OPTIMAL CAMERA AND LIGHT SOURCE PLACEMENT FOR SURVEILLANCE APPLICATIONS

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Submitted By
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Certificate

This is to certify that the thesis titled "Optimal Camera and Light Source Placement for Surveillance Applications" being submitted by Ritu Garg, 13/SE/09, in partial fulfilment of the requirements for the award of the degree of Master of Technology in Software Engineering, Department of Computer Engineering, Delhi Technological University, Delhi, is a bonafide record of the work carried out by her under my supervision. The matter submitted in this dissertation has not been admitted for an award of any other degree anywhere.

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Abstract

Surveillance applications are gaining research importance day by day. Visual sensor arrays form the backbone of any surveillance applications. Correct visual sensor placement along with good lighting conditions is indispensable for the successful execution of such applications. For given application specific restrictions, constraints, and visual occlusion it can be difficult to find optimal positions for sensor placement. The complexity of these constraints suggests that automated methods for sensor placement are likely to be useful, particularly when the workspace is cluttered and application demands maximum coverage with minimum cost and good quality of service. Illuminating the space under surveillance is also equally important for good quality imaging.

We present a novel approach for placement of both cameras and light sources for surveillance applications. Camera and light source placement depends on the geometry of the space under surveillance, considering the factors such as occlusion and shadowing effect due to presence of objects in the environment, reflection, spatial resolution to assure better coverage of the most probable event locations, *et cetera* . The deployment strategy places cameras for maximum coverage of the multiple sensitive areas and light sources are placed for illuminating these areas to enhance the quality of the vision system. Since, constrained discrete optimization problems do not have efficient algorithmic solutions, use of evolutionary algorithms is preferred. Thus, solution to the problem of finding optimal camera and light source locations has been concluded using multi-objective genetic algorithm based optimization.

Acknowledgements

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Dedicated to my family and my teachers

Chapter 1

Introduction

With the improvements in vision based algorithms and tracking using multiple cameras, the use of multi-camera surveillance systems to monitor complex indoor and outdoor environments has increased. Such applications require a camera network, as it becomes difficult to monitor discrete events in a large space with a single camera and also single camera cannot always take care of occlusion. An important issue in designing such a network is the placement of these cameras, which optimizes the coverage of the discrete spaces with optimum resolution. Another main limitation when applying vision system to industrial automation, is the high cost of designing and installation of the vision system. Thus, while designing a vision-based system it is important to define an optimization process to automate the sensor placement and do better than a human designer. To address these concerns, researchers have been investigating the relationship between a vision task and acceptable sensor configurations for executing it. Decreasing cost of associated hardware and increasing practical need for such systems are among the reasons attracting more and more researchers to focus in this area.

Different visual applications have different requirements. For instance, for an intruder detection system, complete visual coverage of the region of interest may be needed. For a multi-view reconstruction task, it may be desirable to have a minimum number of video sensors with some given angular separation. For some systems the aggregate video sensor network, depending on the specific system design and architecture, should be made fault tolerant to the occasional failures of cameras, temporarily obstructed camera views, etc. Similarly in video sensor networks, the layout of sensors should assure a minimum level of image quality needed to satisfy certain task specific requirements, e.g., sufficient image resolution, depth of field, pan-tilt-zoom cameras, etc. Visual sensor arrays are used in many novel multimedia applications such as video surveillance, sensing rooms, or smart conference rooms. An important issue in designing sensor arrays is the appropriate placement of the visual sensors such that they achieve a predefined goal.

1.1 Problem Definition

Our main objective is to find optimal locations for deployment of visual sensors and light sources in large surveillance space. Placement of visual sensors for optimal coverage is quiet complex due to the directionality of visual sensors and the uncertainty of the event location in space. PTZ camera itself is complex due to its pan tilt motion. Further the quality of image depends on zoom level of the camera and the illumination of the area.

Many of the existing approaches assume constant zoom level. Thus, we need to modify the camera model for incorporating zoom/depth-of-field as a constraint for placing visual sensors. Due to the pan-tilt motion of the PTZ camera, the time for which the sensing space is covered is not uniform. Hence, we require probabilistic modelling of space assuring better coverage of most probable event location or the priority areas.

The functioning of such a camera network can be effective only if the priority areas are properly illuminated. Proper illumination means,no light ray from the source should directly fall on the camera and the objects in the priority area should reflect optimum light towards camera. Hence, we need an efficient approach for light source placement to avoid failure in the vision system due to shadow and occlusion.

The placement problem is an *optimization problem* with interrelated and competing constraints. The constraints being the geometry of sensing space, the camera and light source models. Since, constrained discrete optimization problems do not have efficient algorithmic solution, we propose to use an evolutionary algorithm. Thus, the major motivation behind this work is the multi-objective nature of the problem with discrete set of variables and constraints. We aim for simultaneous optimization of camera and light source placement problem.

1.2 Our Approach

We have developed a CAD tool for 3-D modelling of the space under surveillance. The sensing space is modelled as voxels. The CAD tool allows the user to mark regions that need to be monitored at a higher priority. It also permits user to mark obstacles present in the space under surveillance and the feasible areas where camera and light source can be placed, *e.g.* walls and ceilings. We have developed a MATLAB based GUI for feeding these data. This 3-D model is used for finding optimal camera and light source locations with appropriate pan and tilt angles and minimum required zoom level for assuring the quality of service. The placement problem demands a effective mathematical modelling of camera, light source and sensing space.

We have used PTZ camera model. PTZ cameras can cover a larger volume compared to pin hole cameras due to its pan-tilt motion and with better resolution. For assuring better coverage of the sensitive areas, we need a probabilistic modelling of sensing space in terms of coverage. Thus, each visible voxel is assigned a probability measure depending on the camera location, pan-tilt angle and zoom level. The probability of occlusion by randomly moving objects is minimised by covering the priority areas by multiple sensors. Illumination of the sensing field is equally important for good quality image. We use a conical light source model. The light sources should be placed in such a way to avoid direct light falling in any of the cameras, taking care of shadowing and occlusion. Hence, we need to place more than one camera and light source for ensuring good quality imaging. We have developed a light source placement scheme for addressing these issues.

Given a number of issues, the optimization problem of finding the optimum camera and light source placement in a given environment has been solved using genetic algorithm. To achieve this task we use the NSGA-II algorithm to perform the optimization in a multi-objective environment. The objective functions being camera coverage and appropriate illumination of the sensing region to be optimized concurrently.

1.3 Looking Forward

The layout of the thesis is as follows :

1. In Chapter 2 we present a brief literature survey related to the camera placement problem. Next we talk about the efforts reported in literature by many researchers to automate the camera and light source placement. We also introduce a brief summary on the emergence of multi-objective optimization.

2. In Chapter 3 presents the camera and light source placement formulation. The objective functions designed such that the camera are placed for maximum coverage while the light source are localized in such a way that the space under surveillance is well illuminated nullifying the effect of shadows or occlusion due to obstacles.

3. In Chapter 4 presents the multi-objective framework for optimization of camera and light source arrangement for large surveillance space.

4. In Chapter 5 results are illustrated through our simulated environment, as well as we illustrate the experimental set-up for multi-camera configuration.

5. Finally in Chapter 6 we conclude our work and outline the future work in this area.

Chapter 2

Related Work

In this chapter we analyze the related work reported in literature and where ever necessary we also draw comparisons with our work. We also highlight the inadequacies and deficiencies in the current techniques. We also introduce the work done in the field of multi-objective optimization.

2.1 Camera Placement

Although significant amount of research exists in designing and calibrating video sensor arrays, visual sensor placement using PTZ cameras in general has not been addressed specifically for surveillance applications. The different research work carried out for placement of cameras included photogrammetric networks, camera networks based on scene reconstruction, task constraints, motion recognition, multi-camera tracking etc.

In the initial stages the sensor planning is done based on occlusion pattern [1]. We can broadly classify the research in this field into following main categories, (a) No information about the surveillance field is known, (b) The models of some set of information about the objects of the field are known, (c) Complete geometric information about the space is known, (d) Automatic placement of camera based on the information obtained from images, and (e) Camera and light source placement for specific task.

The Art Gallery Problem (AGP) was one among the initial research work similar to the current work, where minimum numbers of Guards are determined so that all points of the polygon can be observed for their static positions. The exact solution of the same is found to be NP-Hard, even though efficient algorithms exist giving a lower bound for AGPs with simple polygons [2], [3], [4], [5]. Current solutions to the AGP and its variants employ unrealistic assumptions about the camera's capabilities like unlimited field of view, infinite depth of field, infinite servo precision and speed that make these algorithms unsuitable for most real world computer vision applications.

Camera calibration was extensively studied by many researchers such as Christopher R. Wren and et. al. for automatically retrieving contextual information from different camera images [6], Ioannis Rekleitis and et. al. for obtaining 3D pose of the cameras in a common reference frame using a mobile robot [7], E. Hoster and et. al. for automatic position calibration of visual sensors without synchronization [8], Marta Wilczkowiak and et. al. for 3D reconstruction [9]. Richard I Hartley have proposed self calibration of camera from different views taken from a point with different poses [10]. The camera calibration may be used along with camera placement for on line optimization of the camera poses which can be considered as an extension of our work.

Some others developed vision systems based on image information. Mohan.M.Trivedi and et.al.[11] developed a distributed interactive video array for both tracking people and identifying people, where as Huang Lee and et. al have addressed node and target localization [12]. Ali Maleki Tabar and et. al. developed a smart home care sensor network using different types of sensor nodes for event detection [13]. These three works are silent about camera placement. There are certain works in which the next optimal camera parameter was found out on the basis of the visual data history of the scene [2], [3], [4] by Krishnendu chakraborthy and et. al.

