# Study on Models for Smart Surveillance through Multi-Camera Networks


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# Study on Models for Smart Surveillance through Multi-Camera Networks

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# Certificate

This is to certify that the work in the thesis entitled ***Study on Models for Smart Surveillance through Multi-Camera Networks*** by ***Rahul Raman***, is a record of an original research work carried out by him under my supervision and guidance in partial fulfilment of the requirements for the award of the degree of *Master of Technology (Research)* in *Computer Science and Engineering.* Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

***Pankaj K Sa***

# Acknowledgment

अमंत्रमक्षरं नास्ति नास्ति मूलमनौषधम्।
अयोग्यः पुरुषोनास्ति योजकस्तत्र दुर्लभः॥
भर्तृहरिः

There is no sound that is not a mantra,
no plant that is not medicinal.
There is no person unworthy,
but rare is the person who transforms them into.
**Bartrihari**

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# Abstract

With ever changing world, visual surveillance once a distinctive issue has now became an indispensable component of surveillance system and multi-camera network are the most suited way to achieve them. Even though multi-camera network has manifold advantage over single camera based surveillance, still it adds overheads towards processing, memory requirement, energy consumption, installation costs and complex handling of the system.

This thesis explores different challenges in the domain of multi-camera network and surveys the issue of camera calibration and localization. The survey presents an in-depth study of evolution of camera localization over the time. This study helps in realizing the complexity as well as necessity of camera localization in multi-camera network.

This thesis proposes smart visual surveillance model that study phases of multi-camera network development model and proposes algorithms at the level of camera placement and camera control. It proposes camera placement technique for gait pattern recognition and a smart camera control governed by occlusion determination algorithm that leads to reducing the number of active camera thus eradicating many overheads yet not compromising with the standards of surveillance.

The proposed camera placement technique has been tested over self-acquired data from corridor of Vikram Sarabhai Hall of Residence, NIT Rourkela. The proposed algorithm provides probable places for camera placement in terms of 3D plot depicting the suitability of camera placement for gait pattern recognition.

The control flow between cameras is governed by a three step algorithm that works on direction and apparent speed estimation of moving subjects to determine the chances of occlusion between them. The algorithms are tested over self-acquired as well as existing gait database CASIA Dataset A for direction determination as well as occlusion estimation.

***Keywords*:** Visual surveillance, Multi-camera network, Multi-camera localization, Gait biometric and camera placement, Height based identification, Perspective view analysis, Occlusion determination algorithm, Motion direction estimation.

# Contents

**Certificate** ii

**Acknowledgement** iii

**Abstract** iv

**List of Figures** vii

**List of Tables** ix

**1 Introduction** 1

1.1 Research Challenges in MCN . . . . . . . . . . . . . . . . . . . . . . . . 2

1.2 Literature Survey . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 7

1.2.1 Camera Localization and Calibration . . . . . . . . . . . . . . . 7

1.2.2 Camera Placement for Gait Based Identification . . . . . . . . 25

1.2.3 Camera Control for Occlusion Avoidance . . . . . . . . . . . . 30

1.3 Thesis Organization . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 32

**2 Study on Efficient Camera Placement Techniques** **33**

2.1 Gait Biometric . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 34

2.2 Proposed Model . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 36

2.2.1 Locus Tracking of Subjects' Movement . . . . . . . . . . . . . 38

2.2.2 Direction Vector Calculation . . . . . . . . . . . . . . . . . . . . 39

2.2.3 Path-band Estimation . . . . . . . . . . . . . . . . . . . . . . . . 40

2.2.4 Finding Efficient Camera Placement . . . . . . . . . . . . . . . 41
2.2.5 Localization and Working of Camera Network . . . . . . . . . 42
2.3 Experiment . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 43
2.4 Concluding Remarks . . . . . . . . . . . . . . . . . . . . . . . . 46

**3 Study on Smart Camera Control 48**
3.1 Database Used . . . . . . . . . . . . . . . . . . . . . . . . . . . 50
3.2 Motion analysis . . . . . . . . . . . . . . . . . . . . . . . . . . . 51
3.2.1 Determination of Direction of Motion . . . . . . . . . . . . . . 51
3.2.2 Apparent Speed Determination . . . . . . . . . . . . . . . . . 62
3.3 Occlusion Determination . . . . . . . . . . . . . . . . . . . . . . 64
3.3.1 Lookup table generation . . . . . . . . . . . . . . . . . . . . 65
3.3.2 Time and Location of Occlusion Calculation . . . . . . . . . . 67
3.4 Mitigation of Occlusion . . . . . . . . . . . . . . . . . . . . . . . 71
3.5 Results . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 71
3.6 Concluding Remarks . . . . . . . . . . . . . . . . . . . . . . . . 73

**4 Conclusion 75**

**Bibliography 78**

**Dissemination 87**

**Vitae 88**

# List of Figures


1.1 Research challenges in MCN. Rectangular blocks states the contribution made in the thesis. . . . . . . . . . . . . . . . . . . . . . . . 4

1.2 Images of Different camera network. . . . . . . . . . . . . . . . . . . . . 6

1.3 Analogy between formation of sensor connectivity graph and vision graph . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 11

1.4 Formation of epipolar geometry . . . . . . . . . . . . . . . . . . . . . . . 13

1.5 Simultaneous localization techniques . . . . . . . . . . . . . . . . . . . . 16

2.1 A complete gait cycle . . . . . . . . . . . . . . . . . . . . . . . . . . . . 35

2.2 Change in width of bounding box of moving object with different camera placement angle . . . . . . . . . . . . . . . . . . . . . . . . . 38

2.3 Loci of different subjects tracked by the overhead-camera . . . . . . 39

2.4 Inference of angles from discrete pixel patterns in $8 \times 8$ grid . . . . . 40

2.5 (a) Grid indicating unique direction of movement, (b) chaos region, (c) grid with no locus . . . . . . . . . . . . . . . . . . . . . . . . . . 41

2.6 Finding efficient camera placement . . . . . . . . . . . . . . . . . . . . 42

2.7 Corridor sequence . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 43

2.8 Finding trace of the subjects by optical flow . . . . . . . . . . . . . . 44

2.9 Plotting traces over grid-map from captured images by homography . 45

2.10 Sample grid and histogram for orientation of movements in the grid . 45

2.11 3D mesh plot where two of the humps depicting probable places for camera placement . . . . . . . . . . . . . . . . . . . . . . . . . . . . 47

3.1 Proposed camera control model governed by occlusion determination algorithm . . . 49
3.2 Discrete directions of motion with respect to camera . . . 52
3.3 Pattern change in the dimension of subject . . . 53
3.4 Variation of height with respect to frame number for four different direction of subject's motion . . . 54
3.5 Plot of width for different direction . . . 54
3.6 Frame rectification and unwanted blob removal . . . 56
3.7 Morphological operations and tracking of subject . . . 57
3.8 Envelop over the plot . . . 58
3.9 Detection and removal of soft extremas . . . 58
3.10 Envelop and average line drawn based on envelop . . . 61
3.11 Distance invariant direction of motion estimation through phase . . . 61
3.12 Direction estimation result based on height of the subject . . . 63
3.13 Direction estimation result based on width of the subject . . . 63
3.14 Test cases depicting occlusion over CASIA Dataset A . . . 72
3.15 Test cases depicting occlusion and non occlusion . . . 73

# List of Tables


1.1 Different approaches to solve point correspondence problem . . . . . . 14

1.2 Review of related researches on multi-camera localization . . . . . . . 19

1.3 Task specific optimal camera placement . . . . . . . . . . . . . . . . . . 29

3.1 Matrix for direction based occlusion probability estimation . . . . . . 68

3.2 Matrix for speed based occlusion determination with directions $(D_i, D_j)|(i,j) \in \{2,3,4\}$ . . . . . . . . . . . . . . . . . . . . . . . . . 68

3.3 Matrix for speed based occlusion determination with directions $(D_i, D_j)|(i,j) \in \{6,7,8\}$ . . . . . . . . . . . . . . . . . . . . . . . . . 68

# Chapter 1

# Introduction

Vision is an ideal sensing mechanism and since the evolution of cameras, image processing are perceived as solution of many complex real world problems. Processing of images first require that they should be represented in proper format for which the one dimensional signal has up-scaled its dimension to image and thereby increasing its processing complexity. The complexity has further uplifted in video processing with an additional dimension. Complexity in video processing is also compounded by inter frame and intra frame processing. The wide scope of image and video processing find its implementation in almost every walk of life, be it medicine or engineering, space or mining, agriculture or weather forecast, image and video processing are omnipresent. In recent days, visual surveillance has became an important issue that has been greatly deciphered through video processing. An important application of video processing is visual surveillance. As the demand of sophisticated visual surveillance mechanism prevailed, so is the research over the constraint of earlier surveillance systems are much discussed and it resulted in a paradigm shift toward visual surveillance through multi-camera network.

