Camera Placement for Surveillance Applications

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1. Introduction

Surveillance application is gaining research importance day by day. The application can be monitoring a production plant, an area for security reasons, industrial products etc. Visual sensor arrays form the backbone of any such surveillance applications. Proper placement of visual sensors (cameras) is an important issue as these systems, demand maximum coverage of sensitive areas with minimum cost and good quality of service. The quality of the images depend on the position and poses of the cameras. Depending on specific applications, the required view may vary, however, all vision based applications need a camera layout which assure acceptable quality of image. The main driving force of this work is to improve the off-line camera placement for surveillance applications. Camera placement depends on feasible location of cameras, obstacles present in sensitive areas, and the assigned priority of the area. Hence the placement problem becomes an optimization problem with inter related and competing constraints. Since, constrained discrete optimization problems do not have efficient algorithmic solution, evolutionary algorithm is used. A design tool for camera placement for surveillance apllication is presented in this chapter. This genetic algorithm based CAD tool is simple and efficient. Using this tool cameras can be placed for maximum coverage of the multiple sensitive areas defined by the user. The tool determines the position and poses of PTZ cameras for optimum coverage of user defined area. This tool can be used as camera placement planner for surveillance of large spaces with discrete priority areas like a hall with more than one entrance or many events happening at different locations in a hall etc. (Casino) or even a big sea port. As we are optimizing the parameters like pan, tilt, zoom and even the locations of the cameras, the images will provide maximum information with good resolution. Thus enhancing the QOS of the vision system.

Camera placement

The sensitive space is logically divided into cubical grids and probabilistic modelling of space is done for ensuring better coverage. The probability of occlusion by randomly moving objects is minimised by covering the priority areas by multiple sensors. The optimum camera locations with their respective poses are determined by mapping the camera model and space model into genetic algorithm. Many of the existing similar works S.Indu et al. (2008), Dunn & Olague (October 2006), Horster & Lienhart (2006) have kept zoom level constant, whereas we have developed a novel method for the same, with zoom level, as a constraint which will enhance the quality of the image. The proposed method do not require any synchronization and hence computationally light and can be easily used for large spaces using more number of cameras.

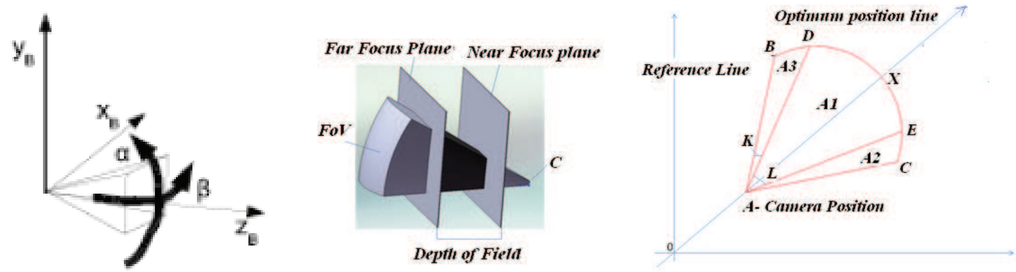
2. Related work

Visual sensor planning has been extensively researched by many researchers. In the initial stages the sensor planning is done based on occlusion pattern Maver & R.Bajcsy (1993). We can broadly classify the research in this field into 4 main categories. (1) No information about the surveillance field is known (2) the models of some set of information about the objects of the field are known. (3) Complete geometric information about the space is known (4) automatic placement of camera based on the information obtained from images and (5) Camera and light source placement for specific task. The work we carried out belongs to the third category. 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 Rourke (1987) Suzuki et al. (2001) Bose et al. (1997) Estivill-Castro et al. (1995). Current solutions to the AGP and its variants employ unrealistic assumptions about the cameras' 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 (1) Christopher. R. Wren and et. al. for automatically retrieving contextual information from different camera images Wren et al. (n.d.), (2) Ioannis Rekleitis and et. al. for obtaining 3D pose of the cameras in a common reference frame using a mobile robot Rekleitis (n.d.), (3) E. Hoster and et. al. for automatic position calibration of visual sensors without synchronization Lienhart et al. (n.d.), (4) Marta Wilczkowiak and et. al. for 3D reconstruction Wilczkowiak & Sturn (2001), (5)Richard I Hartley did the self calibration of camera from different views taken from a point with different poses Hartley (1993). 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.Trivedi et al. (2005) 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 Lee & Aghajan (n.d.). Ali Maleki Tabar and et. al. developed a smart home care sensor network using different types of sensor nodes for event detection Tabar et al. (n.d.). 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 Rourke (1987) Bose et al. (1997) Suzuki et al. (2001) Krishnendu chakraborthy and et. al. Developed Grid based placement for Omni directional circular range sensors K.chakraborty et al. (2002). Sensor planning methods using more realistic model is given by Tarabanis K. et al. (1996). Siva Ram et.al in their work "selection and placement of sensors in multimedia surveillance systems" explained a real time control of PTZ cameras using cheap motion sensors Kankanhalli et al. (2006). 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. in their work "multi camera human activity monitoring and Optimal camera placement for automated surveillance tasks" Fiore et al. (2008) Bodor et al. (2007) find out optimal locations of the camera after learning the activity. This method will be