Developed Grid based placement for Omni directional circular range sensors [14]. Sensor planning methods using more realistic model is given by Tarabanis [15]. Siva Ram et.al explained a real time control of PTZ cameras using cheap motion sensors [16]. They have addressed the placement of cameras using a performance index which is calculated on a trial and error basis. They have neither considered the quality of images and nor the optimization of pan angle and tilt angle of cameras. Robot Bodor and et.al. [17], [18] find out optimal locations of the camera after learning the activity. This method will be computationally intensive and will not be suitable for large space. The off-line camera placement problem considering random occlusion was initially addressed by Xing chen [19]. Later same work was extended by Larry Davis and Anurag Mittal [20]. They used pinhole cameras. Anurag mittal [21] have presented a camera placement algorithm using a probabilistic approach for 3D spaces considering occlusion due to randomly moving dynamic objects. They used a pin-hole camera in their design which again can be optimized by using PTZ cameras.

2.2 Camera and light source placement

Automatic placement of light source in general has developed research interest recently. Among the few research papers available for placement of light source, most / all of them depends on image information and are designed for specific vision applications where as the proposed method is more general and completely off line. Also it is based only on the geometry of the space and camera and light source model.

S. Sakane and et. al [22] calculated location of multiple light source which will avoid the shadow caused by the surroundings while the robot is moving. This method assumed pin hole camera and point light sources and the method depends on pixel intensity of the image which is obtained either by moving camera or the light source. Creg.K. Cowan [23] compute the camera position and light position after detecting the shape of the object by identifying edges of the object, using CAD. Further in their work "Edge based placement of light source" [24], [25], they calculated locations of light source using a better edge detection algorithm. This method may fail for a spherical object.

K.W. Khawaja developed a better system of camera placement and light source placement [26]. They calculated camera location and light source location from physical parameters of the environment and features, but the method is object specific. Eric Marchand [27] have devised placement of light source or camera for optimum illumination of object while tracking, using optical flow method. Either camera or the light source should move for using optical flow.

We discuss a simple and efficient CAD tool for camera and light source placement for surveillance applications. Using the proposed CAD tool the cameras can be placed optimally for maximum coverage of the sensitive areas, and then light sources can be placed for proper illumination of these sensitive areas which can reflect optimum light to the camera. The existing methods of camera and light source placement are devised for specific application and involves light source or camera movement, which will not be suited for large spaces. Whereas the the proposed tool is neither real time nor object specific, and uses better camera and light source model to enhance the accuracy of placement. Hence this tool is well suited for surveillance applications.

2.3 Multi-Objective Framework for Optimization

Multiple evaluation criteria often arise when solving real-world problems, specially when deciding on a set of constraints. While a given task goal may be evident from the onset, these additional merit functions normally emerge as a product of other high level considerations regarding task execution. A MO problem solving approach attempts to address these scenarios in a general manner by studying the performance trade-offs of different problem solutions and incorporating such insight into the decision making process.

The study of the concurrent optimization of multiple objectives dates back to the end of the XIX century in the works of Pareto [28] and Edgeworth on economic theory. However, for many years the interest on these problems was limited to specialized fields such as operations research and economics. In the second half of the XX century, the works of Kuhn & Tucker [29] , Koopmans and Hurwicz [30], established the theoretical principles for the emergence of multi-objective optimization as a mathematical discipline. Afterwards, the seminal work by Charnes & Cooper [31] studied the algorithmic aspects of solving vector maximum problems, initiating the research on mathematical programming techniques for MO problems. In order to incorporate such concepts into functional systems the issue of preference articulation needed to be studied. In this respect, the works of Keeney & Raiffa [32] on Multi-Attribute Utility Theory, the work of Roy on outranking procedures and that of Saaty on the Analytic Hierarchy Process, initiated the research on Multi-Criteria Decision Making (MCDM). The ongoing studies on the generalization of single objective optimization techniques and theory for multiple objectives, have resulted in a wide variety of algorithmic approaches for MO problems. However, the difficulties on approaching real world problems (i.e. high non-linearities, constraint satisfaction, isolated minima, combinatorial aspects), as well as the inherent conceptual complexity of MO optimization has resulted in the development of specialized sub-fields such as Goal Programming, Fuzzy MO

Programming, Data Envelopment Analysis, Combinatorial MO Optimization and Evolutionary MO Techniques. In literature, use of evolutionary techniques focuses on solving camera placement problems [40],[41]. [33] provides an extensive survey on this field.

Chapter 3

Camera and Light Source Placement

3.1 Introduction

Correct placement of cameras with appropriate illumination is an important issue in vision based applications. Camera network in surveillance applications demand maximum coverage of sensitive areas with minimum cost and good quality of service. With given number of cameras and light sources the quality of the images depend on their spatial arrangement and orientation (pan and tilt angles) of the cameras. However, many vision based applications require camera and lighting arrangement ensuring minimum acceptable quality of images.

In this chapter we define the objective functions used for the search of the optimal camera and light source placement. The formulation of the objective function considering the geometry of the space under surveillance is adopted from work presented in [34], [35] and [36]. An extension of the formulation is presented in this chapter.

To estimate optimal camera and light source location we model the space under surveillance. For ensuring better coverage of the regions of interest, we perform probabilistic modelling of sensing space. The probability of occlusion due to randomly moving objects in the sensing space has been incorporated by covering the priority areas by multiple sensors. Random placement of light sources may lead to over or under illuminated regions. For optimum illumination of the sensing space, it is required to place the light sources appropriately to avoid occlusion and shadowing instead of placing the light source randomly. To avoid occlusion and shadow it is required to place more than one camera and light source.

In other words, it is required to compute camera locations with their respective orientations and zoom levels for optimum coverage of sensing space and light source locations for proper illumination with respect to the camera location.

3.2 Camera Placement Problem

Formally the camera placement problem is to determine optimal positions, orientation and zoom levels of N cameras which provide maximum coverage of the priority areas in a predefined surveillance space satisfying the task based constraints which may be static or dynamically varying according to the requirements. Before presenting the camera coverage formulation we study the camera model as well as the 3-D model created for the space under surveillance.

3.2.1 Camera Model

We first define few important terms that are crucial parameters for the camera:

1. **Spatial Resolution:** Spatial resolution of a camera is defined as the ratio between the total number of pixels on its imaging element excited by the projection of a real world object and the object's size. Higher spatial resolution captures more details and produces sharper images.

2. **Field of View (FoV):** The maximum volume visible from a camera. The FoV is determined by the apex angles (azimuth and latitude) of the visible pyramidal region emanating from the optical center of the camera. This pyramid is also known as the viewing frustum and can be skewed by oblique projection.

3. **Depth of Field (DoF):** Depth of field is the amount of distance between the nearest and farthest objects that appear in acceptably sharp focus in an image. The nearest distance in focus is called near focus limit and the farthest distance is called far focus limit. These limits are represented by near

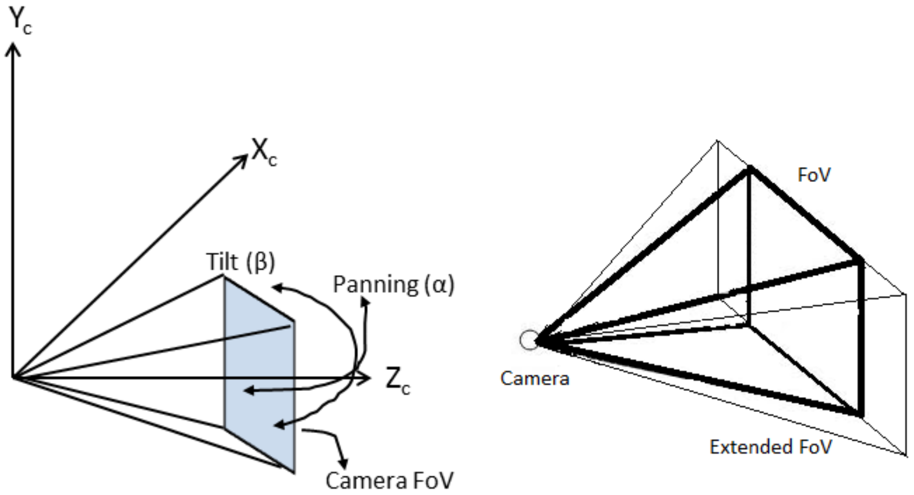
focal and far focal planes. If the subject image size remains the same, then at any given aperture all lenses will give the same DoF. DoF is independent of focal length of the visual sensor but depends on the magnification. For surveillance applications since the camera is fixed, the DoF changes with change zoom. Higher zoom level shallower will be the DoF and lesser will be the number of points in the viewing frustum.

4. **Floor plan:** The term floor plan denotes a 3-D model sensing space. In the space under surveillance, there are regions of high priority where the occurrence of an event is high while the rest are non-priority regions. The floor plan also indicates the presence of obstacles in the sensing space.

5. **Zoom:** Zoom level of any visual sensor is directly proportional to its focal length. Two type of zoom levels are defined namely digital zoom and optical zoom. Since we work on optimization of camera parameters thus we shall deal with optical zoom of the camera being used for deployment. As zoom level increases the focal length increases and the angle of view decreases. And change in the viewing angle means change in the dimensions of the viewing frustum of the visual sensor. Thus, with increasing zoom, angle of view decreases and hence the field of view of the camera decreases.