*Multi camera network* (MCN) overcomes many limitations of single camera surveillance systems like restricted field of view, no options for best view synthesis, partial and full occlusion of subject during tracking. Multi-camera based surveillance although considered as the solution to overcome these limitations of single camera

based surveillance but are more complex. They require higher installation cost and complex algorithm for handling as well. This thesis concentrates on understanding research challenges in multi-camera based visual surveillance and presents survey, proposals, experiments and results towards development of smart multi-camera network based surveillance system.
Next section discusses various research challenges in MCN. Some of the research challenges are extensively studied and discussed in Section 1.2. The organization of the thesis is presented in the last section.

## 1.1 Research Challenges in MCN

As the demand for fool-proof tracking algorithm prevailed, so is the paradigm shifted from single to multi-camera network model. These systems are more useful for tracking in crowded places and highly protected areas. This can be equipped with a variety of cameras and distributed processors to even amend the functionality of tracking. Here are a few reasons that made the mode of surveillance to change from single camera to MCN:

(i) Growing importance of visual surveillance

(ii) Coverage area becoming larger and more complex.

(iii) Occurrences of occlusion can be avoided.

(iv) Best view synthesis algorithms can be applied when multiple views of the same scene are available.

(v) Decreased cost of sensors and other hardware in recent years.

(vi) Can be made smart and interactive with variety of cameras, distributed processors, and state of the art software.

A multi-camera system can avoid occlusion and can provide robust tracking but are not as simple and energy-efficient as single camera systems. Although a camera system installed in master-slave mode [9], has the energy efficiency but the entire region under coverage should come under master camera's view. Towards making the multi-camera model efficient, few other works have also been proposed. Kulkarni *et al.* have proposed an approach for efficient use of multiple cameras by devising multi-tier camera network called SensEye [1, 2]. This approach is energy efficient although it has a complex hardware architecture and diverse software requirement. Even though surveillance through MCN has many advantages over single camera system, yet it has some bottlenecks that restrict the use of MCN to serve only some vital requirements. Some of the limitations are:

(i) Need additional processing.

(ii) Require extra memory.

(iii) Consume superfluous energy.

(iv) Have higher installation cost.

(v) Demand complex handling and implementation.

(vi) Obligate localization and calibration.

(vii) Need suitable camera placement.

Some of the key research challenges are identified as in Figure 1.1 and are briefly discussed here.

**Camera and Camera Network** When many cameras are allied via a network, so that they can interact among them, they form a camera network. Deciding the type of camera network is one of the major issue in MCN. Based on inter-sensor communication, a camera network may follow centralized, decentralized, or distributed architecture for interconnection. Figure 1.2 shows the diagrammatic representation of centralized, decentralized, and distributed camera network. In centralized network, a single node receives raw information from all the cameras

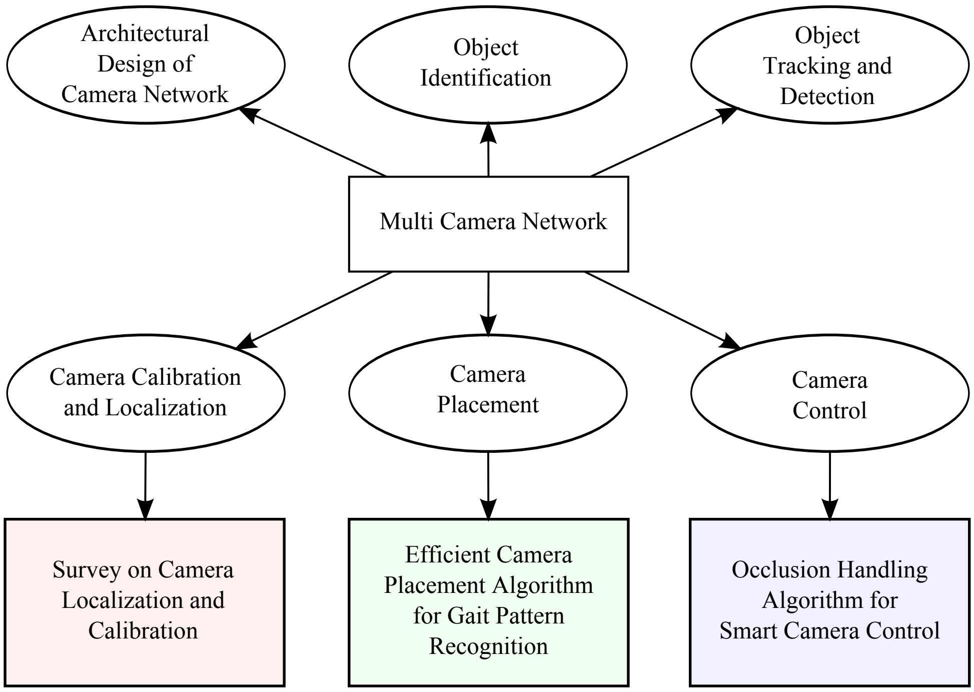



Figure 1.1: Research challenges in MCN. Rectangular blocks states the contribution made in the thesis.

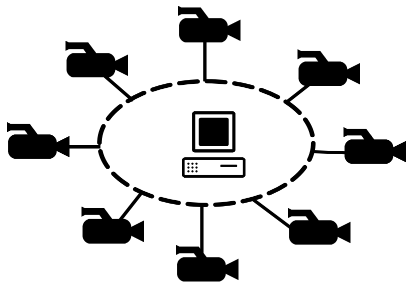
and processes them at a central place. This architecture is although not suitable for real time implementation and larger networks due to lack of scalability, high energy inefficiency, and amount of data transfer at the central processor. In decentralized network, cameras are clustered and member of each cluster communicate to their local centres. Here communication overhead is reduced and higher scalability is achieved. To even uplift the scalability, and reduce communication cost; distributed camera network is castoff, which does operate without local fusion centres. In distributed camera network, small processing units are assembled with each camera unit that enables them to process their acquired information in distributed way and hence the system makes a smart and efficient usage of bandwidth. They are ideal for complex utilities like intricate surveillance and coverage of outdoor games, as they provide faster communication and also the bandwidth and computations are distributed and shared.

**Identification** In MCN based surveillance, identification is an important task. A surveillance system is expected to identify objects, people or an event and should be smart enough to analyse the identification results and draw conclusions. Event recognition is a challenging task and finds challenges at the levels of acquisition, training of the system and analysis. People identification suffers from acquisition challenges, occlusion, and low resolution imaging. Face identification, visual tagging, and gait based identification are perceived as solution of identification.

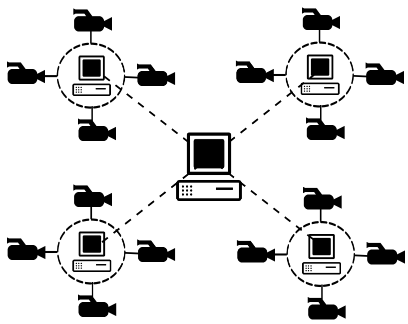
**Object Tracking** Object tracking is achieved by estimating the trajectory of an object in an image plane as it moves around a scene. Regions, contour, feature points and templates are used in different methods of object tracking. In visual surveillance using MCN, object tracking is a famous research issue. The cost associated with computing and communication in MCN depends on the amount of co-operation performed among cameras for information gathering, sharing and processing for decision making and towards reducing estimation error. With different camera networks, the number of data fusion centres for the network varies and hence with different camera networks, different challenges are introduced.

**Camera Calibration and Localization** The position and orientation of a camera plays an important role in the performance of MCN. A well calibrated and localized camera network reduces the overheads at the level of acquisition as well as processing. A detailed survey has been presented in the next section that discusses the evolution of camera localization in detail.

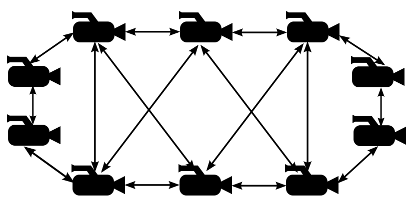
**Camera Placement** Placement of camera is also one of the major research issue in MCN based surveillance. Most of the early camera placement techniques are developed for minimizing number of field cameras or maximizing the the coverage areas. However, with advancement in research towards surveillance issues task specific camera placement has been also studied. A study over camera placement has been presented in the next section.



(a) Centralized Camera Network



(b) Decentralized Camera Network



(c) Distributed Camera Network

Figure 1.2: Images of Different camera network.

**Camera Control** In MCN based surveillance the flow of control among the camera is very crucial in order to exploit its architecture. An algorithm of camera control determines condition or set of conditions that trigger the control from one camera to another. In the next section a study has been presented where occlusion avoidance is the issue of camera control.