(a) (b) (c)

Fig. 1. (a) Camera Model (b) Depth Of Field (c) Extended FoV along optimum position axis

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 Chen & Davis (1999) in their work "Camera placement considering occlusion for robust motion capture". Later on the same work was extended by Larry Davis and Anurag Mittal Mittal & Davis (2004). They used pinhole cameras. Anurag mittal A.Mittal & Davis (2008) 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.

3. Camera placement problem

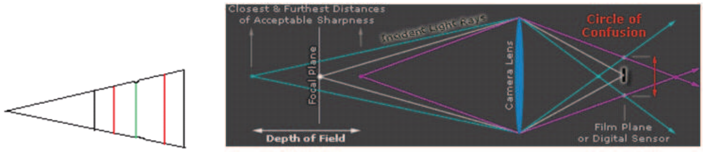
To determine optimal positions, poses and zoom levels of cameras which provide maximum coverage of the priority areas in a predefined surveillance space satisfying the task based constraints which may be static or dynamically varying according to the requirements.

Definitions

We first define terms that have been used in this paper. The crucial parameters for the cameras are:

- 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.
- 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.
- 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 term floor plan denotes a physical three dimensional room which we aim to cover. A point is said to be covered if it is captured with a minimum required resolution. This constraint is satisfied if the point lies in the field of view of at least two cameras. We can divide the floor plan into different sections namely priority areas and non priority areas.



(a) (b)

Fig. 2. Showing the variation in zoom (a) Red vertical lines - higher zoom level, black vertical lines-lower zoom level and green vertical line- reference focal plane (b) Circle of confusion

Basic definitions and concepts related to Zoom

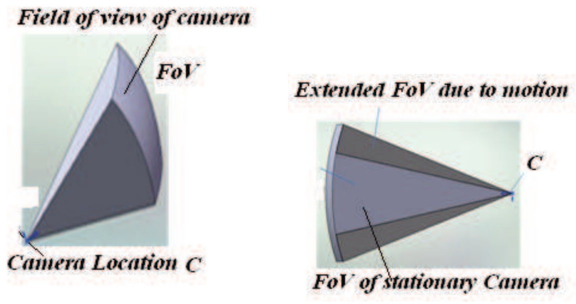
Zoom lenses are often described by the ratio of their longest to shortest focal lengths. For example a zoom lens with focal lengths from 100mm to 400mm may be described as a 4:1 or "4X" zoom. That is, the zoom level of a visual sensor is directly proportional to its focal length. There are two types of zoom, Digital zoom and optical zoom. The optical zoom is affected by camera parameters and hence this report will deal with optical zoom only. The perspective and depth of field will change with variation in zoom level. A change in perspective or angle of view means change in the dimensions of the viewing frustum of the visual sensor. As zoom level increases the focal length increases and thus the angle of view reduces. Field of View (FoV), the maximum volume visible from a camera, is determined by the apex angles (azimuth and latitude) of the visible pyramidal region (frustum) emanating from the optical centre of the camera. So reduction in angle of view reduces the field of view of the camera, as shown in fig. 3.