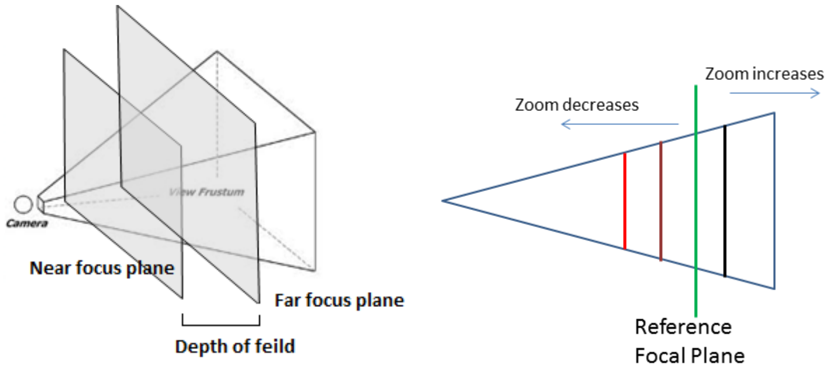
We have employed PTZ (Pan Tilt Zoom)cameras. The Figure 3.1(a) shows the model of a PTZ camera developed by E. Horster [37]. The pan and tilt motion of PTZ camera is modelled as two idealized rotation around the origin along X-axis and Y-axis aligned with image plane and through camera's optical centre. The field of view of the camera can be considered as a pyramid. Since these camera rotate $\pm\theta$ degrees about their axis along their pan and tilt axis so they have an extended field of view as shown in Figure 3.1(b). Thus, they are preferred over pin-hole camera.

The zoom level of a camera is directly proportional to its focal length. For a given zoom level multiple focal planes have been considered. The concept of multiple focal planes for a particular zoom level is similar to extended field of view. The effective area covered in this case is the union of voxels covered by the camera when focused at individual focal planes. Due to the continuous motion of the camera, we sample the pan-tilt motion and the zoom levels at discrete positions. The covered area of viewing frustum is calculated using modified camera model shown in Figure 3.2(a) and Figure 3.2(b) with zoom as a constraint.



(a) Camera Model (b) Extended Field-of-View(FoV)

Figure 3.1: Camera Modelling



(a) Depth of Field (DoF) (b) Showing the variation in zoom, black vertical lines - higher zoom level, red vertical lines-lower zoom level and green vertical line - reference focal plane

Figure 3.2: Modified camera model

If a voxel lies in the extended field of a certain number of cameras say n, the voxel is covered. The Figure 3.3 shows the intersection of field of view of 2 cameras. Considering camera c_1 and C_2 are placed at optimal locations, then any voxel lying in the region II is covered by $n = 2$ cameras. Therefore, as number of camera n increases the probability of occlusion due to randomly moving object reduces.

3.2.2 3-D space Modelling

A 3-D model of the area under surveillance is defined. The space to be monitored is logically divided into cubical blocks, *voxels*. Each voxel is marked as one of the

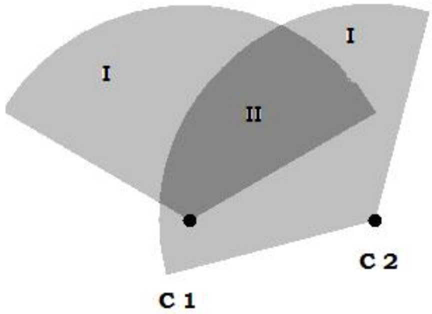


FIGURE 3.3: Intersection of Field-of-View

following:

- Priority area (most probable event locations, e.g. multiple entry points to a large hall)
- Non-Priority area
- Obstacle
- Feasible area (areas where camera and light sources can be placed except the floor)

Figure 3.4 shows a 3-D space model of the sensing space considered for arranging cameras and light sources. The priority areas are marked by blue color, the obstacles by red and the feasible areas by pink. The feasible locations of camera, the size and shape of obstacles and the sensitive areas with their respective assigned priority can be fed as inputs to the system through GUI. The dimensions of the 3-D model for the sensing space is defined as $(m \times n \times s)$, where m is the width, n is the length and s is the height of the sensing space (e.g. room). In 3-D model shown in figure 3.4, m = 10, n = 5 and s = 5.

The mathematical modelling for 3-D surveillance space, is outlined as follows. Any point in space is said to be covered if it is captured with a minimum required resolution i.e. when it lies in the DoF and within the extended field of view of n cameras. The inputs to this model are converted to priority matrix $\mathcal{P}$, feasible matrix $\mathcal{F}$ and obstacle matrix $\mathcal{O}$ with dimension $m \times m \times m$, where m is the largest value of dimension among m, n and s of the 3-D space to be covered. These matrices are defined in equation 3.1, 3.2 and 3.3 respectively.

The priority matrix is defined as

$$\mathcal{P} = [P_{ijk}]_{m \times m \times m} \tag{3.1}$$

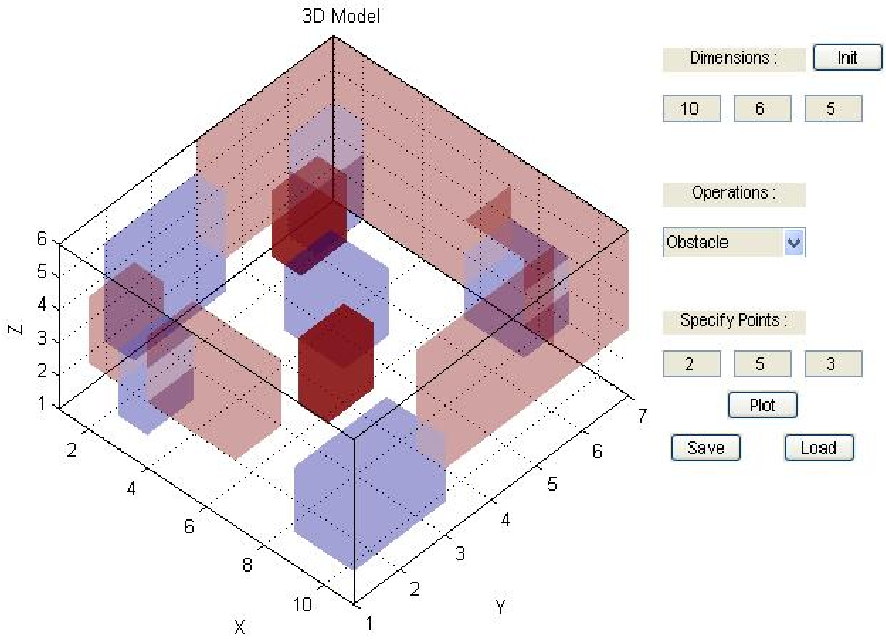


FIGURE 3.4: 3-D space model

Where

$$P_{ijk} = \begin{cases} 1, & if(i,j,k) \text{ point is a priority point} \\ 0, & if(i,j,k) \text{ point is not a priority point} \end{cases}$$

The feasible matrix is defined as

$$\mathcal{F} = [F_{ijk}]_{m \times m \times m} \tag{3.2}$$

Where

$$F_{ijk} = \begin{cases} 1, & if(i,j,k) \text{ point is a feasible point} \\ 0, & if(i,j,k) \text{ point is not a feasible point} \end{cases}$$

The concept of line of sight has been used to model the effect of obstacles on the coverage area of the sensors. Areas which come under the shadow of the obstacles from the line of sight have been removed from the covered area of that sensor as shown in Figure 3.5. The obstacle matrix is defined as

$$\mathcal{O} = [o_{ijk}]_{m \times m \times m} \tag{3.3}$$

Where

$$o_{ijk} = \begin{cases} 1, & if(i,j,k) \text{ lies in obstacle region} \\ 0, & if(i,j,k) \text{ does not lies in obstacle region} \end{cases}$$

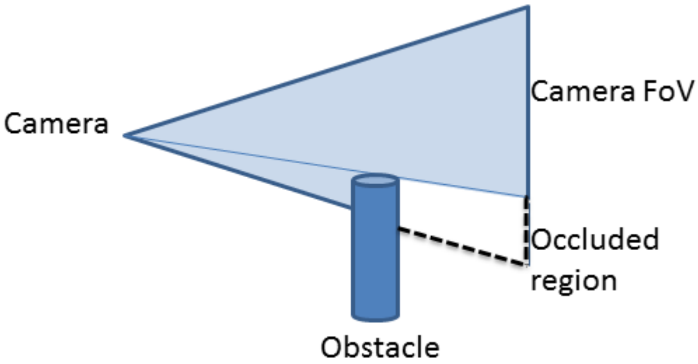


FIGURE 3.5: Field of view with obstacle

We have used PTZ cameras to enhance the coverage. Due to rotation along X and Y direction, the time of coverage of each priority point will not be the same. Hence, *probabilistic modelling* of the space is required. The voxels covered by at least one camera is considered as visible. The following parameters are therefore defined for computing the *visibility measure.*

1. The probability of covering the space in the field of view of the camera placed at an optimal location is more as compared to the other portions of the priority area during the camera motion (Refer Figure 3.6). Relative time for which a point is under coverage is measured in terms of parameter b, Where b is an average of $b1$ and b_2 (see equation 3.4). Here α is the pan angle and α_{max} is maximum pan angle. Similarly, β is the tilt angle and β_{max} is maximum tilt angle.