## 1.2 Literature Survey

In order to understand the challenges identified at different levels of MCN based surveillance, study has been performed on different domain of MCN based surveillance.

Section 1.2.1 presents an extensive survey on camera calibration and localization that portrays the diversity in the approach of achieving camera localization. The survey explores evolution of camera localization, different approaches of camera localizations and comparison among different localization methods. Section 1.2.2 highlights the need of camera placement in MCN based surveillance. Task specific camera placement has been explored for different task and a study on camera placement with gait pattern recognition as test case has been presented. Section 1.2.3 presents a study over camera control in MCN for occlusion avoidance. Various approaches where camera control is governed by occlusion avoidance mechanism are discussed in the context of single camera as well as multi-camera based surveillance.

### 1.2.1 Camera Localization and Calibration

Location of camera in an MCN plays important role in its performance. These locations are given by certain number of parameters, which define its position in global frame. These parameters help in achieving view interpretation and multi-camera communication in MCN and are called camera calibration parameters. Camera calibration parameters include a set of intrinsic constraints i.e. focal range, principal point, scale factors, and lens distortion and a set of extrinsic calibration parameters like camera position and its orientation. Intrinsic calibration parameters are very much dependent on camera make and are valuable in deciding the suitability of camera for a typical purpose. On the other hand, extrinsic parameter give the camera pose (position and orientation) and decides the position of camera as well as the subject in global frame. These extrinsic calibrations in a network of multiple cameras are also called as camera localization. This section presents an in-depth study on camera localization, exploring the advent of localization techniques with gradually increasing complexity of MCN.

For the operation of multi-camera network, information of location of other cameras is the pre-requisite for each camera. This process of establishing a relation among the camera coordinates is termed as camera localization. Manual localization methods of multi-camera network failed to handle large number of cameras in network. Automation of the localization process started gaining importance to ascertain accuracy and real-time localization. One of the primitive automated solutions to localization has been through GPS [3]. However, it has failed mostly due to the poor resolution. Efforts have also been made towards developing localization algorithms on single processor after collecting images from all the networked cameras in a single room [4, 5]. But in practical scenario, large number of cameras producing high volume of images and video data makes the analysis time-consuming on single processor. The subsequent attempts of developing localization algorithms deploy more than one processor concurrently to achieve real-time localization. These approaches differ in variety of coverage areas, assumptions made on deployment of the nodes, and the way sensors work [6].

### Pioneer works

Early automated localization techniques for static sensors, viz. non-camera equipped networks have used ultra-sound, radio, or acoustic signals [7]. Likewise, moving sensors like robots have exploited LED based techniques for their localization. However all the methods proposed have been based on heuristic approaches and lagged theoretical foundation of network localization until Aspnes *et al.* [8] have identified specific problems and solved them theoretically. This work, motivated by previous work of Eren *et al.* [9], have attempted to give systematic answer to the following questions:

(i) conditions for unique network localizability.

(ii) computational complexity of network localization.

(iii) complexity of localization in typical network deployment scenario.

The authors have established the localization problem in sparse graphs to be $NP$-hard unless $P = NP$. For dense graphs, localization has been shown to be possible as explained by Biswas and Ye [10].

The notion of centralized processing has been predominant in early camera sensor localization techniques. Authors of [4] have analyzed human action in a closed environment. Stereoscopic reconstruction of virtual world based on depth calculation from multiple real scenes captured through multiple cameras have been attempted in [5]. Aforementioned experiments revealed the importance of proper positioning and orientation of cameras for best coverage of view area. Various researches have attempted to solve the pose (location and orientation) of cameras in the network. Funiak *et al.* [11] have proposed a novel approach of relative over-parameterization (ROP) of the camera pose. However, some approaches have been successful to calculate relative locations only, but failed to estimate orientation of each camera. GPS based approaches Hartley and Zisserman [3] have been successful in finding approximate relative location of cameras however the reasons of its failure are:

(i) inability to resolve camera orientation.

(ii) low resolution results.

(iii) costly hardware requirement.

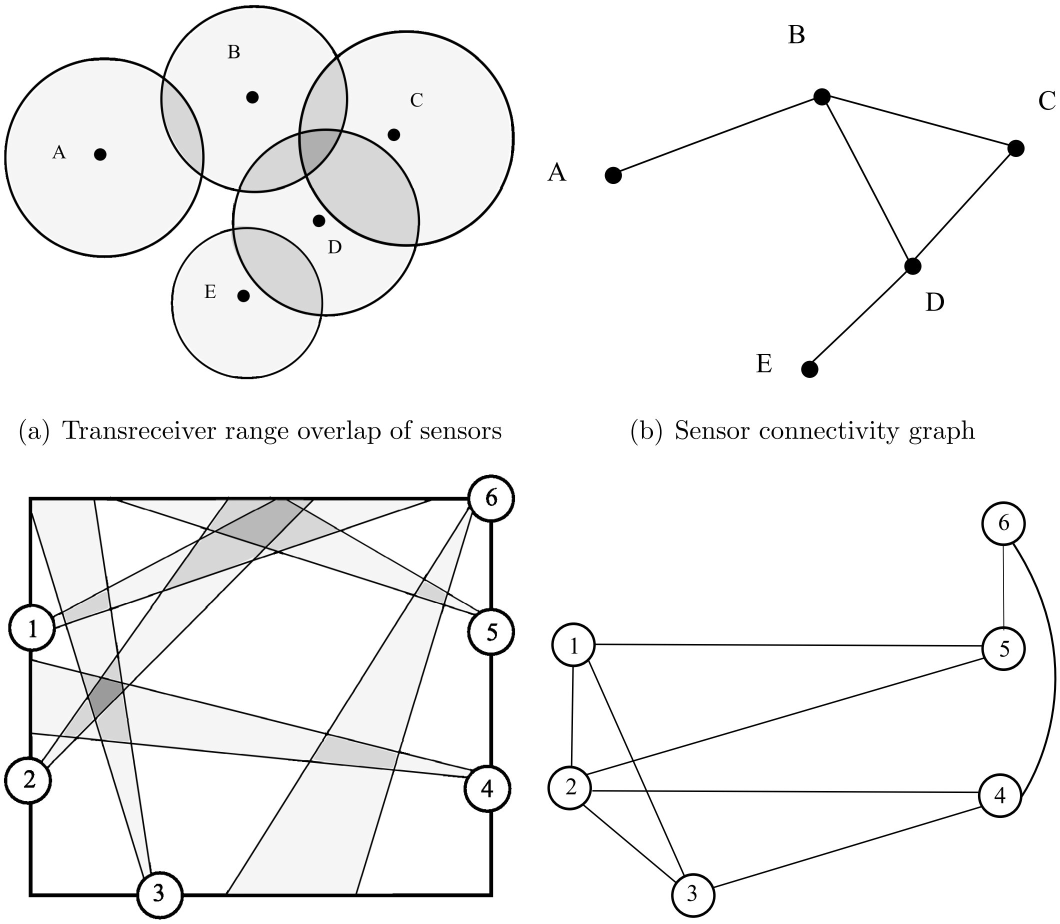
(iv) high power consumption.

Work in [12] proposes a protocol that utilizes GPS and LED based localization. But this protocol needed human-assistance, which failed for large number of cameras deployed in a wide coverage area. Hence several distributed computing algorithms [11, 13–15] have come into play to produce accurate and real-time localization solution to large number of networked cameras.

### Vision-based localization

A stringent requirement of vision-based approach has been foreseen by the researchers as localization through GPS was neither accurate nor able to provide orientation. The necessity of vision-based localization is only image data. However, vision based localization algorithms impose a deployment constraint that there must be an overlap between view of cameras in the network. This constraint is analogous to the constraint in general transreceiver sensor network. Inspired by the graph theoretic representation [16] of connectivity among sensors (Figure 1.3), vision graph [13] with $M$ networked cameras is introduced to be $G(V, E)$ defined on $V = \{V_i | i = 1, \ldots, M\}$, and $E = \{E_{ij} | E_{ij} \in \{0, 1\}; i, j = 1, \ldots, M\}$ representing cameras as vertices and vision overlap as edges respectively. [17] introduced the concept of weighted vision graph, where each $e_{ij}$ has been assigned a weight $w_{ij}$ corresponding to the number of common points between $i^{th}$ and $j^{th}$ cameras. To serve the purpose of realigning all camera pose to a single network-wide coordinate frame, some researchers have come up with solutions that require triple-wise camera overlaps [13, 18], implying the need of densely deployed network, where as some researchers have proposed to position a camera in the network such that it is in view-overlap with all other cameras in the network [19]. Some researchers have used an LED-lit rod of known length to be placed at a position visible from all cameras to establish consistent scale [17, 20]. As the densely deployed network is not cost-optimized, researchers have come up with localization solution for relatively sparsely deployed network [17, 21], and subsequently also for networks with non-overlap [22, 23]. The following paragraphs explain visible and invisible LED based techniques, and the formation of epipolar geometry behind resolving view-overlap.