Depth of Field (DoF) is the amount of distance between the nearest and farthest objects that appear with 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 i.e. DoF is independent of focal length of the visual sensor but depends on the magnification. For surveillance purposes the camera is fixed, so DoF changes with change in the zoom level as image size varies with zoom. Higher the zoom level, shallower will be the DoF and lesser will be the number of points in the viewing frustum. Thus the viewing frustum is the volume now bounded by the near focus and the far focus planes. Any point on focal plane is considered sharply in focus. With increase in zoom level, for the same focus distance, the near focal plane and the far focal plane move towards the focal plane as shown in fig. 2 (b)

The depth of field does not abruptly change from sharp to un-sharp, but it is a gradual transition. In fact, everything immediately in front of or in back of the focusing distance begins to lose sharpness, but this will not be perceived by our eyes or by the resolution of the camera. Since there is no critical point of transition, a more rigorous term called the "circle of confusion" (fig. 2 (a))is used to define how much a point needs to be blurred in order to be perceived as un-sharp. When the circle of confusion becomes perceptible to our eyes, this region is said to be outside the depth of field and thus no longer "acceptably sharp" .An acceptably sharp circle of confusion is loosely defined as one which would go unnoticed when enlarged to a standard 8x10 inch print, and observed from a standard viewing distance of about 1 foot.

Camera Model

The Figure.1(a) shows the model of a PTZ camera developed by E. HorsterHorster & Lienhart (2006). The pan and tilt motion of each 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



(a) (b)

Fig. 3. (a) Field of view of camera (b) Extended Field of View

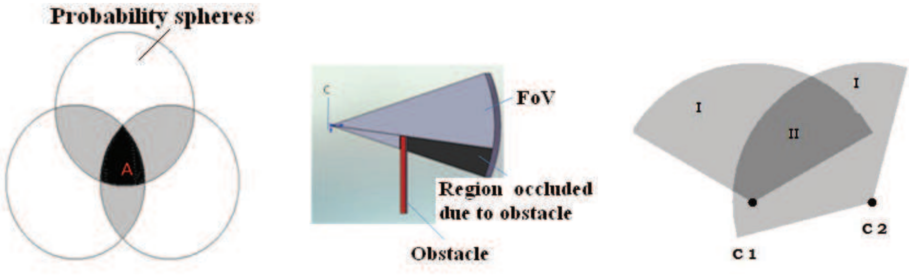
optical center. The field of view of the camera can be considered as a pyramid (fig.3 (a)). These cameras can be made to rotate $\pm\theta$ degrees about their optimum position along their pan and tilt axis so that they have an extended field of view as shown in Figure.3(b) and hence offer better coverage than pin hole cameras. For surveillance purposes the camera is fixed, so DoF changes with change in the zoom level as image size varies with zoom. Higher the zoom level, shallower will be the DoF and lesser will be the number of points in the viewing frustum. Thus the viewing frustum is now redefined as the volume bounded by the near focus and the far focus planes as shown in figure.1(b).
The zoom level of a visual sensor is considered proportional to its focal length. For a given zoom level of the optical sensor, 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 grids covered by the sensor when focused at individual focal planes. As the problem cannot be solved for infinite values of poses and zoom levels (case of continuous sensor motion), we approximate the continuous case by sampling the poses and the zoom levels. While considering the covered area we considered the modified model of camera considering zoom as shown in figure.1(b). If a grid lies in the extended field of a certain no. of cameras say (n), the the grid is covered. The figure.4(c). shows the intersection of field of view of 2 cameras placed at C_1 and C_2. Any grid in the region II is covered by 2 (n = 2) cameras, and as 'n' increases the probability of occlusion due to randomly moving object reduces.

Probabilistic space model

The sensitive space to be monitored is logically divided into cubical grids (fig.5). The cameras are set to rotate along X and Y direction to enhance coverage. Because of these rotation, the space around the centre of the priority area will be covered for longer time than area near the edges as the most probable location of event will be the centre of the selected area. The probabilistic space model is explained as follows

1. Amount of time for which the space under consideration is covered

   As it can be seen from the Figure. 1(c), the space in the viewing frustum of the camera at the optimum position (centre of field of view) will be covered for the maximum period of time in course of camera motion. That is, the probability of the space at the centre of the field of view, being covered is more compared to the remaining portion of the priority area. A mathematical measure of the amount of relative time a space is under coverage, is



(a) (b) (c)

Fig. 4. (a) Region marked A is under the influence of three probability spheres and has the max. weightage compared to other regions (b) Field of view with obstacle (c) Intersection of Field of View

measured as "b" the average of "b_1" and "b_2" on a scale of 0 to 1, for α (pan angle) and β (tilt angle) using equations (1),(2) and(3) where α_{max} and β_{max} are the maximum pan angle and tilt anle respectively.