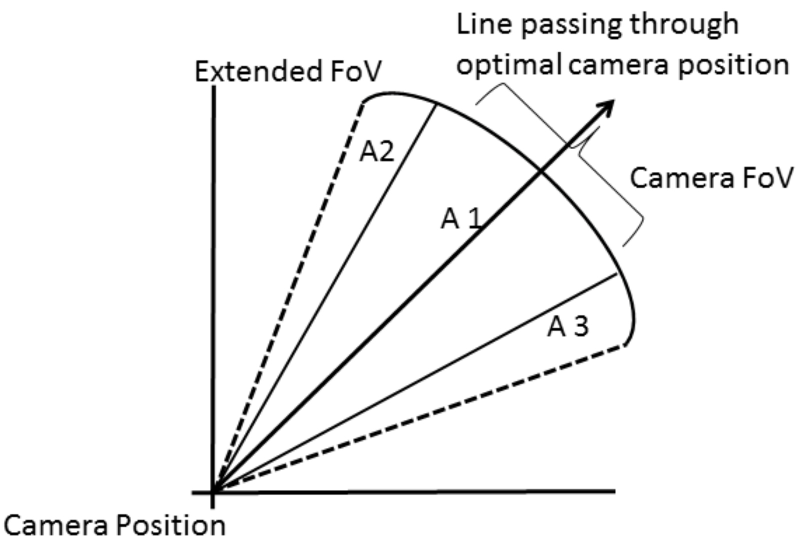


FIGURE 3.6: Extended FoV along the optimum camera axis

$$b_1 = 1 - \frac{\alpha}{\alpha_{max}} \quad , \quad b_2 = 1 - \frac{\beta}{\beta_{max}} \tag{3.4}$$

$b = 1$ indicates that the voxel is located at the centre of the FoV of the camera. $0 < b < 1$, depending on the offset of the pan and tilt angles from there optimum positions.

2. The probability of an object being placed in the priority region is higher compared to the object being placed anywhere else. Such regions should be covered with higher resolution, i.e. cameras should be placed in such a way that the priority regions lie close to their focal planes. Relative position of priority area with reference to the focal plane is measured in terms of parameter a (refer equation 3.5).

$$a = 1 - \frac{q}{q_o} \tag{3.5}$$

Where q is the distance of priority region or voxel under consideration from the focal plane of the camera and q_0 is the maximum distance from the focal plane within the depth of field. $0 < a < 1$, depending on the distance of the point under consideration from the focal plane.

We define *visibility matrix* A to represent the *visibility measure* computed for particular camera location, orientation (pan ad tilt) and zoom level. This matrix is generated using the priority, feasible and obstacle matrices defined above. The visibility matrix is sufficient to tackle the optimization of camera coverage. A simple concatenation of all three matrices ($\mathcal{P}$, $\mathcal{F}$ *and* $\mathcal{O}$) will output a 9-dimensional matrix. Thus, to ease the computation complexity we compute a 4-dimensional matrix. Every point covered in 3-D space is mapped to particular location, pose and zoom level as per equation 3.7, 3.8, 3.9 respectively.

$$position(i, j, k) = (j - 1) \times N \times N + (i - 1) \times N + k \tag{3.6}$$

where N is the largest value of dimension among m, n and s of the 3-D space

$$pose(\alpha, \beta) = M \times (\beta - 1) + \alpha \tag{3.7}$$

where M is the no of discrete pan(α) or tilt(β) angles the camera can assume

$$Zoom(z) = (highestzl - lowestzl) \times \frac{z}{zl} \tag{3.8}$$

where zl is the no discrete zoom levels the camera can assume. $1 \leq z \leq zl$

A point in 3-D model is said to be visible by a camera located at point i, with pose j and zoom level z, if it lies in the field of view of that camera. If a point is visible, it is represented by visibility measure in the visibility matrix. The performance measure due to the camera poses of all visible points are calculated and represented in the visibility matrix A. The visibility matrix A is defined in eqaution 3.9.

$$A = [a_{ijkz}]_{m^3 \times M^2 \times m^3 \times z1} \tag{3.9}$$

The *visibility measure* of each voxel is defined as $a_{ijk} = a + b$ for given camera location(ijk). In other words, the visibility matrix provides a visibility measure for the camera being placed at point i, with pose j and zoom level z covering point k. Thus, if a priority point K is covered by one camera the visibility measure is defined as $A_1(i, j, k, z) = a_1 + b_1$. Similarly, if a priority point is covered by two cameras placed at different locations with different pose and zoom levels, then the visibility measure is defined as $A_2(i, j, k, z) = a_1 + a_2 + b_1 + b_2$ and so on. Also, if k is a non-priority point then measure is given as $A_n(i, j, k, z) = a_n + b_n$.

3.2.3 Coverage Metric

A coverage metric incorporates all the above said constraints and formulated based on following assumptions:

(a) A simple, single lens element has been used to represent the optical sensor .

(b) Aperture of the lens of the optical sensor has been assumed to be constant throughout the algorithm.

(c) Effect of geometric distortion or blurring of objects has been neglected.

We approximate the continuous motion of cameras into discrete poses by sampling, due to which the cameras can adopt only those particular poses. The coverage metric is computed for all the visible points. For every visible point, the probability measure is added accordingly if the point is covered by one camera, or two cameras or more. The probability measure is defined in equation 3.9. The *coverage metric* (C) formulation is given in equation 3.10.

$$C = w' \sum_{2cam} A_2(i,j,k,z) \ + \ v' \sum_{1cam} A_1(i,j,k,z) \ + \ u' \sum_{non-priority} A_n(i,j,k,z) \tag{3.10}$$

Where w' v' and u' are weights and $A_2(i,j,k,z)$, $A_1(i,j,k,z)$ and $A_n(i,j,k,z)$ are described above. The assigned weights are such that the following constraints hold:

- $w' > v' > u'$. Higher weight is attached to points that are covered by two cameras while the non-priority points are assigned minimum weights. This is done so that the visibility measure for the priority area covered by 2 camera is maximized and for the covered non-priority areas it is minimized. In our experiments the chosen values for the weights are $w' = 0.75, v' = 0.15 \ \ and \ \ u' = 0.1$.
- $w' + v' + u' = 1$

3.3 Light Placement Problem

To determine the light source positions such that the priority areas are well illuminated for enhancing the quality of images. For surveillance applications, the sensitive areas should be scanned continuously and hence proper illumination of sensitive areas is very important. Human beings are considered as objects as the application is surveillance of public places. Before proceeding to the actual calculation of light source locations, let us describe the effect of light source location with respect to the geometry of the specified area regarding illumination, shadow due to the object itself or surroundings and reflected light to the camera. We have used a conical Light model as shown in figure 3.7.

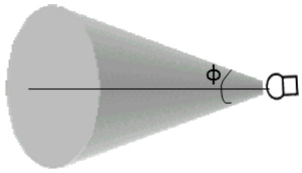


FIGURE 3.7: Conical Light Source Model

1. The first factor is defined as *Illumination*. This factor takes into account the fact that if any light source is placed facing the camera the vision system fails. To avoid that the following condition should hold true.

$$\left(\pi - (\beta + \frac{\Phi}{2}) > \frac{\Psi}{2}\right)$$

   Where Φ and Ψ are the light source cone angle and camera FOV and β is the angle between the camera FOV and light source cone (Refer figure 3.8).

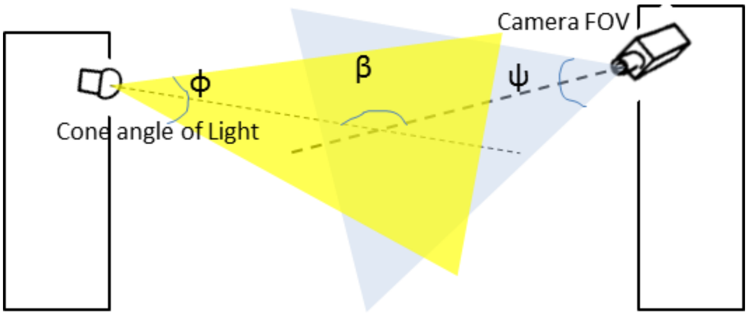


FIGURE 3.8: Light source location w.r.t. camera

   Based on this we define an illumination score S_{illum} defined in equation 3.11,

$$S_{illum} = \frac{P_{ij}\beta_{ij}}{\Phi} \tag{3.11}$$

   Where P_{ij} is given as,

$$P_{ij} = \begin{cases} 1, & if(\pi - (\beta + \frac{\Phi}{2}) > \frac{\Psi}{2}) \\ 0, & otherwise \end{cases}$$

2. The next factor contributes for *Shadow* avoidance. For even distribution of light and to avoid showing effect due to the objects in the environment, we

identify the regions near the camera, for the the placement of light sources. The regions immediately near the camera are given higher preference than the regions far from the camera (refer figure 3.9). Hence we define a score S_{shadow} as,

$$S_{shadow} = \omega_{ij} l_{ij} \tag{3.12}$$

Where ω_{ij} is the distance between i^{th} camera and j^{th} light source, and $l_{ij} = 1$ for $\omega < \tau$, and zero otherwise.

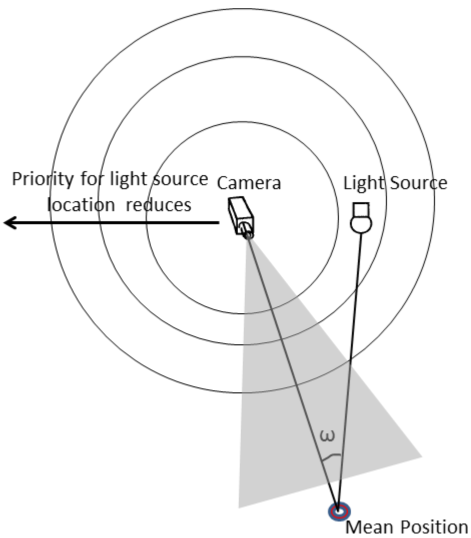


FIGURE 3.9: High preference regions surrounding the camera for light source placement

3. Next factor is the *Reflection*. Knowing the fact that the $I \propto \frac{1}{d}$. Where I is the intensity of illumination and d is the distance between the light source and the object (see Figure 3.10). We restrict the possible locations for light sources to a virtual sphere around the object, assuming the object is placed at the mean position in the priority region of the 3-D space. The mean position is defined as the point lying along the axis of camera FOV such that a line when projected from the centre of the light source passes through it (Refer figure 3.9).