**LED based approaches to minimise view-overlap** Techniques based on LED (emitting visible or infrared spectrum) have reduced the view overlap leading to relatively sparsely deployed network. Use of LED reduces the view-overlap to be




(a) Transreceiver range overlap of sensors

(b) Sensor connectivity graph

(c) View overlap of networked cameras

(d) Vision graph

Figure 1.3: Analogy between formation of sensor connectivity graph and vision graph

pair wise. A few recent works based on epipolar geometry have been reported to reduce the density of overlap while maintaining the localizability of each camera.

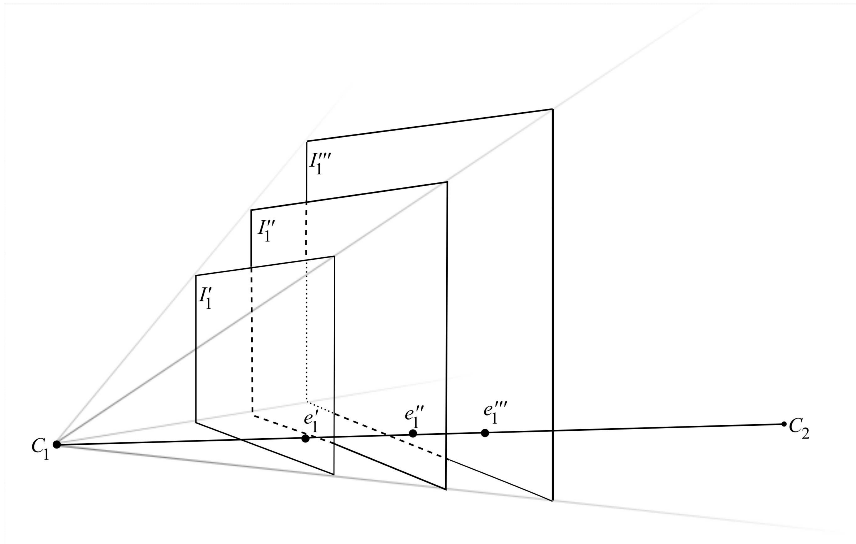
In some other reported literature, two LED markers are placed on both ends of a fixed metal rod of known length. The time synchronized detection of LED provides correlated feature points [17, 20]. From the known length of the rod, unknown scale factor has been resolved. Authors in [24, 25] have also exploited LEDs for modulated emission.

Depth measurement is required for 3D localization. Since a camera cannot fetch depth information from a perspective view, hence an explicit distance measurement technique is essential. Authors in [19] have used three LED markers to form a triangle to estimate distance measurement needed for 3D localization. Authors in [24] have experimentally verified that three LEDs in a triangle with known dimensions can avoid explicit distance measurement. Earlier, explicit distance measurement had been in common practice [26, 27]. In another work, global co-ordinates are taken from GPS-based calibration device for computing pose of camera, while image coordinates are calculated from LED of the camera [12].

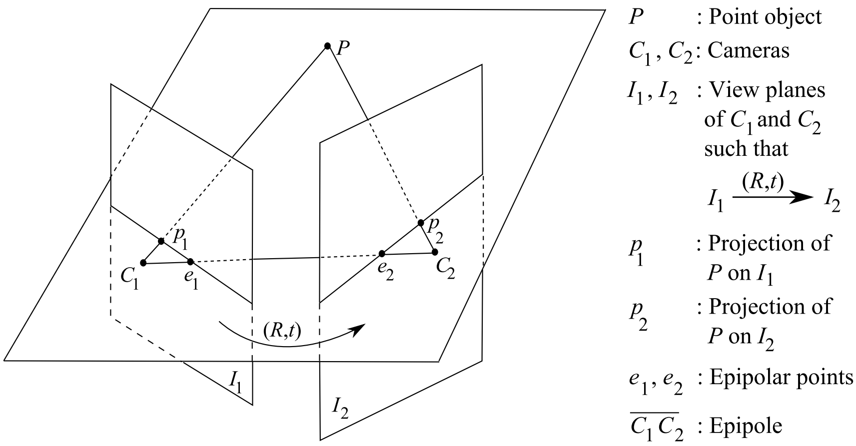
While most of the research in this direction employ visible LEDs to mark location and general cameras to sense the LEDs, techniques for localization through invisible markers (sensed with IR sensors) also gained its importance as invisibility of markers do not impair the scenery. The invisible markers are made of translucent retro-reflectors which are visible only in IR illumination [28]. Localization techniques through invisible markers are costlier than localization through visible markers as they employ extra IR sensor along with general cameras that are intended to be localized [29]. Early invisible marker techniques have used infrared markers for estimating positions while orientations have been estimated through gyro meter only [30, 31]. However, later the known geometry of the invisible markers has been exploited to estimate both the position and orientation of the markers from its view projection [32].

**Epipolar geometry to resolve view-overlap** Epipolar geometry [33, 34] provides a $3 \times 3$ singular matrix describing the relation between two perspective images of the same rigid object from two cameras. Epipole is the line connecting any two cameras seeing the same object (Figure 1.4). The point where epipole meets the camera frame is epipolar point and hence epipole can also be realized as a collection of epipolar points between corresponding frames of two cameras (Figure 1.4(a)).

Epipolar geometry has the basis that any object (in 3D coordinate) observed by two cameras and their projections are co-planar [3] (Figure 1.4(b)). The essential matrix formulated from epipolar geometry is further used for localization and camera




(a) Epipole as a collection of epipolar points




(b) Epipole and epipolar plane

Figure 1.4: Formation of epipolar geometry

calibration [17,35]. Kurillo *et al.* and Medeiros *et al.* [17,20] have employed Epipolar geometry to resolve point correspondence problem [36] and unknown scale factor [37].

In decentralized and distributed communication paradigm of multi-camera network, point correspondence problem can be solved through:

(i) measurement correspondence (where features of an object seen from different cameras are wrapped into a common view prior to state estimation).

(ii) trajectory correspondence (where state estimates are computed independently in each view) [38, 39].

A recent work of Bulusu *et al.* [40] exploits correspondence among trajectories estimated by Kalman filter to recover poses of non-overlapping cameras. Table 1.1 summarizes few landmark researches towards solving point correspondence problem.

Authors in [17] have used it for camera position and orientation. Researchers in [13, 40] have also used epipolar geometry for camera localization. Authors in [19] have proposed sensor assisted camera localization and have examined Measured Epipoles (ME) [41] and Estimated Epipoles (EE) [3]. They have also formulated a more constrained optimization problem, Optimized Estimated Epipole (OEE) to reduce the error in noisy Estimated Epipoles.

Table 1.1: Different approaches to solve point correspondence problem

| **Year** | **Author** | **Approaches** |
|---|---|---|
| 2004 | Mantzel et al. [13] | Time-synchronization correlation of feature points (extracted by tracked motion) |
| 2005 | Lymberopoulos et al. [19] | Deploying nodes with self-identifying lights (fails in bright or specular-filled environment) |
| 2006 | Devarajan et al. [42] | Scale Invariant Feature Transform (SIFT) based feature point correlation |
| 2008 | Medeiros et al. [20] | Time-synchronization correlation of feature points (using LED rod) + Recursion on fundamental matrix to refine camera positions |
| 2008 | Kurillo et al. [17] | Time-synchronization correlation of feature points (using LED rod) + Bundle adjustment to refine camera positions |
| 2010 | Kassebaum et al. [43] | 3D Target of known geometry and pairwise projection matrix estimation for point correspondence |

### Consensus and Belief Propagation-based Localization

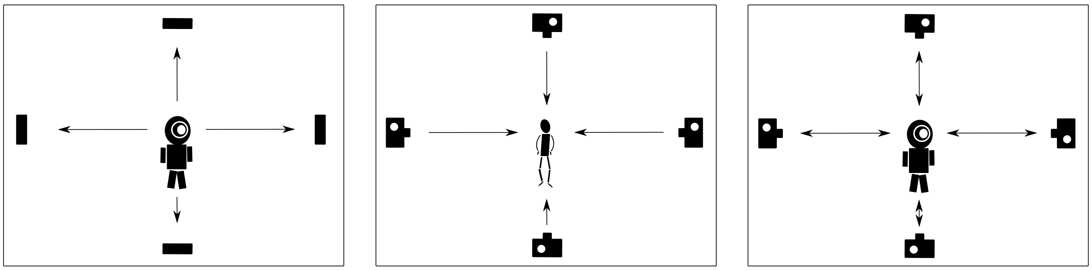
A consensus algorithm is an interaction rule that specifies the information exchange between an agent and all of its neighbours on the network. Consensus algorithms are used in many situations, viz. distributed formation control, synchronization, rendezvous in space, distributed fusion in sensor, flocking theory [44].