$$b_1 = 1 - \alpha/\alpha_{max} \tag{1}$$

$$b_2 = 1 - \beta/\beta_{max} \tag{2}$$

$$b = (b_1 + b_2)/2 \tag{3}$$

2. Identification of the high activity areas
   The probability of the presence of an object at the high active area of the priority area is more compared to that it being anywhere else. Hence more importance is given to the focal planes assigned to these high active areas.
3. Quality of image
   The resolution of the image of an object placed at space nearer to the focal plane will be more compared to that of an object placed at space farther from the focal plane. An appropriate distribution has been considered to accommodate this.
   The performance measure corresponding to the above two points, depends on the distance of the space with respect to the focal plane and is calculated as 'a ', a quantitative measure of the quality of the image.
   $$a = 1 - q/q_0 \tag{4}$$
   where q is the distance of point 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.
4. Probability of an image being at the centre of the priority area.
   Probability of an object being placed at the centre of the priority area will be more compared to that being on edges. This can be modelled by assuming a logical sphere of priority which decreases with distance surrounding the priority point. We have modelled the same using Gaussian function as shown in Figure.4(a). If W (eq: 5) is the net performance measure of a priority point under the influence of n Gaussian spheres, then
   $$W_i = W1_i + W2_i + W3_i + - - - - - - - - + Wn_i \tag{5}$$

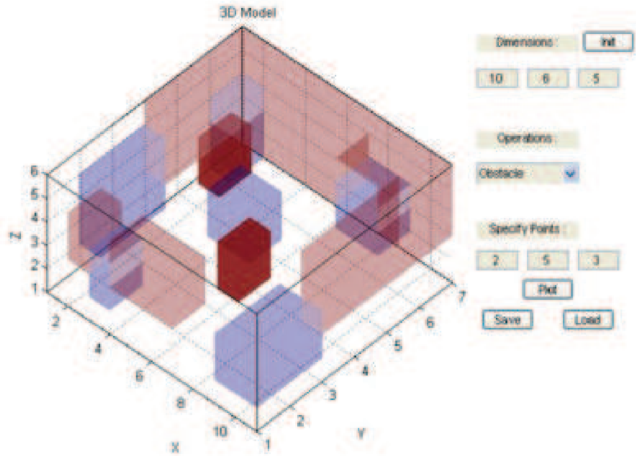


Fig. 5. GUI-Blue colored points represent the priority points, light Maroon colored points represent the feasible points and red colored points represent the obstacles

Where i represents the priority point under consideration, W_i, the performance measure of point i and W_{ji} is the effective performance measure considering the influence of jth on ith point, $1 \leq j \leq n$ for n priority points

Matrix P (eq: 6) denotes the location and performance measure of priority points and is defined as

$$P = P[i, j, k]_{(mXmXm)} \tag{6}$$

where

$$P[i, j, k] = \begin{cases} \sum exp(-((d)^2/constant)) & \text{if } d \leq r \\ 0 & \text{if } d > r \end{cases} \tag{7}$$

Where d is the distance of the point from all the priority points and r is the radius of influence that a particular priority point has. Thus P(i,j,k) (equation 7) is the value of the priority point based on the extent of influence of probability spheres affecting that particular priority point.

Floor plan model

The term floor plan denotes a physical three dimensional space which we aim to cover. 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 the camera. The feasible locations of camera, the size and shape of obstacles and the sensitive areas with assigned priority for each one can be fed as inputs to the system through GUI (fig.5). 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.4(b).These inputs are then converted to priority, feasible, visibility and obstacle matrices S.Indu et al. (2008) with dimension m*m*m, where m is the largest value of dimension among m, n and s of the floor plan so that the algorithm can handle cuboidal floor plan with cubical grids. All the objects and areas have a definite value.

3.1 Coverage metric

A coverage metric is formulated which incorporates all the above said constraints which is formulated based on following assumptions

- A simple, single lens element has been used to represent the optical sensor .
- Aperture of the lens of the optical sensor has been assumed to be constant throughout the algorithm.
- Effect of geometric distortion or blurring of objects has been neglected.

We approximate the continuous motion of cameras into discrete poses by sampling and hence cameras can adopt only those particular poses. The coverage metric is defined as in equation 8.

$$\mathcal{C} = \alpha \sum_{priority(2-cam)} t_x + \sum_{non-priority} m_y + \sum_{priority(1-cam)} n_z \tag{8}$$

where

$$t_x = \begin{cases} performance\ measure\ of\ zoom+ \\ performance\ measure\ of\ priority\ points\ covered \\ by\ 2\ cameras + A(i,j,k) \end{cases} \tag{9}$$

$$n_z = \begin{cases} performance\ measure\ of\ zoom+ \\ performance\ measureof\ priority\ points\ covered \\ by\ 1\ camera + A(i,j,k) \end{cases} \tag{10}$$

$$m_y = \begin{cases} performance\ measure\ of\ zoom+ \\ A(i,j,k) \end{cases} \tag{11}$$

A (i,j,k) is the value of visibility matrix at the given point
In the total surveillance area some of the priority points will be covered by 2 cameras and some of them by only one camera and some of the non priority points also will be covered by cameras. The fitness function should be properly defined in such a way that the priority area covered by 2 cameras should be maximised and the covered non priority area be minimized. To increase the probability of covering maximum no. of priority points using 2 cameras we used a weightage factor α in the fitness function. Here t represents priority points covered by two cameras while m represents non priority points. α is the weightage to be given to the coverage of priority points by two cameras over priority points covered by one camera and all non priority points. With increasing value of α the probability of occlusion decreases. As zoom-level increases the DoF reduces and thus the number of points in the viewing frustum reduces. Better solutions will have a higher value of Coverage *C*. We used GA based optimization for maximising the coverage matric.
The user defined input is used to determine feasible matrix, obstacle matrix, location based priority matrix etc. as follows

$$\mathcal{F} = [f_{ijk}]_{mXmXm} \tag{12}$$

Where

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

And obstacle matrix as

$$\mathcal{O} = [o_{ijk}]_{mXmXm} \tag{13}$$

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

Matrix P denotes the location based performance measure of priority points and is defined by equation 6 The visibility matrix generated from matrices F,O,P (equations 12, 13, 14) becomes 9 Dimensional which is very inconvenient to work with. To get a convenient dimension, we map every grid point, every pose and every zoom level to a particular number Erdem (2006) according to the mapping described by the equations (14, 15, 16)

$$position(i,j,k) = (j-1)*N*N + (i-1)*N + k \tag{14}$$

And every pose by

$$pose(\alpha,\beta) = M*(\alpha-1) + \beta \tag{15}$$

where M is the no of discrete pan or tilt angles the camera can assume. and

$$Zoom(z) = (highest\ zl - lowest\ zl)*z/zl \tag{16}$$

where zl is the no discrete zoom levels the camera can assume. The value of 'z' varies from 1 to zl. Now the visibility matrix (equation 17) is reduced to a 4 Dimensional matrix which can be expressed as

$$A = [a_{ijkz}]_{m^3XM^2Xm^3Xz1} \tag{17}$$

Where

$$a_{ijkz} = a + b \tag{18}$$

$0 < a < 1$, depending on the distance of the point under consideration from the focal plane. $0 < b < 1$, depending on the offset of the pan and tilt angles from there optimum positions. This visibility matrix along with the priority matrix is then used to calculate the coverage score of any set of cameras placed at different locations.

3.2 Genetic Algorithm Mapping

The first and the foremost step in a design using genetic algorithm is to select all the variables of the problem to be solved. This is a crucial point since other features of the algorithm depend on this selection. Each variable should represent size of the search space, efficiency of the genetic operators etc. The most natural way of representing solutions of the said problem would be a sequence of genes, each coding the actual position the pose and zoom level of individual camera.

Optimization criteria: max

A simple way of encoding would be through a binary bit string:

The Gene of a camera

$$(C(i)) = (X(i), Y(i), Z(i), \alpha(i), \beta(i), zoom[i]) \tag{19}$$

$1 \leq\ i\ \leq no.of camera$

where

$X(i) = \{\ a_1, a_2, ...a_k\}_{10}$

$Y(i) = \{\ b_1, b_2, ...b_k\}_{10}$

$Z(i)= \{ c_1, c_2, ...c_k\}_{10}$
$a_r ,b_r, c_r , \varepsilon \{0,1\} \quad 1 \leq r \leq k \quad k= log_2(N)$.
where coordinate feasible space is of dimension N^3 i.e. $0\leq$ x[i],y[i],z[i] $\leq$ N-1
$\alpha(i)= \{ h_1, h_2, ...h_s\}_{10}$
$\beta(i)= \{ j_1, j_2, ...j_s\}_{10} \quad h_t , j_t, \varepsilon \{0,1\} \quad 1 \leq t \leq s$
and s = $log_2(N_0)$ where pan-tilt space is of cardinality $(N_o)^2$
$N_0 \leq \alpha$[i], β[i] $\leq N_0$-1 and $zoom[i] = \{ q_1, q_2, ...q_v\}_{10}$
$q_b \epsilon \{0,1\}$, $1 \leq b \leq u$
$u = log_2(N_1)$ where zoom is of cardinality N_1 i.e. $0 \leq zoom[i] \leq N_1 - 1$ $\{ ..,..,..\}_{10}$
is decimal representation of a binary bit string with left most bit as MSB. The gene of each camera C[i], is simply a concatenation of two bit strings. Alternatively speaking, the gene of camera is an abstraction of its location and orientation of its pose in the space. Being a collection of genes, a chromosome would therefore be a representation of an array of cameras belonging to the solution space. Hence problem is redefined to look into the solution space to choose the fittest among them. The fitness function (equation 8) very obviously is the coverage metric for each set of cameras.

3.3 Algorithm

1. An initial random population of N belonging to the search space (within the feasible region only) is chosen and encoded by the above procedure.
2. Next we evaluate the fitness value for each of the population using the matrices of coverage of priority and non priority points generated and a comparison is made regarding the optimality of the solution.
3. Then, we select a population of "good" networks by tournament selection method, two best individuals are simply passed on and we proceed for reproduction.
4. From this population we recombine the species using the following operations:
   a. Crossover with a probability of 0.8 using scattered crossover function.
   b. Mutation with a probability of 0.001 is essential to maintain diversity.
5. These operations yield a new population which replaces the existing one.
6. Steps 2, 3, 4 are repeated until the optimization criterion stabilizes.

All the above implementation has been achieved through the GA package (and toolbox) provided with MATLAB Version 7.0.

4. Validation of tool

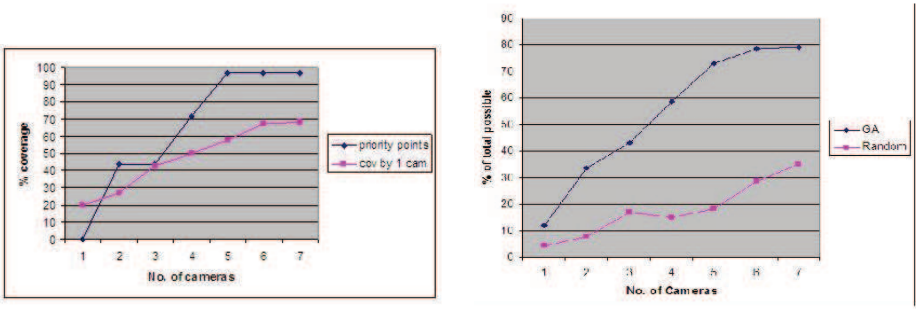
Simulation

Both 2D and 3D simulations for camera placement are done and the results are as shown in fig. 9, fig. 10 fig. 11 and fig. 12. For simulation purposes, the floor plan is considered as a simple 10X10X10 cube. Also all the sides of the cube except the floor are being considered as a feasible camera location. The priority area is considered to be a smaller 4x4x4 cube with its center coinciding with the center of the floor plan fig. 11. An obstacle is considered as a pillar extending from grid points 3 to 5 in x, y directions from floor. We used of Genetic Algorithm to solve this optimization problem. The visibility matrix and the priority matrix help the Genetic Algorithm to evaluate the fitness function of various generations. All the coding and matrix representations have been implemented in Matlab. For the purpose of drawing 2-D spaces we have used the help of JAVA- 2D classes to visualize our task. In the case of 2D for simplicity

Pan angle	Tilt angle	Zoom Level	X	Y	Z
45	180	0	0	0	1
315	180	0	0	0	8
315	135	0	0	8	0
135	225	1	1	5	7
135	45	2	1	5	5
45	45	2	1	0	7

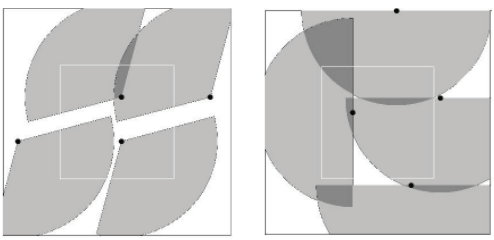
Table 1

we have considered the camera field of view to be an arc of variable subtended angle and feasible space containing the whole floor plan. while in case of 3D a simple cube has been considered.
The graph shown in Figure. 6(a) shows that we require only 4 cameras to cover the specified area and 6(b) shows the coverage variation by random placement of cameras and Placement using GA. Figure. 7 shows that the maximum value of α we can assume is 10. The positions and poses of camera when we use 3D model and 2D model are shown in Figure. 11, Figure. 12 and Figure. 9 and Figure. 10 respectively. Table 1 shows results of locations of 6 cameras with their corresponding pan angle, tilt angle, zoom level and coordinates x, y, z



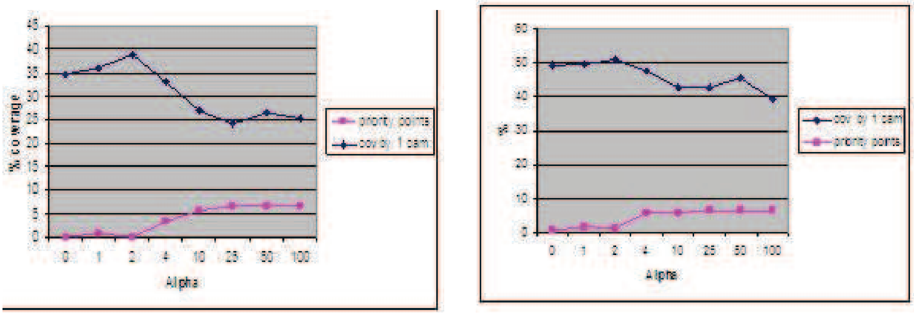
(a) (b)

Fig. 6. (a) No of cameras vs percentage Coverage (b) GA vs Random placement



(a) (b)

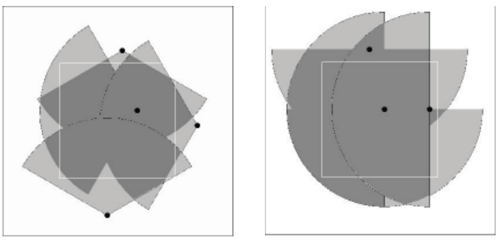
Fig. 10. Shows the position and pose of the camera to cover an area, for (a) and (b) Equal priority for both inner and outer square



(a) (b)

Fig. 7. Effect of variation of α vs priority points covered by one camera or more than one camera

Fig. 8. Experimental set up with 3 cameras



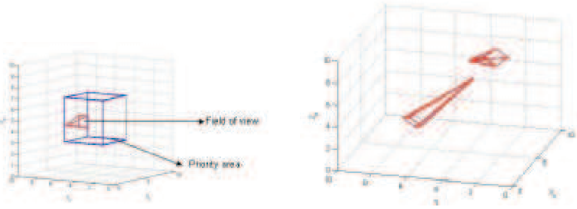
(a) (b)

Fig. 9. Shows the position and pose of the camera to cover an area, for (a) and (b) Inner square as the priority area and for

Experimental evaluation

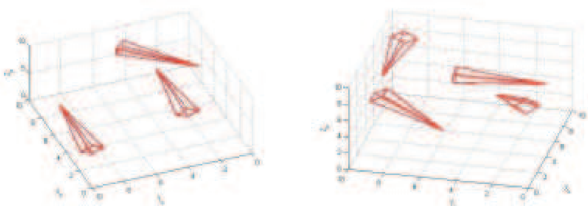
We validated the proposed tool by placing 3 PTZ cameras. Six discrete clusters of priority points each with different number of points were randomly distributed throughout the space.

We have done the experiment in the digital lab of ECE Department of Delhi Technological



(a) (b)

Fig. 11. Shows the position and pose of the camera to cover a volume (a) using 1 camera (b) using 2 cameras



(a) (b)

Fig. 12. Shows the position and pose of the camera to cover a volume (a) using 2 camera (b) using 4 cameras

University, Delhi having the dimensions 60 feet x 30 feet x 10 feet and in the Multimedia lab of Indian Institute of Delhi with dimension 80 feet x 40 feet x 10 feet . Graphical user interface was used to model the lab. A total of 48 and 60 feasible points were identified respectively. Optimum positions, poses and zoom levels of the three cameras were determined using the proposed tool. The cameras were made to rotate 15 degrees about their optimum position along pan and tilt axes. Cameras were coordinated at the start so that their common coverage area is covered at different times to ensure maximum visibility. We observed that the zoom level of farthest area is smaller than nearby area so that we can have detailed information. Using camera locations, pan, tilt angles and zoom level, we can compute mean position corresponding to each camera which will be assigned highest priority as the probability of event at this location is more. Now using camera locations and mean positions the light source locations are determined using the proposed tool. The experimental set up in Digital Lab of Delhi College of Engineering is as shown in fig. 8.It has been observed that:

1. The priority area with largest number of priority points was covered by two cameras and the clusters with fewer number of priority points were covered by only one camera which validates our probabilistic framework.
2. The cameras that were focused at small distances as shown in Figure.14 (a) and Figure.15 (b) had a higher zoom level to capture a detailed image. By doing so it is reducing data redundancy by virtue of capturing fewer non priority points as the region under consideration had a low priority to non priority point ratio. Whereas the cameras focused at large distances as shown in Figure.13 (a) and Figure.14 (b) had a comparatively

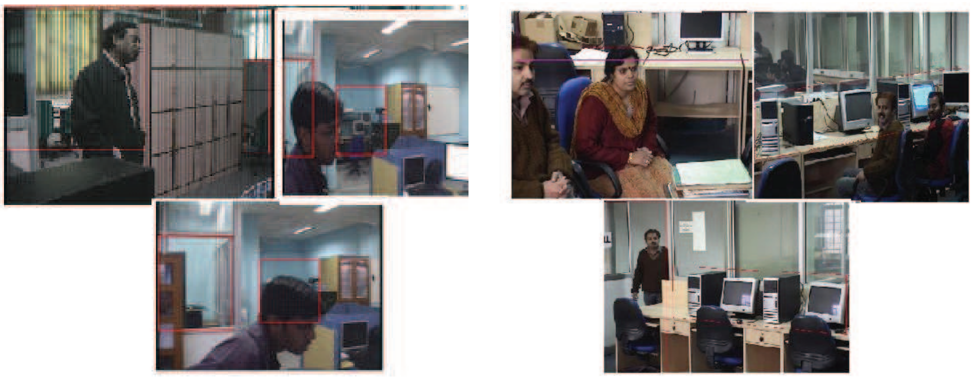
lower zoom level to increase the number of points in its viewing frustum. By doing so it is increasing the coverage area to cover maximum priority points (as the region had higher priority to non priority points ratio) while maintaining the requisite resolution. Figure.13 (b) and Figure.15 (a) shows moderate zoom level.

3. The priority areas were covered for a larger time period during the camera motion than non priority areas. This is clear from the pictures shown below taken during camera motion.

   Thus all the six discrete priority areas were covered by the 3 cameras with satisfactory image quality. These observations clearly validate our probabilistic approach for optimization criterion. (Priority areas have been marked with a red boundary in the figures)

(a) (b)

Fig. 13. Shows the image taken by camera placed in IITD (a) camera1 (b) camera2



(a) (b)

Fig. 14. Shows the image taken by (a) camera3 at IITD (b) camera1 at Delhi College of Engineering

(a) (b)

Fig. 15. Shows the image taken by cameras placed in Delhi college of Engineering (a) camera2 (b) camera3

5. Conclusion

We have developed a novel tool for placement of cameras for surveillance applications. Apart from camera location, the tool provides optimum pan-tilt angles and zoom level. As the tool is based on extended field of view, it avoids redundancy in sensor placement. Unlike other placement methods, the proposed method calculates the optimum zoom level which improves the quality of service of the vision system . The tool is completely off line and do not depend on camera parameters or image parameters and hence computationally light. The experimental results validates the tool. The tool will be instrumental in designing camera locations for surveillance of a port or such bigger areas.

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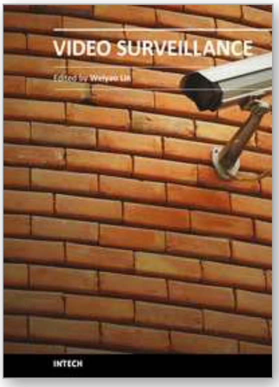

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This book presents the latest achievements and developments in the field of video surveillance. The chapters selected for this book comprise a cross-section of topics that reflect a variety of perspectives and disciplinary backgrounds. Besides the introduction of new achievements in video surveillance, this book also presents some good overviews of the state-of-the-art technologies as well as some interesting advanced topics related to video surveillance. Summing up the wide range of issues presented in the book, it can be addressed to a quite broad audience, including both academic researchers and practitioners in halls of industries interested in scheduling theory and its applications. I believe this book can provide a clear picture of the current research status in the area of video surveillance and can also encourage the development of new achievements in this field.

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