   Since we are working with a cuboidal space model with limited expanse, therefore, we need to find optimal light source location for avoiding over-illumination rather than under-illumination. So the locations farther from mean position are preferred. For experimentation we have used a monochromatic light source and assuming reflection coefficient R for human skin to

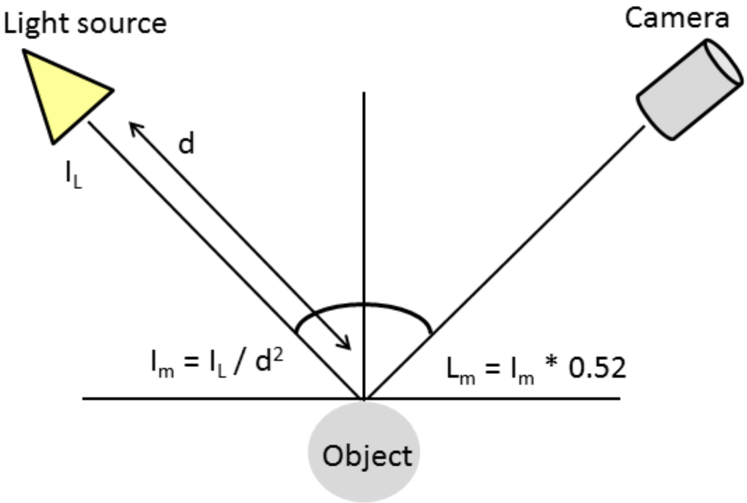


FIGURE 3.10: Distance between object and light source, assuming the objects are humans present in sensing space

be 0.52. To consider these constraints *reflection score* is defined in equation 3.13.

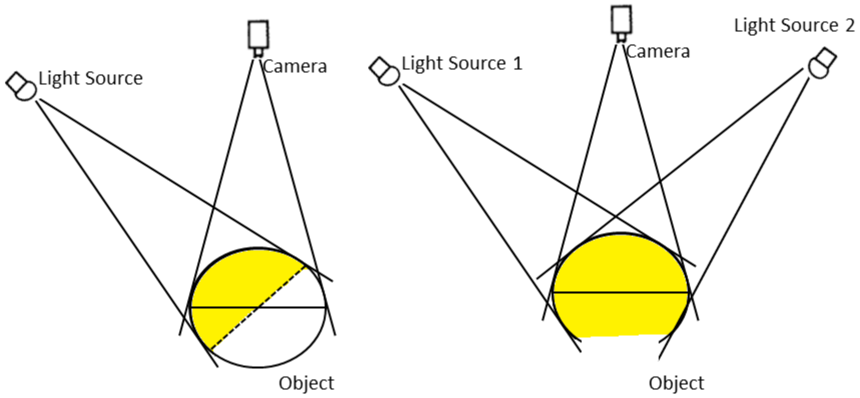
$$S_{reflection} = (\frac{0.52}{d^2}) \tag{3.13}$$

4. Another factor to be considered for correct positioning of light sources is to avoid *Occlusion*. It is observed that placing light source on one side of the camera, partly illuminates the object as shown in figure 3.11(a). This can be done by placing light source on both sides of the camera, minimising the uncovered area shown in figure 3.11(b). The *Occlusion avoidance score* is defined as,

$$S_{occ} = r_j \frac{\Omega_j}{\pi} \tag{3.14}$$

Where, if $\Omega_j < \pi$, $r_j = 0$, otherwise 1 for reducing priority progressively with increase in uncovered area.

Illumination Index defined in equation 3.15 takes into account the effect of light source location w.r.t. the 3-D space model as well as it considers the effect of the above defined factors. It is a minimization function defined to obtain the best possible locations of the light sources.



(a) (b)

FIGURE 3.11: (a) Showing the occluded area Ω with the possible placement of camera and light source (b) Possible light source placement for better illumination and avoiding occlusion

$$\mathcal{I} = \sum_{i=1}^{m}\sum_{j=1}^{n}(\frac{P_{ij}\beta_{ij}}{\Phi})W_1 + (\omega_{ij}l_{ij})W_2 + \sum_{j=1}^{n}\sum_{i=1}^{m}(\frac{0.52}{d_{ij}^2})W_3 + (r_j\frac{\Omega_j}{\pi})W_4 \qquad (3.15)$$

Where m and and n is the number of cameras and light sources respectively. In equation 3.15, the term $\sum_{i=1}^{m}\sum_{j=1}^{n}(\frac{P_{ij}\beta_{ij}}{\Phi})$ is computed for every camera position and every light source position. For a given camera position it checks each light source location such that the light does not fall directly into the camera. Similarly in the term $\sum_{j=1}^{n}\sum_{i=1}^{m}(\frac{0.52}{d_{ij}^2})W_3$, for a given light source location it check if the light is reflected from the object to the camera. It is done for each camera location given a light source location.

The effect of illumination and reflection terms are summed for each camera and light position. While the effect of the shadow and occlusion are computed for a particular light source position. The illumination index being dependent on the number of cameras and the light sources, the importance of different factor discussed above vary. Each term should be associated with weight such that highest weight is given to the first term, since no light source should face the camera, hence W_1 is the highest. Similarly weights are assigned to other terms also W_2, W_3 *and* W_4 respectively. Let there be m cameras and n light sources. When the number of light sources is less than number of cameras $(m > n)$, each light source should illuminate the sensitive areas being covered by more than one camera, hence higher weight is attached to occlusion term compared to the term contributing for shadow i.e. $W_4 > W_2$. For same number of camera and light source, for instance for one camera and one light source, $W_2 > W_4$. When $m < n$, to relate each camera with a light source and then deploying extra light source for occlusion avoidance and hence $W_1 > W_2 > W_3 > W_4$. Similarly for extra light sources the weights are arranged in the following precedence for avoiding occlusion $W_1 > W_4 > W_3 > W_2$. The experiments have been performed for equal number of camera and light source location, we have assigned following values to different weights $W_1 = 10, W_3 = 5, W_2 = 2, W_4 = 1$.

Hence, the weight assignment can be summarized as follows for m cameras and n light sources:

1. For $m > n$, $W_1 > W_3 > W_4 > W_2$.
2. For $m = n$, $W_1 > W_3 > W_2 > W_4$.
3. For $m < n$, $W_1 > W_2 > W_3 > W_4$
4. For $m << n$, $W_1 > W_4 > W_2 > W_3$

Chapter 4

Multi-Objective Optimization Using Genetic Algorithm

As described in previous chapter, the objective function formulation for camera and light source placement depends on the multiple factors such as geometry of the space under surveillance, most probable event locations also called priority or sensitive areas, obstacles present in these sensitive areas. Other factors include modified camera model with zoom as a constraint, light source model, reflection, occlusion, shadowing due to objects in the sensing space etc. Hence, the placement problem is an optimization problem with inter related and competing constraints. Considering the discrete nature of optimization problem in such constrained parameter space, conventional gradient based approaches are not applicable. Therefore, we formulate our optimization problem in evolutionary algorithm paradigm to obtain feasible solution.

In this chapter we present the multi-objective framework for camera and light source placement. Considering a large surveillance space, camera placement for effective coverage with proper lighting conditions are two objectives incorporated into our methodology for concurrent optimization. The multi-objective nature of the problem is based on the assumption of conflict among the considered objectives. Hence, the optimal compromises will be those camera and light source placement configurations which comply with the concept of Pareto Optimality.

4.1 Optimization Framework : Overview

The camera placement and light source placement problem has been addressed sequentially by S. Indu et. al in [36]. The framework first computes optimal camera locations to ensure maximum coverage of the user defined areas and then using these camera location light sources are placed for optimum illumination of the sensitive areas. The camera and light source placement are two separate optimization problems solved using Genetic algorithm. GA's are usually slow, but always find best solution. Here, the optimal camera and light source locations are obtained sequentially so the approach tends to be more time consuming as compared to the multi-objective framework. Moreover, it is an off-line process and cannot be extended for real-time applications.

An approach for linear combination of objective function for optimization has been addressed in [38]. Simplification of multiple objective problem as a linear combination of different objectives present a possible approach to solve the problem. However it is not justifiable because of the non-conforming parameter space of both the objectives. Additionally, both the objectives are defined for distinct solution spaces. In this direction a logical approach would be to define a parametrized linear combination of objective where the weights would be learned through some learning technique. Learning optimal weights is the major disadvantage. If the weights are too high and too low, then one of the objective function will be inadequately represented as compared to the other function. The authors in [38] have presented a min-max approach for computation of weights. The Fibonacci search technique proposed in [39] is a good choice as the total cost is a unimodal function.

Many realistic optimization problems require the simultaneous optimization of more than one objective function. In our case multi-objective optimization technique has proved to be a suitable approach for camera and light source placement for large surveillance space. In many real world problem objective functions are defined such that the objectives are non-commensurable and also the decision maker is not clear if the objectives are related to each other. Usually for many multi-objective problems the objectives are generally conflicting preventing simultaneous optimization of each objective. Hence, optimizing the solution space x with respect to a single objective gives unacceptable results with respect to other objectives, i.e. there exists no unique solution to the problem. A reasonable solution for simultaneous optimization of multiple objective functions is to investigate a set of solution, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. Thus, the concept of Pateto optimality is used to characterize the objectives. We want our evolutionary optimization method to be able to concurrently search for camera and light source network of different complexity. In order to achieve this an approach based on Genetic Algorithm is adopted.

4.2 Multi-Objective Optimization Formulation

Our MO optimization module is based on the Non Dominated Sorting Genetic Algorithm (NSGA-II) proposed in [42]. Here, the concept of ranking the population according to dominance relations is employed. Hence, the worthiness of a single solution is proportional to its rank among the population. Diversity among the population is maintained by crowding penalization. Additionally, generational elitism is enforced based on rank.

A multi-objective problem with K objectives is defined as follows: Given an n-dimensional decision variable vector $x = x_1, x_2, ..., x_n$ in a solution space X, find a vector $x^{\star}$ that minimizes a given set of K objective functions $z(x^{\star}) = z_1(x^{\star}), z_2(x^{\star}), ..., z_n(x^{\star})$. The solution space X is generally restricted by a series of constraints, such as $g_j(x^{\star} = b_j$ for $j = 1, 2, ..., m$, and bounds on the decision variables.

In our problem we have already mentioned a viewpoint based specification, where depending on the specification of the sensing space, we have adopted two objective function i.e. $K = 2$. The number of decision variable is calculated as follows, for 1 camera and 1 light source the number of decision variable is 6 variables for camera $(x_{c_1}, y_{c_1}, z_{c_1}, \alpha_{c_1}, \beta_{c_1})$ and 3 variables for light source $(x_{l_1}, y_{l_1}, z_{l_1})$, totalling to 9 decision variables. Similarly, for 2 camera and light source there will be 18 decision variables, and so on. The solution space X is defined by the upper and lower bounds related to each variable. These variables are coded as real values. Therefore, N camera and light source network is represented by $X = x_i \forall i = (1, ..., n), x_i \in \mathbf{R}$. The values of the coordinates for the camera and light source locations lie in the following range: $1 \leq x \leq m$, $1 \leq y \leq n$ and $1 \leq z \leq s$, where

(m, n, s) are the dimensions of the space under surveillance. Similarly, we have assumed 8 zoom levels and 4 focal planes for each zoom level.

4.2.1 Pareto Dominance Based Ranking

The population is initialized as usual, based on the problem range or solution space and constraints if any. Fitness for each solution is evaluated. Once the population in initialized the population is sorted based on non-domination using *Pareto Ranking Technique* into each front. Pareto ranking approach explicitly utilizes the concept of *Pareto Dominance* in evaluating fitness or assigning selection probability to solutions. The population is ranked according to a dominance rule, and then each solution is assigned a fitness value based on its rank in the population, not its actual objective function value. Since, in our case all objective functions are for minimization, a feasible solution x is said to dominate another feasible solution y, if and only if, $z_i(x) \leq z_i(y)$ for all objective functions and $z_j(x) < z_j(y)$ for at least one of the objective function j. A solution is said to be pareto optimal if it is not dominated by any other solution in the solution space. A pareto optimal solution cannot be improved with respect to any objective without worsening at least one other objective. The set of all feasible non-dominated solutions in X is referred to as the Pareto optimal set, and for a given Pareto optimal set, the corresponding objective function values in the objective space are called the Pareto front. Therefore, lower rank corresponds to a better solution. The first front being completely non-dominant set in the current population and the second front being dominated by the individuals in the first front only and the front goes so on. Each individual in the each front are assigned rank (fitness) values or based on front in which they belong to. Individuals in first front are given a fitness value of 1 and individuals in second are assigned fitness value as 2 and so on. The algorithm for *Pareto ranking* is defined in Figure 4.1.

4.2.2 Diversity : Crowding Distance

In addition to fitness value a new parameter called crowding distance is calculated for each individual. The crowding distance is a measure of how close an individual is to its neighbours. Large average crowding distance will result in better diversity in the population. Crowding distance approach aim to obtain a uniform spread

Pareto Ranking Technique

- For each individual p in main population P do the following:
  - Initialize $S_p = \emptyset$. This set would contain all the individuals that are being dominated by p.
  - Initialize $n_p = 0$. This would be the number of individuals that dominate p
  - For each individual q in P
    - If p dominates q, then
      - Add q to the set S_p i.e. $S_p = S_p \cup \{q\}$.
    - Else, if q dominates p then
      - Increment the domination counter for p i.e. $n_p = n_p + 1$
  - If $n_p = 0$ i.e. no individuals dominate p then p belongs to the first front; Set rank of individual p to one i.e $p_{rank} = 1$. Update the first front set by adding p to front one i.e $F_1 = F_1 \cup \{p\}$.
- This is carried out for all the individuals in main population P.
- Initialize the front counter to one, $i = 1$.
- Following is carried out while the i^{th} front is non-empty i.e. $F_i = \emptyset$.
  - $Q = \emptyset$, the set for storing the individuals for $(i+1)^{th}$ front.
  - For each individual p in front F_i
    - For each individual q in S_p (S_p is the set of individuals dominated by p).
      - $n_q = n_q - 1$, decrement the domination count for individual q.
      - If $n_q = 0$ then none of the individuals in the subsequent fronts would dominate q. Hence set $q_{rank} = i + 1$. Update the set Q with individual q i.e. $Q = Q \cup q$.
  - Increment the front counter by one.
  - Now the set Q is the next front and hence $F_i = Q$.

FIGURE 4.1: Algorithm for Pareto Ranking

of solutions along the best-known Pareto front. Crowding distance is finding the euclidean distance between the individuals in a front. The crowing distance is calculated as below in figure 4.2.

The main advantage of the crowding approach is that a measure of population density around a solution is computed without requiring a user-defined parameter. In NSGA-II, this crowding distance measure is used as a tiebreaker in a selection technique called the crowded tournament selection operator : Randomly select two solutions x and y; if the solutions are in the same non-dominated front, the solution with a higher crowding distance is the winner. Otherwise, the solution

Crowding Distance Computation

- For each front F_i, n is the number of individuals.
  - Initialize the distance to be zero for all the individuals i.e. $F_i(d_j) = 0$, where j corresponds to the j^{th} individual in front F_i.
  - For each objective function m
    - Sort the individuals in front F_i based on objective m i.e. $I = sort(F_i, m)$.
    - Assign infinite distance to boundary values for each individual in F_i i.e. $I(d_1) = \infty$ and $I(d_n) = \infty$
    - For $k = 2, ..., (n-1)$
      - $I(d_k) = I(d_k) + \frac{I(k+1).m - I(k-1).m}{f_m^{max} - f_m^{min}}$
      - $I(k).m$ is the value of the m^{th} objective function of the k^{th} individual in I.

FIGURE 4.2: Steps for Crowding Distance computation

with the lowest rank is selected.

4.2.3 Selection

Parents are selected from the population by using binary tournament selection based on the rank and crowding distance. An individual is selected in the rank is lesser than the other or if crowding distance is greater than the other [1]. The selection is carried out using a crowded-comparison-operator ($\prec$). The comparison is carried out as below based on the following criterion:

1. non-domination rank p_{rank} i.e. individuals in front F_i will have their rank as $p_{rank} = i$.
2. crowding distance $F_i(d_j)$
   - $p \prec q$ if,
     - $p_{rank} < q_{rank}$
     - or if p and q belong to the same front F_i then $F_i(d_p) > F_i(d_q)$ i.e. the crowing distance should be more.

[1] Crowding distance is compared only if the rank for both individuals are same

4.2.4 Recombination and Selection

The choice of genetic operators is also a crucial factor. In our work, simulated binary crossover (SBX) [44], [45] and polynomial mutation [44], [46] has been used for real coded variables. The crossover probability of $p_c = 0.9$ and mutation probability of $p_m = \frac{1}{n}$, where is n the number of decision variables for real-coded GA's. For real-coded NSGA-II, we use distribution indexes for crossover and mutation operators as $\eta_c = 20$ and $\eta_m = 20$, respectively. The offspring population is combined with the current population and selection is performed to set the individuals of the next generation. Since all the previous and current best individuals are added in the population, elitism is ensured. Population is now sorted based on non-domination. The new generation is filled by each front subsequently until the population size exceeds the current population size. If by adding all the individuals in front F_j the population exceeds N then individuals in front F_j are selected based on their crowding distance in the descending order until the population size is N. And hence the process repeats to generate the subsequent generations.

The validation of the multi-objective framework defined for camera and light source arrangement for large surveillance space is presented in the chapter 5. Chapter 5 demonstrates simulated as well as experimental results.

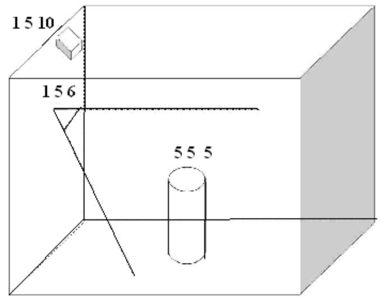
Chapter 5

Results and Discussion

The main motivation of this study is to provide a framework for camera and light source placement in a large surveillance space. This framework allows concurrent optimization of the objective function considering different constraints of the given surveillance space in the multi-objective optimization paradigm. The detailed discussion of the framework is presented in Chapter 3 and Chapter 4. In this chapter we present the results for camera and light source placement, generated in a simulated environment. Experiment results for camera placement in a real environment is also presented in this chapter.

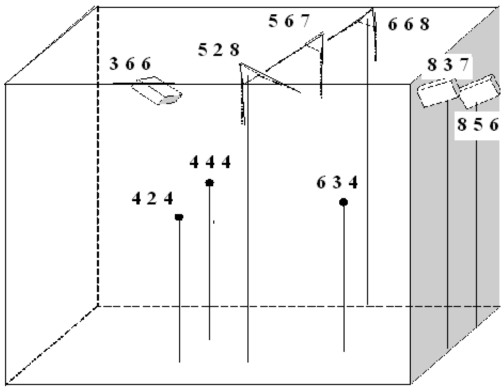
5.1 Simulation Results

The problem of camera and light source placement has been done sequentially in [36]. The cameras are placed for maximum coverage of the priority areas. In case of sequential placement of camera and light source, we require to compute mean position as a reference for light placement. The mean position is computed from the camera parameters (location and orientation) and center of the priority area. Since the process is sequential therefore a small error in camera placement will lead to erroneous mean position computation which in-turn will make light source placement calculation incorrect. In the proposed method the camera and light position are simultaneously calculated therefore the error in computing light source position is minimized. The results of the sequential approach are presented in Figure 5.1 and Figure 5.2.



S. No.	x	y	z
Cam 1	1	5	10
Light 1	1	5	6

FIGURE 5.1: Results of sequential approach for one camera and one light source placement



S. No.	x	y	z
Cam 1	3	6	6
Cam 2	8	3	7
Cam 3	8	5	6
Light 1	5	2	8
Light 2	5	6	7
Light 3	6	6	8

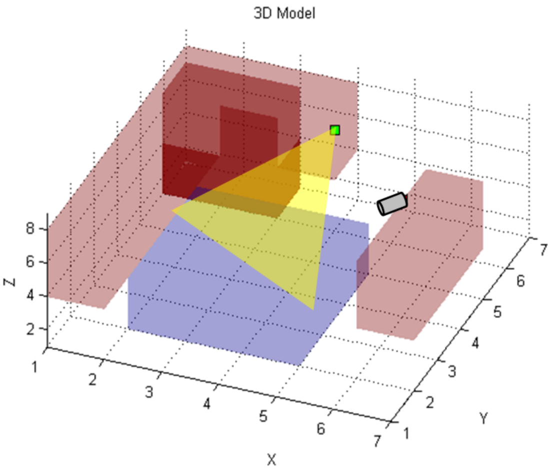
FIGURE 5.2: Result of sequential approach for three camera and three light source

In case of sequential placement, the mean position is considered as a reference and hence as shown in Figure 5.1, the mean is illuminated. Where as the case of multi-objective framework, the light source is placed such that the entire priority area is illuminated uniformly as shown in Figure 5.3.

We tried out the following experiments using our set-up and multi-objective real-coded GA. For all the runs of the GA we used cross-over probability as 0.9 and mutation probability as 0.0125.

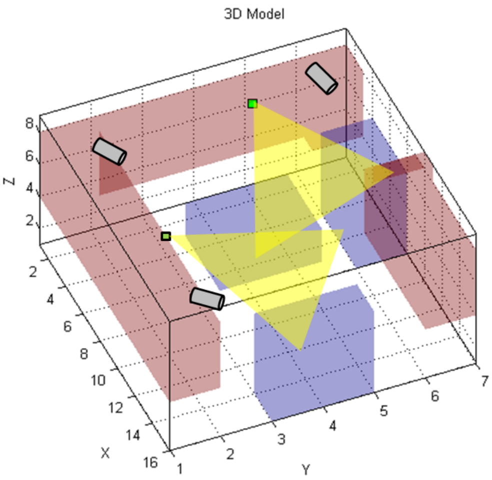
The results presented here ensure that the priority regions are well illuminated and camera are placed such that the priority areas are covered. Figure 5.3 shows one camera and one light position. The light source illuminating the priority region. Figure 5.4 shows three camera and two light positions.

Placement of two cameras and two light sources is shown in Figure 5.5 and for three camera and three light source is shown in Figure 5.6. The light sources are illuminating the sensitive areas, in both cases.



S. No.	x	y	z
Cam 1	6	6	8
Light 1	4	7	6

FIGURE 5.3: One Camera & one Light Source



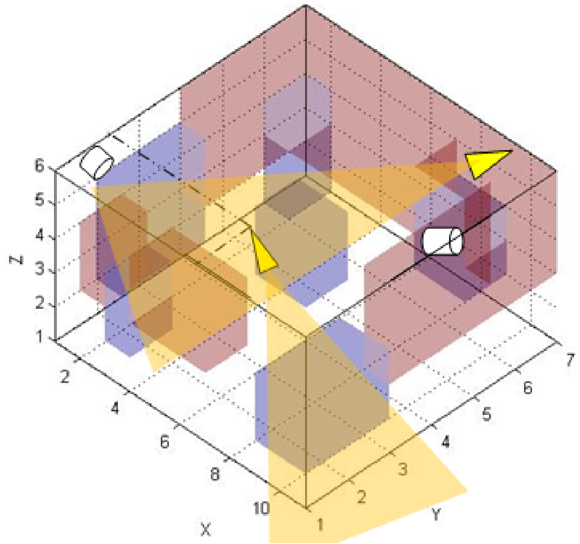
S. No.	x	y	z
Cam 1	14	2	8
Cam 2	2	2	7
Cam 3	2	6	7
Light 1	1	6	6
Light 2	7	2	7

FIGURE 5.4: Three Camera & Two Light Source

5.2 Experimental Set-up and Results

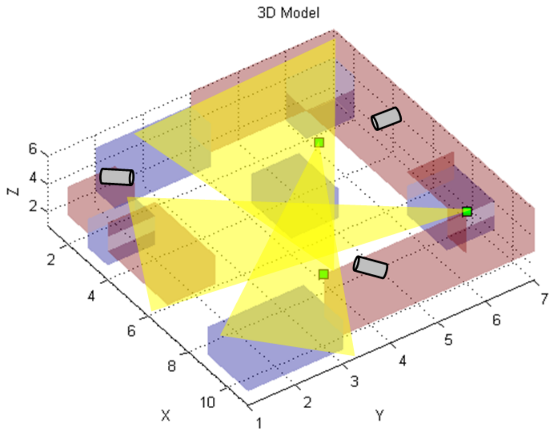
We were given a task for deploying six PTZ camera in Multimedia Lab of IIT Delhi. The dimensions of the lab were $30 \times 60 \times 20$ in feet. To ease the computation we scale down the dimensions to $5 \times 10 \times 4$. The matlab based GUI is used to generate a 3-dimensional model of the lab. The ceiling is used for camera deployment as all walls are mostly covered by windows. The model of the lab is sown in figure 5.7.

A total of 78 feasible points were identified. Optimum positions, poses and zoom levels of the six cameras were determined using the proposed camera placement formulation and genetic algorithm based optimization. The cameras were made to rotate ± 15 degrees about their optimum position along pan and tilt axes. The visibility matrix and the priority matrix help the Genetic Algorithm to evaluate the



S. No.	x	y	z
Cam 1	1	2	6
Cam 2	10	6	6
Light 1	4	4	6
Light 2	8	7	6

FIGURE 5.5: Two Camera & Two Light Source



S. No.	x	y	z
Cam 1	1	1	5
Cam 2	10	5	6
Cam 3	4	7	5
Light 1	8	3	6
Light 2	9	7	6
Light 3	3	6	5

FIGURE 5.6: Three Camera & Three Light Source

fitness function of various generations. All the coding and matrix representations have been implemented in MATLAB. The simulation results showing the camera placement at optimal locations is shown in Figure 5.8.

The Experimental setup shown in Figure 5.9 and the results showing the covered priority area are shown in the Figure 5.11.

It has been observed that if a region being focused lies at a small distance as shown in Figure 5.10(a), the camera had a higher zoom level to capture a detailed image. This ensures fewer non-priority points are covered.

Whereas the cameras that focused at regions lying far as shown in Figure 5.11(a) and (b) had comparatively lower zoom level to increase the number of points in the

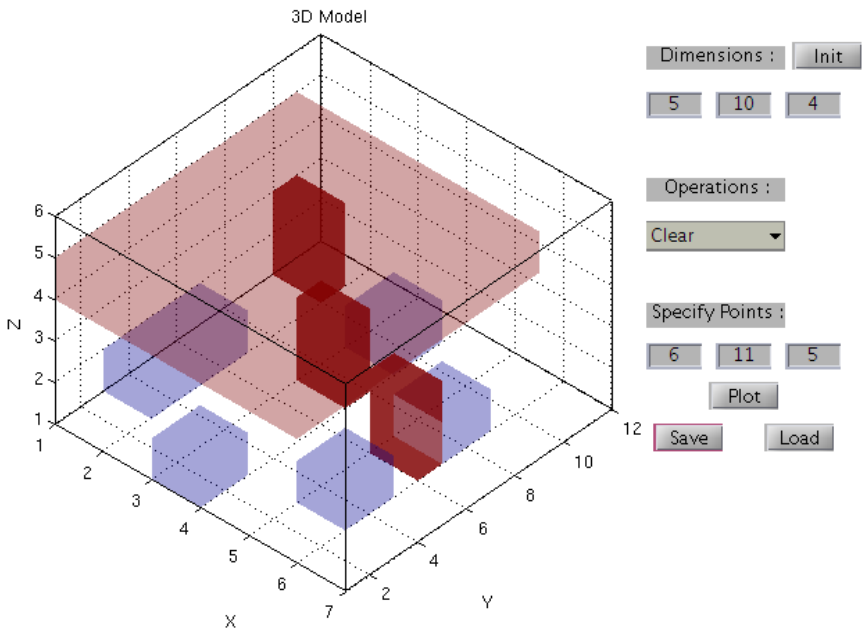
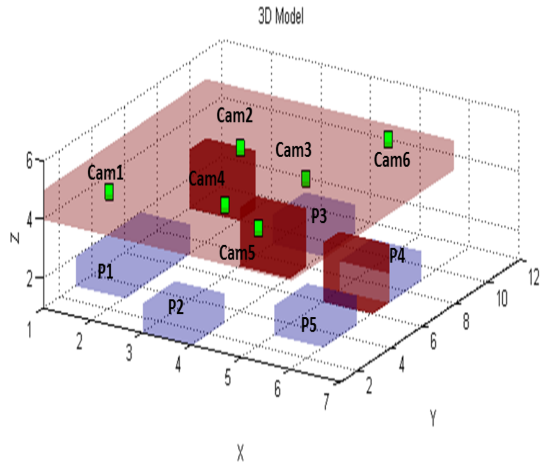


FIGURE 5.7: 3-D model of the IIT Lab for camera deployment



Camera No.	x	y	z
1	2	2	5
2	3	7	5
3	4	8	4
4	4	3	5
5	5	10	5
6	5	2	5

FIGURE 5.8: Simulates Results for deploying six cameras (The points marked by green indicate the optimal camera location calculated using our approach) covering the marked priority areas (P1 - P5)

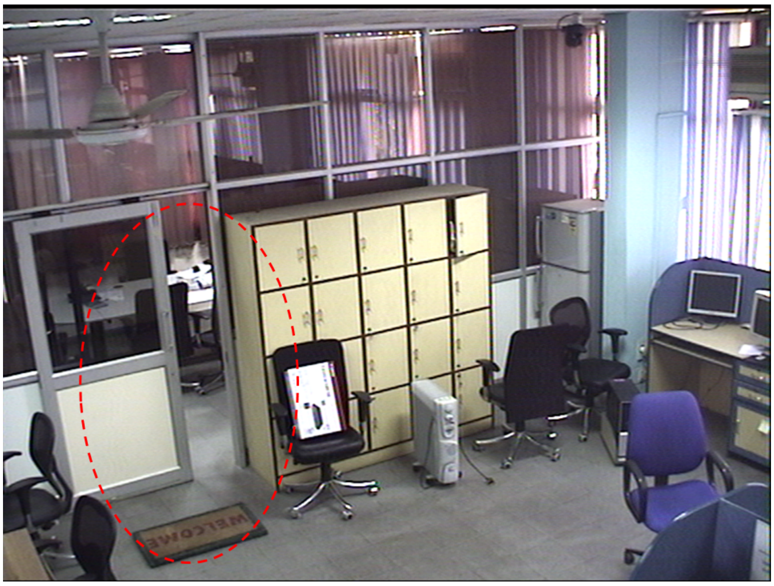
camera viewing frustum. Such placement ensures maximum coverage i.e. covering maximum priority points maintaining a reasonable resolution. It is also observed that the regions with large number of priority points is covered two cameras and the regions with fewer priority points were covered by only one camera.

(a) Image taken from cam6 showing placement of cam1, cam2 and cam3

(b) Image taken from cam3 showing placement of cam4, cam5 and cam6

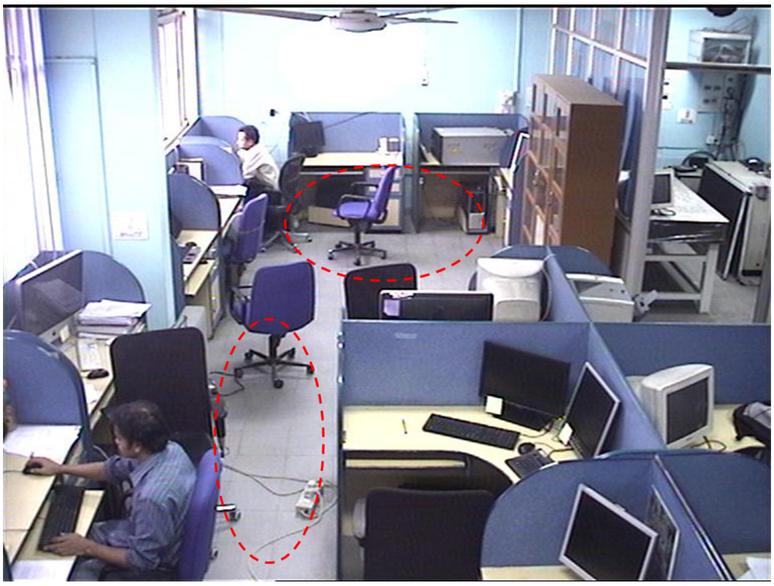
FIGURE 5.9: Camera Set-up at Multimedia Lab IIT Delhi

(a) Camera 2 covering priority area P2

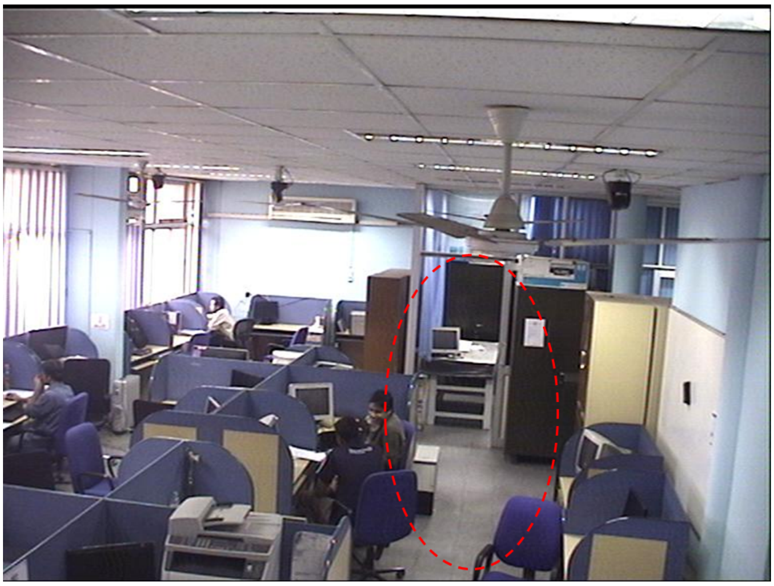


(b) Priority area P1 covered by camera 4

FIGURE 5.10: Results showing the priority areas (P1- P5) being covered by cameras



(a) Image showing priority areas (P3 and P4) covered



(b) Priority area P5 cpvered by camera 1

FIGURE 5.11: Results showing the priority areas (P1- P5) being covered by cameras

Chapter 6

Conclusion

6.1 Summary

Surveillance applications have gained significant importance recently. A well equipped camera network forms the backbone of such applications. Large networks of cameras are employed to capture dynamic events distributed throughout a large area. We started our discussion with an introduction to camera and light source placement problem, where we identified the key features associated with the problem. Traditional approaches have addressed camera placement for various applications in the domain of tracking and surveillance assuming sensing space properly illuminated. Camera placement approaches have not considered variation in zoom parameter rather assumed constant zoom. Thus, It has been observed that proper illumination and computing optimal zoom plays an important role in improving the quality of images captured by the camera. Moreover, we require such an approach that uses limited number of camera and light sources judiciously.

Here we investigate the problem of placement of camera and light sources in large surveillance spaces. Ensuring an optimal placement of the cameras and light sources is an essential step in the development of vision systems. Indeed good lighting conditions ensure good image quality and thus improving the reliability of vision algorithms. We study the placement problem under a multi-objective framework. Our approach is based on the initial assumption of conflict among the considered objectives. Hence, the expected results are in the form of Pareto Optimal compromise solutions. In order to solve our optimization problem an evolutionary based technique is implemented.

6.2 Conclusion

In this thesis we addressed an optimization framework that ensures simultaneous optimization of camera and light sources, considering the geometry of surveillance space and other factors such as reflection, clutter, etc.

The proposed framework is scalable and efficient. We formulated the placement of visual sensors such that we obtain optimal locations that maximize the coverage of highly active areas (Refer Chapter 3). Illumination of the sensitive area is also equally important for good quality images. Hence, the light source placement algorithm for optimum illumination of the sensing space is also discussed in Chapter 3.

The scheme proposed here provides optimal camera locations, pan-tilt angle, zoom level and light source locations. We have used PTZ camera as visual sensors as it can cover larger volume compared to pin hole cameras. We have modified the camera model for incorporating zoom or depth-of-field. Since, the camera covers a larger volume, the time of coverage of every point in the sensing region is not uniform due to the pan tilt motion of the camera. To address such issues we have a proposed a probabilistic model for space, and used for determining camera locations for optimizing coverage, so that the most probable event location is covered for longer time and with better resolution.

Proper illumination of the sensitive area is equally important for a good vision system. Hence, the light source placement formulation has been proposed here. The light sources are placed such that, the light directly falling on the camera can be avoided from any of the light sources and to avoid shadow due to illumination of one side of the object. This approach described here entirely depends on geometry of the space and hence computationally very light. We validated the tool by simulation and experiment.

A *Multi-Objective* approach based on evolutionary techniques has been applied to the camera and light source placement problem for large surveillance space like halls, airports etc. Multiple objective optimization is considerably more elaborate than single criteria optimization. The major discrepancy lies in the concept of optimality under multiple criteria. Here, optimality is based on dominance relations among solutions in a multidimensional objective function space. This is in contrast to single objective optimization, where a solution is mapped by the criterion function into a point along the real number line, where the decision of an optimal point is trivial. Experimental results validate the assumption of conflicting objectives within given criteria of execution. Such an approach indeed provides insight into the complex interdependencies of our planning.

6.3 Future Work

Although the current work is complete in itself, various issues need to be addressed in further research efforts such as:

1. Experimentation with more number of camera and light sources for different dimensions of surveillance space covering most of the real world cases.
2. Modifying the light source placement formulation by incorporating the effect of presence of object other than humans in the environment.
3. Converting the off-line process to real-time processing.

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