Consensus algorithms are used for getting global pose of a camera in a network, and have been used for localization with range measurements [45, 46]. Tron and Vidal [47] have generalized the consensus algorithm for estimating pose of each node from noisy and inconsistent measurements.

On contrary to this, notion of belief propagation have also been proposed for establishing localization [14]. Belief propagation is a message passing technique for graphical network model which have been applied for scene estimation, shape finding, image segmentation, restoration, and tracking [48–52]. Belief propagation has originally been developed for trees. When applied for graphs with cycles, inferences (belief) might not converge, and even if convergence occurs, density is not guaranteed [53, 54]. The non-convergent form of belief propagation (Loopy Belief Propagation (LBP)) [53] is used in sharing localization parameters in multi-camera localization.

Authors in [55] have presented a more robust algorithm than belief propagation in several aspects. This approach has been extended by researchers in [56] for localization of robot in multi-camera scenario (SLAM: Simultaneous Localization And Mapping) [57] where a robot observes all the landmarks and estimates its location and position of the landmarks. A similar concept has been proposed by Funiak *et al.* [11] for camera localization (SLAT: Simultaneous Localization And Tracking), where the camera replaces the landmarks and robot is replaced by a moving object. Robot observes the landmarks in SLAM (Figure 1.5(a)), whereas cameras observe the object in SLAT (Figure 1.5(b)). Funiak *et al.* [11] has also proposed Relative Over-Parameterization (ROP) to represent the distribution in SLAT problem using single Gaussian.

There had been efforts to find the trajectory of object and pose of camera simultaneously [11, 58]. In particular, Rekleitis *et al.*. have addressed the issue of localization in hybrid context of robot-camera network system [59], where object localization takes place along with camera localization (SPLAM: Simultaneous Planning Localization And Mapping) (Figure 1.5(c)). Here Robot can localize itself treating cameras as its landmarks (similar to SLAM). Likewise, cameras can localize themselves treating the robot as moving object (similar to SLAT). Estimation, local planned behavior, and data fusion are done for effective collaboration of camera network and robot in SPLAM.



(a) Simultaneous Localization And Mapping (SLAM) (b) Simultaneous Localization And Tracking (SLAT) (c) Simultaneous Planning Localization And Mapping (SPLAM)

Figure 1.5: Simultaneous localization techniques

### Wireless and 3D Localization

With increasing coverage area and number of cameras in a network, wireless mode of communication has grown its significance. Even though some research have been performed over wireless sensor network, their localization algorithms [60–67] do not hold good for camera network due to two main reasons:

(i) they do not achieve required accuracy for computer vision tasks.

(ii) they do not provide orientation of a sensor.

Lee and Aghajan [58] have proposed a wireless camera (connected by IEEE 208.11b protocol) localization algorithm capable of estimating both camera pose and trajectory of the object. This work has been experimented in 2D plane with only five cameras, while authors in [20] have proposed four different localization approaches simulated in a $20 \times 20 \times 20m^3$ 3D region with 50 randomly placed cameras. The system developed in [20] can perform in fully-distributed scenario, and does not require anchor-nodes. This approach employs feature-based object trajectory estimation, and hence performs depending on robustness of the used feature-extraction algorithm.

3D image reconstruction has remained an active research area in computer vision for many years. Tomassi and Kanade [68] have used matrix factorization as a way for reconstructing a scene, as well as to estimate camera parameters and frame point localization. This work has employed orthographic projection whereas authors in [69] have used perspective projection to serve the same. Sturm and Triggs [27] has also proposed more complete solution for measuring camera depth. Rahimi *et al.* [23] have pre-computed the homographies between image plane of each camera, and a common ground plane leading to 3D localization of cameras.

Lymberopoulos *et al.* [19] have proposed an algorithm that combines a sparse set of distance measurements with image information of each camera. It uses three LED triangles of known geometry for depth measurement. Tron and Vidal [47] have taken the work to distributed level by applying consensus algorithm and thereby enhancing the work of [6] and have generalized it from 2D to 3D.

Latest works on 3D camera localization include the work of [43]. Kassebaum *et al.* [43] have used 3D target. This is similar to the 2D targets like checker boards used earlier in [70, 71]. The advantage of 3D target is that in one frame it provides all the feature points needed by a camera to determine its position and orientation relative to the target. On detected feature points, DLT [72] is used to estimate projection matrix. The algorithm reduces the cost of feature point detection, number of overlaps and eliminates the unknown scale factor problem. Kassebaum *et al.* [43] have experimented with error less than $1in$ when 3D target feature point fills only

2.9% of the frame.

**Concluding Remarks**

Networked communication in early days used to exploit sound, radio and other acoustic signals for localization of static sensors. However, with the development of multi-camera network, it gradually became stringent to localize the nodes for initialization of a camera-network. There are several method devised depending on different types of coverage area, different strength of cameras in network, different types of camera used, and different purpose of the camera-network. The variation has been as wide as ranging from the work of Mantzel *et al.* [13] using 2D object (checkerboard) to be feature for localization till latest work of Kassebaum *et al.* [43] employing 3D target with error less than 2.9% and with decreased cost of feature point detection. Table 1.2 illustrates and compares few landmark researches to portray the variety of algorithms used, assumptions, experimental setups and results thus obtained. There has also been change in application domain of camera-localization and hence the need of precise localization. 3D localization addresses the issue of localizing more number of unknown parameters, whereas previous 2D localization dealt with less number of unknown parameters considering few parameters to be known. Sensing the availability of low-cost cameras, parallel research is going to make the localization algorithms distributed rather than centralized. Researches have also been perceived in the direction of accurate localization in presence of noisy environments, e.g. less number of available feature points, feature points on the visual boundaries of the cameras etc. These kind of algorithms are useful when number of cameras in a network is very high. However, scope for future research lies in achieving precision towards 3D pose calculation of camera.

Table 1.2: Review of related researches on multi-camera localization

| **Approaches** | **Algorithm** | **Assumption** | **Experimental Setup** | **Constraints** | **Results** |
|---|---|---|---|---|---|
| Mantzel et al. (2004) [13] | DALT (localization through triangulation, refinement through re-triangulation of 3D points through iterations | Assumes at least 2 or more cameras to be pre-localized | Not experimented practically; simulated using 20 actual views of checker board pattern with 156 corners (as feature points) | Each camera linked to 8 to 16 other cameras; cameras were pre-localized | 0.25% of planarity error; 14mm error in 3m scale |
| Lymberpou-los et al.(2005) [19] | Pairwise view overlap and epipolar geometry based estimation; ME and EE are evaluated to propose OEE; refinement through iteration | Coordinate transformations to distribute rotation and transformation between camera pairs | Indoor setup: 2 camera, 16 non camera nodes; Outdoor setup: 80 nodes. Each camera node consists of COTS OV7649 camera module having motion detection and LED identification; all nodes carry Lumex CCI-CRS10SR omnidirectional LED | Resolutions used: $640 \times 480$ (VGA), $352 \times 288$ (CIF), $240 \times 180$, and $128 \times 96$ (SQCIF); cameras can observe LEDs up to $4m$. | Indoor experiment: error of $2 - 7cm$ in a $6 \times 6m^2$ room; outdoor experiment: error of $20 - 80cm$ in an area of $30 \times 30m^2$; maximum error at lowest resolution is $3.32cm$ |
| Funiak et al. (2006) [11] | Complex distribution of SLAT is represented using novel approach of single Gaussian model ROP (Relative Over positioning); Quality of the solution is represented explicitly by uncertainty in estimate of camera poses | Out of 3 position parameters and 3 angles, paper focuses on 3 parameters $(x, y, \theta)$ assuming rest to be known | Simulated in square area with 44 side-facing cameras tilted down about 35° and 50 downward-facing cameras with pose estimation within 95% confidence intervals; Experimented practically in real network of 25 overhead cameras, and a remote controlled toy-car carrying a color marker moving around. | The subject is made to move in a circular path within the square area | Results of camera placements are shown in diagram for simulation as well as experiment in the article. |

Continued on next page ...

**Table 1.2 – continued from previous page . . .**

| Approaches | Algorithm | Assumption | Experimental Setup | Constraints | Results |
|---|---|---|---|---|---|
| Rekleitis et al. (2006) [59] | SPLAM for both target and camera localization; uses 3D markers over moving robots as feature points; information propagation among cameras using extended Kalman filter | The moving object is a robot | 7 camera nodes in a closed area consisted with rectangular loop triangular loop and a hall way of around $50m$ length; robot traversed 3 times covering more than $360m$ with 5 different movement patterns to perform 10 trials each | Automated detection and calibration system allows 50 trials and 1500 pattern detections; occurred in 3 hours using 3.2 GHz processor and Linux | 4 different paths: Stationary, 2 panel translation, rotation, and square are compared; Standard deviation of MSE in square pattern is maximum as $u_x$ and $u_y$ are 2.4 and 13.9 while in 2 panel translation it is minimum as 3.6 and 5.0 respectively |
| Sweeney et al. (2006) [24] | Based on OEE as an enhanced version of direct epipole observation (Measured Epipole) and Extracting epipole from fundamental matrix (Estimated Epipole); LED triangle of known geometry for depth measurement | Pair wise view overlap; modulated LED emission for unique identification | Camera used: imot2 nodes with COTS camera; 2 camera nodes and 16 non-camera nodes with blinking LEDs; indoor experiment in $6 \times 6m^2$ area and outdoor experiment in $30 \times 30m^2$ area | Cameras can see LEDs up to $4m$ in test condition; node to node distance is taken as $85cm$ (in indoor condition) and $297cm$ (in outdoor condition) | Indoor Experiment: OEE $7cm$ and ME $2cm$ with probability 90%; Outdoor Experiment: OEE $60cm$ and ME $20cm$ with probability 90% |

Continued on next page . . .

**Table 1.2 – continued from previous page ...**

| **Approaches** | **Algorithm** | **Assumption** | **Experimental Setup** | **Constraints** | **Results** |
|---|---|---|---|---|---|
| Taylor et al.(2006) [7] | Camera with controllable light source for signalling its position to other cameras for determining epipolar geometry; triangulation to determine the pose of non-camera nodes; refinement of pose values through bundle adjustment. | At least 2 camera nodes with light sources are required; rest of the node poses can be estimated using triangulation | Algorithm is only proposed; no simulations and practical experiment | Not simulated or experimented; hence no experimental setup | Only algorithm is proposed; hence no experimental results |
| Farrell *et al.* (2007) [25] | Localizes both camera and target; initially PTZ cameras are used for localization, then motes are localized using magnetometers (a non-imaging sensor); The algorithm can perform in centralized as well as distributed scenario | PTZ cameras are used initially for localization of nodes, once localized, non-imaging sensors are used further. | Simulated with 100 nodes distributed randomly in $100 \times 100m^2$ area; a subset of 5, 10, 20 and 50 nodes are taken for simulation; Experimented with 12 MicaZ motes with omnidirectional LEDs and 2 PTZ cameras (each with 3 position and 3 DOF rotation parameters); a subset of 6 motes is considered | For each node many PTZ parameters are obtained, their average is used for final location; noise is modelled synthetically to match observed noise | Simulation with different subsets of 100 nodes are taken, that shows the MSE is minimum of $11.73cm$ with a subset of 50 nodes and maximum ($96.25m$) with a subset of 5 nodes |
| Kurillo et al. (2008) [17] | Pairwise view overlap is considered; Epipolar geometry employed to calculate essential matrix for pose estimation; scale factor determined by markers on calibration bar; bundle adjustment for refinement | All cameras are pre calibrated and synchronized | Simulated with 5 cameras.While experimenting practically cameras are internally calibrated using $10 \times 15$ checker board; 12 dragonfly firewire cameras with resolution $640 \times 480$ pixels are used in $4.0m \times 4.0m \times 2.5m$ area | Two of the cameras (7th & 11th) are installed with $4mm$ lens and rest with $6mm$ lenses. In vision graph, camera # 3 is chosen as reference camera | Simulation errors are below 0.2% for noise levels of 0.6 pixels and less; in practical experiment image re-projection error varies from 0.0417 to 0.6750 as noise level changes from 0.0 to 0.7 |

Continued on next page ...

**Table 1.2 – continued from previous page ...**

| Approaches | Algorithm | Assumption | Experimental Setup | Constraints | Results |
|---|---|---|---|---|---|
| Medeiros et al. (2008) [20] | Pairwise view-overlap and epipolar geometry based estimation used; LED bars used for feature point detection and iterative refinement; Four different centralized and distributed approaches are introduced | Cameras are pre-calibrated | Not experimented practically, simulated in an environment with the dimension of the area is $20 \times 20 \times 20m^3$; 50 cameras on side planes and top plane are randomly placed; Single target moves randomly in the area to calibrate the cameras | Bundle adjustment or any such refinement process is not applied to keep it portable to wireless setup; $8 \times \log_2 k$ bits are required for estimation of each parameter, where $k$ is the number of objects used for calibration | Translation error $< 60mm$ and converges to around $30mm$ when simulated for longer time; Rotation error $< 1.20$ and converges to around 0.50 when simulated for longer time. |
| Piovan et al. (2008) [6] | Node orientation calculated using least square estimate in a ring topology based on angle of arrival sensing; iterative estimation algorithm to reduce the effect of noise | A reference frame is assumed to be attached with each of the node, the first node is labelled as reference node | Simulated using complete graph with 10 points (as 10 different nodes) making 36 independent cycles; not experimented practically. | The graph representation of camera-nodes is considered to be planner; noise between a pair of nodes in both the directions is assumed to be different | Orientation localizability error (shown as Mean Square Error) reduces with more iterations. As the number of independent cycle increases from 10 to 21 to 36, MSE reduces from 0.08 to 0.03 to approximately 0.025 respectively |

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**Table 1.2 – continued from previous page . . .**

| **Approaches** | **Algorithm** | **Assumption** | **Experimental Setup** | **Constraints** | **Results** |
|---|---|---|---|---|---|
| Tron and Vidal (2009) [47] | Consensus algorithm is generalized for estimating pose of camera nodes; optimization of translation and rotation through iterations | Each camera extracts a set of 2D points from each image; Neighbouring cameras can have point correspondence between them; All cameras are synchronized; communication among cameras is lossless | 7 cameras each of focal length 1 are distributed roughly in a circle of radius $8f$; Cameras connected as 4 regular graph; 30 randomly distributed feature points in a cubic area of $4.5f$ are taken; 8 point algorithm used for point correspondence problem; optimization of rotation with 600 iteration, optimization of translation with 3000 iteration and optimization of overall variables with 100 iterations; experiment repeated for 100 times for each level of noise | Error in rotation and translation with zero-mean Gaussian noise and standard deviation of 0, 1, 2, and 3 pixels in $1000 \times 1000$ pixels | Error in rotation reduces from 4.809% (initial) to 0.393% (after iterations) when the image is corrupted with zero-mean Gaussian and 3pixel standard deviation; error in translation reduces from 0.291% (initial) to 0.331% (after iterations) when the image is corrupted with zero-mean Gaussian and 3pixel standard deviation; scale error remained between 1.000% to 1.005% as the deviation ranges from 0 to 3 pixels |
| Kassebaum et al. (2010) [43] | Localization through feature point detection of a 3D target moved through the network; DLT method used for estimating projection matrix, further decomposed to get position and orientation parameters | Connected vision graph for pairwise view overlap | A 3D target moved for feature point collection; 5 smart cameras, other nodes are COTS webcams of $640 \times 480$ pixel resolution; simulated with 5 intrinsic parameters and 14 lens distortion parameters (estimated using Zhang's algorithm) | Experimented 3 times with feature points occupying less than 3% of frame area; 16, 24, or 32 out of 48 available feature points per grid are considered | Position error $< 1 inch$ when the 3D target feature points fill only 2.9% of the frame |

Continued on next page . . .

**Table 1.2 – continued from previous page . . .**

| Approaches | Algorithm | Assumption | Experimental Setup | Constraints | Results |
|---|---|---|---|---|---|
| Anjum (2011) [73] | Camera Localization Using Trajectory Estimation (CLUTE) is proposed; Works on distributed network of non-overlapping cameras; Uses Kalman filter to recover pose of camera | Known intrinsic parameters of cameras; Cameras aligned with respect to presumed reference camera during registration | Simulated with 4 and 8 camera network, experimented with 4 camera networks; To analyse in noisy environment, 5% Gaussian noise is introduced in the field of view of cameras | 4 cameras used in real time experiment with cameras placed $3-4m$ apart; Field of view of cameras are limited to square region of $1.5m^2$ coverage area | Through simulation, minimum translation error: $0.13unit$ and rotation error: 1.29°; Through experiment with real data: minimum translation error: $0.7unit$ and rotation error: 10.33° |

### 1.2.2 Camera Placement for Gait Based Identification

Since the evolution of MCN; and with the increasing affordability and adaptability of the system, many novel applications of MCN are developed. Sensing rooms, assisted living for old age or disabled people, immersive conference rooms, coverage and telecast of games and diverse applications in visual surveillance are to name a few. With difference in priority of coverage, types and numbers of camera and geographical conditions of coverage area, the placement of camera becomes an important issue of research. Moreover, as the number of camera in such system grows, the development of automatic camera placement technique becomes very essential. Optimizing the placement of camera not only reduces the cost of installation, but also increases the suitability of the system for specific task, thus increasing its performance efficiency.

Approach towards achieving suitability in the camera placement depends on the task MCN is intended for. Some of the strategies for camera placement with different goals are:

(i) Minimizing the number of camera, to cover a given area.This type of constraint helps in lowering the installation cost by reducing the number of camera.

(ii) Maximizing the coverage area with fixed number of camera. This type of constraint helps in increasing coverage with fixed number of cameras thus providing best coverage with given number and type of camera

(iii) Covering a human subject with maximum frontal view. This kind of constraints gives better result in face identification, gesture recognition, and visual tagging.

(iv) Covering for maximum orthogonal view. This kind of constraints are useful in surveillance oriented task like identification through gait patterns, occlusion handling while object tracking, height, and profile face based identification.

(v) Covering for best view synthesis. Complex set of constraints like nearer view, frontal view and/or larger view are used to achieve best view of a subject, such constraints are required in covering games and identification oriented tasks.

**Different Approaches for Suitability of Camera Placement**

Different approaches have been employed to achieve optimality in camera placement, viz. exact algorithms, heuristic algorithms, random selection and placement etc. Exact algorithms are considered to be giving proper solution although it is complex and time consuming. Such algorithms are preferred to solve strategies that involve minimizing or maximizing a value, constraint to other variable. Aghajan and Cavallaro [74] has discussed the cases where binary integer programming (BIP) is used to achieve optimal camera placement. Some of the cases preferably solved by BIP are :

(i) Maximizing the area under coverage with constraint to fixed number and type of camera (having different sensor resolution and optics), different FOV parameters and cost.

(ii) Minimizing the number of camera with constraint to fixed area under coverage, different FOV and cost.

There are some scenario where mathematical modelling are rather complex and hence exact solutions are time consuming. Such scenarios are solved by heuristic approaches like Greedy search and Duel Sampling. There are some cases that are solved with random selection and placement.

The problem targeted with BIP are mostly to cover maximum area or to minimize the number of camera in camera array, however in many scenario, typically in surveillance only covering a subject is not sufficient. Along with coverage of subject its identification, gesture recognition, and occlusion avoidance are also necessary.

Ercan and Yang [75] have proposed algorithm for optimal placement of camera arrays so as to accurately localize a point object in camera co-ordinate. In case of moving subjects Chen [76] has presented a camera placement algorithm that concentrates on eradicating probability of occlusion while maintaining resolution. This work has been further amended by Chen and Davis [77] for handling dynamic occlusion. These solutions does not produce global optimum, however they are best suited for the given constraints. Similar goals has been targeted by Ram *et al.* [78] that has also considered orientation of the subject into account. This work has been further enriched by Zhao *et al.* [79] for orientation and visual tagging of the subjects. The work of Takashshi *et al.* [80] have also proposed optimal camera placement for object recognition.

In case of large coverage area, linear programming based approaches are used for determining minimum cost of sensor array for given area [81], however similar work on visual sensors are used by Aghjan and Cavallaro [74] where coverage area is divided into rectangular grids. The concept of divide and conquer are used to approximate the optimal placement problem for large spaces, where each region is divided into rectangular grids and the optimal solution for grids are merged for total coverage space.

Optimal camera problem as such is a well studied problem and has close resemblance with art gallery problem [82], however, it has some additional facts like field of view of camera and camera pose. These camera placement problems are further modelled to optimality problem with maximizing coverage area or minimizing the number of cameras. These approaches provide a good job for view coverage of an area. But this may not be appropriate for such problems where the purpose of camera placement are task specific.Table 1.3 presents a few landmark research where first two column are orthodox optimality problems and rest are application specific. The table illustrates camera placement in different application domain to achieve different objectives apart from optimality.

The proposed multi-camera based surveillance model presented in this thesis has the goal of subject identification and uninterrupted track of the subject. In chapter 3, a divide and conquer based method for efficient camera placement has been presented that finds suitable camera placement for gait pattern and height based identification. It has been justified with a conducted experiment that orthogonal view of a camera is best suited for height and gait pattern based identification. The large coverage area is divided into rectangular grids and solution for each grid is merged to get final camera placement.

Table 1.3: Task specific optimal camera placement

| **Authors** | **Application Domain** | **Objective** | **Basic Algorithm** | **Assumptions** | **Claims** |
|---|---|---|---|---|---|
| O'Rourke [82] | Art gallery problem | Minimize number of guards to cover an art gallery, with variations like mobile guards, exterior visibility and polygon with holes | Triangulation | All guards (cameras) have same capability. No limitations of resolution and sensor property | No or minimum camera view overlap |
| Chakrabarty *et al.* [81] | Minimum cost sensor problem | Minimizing the overall cost of sensors in the network, that minimizes costs of camera setup and operation | Integer Linear Programming and Divide and Conquer | Circular range of sensors, hence not directly applicable for visible sensors | Unique identification of positions. Minimum sensor cost. |
| Olague and Mohr [83] | Camera network design in photogrammetry | Camera placement to reduce error while 3D object reconstruction | Genetic Algorithm | Pinhole camera assumptions. Projective parameters are assumed to be error free. | Proposed EPOCA system produces two and three camera network design successfully and proposes a four camera design |
| Chen and Davis [77] | Social surveillance for dynamic occlusion handling | Camera configuration for handling dynamic occlusion | Triangulation | Occlusion probability is independent of spatial location. | Higher and lower quality configurations for feature capturing. |
| Zhao *et al.* [79] | Visual tagging and frontal face based identification | Maintaining individual identity through tagging and frontal face coverage for face identification | Binary Integer Programming and Greedy Algorithm | All tags are in shape of square of known length. All tags have same height. | Camera placement for both self and mutual motion. Greed algorithm to compensate BIP. |

### 1.2.3 Camera Control for Occlusion Avoidance

For an MCN system that aims towards optimal usage of its resources, the efficient handling and control of the system is as important as the localization and task specific placement of camera. The previous sections of this chapter so far discuss the developments in the mode of camera calibration in the form of an extensive survey and discusses different approaches for finding suitable placement of cameras in diverse contexts. This section presents a study on different approaches towards handling occlusion in different camera models.

The efforts in technological growth have made way for the emergence of variety of methodologies for tracking objects in diverse contexts. Different algorithms have been designed for different requirements depending upon the mode of tracking, location, significance and specific needs. The earlier tracking approaches have implemented several image processing algorithms on the video output from a single camera. Contour based tracking, background subtraction based tracking, Gaussian based tracking, median filter based tracking, are some of the most studied and refined technologies among them [84]. These algorithms are simple in implementation, fast in processing and analysis. However, they are limited with constant field of view and suffer from occlusion of the tracked subject.

As the demand for fool-proof tracking algorithm prevailed so is the paradigm shifted from single to multi-camera model. These systems are more useful for tracking in crowded places and highly protected areas. This can be equipped with a variety of cameras and distributed processors to even amend the functionality of tracking. But multi-camera systems have their complexities and trade-offs. As compared with single camera tracking, multi-camera tracking needs additional processing, extra memory requirement, superfluous energy consumption, higher installation cost, and complex handling and implementation.

Occlusion handling is one of the major problems in single camera based tracking. In the model proposed by Sinior *et al.* [85] background subtraction is used for object tracking and occlusion detection. It uses appearance based model to estimate the centroid of the moving object more accurately. This technique is although reliable but works with fixed background. Authors in [86, 87] have handled occlusion based on measurement error for each pixel. Authors in [88] have devised a motion based tracking algorithm that is adaptive with natural changes in appearance or variation in 3D pose and hence remain robust with occlusion but does not resolve or predict occlusion. In [89] two different approaches to cope occlusion are proposed; one using evaluation of correlation error in templates and other using infra-red images to detect occluded region by human hand. Authors in [90] have exploited contextual information; it does better occlusion analysis but has tracking errors. It uses block motion vectors for calculating object boundary to predict occlusion. Amizquita *et al.* [91] have proposed an algorithm for auto detection of occlusion using motion based prediction of objects movement during the stages of entering occlusion, full occlusion, and exit occlusion.

On the other hand a multi-camera system can avoid occlusion and can provide robust tracking but are not as simple and energy-efficient as single camera systems. Although a camera system installed in master-slave mode [74], can achieve some level of efficiency but the entire region under coverage should come under master cameras view. Towards making the multi-camera model as an efficient approach a few other works have also been proposed. Kulkarni *et al.* [1] have proposed an approach for efficient use of multiple cameras by devising multi-tier camera network called SensEye [2]. This approach is energy efficient although it has a complex hardware architecture and diverse software requirement. It is observed from the literature that single camera based object tracking is simple, energy efficient and has the ability to predict occlusion. However, there is no scope for occlusion avoidance. To alleviate the occlusion occurrence, a multi-camera model is necessary where the field of view is tracked by multiple cameras. Generally, a multi-camera based approach utilizes the cameras always in the active mode. But this leads to energy inefficiency and more processing requirement. Our approach, as discussed in chapter 3 has been been designed to bridge the gap between single camera and multi-camera based surveillance system.

## 1.3 Thesis Organization

The rest of the thesis is organised as:

**Chapter 2: Study on Efficient Camera Placement Techniques** Placement of camera is a vital step while bringing efficiency in camera usage of MCN. The camera placement techniques changes vastly depending on the deployment conditions like limited number of cameras, constraint of area under cover, condition of best view synthesis, 3D image reconstruction or condition of gait based identification. This chapter studies the importance of camera placement in bringing optimality in camera usage of MCN. An efficient camera placement algorithm has been proposed taking gait based identification as test condition. Simulation has been performed and results have been presented towards the proposed algorithm.

**Chapter 3: Study on Smart Camera Control** Camera control is a crucial stage in MCN. It defines conditions that governs the control among the cameras in an MCN. A resource efficient MCN based surveillance model has been presented that is governed by proposed occlusion determination algorithm. The proposed algorithm determines the chances of occlusion, position and time to occlusion in prior so that necessary action can be taken towards its mitigation. The proposal has been experimentally justified on self acquired as well as publicly available database.

**Chapter 4: Conclusion** This chapter provides the concluding remarks with a stress on achievements and limitations of the proposed schemes. The scopes for further research are outlined at the end.

# Chapter 2

# Study on Efficient Camera Placement Techniques

Placement of camera is a vital issue towards development of multi-camera based smart surveillance system. Previous chapter highlights the necessity of calibration for efficient operation and smart handling of MCN. Camera placement along with its calibration completes the infrastructure of Multi-Camera Network (MCN). An MCN designed with the goal of surveillance must provide uninterrupted track and prospect for subject's identification. This chapter proposes a camera placement technique with a task of capturing orthogonal view of the subject that creates the prospect of identification based on gait, height and profile face of a subject for the sake of surveillance. Placement of camera is very crucial in surveillance. A suitably placed array of camera brings two way benefits for the system, cost optimization of MCN and enhanced performance due to tailor made camera placement approach for specific task.

In the proposed surveillance model presented in this thesis, efficiency at the level of camera placement has been identified as an important measure for achieving the goal of optimal multi-camera set-up without compromising with standards of surveillance. The proposed model is considered to be performing identification of moving subject through its gait patterns, its height and profile face, and also ensuring uninterrupted track of the subject. With these goals, cameras are proposed to be placed in such a way that it finds the path of the moving subject orthogonal to the view axis of the camera. Further sections discuss about the unique behavioural biometric feature called gait; which is a special cyclic pattern an individual repeats during a walk. It has been justified through conducting an experiment and also through the support of some existing results that orthogonal view is suggested as best view for capturing gait information. Further, a novel approach has been presented for estimating the best place for camera placement in an open space, with maximum chances of capturing subjects' movement orthogonal to the walk direction. This proposal is been experimentally conducted at Vikram Sarabhai Hall of Residence, NIT Rourkela and the model has been justified with proper results.

Section 2.1 presents introduction to gait biometric. Section 2.2 proposes a novel approach of camera placement for gait pattern based identification. The experiment towards the proposed model has been presented in Section 2.3. A few conclusive remarks based on the experiment are discussed towards the end in Section 2.4.

## 2.1 Gait Biometric

Locomotion of an individual which is repetitive with same frequency and carries a temporal pattern is termed as gait [92]. Walk, trot, run, and to climb stairs are among such locomotion in which an individual has a temporal pattern that repeats with same frequency. This makes these activities candidates for being gait.

The earlier progress towards establishing gait as a biometric trait is successor to the research of Johansson [93] where experiments have been performed to differentiate among different human postures by examining 10-12 nodal points over

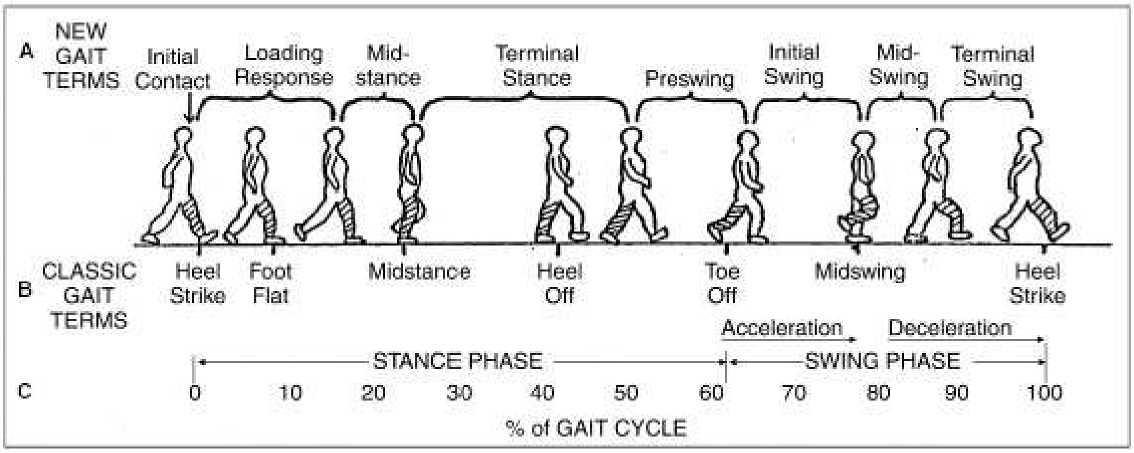



Figure 2.1: A complete gait cycle

human body based on different sequence of biological motions done by the body and hence by the points. In recent past, gait biometric has been commonly used in sport biomechanics to study and rectify the posture and movement of an athlete. Gait has been used in the medical field over the patients for rectification of ill-movement of a part of the body. In both the above cases there are predefined ramp and individuals are restricted to walk over that. Recently gait is used for identification of an individual and is therefore employed as a part of surveillance system. In such situation gait recognition is done in unconstrained scenarios. Since there is no predefined path of movement, therefore there are no perfect camera positions and there remains scope for minimizing the number of cameras, improving the position of cameras, and to optimize their usage.

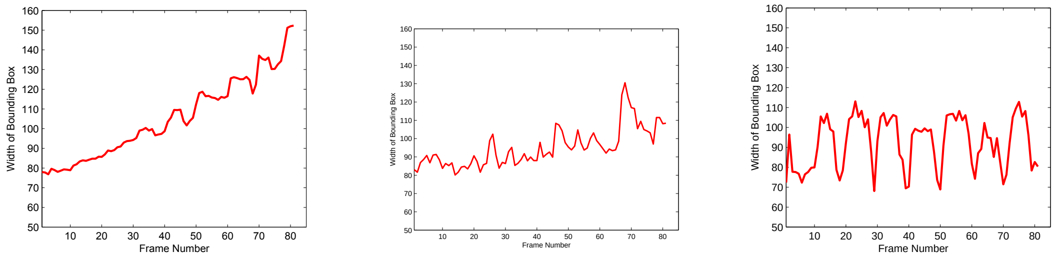
A few works have been done towards identification through gait where computer vision techniques are not used. Mantyjarvi *et al.* [94] have used accelerometer and does not rely on computer vision. However majority of the works further includes camera-view for analysis and feature extraction of gait pattern. In [95], Teixeira *et al.* have proposed a PEM-ID system using cameras and accelerometer to identify and localize people through their gait pattern. Goffredo *et al.* [96] have proposed gait identification through single camera to avoid the complexity of calibration of multiple cameras. Bouchrika *et al.* [97] have presented a new approach for tracking and identification between different non-intersecting uncalibrated cameras based on gait pattern analysis. Jeges *et al.* [98] have worked towards estimating human height in calibrated cameras that can be used as a supportive feature for identification. This justifies why camera placement plays a crucial role for gait analysis in unconstraint scenario.

A camera can best capture the gait features when it is placed orthogonal with respect to the motion of the subject. Such positions of camera also make tracking easier and are best placed for height measurement. Our proposed model has an overhead-camera that prepares a path-band, based on the locus of various subjects traversed over a span of time. Other field-cameras are PTZ cameras that are placed at such positions where they can get maximum orthogonal views. These positions are estimated by overhead-camera using the proposed algorithm and path-band information. Further camera set-up works in master-slave mode so that overhead-camera guides field-cameras to track the target efficiently. Section 2 of this chapter states the problem under consideration in detail. The subsequent steps of proposed model towards the solution of the problem are illustrated in Section 3. