to spawn the new solution. Future work includes further tuning the algorithm and evaluating the inclusion of other stop criteria to have a better final solution. Additionally, it will be interesting to adapt the algorithm so it works with an existing network of surveillance cameras already in place. Also an overlap threshold for the camera visibility polygons can be implemented by using Jaccard's similarity coefficient to reduce the redundancy of information captured by the solution and maximize the observed surface.

References

1. Bennett, T., Gelsthorpe, L.: Public attitudes towards CCTV in public places. Stud. Crime Crime Prev. **5**(1), 72–90 (1996)
2. Waples, S., Gill, M., Fisher, P.: Does CCTV displace crime? Criminol. Crim. Justice **9**(2), 207–224 (2009)
3. Li, A.: Pros and Cons of Surveillance Cameras in Public Places (2017). https://reolink.com/pros-cons-of-surveillance-cameras-in-public-places
4. Bowcott, O.: CCTV boom has failed to slash crime, say police (2008). https://www.theguardian.com/uk/2008/may/06/ukcrime1
5. Norris, C., McCahill, M., Wood, D.: The growth of CCTV: a global perspective on the international diffusion of video surveillance in publicly accessible space. Surveill. Soc. **2**(2–3), 110–135 (2004). Editorial
6. Kelly, H.: After Boston: The pros and cons of surveillance cameras (2013). https://edition.cnn.com/2013/04/26/tech/innovation/security-cameras-boston-bombings/index.html
7. Bodor, R., Schrater, P., Papanikolopoulos, N.: Multi-camera positioning to optimize task observability. In: IEEE International Conference on Advanced Video And Signal Based Surveillance - Proceedings of AVSS 2005 (2005). https://doi.org/10.1109/AVSS.2005.1577328
8. Hu, W., Tan, T., Wang, L., Maybank, S.: A survey on visual surveillance of object motion and behaviors. IEEE Trans. Syst. Man Cybern. Part C **34**(3), 334–352 (2004). https://doi.org/10.1016/j.artint.2008.12.005
9. Jun, S., Chang, T., Yoon, H.: Placing visual sensors using heuristic algorithms for bridge surveillance. Appl. Sci. **8**(1) (2018). https://doi.org/10.3390/app8010070
10. Morris, B.T., Trivedi, M.M.: A survey of vision-based trajectory learning and analysis for surveillance. IEEE Trans. Circ. Syst. Video Technol. **18**(8), 1114–1127 (2008). https://doi.org/10.1109/TCSVT.2008.927109

11. Hogan, K., ReVelle, C.: Concepts and applications of backup coverage. Manag. Sci. **32**(11), 1290–1306 (2012)
12. Rana, S.: Isovist Analyst - An Arcview extension for planning visual surveillance. ESRI International User Conference. ESRI (on CD-ROM), 1(Chvátal), 9 (2006). http://eprints.ucl.ac.uk/2104
13. Basu, S., Sharma, M., Ghosh, P.S.: Metaheuristic applications on discrete facility location problems: a survey. OPSEARCH **52**, 530 (2015). https://doi.org/10.1007/s12597-014-0190-5
14. Jordanski, M.: Metaheuristic approaches for solving facility location and scale decision problem with customer preference. IPSI BgD Trans. (Two Res. Oriented J.) **13**(1) (2017). http://ipsitransactions.org/journals/papers/tir/2017jan/p2.pdf
15. Xie, Y., Wang, M., Liu, X., Wu, Y.: Surveillance video synopsis in GIS. ISPRS Int. J. Geo-Inf. (2017). https://doi.org/10.3390/ijgi6110333
16. Konda, K.R., Conci, N.: Global and local coverage maximization in multi-camera networks by stochastic optimization. Infocommun. J. (2013). https://doi.org/10.1200/jco.2011.35.9182
17. Xu, Y.C., Lei, B., Hendriks, E.A.: Camera network coverage improving by particle swarm optimization. EURASIP J. Image Video Process. (2011). https://doi.org/10.1155/2011/458283
18. O'Rourke, J.: Art Gallery Theorems and Algorithms. Oxford University Press, Oxford (1987)
19. Church, R., Meadows, M.: Location modeling utilizing maximum service distance criteria. Geogr. Anal. **11**(4), 358–373 (1979)
20. Murray, A., Kim, K., Davis, J., Machiraju, R., Parent, R.: Coverage optimization to support security monitoring. Comput. Environ. Urban Syst. (2007). https://doi.org/10.1016/j.compenvurbsys.2006.06.002
21. Giagkiozis, I., Purshouse, R., Fleming, P.: An overview of population-based algorithms for multi-objective optimization. Int. J. Syst. Sci. **46**(9), 1572–1599 (2015). https://doi.org/10.1080/00207721.2013.823526
22. Tong, D., Murray, A.: Spatial optimization in geography. Ann. Assoc. Am. Geogr. **102**(6), 1434–1444 (1986)
23. Storn, R., Price, K.: Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. J. Glob. Optim. **11**, 341 (1997). https://doi.org/10.1023/A:1008202821328
24. Li, X., Yin, M.: Application of differential evolution algorithm on self-potential data. PLoS ONE **7**(12), e51199 (2012). https://doi.org/10.1371/journal.pone.0051199
25. Datos de Afluencia. Patronato de la Feria Nacional de San Marcos - Coordinación Estatal de Planeación y Proyectos. http://www.aguascalientes.gob.mx/ceplap/datos/default.aspx
26. Historia de la Feria Nacional de San Marcos en Aguascalientes: México Desconocido, 31 March 2016. https://www.mexicodesconocido.com.mx/feria-san-marcos-aguascalientes.html