Optimal Video Camera Network Deployment to Support Security Monitoring

Benoit Debaque, Rym Jedidi, Donald Prévost
Advanced Imaging System
INO
Quebec, CA.
benoit.debaque@ino.ca

Abstract – Designing an optimal video camera network for monitoring ground activities is a critical problem to ensure sufficient performance in video surveillance system. Several authors have addressed this issue in the past, and considered this problem to be essentially a coverage optimization problem. Because of its nature and complexity, this problem is considered to be a multiobjective global optimization problem, which includes the maximum covering location problem (MCLP) and backup coverage location problem (BCLP). We add another criterion that considers optimal target positioning. This paper outlines a possible solution and its related tradeoff.

Keywords: Security monitoring, optimal sensor network design, multi-criteria analysis.

1 Introduction

Video surveillance is becoming a work tool of choice when one has to monitor ground activities. Furthermore, preventing threats or accidents to happen in public areas from security centers is becoming vital as public security is a big challenge in the present day. Also, as imaging sensors are becoming cheaper and easier to deploy, more video cameras will be exploited in the future. Consequently, there arises the problem of optimizing the network performance in terms of coverage.

However, positioning a natural target from a video camera is a difficult task because image processing performance depends on target resolution and discrimination. Therefore, each implementation is necessarily application dependent, where the system design and its subparts are a determinant factor. Therefore two major problems arise for monitoring airport ground activities: the sensor placement problem and the target positioning accuracy.

The sensor placement problem can be formulated as the art-gallery problem [14]; which is proven to be NP-Hard in 2D and 3D dimensions. Many authors have proposed interesting solutions (see [1] for a review). However, this approach which tends to determine the minimum number of sensors used to cover an area is limited because for areas of complex shape, excessive number of sensors must be used to satisfy the requirement. Furthermore, it generally assumes unlimited visibility which is not suitable for realistic locating equipment.

As it was already pointed out in previous papers, much work has been done related to the coverage problem in 2D; the 3D problem is less studied. Also, finding the minimum number of sensors to cover as much area as possible can be reformulated for our positioning goals as well. The purpose of this paper is two-fold. First, we propose an algorithmic approach for the MCLP (maximal coverage location problem) and BCLP (backup coverage location problem) with another objective function that deals with positioning error bounds. Second, we present an approach based on simulated annealing to solve such design.

The next section reviews the related literature on this subject. Section 3 will presents a model for the problem at hand. Section 4 will give preliminary results and performances of the proposed approach. The paper ends with a conclusion and will comment on possible improvements.

2 Related work

Recently, some papers have contributed to the camera placement problem for video monitoring. In [1,3] authors have looked at camera placement with unlimited sensor visibility, however their concerns were to optimize budget, area and sensor visibility redundancy. In [2] the authors propose a solution with a limited sensor visibility but for indoor surveillance and no 3D reconstruction consideration. In [4,5] the authors have looked at 3D reconstruction accuracy given a stereo camera or a camera network positioned around a convex hull in 3D looking at the center of the measured objects. Their proposed solution is specially designed for close range photogrammetric projects or tele-immersive systems.

Therefore, the problem complexity is reduced because the cameras are positioned around a compact region of interest (ROI) and cameras can be positioned on specific points on a grid surrounding the ROI. For outdoor surveillance, region of interest are dispatched around line-of-sight obstacles, and camera can be positioned on many potential locations. Each of these locations is of relative installation cost for the systems integrator. The major contributions of this paper are:
• Adding to the formulation of MCLP and BCLP new criteria to be optimized which includes a simplified positional accuracy cost function.

• Solving the optimization problem using Simulated Annealing combined with a heuristic approach.

3 Problem definition and resolution

3.1 Multiobjective optimization problem

Identifying an optimal configuration of multiple sensors to cover as much area as possible with a minimum number of sensors is a combinatorial problem which involves conflicting objectives. Thus the problem becomes tractable with the progress over recent years of techniques to solve multiobjective optimization problem. We start by defining the problem which is a crucial task and affect substantially the final solution.

The location set covering problem (LSCP) and the art gallery problem approaches (see [1]) require to cover all demand which is sometime infeasible. Thus, we focus here on maximal coverage location problem (MCLP) originally introduced by Church and Re Velle [15] and simultaneously combined with backup coverage location problem (BCLP) introduced by Hogan and Re Velle [16]. BCLP problem has proven to be particularly valuable for coverage location modeling for tracking the movement of people and activities [1, 3]. Also an original 3D reconstruction error formulation (MLEP: Minimum Localization Error Problem) has been developed in this paper to add camera performances to localize ground targets. As depicted in our model, sensors can have different characteristics depending on budget limitations; an evaluation of the installation cost is done for each configuration to help the user to make an optimal decision.

3.1.1 Primary and secondary coverage

Usually for coverage-based location model, an area is considered covered if it was by at least one sensor. The backup coverage location problem (BCLP) is an extension of MCLP which allows secondary coverage of an area. Under budget limitation the problem is formulated considering the following notations

\[ i = \text{index of region}, \ i = 1 \ldots n; \]
\[ j = \text{index of potential position of sensor}, \ j = 1 \ldots m; \]

\[ \lambda_{ij} = \begin{cases} 1, & \text{if region } i \text{ is covered by a sensor at location } j, \\ 0, & \text{otherwise}; \end{cases} \]

\[ N_i = \{j; \lambda_{ij} = 1\}, \]

Using theses notations and following [1], the multiobjective problem is formulated as

\[ \text{Maximize } \mathcal{Z}_1 = \sum_i \alpha_i m_i \] (1)
\[ \text{Maximize } \mathcal{Z}_2 = \sum_i \alpha_i u_i \] (2)

Subject to

\[ \sum_{j \in N_i} s_j - m_i - u_i \geq 0 \] (3)
\[ u_i - m_i \leq 0, \ \forall i \] (4)
\[ \sum_j s_j = p \] (5)
\[ s_j, m_i, u_i = (0,1), \ \forall i, j \] (6)

Where \( \alpha_i \) is added to notify the importance of region \( i \).

The two objectives attempt to maximize both primary and secondary area in spite of their conflicting character. Constraints (3) and (4) track primary and secondary coverage. Constraint (5) indicates that exactly \( p \) sensors are used, where constraint (6) specify integer requirements on decision variables.

3.1.2 Minimum localization error problem

Viewpoint selection is a determining factor for accurate 3D reconstruction. Designing an optimal multiple viewpoint configurations is a complex geometrical problem traditionally studied in the Photogrammetric community, then later on by the computer vision community (see [9] for a review). The photogrammetric network design search space is multi-modal and therefore there exists very different spatial distribution of viewpoints that will give similar reconstruction accuracy. In order to derive useful and low computational cost criteria, we employ a heuristic method for tolerance analysis of our localization functions.

This provides an alternative to traditional propagation of error analysis. Our heuristic methodology is always a worst case analysis for the distribution of error. This will insure that the selected scenario will fall inside the worst case localization error tolerance of the end-user.
Monoscopic localization error (MLE) Given one camera and an image point, then the minimum error of that point localized on the reference plane (which is the plane of the covered area) is given by:

\[ MLE = \max \{ f(x_1), f(x_2), f(x_3), f(x_4) \} \]  

Where \( f \) is a monotonic localization error function; \( [x_1, x_2, x_3, x_4] \) are the image endpoints corresponding to worst case target positioning. \( f \) is the Euclidean distance of the original grid point to the intersection of the ray emanating from the perspective center of the camera passing through the image endpoint and intersecting the reference plane as depicted in Figure 1.

Image endpoints \( [x_1, x_2, x_3, x_4] \) are obtained from projecting point \( P \) onto image plane, and then inserting an artificial worst case parallax \( \delta_x \) on image point \( x \). \( \delta_x \) is derived from an arbitrary constant target image positioning pixel error.

Stereoscopic localization error (SLE) Given two cameras and two paired image points then the minimum localization error of that point is given by:

\[ SLE = \max \{ g(x_1), \ldots, g(x_4) \} \]  

Where \( g \) is a stereoscopic localization error function; \( [x_1, \ldots, x_4] \) are the image endpoints corresponding to worst case target positioning. \( g \) has the same metric as \( f \) but with four points instead of two. The localization of the ground points from two cameras is obtained via the DLT approach [11]. Figure 2 illustrates the four image endpoints for the case of stereoscopic localization error.

N-scopic localization error (NLE) Given n -cameras and one image point, then the maximum localization error is given by the minimum localization error among MLE for each camera and SLE for each camera pair combination, which represents the best viewpoint configuration among available configurations, that is:

\[ NLE = \min \{ MLE, SLE \} \]  

Finally, the MLEP problem can then be formulated as follows:

Maximize \( Z_3 = \sum_i \alpha_i v_i \)  

Subject to:

\[ \sum_{i=1}^n \alpha_i = 1 \]

\[ v_i = \begin{cases} 1, & \text{if error is inside user tolerance, NLE} \leq \text{Threshold}, \\ 0, & \text{otherwise} \end{cases} \]

\[ v_i = (0,1), \quad \forall i \]

3.2 MLEP-BCLP formulation and Implementation

Adding the effect of the localization error in the optimization process the multiobjective problem is then formulated, using a weighted sum model, as:

Maximize \( Z = \omega_0 \sum_i \alpha_i m_i + \omega_1 \sum_i \alpha_i u_i + \omega_2 \sum_i \alpha_i v_i \)  

Subject to

\[ \sum_{j \in N_i} s_j - m_i - u_i \geq 0 \]

\[ u_i - m_i \leq 0, \quad \forall i \]

\[ s_j, m_i, u_i, v_i = (0,1), \quad \forall i, j \]

\[ \sum_j s_j = p \]
where the weighted coefficients verify \[ \omega_1 + \omega_2 + \omega_3 = 1 \]

Recently, a significant progress was observed in the field of multiobjective optimization and computer-aided decision making. The most used methods are the interactive methods, such as simplex and methods that exploit metaheuristics such as simulated annealing, Tabu search and genetic algorithms (see [10] for an exhaustive overview of these methods). The most popular among them are indubitable the evolutionary algorithms. However for its simplicity to be implemented; we choose to apply the simulated annealing approach. A collaboration research is going on with Laval University “Laboratoire de Vision et Systèmes Numériques” for applying evolutionary algorithm to our problem.

The adaptive simulated annealing method was initially developed for sizing devices in analog circuits and proven its efficiency in the circuits design. Other optimization package using simplex methods such as CPLEX [1, 6] are also widely used for solving similar problems either for the art gallery problem or the BCLP problem (see [1] and [6]). Evolutionary algorithm has been applied in [3] and shown to be suitable for such a problem and more effective than weighted sum methods. However, we focus on the feasibility of our multiobjective formulation to converge as fast as possible to an acceptable solution. Indeed, we aim by this approach to eventually give an interactive decision support for the sensor deployment problem.

### 3.3 Proposed algorithm

Our algorithm consists of scene meshing, visibility test, MCLP formulation, BCLP formulation, localization error formulation (MLEP), and Simulated Annealing computation as shown in Figure 3.

**Sensor characteristics** Sensor characteristics in our case have no depth of field or spatial resolution limitations (unlike most authors). Since our sensors have fixed focal length and small field of view, depth of field is supposed infinite; therefore effects of blur due to limited depth of field are not taken into account for this time. Also, sensors have finite field of view and their principal ray is pointing to some designed point of interest (PoI), or look-at points. Depending on the area’s shape, we are aware that the choice of PoI can affect the algorithm decision. Therefore we propose a solution that gives some degree of horizontal rotational freedom to the sensors. The approach used here increases the degree of freedom allowing sensors to look at any of the PoI with a rotation angle chosen arbitrary by the algorithm.

**Scene creation** The scene consists of polygonal region identified by the user directly from Google Maps™ image. First the area of interest is identified and its surroundings are delimited. For our experiments we did not address the case of multiple fragments and inclusion of the area of interest with potential camera sites. Then the walls defining the potentials occlusions are delimited in the same manner, except that one has to guess the height of the occlusion since Google Maps™ does not necessarily provide all the heights. Finally, cameras potential sites are delimited; usually those sites are selected on existing construction.

**Scene meshing** Partitioning the area of interest is a hard task which influences the final solution. The scene is sampled with a uniform grid. We test the sampling step with several degree of granularity to obtain a figure of merit. The area of potential sensor sites is also sampled with a coarse granularity (every 15 meters in our experiment) along its edges.

**Visibility test** The area visible from a given sensor is restricted by occlusions. We therefore defined occlusions to be geographical features like buildings or trees areas. Visibility computation on the surface is based on line-of-sight (LOS). Walls with vertical height define an occlusion (see Fig. 4).

**MLEP-BCLP formulation** See section 3.1 and 3.2.

**SA solution** See [8, 12] for a practical implementation of Asamin for Matlab™. In our case the Monte Carlo sampling has a limited number of draws, which regulate the termination of the search.

Figure 3. Flow of proposed camera placement algorithm.
4 Experimental results

The approach described in the previous sections is applied to an outdoor area to optimize sensor placement. We consider the area presented in Figure 5. Two levels of granularity are chosen for both sensor placement and coverage area. In our notation, Mesh (i, j) is the granularity level, i is the level of the coverage area meshing whereas j represents the level of sensor placement meshing; two indexes are used, 1 for the coarser mesh and 2 for the finer mesh. We present in Figure 6 the percentage of area covered for the different granularity. We allow a maximum number of placed sensors fixed at p=6. In our experiments the value of $\alpha_i$ is set to 1.

In the optimization process, we allow sensor to look at some PoI. For the area considered, we consider four points of interest distributed as in Figure 5, with a rotation angle, in degree, being in the set {-20,-10,-5, 0, 5, 10, 20}. In the following, we propose to compare the two formulations presented above: MLEP-BCLP and BCLP formulations. For the first case we set $\omega_1 = \omega_2 = \omega_3 = \frac{1}{3}$, whereas for BCLP case $\omega_1 = \omega_2 = \frac{1}{2}$ and $\omega_3 = 0$.

To give a good reason for using finer meshing, we present in Figure 6, curves obtained using MLEP-BCLP and BCLP formulations with Mesh(1,1) and Mesh(2,2). We observe that in general, the number of covered area increases when the number of cameras increases. However, we highlight some exceptions, especially for p=5, where for the finer meshing, the number of covered area is slightly bellow the four camera placement. We suspect, as related in [3] that the global optimal value is not reached by the algorithm and this may be caused by the use of a weighted sum in the multiobjective process. Authors in [3] have proposed a solution based on the application of genetic algorithms to overcome these disadvantages. Other authors [13] have proposed an adaptive weighted sum formulation for this special issue. However, even we are not sure that all optimal solutions are reached; we observe a better performance of the MLEP-BCLP formulation especially when Mesh (2,2) is used.

In order to compare efficiency and computational burden of our algorithm, we present in Table 1, the computational time for two levels of granularity with the increase of number of placed sensors. The computational time for finer mesh is approximately four times compared to the coarser one. Here we present only values obtained for the MLEP-BCLP case; values for BCLP case are similar.

<table>
<thead>
<tr>
<th>Placed sensors</th>
<th>Level(1,1)</th>
<th>Level(2,2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>162.9</td>
<td>671.1</td>
</tr>
<tr>
<td>2</td>
<td>307.2</td>
<td>1289.3</td>
</tr>
<tr>
<td>3</td>
<td>457.0</td>
<td>1725.7</td>
</tr>
<tr>
<td>4</td>
<td>569.5</td>
<td>2268.2</td>
</tr>
<tr>
<td>5</td>
<td>710.9</td>
<td>2782.0</td>
</tr>
<tr>
<td>6</td>
<td>867.9</td>
<td>3543.7</td>
</tr>
</tbody>
</table>

Table 1. Time consuming (sec)

We propose in the following to present some optimal solutions reached with different number of placed cameras. Figure 7 illustrates these different cases, where red regions present primary coverage and blue regions present a multiple coverage case. The grey color is kept for non covered regions. The yellow dot represents the camera
origin, and the triangle represents the LOS, and its size depends on the look-at-point position.

It is interesting to observe that the 2 cameras solution is quiet different from the 3 cameras case. However, the SA algorithm gives us the last best scenario computed; the intermediate solutions that have an equal cost are not provided but have equivalent performance in terms of total cost. Thus some design for 2 or 3 cameras are similar, but are not given as a result of not being the last best solution computed. In addition, more work has to be done to globally evaluate the performance of our approach over solutions performed by hand.

5 Conclusion and future work

In this paper, we have presented an algorithm for sensor placement supporting security video monitoring for ground activities in 3D urban environments. The optimal sensor configuration was obtained by the maximal covering location problem (MCLP), the backup coverage location problem (BCLP) and the minimum localization error problem (MLEP). While our formulation for error localization needs improvements since a more generic formulation to n-cameras still to be addressed, it is shown that a simpler expression has a potential to deal with this problem.

In the future, we would like to extend this work by taking into account specific target type’s localization error (human, vehicle, plane, etc.). We would also like to investigate a hierarchical approach to gridding with intermediate multiobjective solution in order to reduce the search space. Finally, we would like to introduce the notion of cost, camera’s cost or price of the camera that we wish to buy if it suits better our solution, and the camera installation cost, which may fluctuate depending on site facilities.
References


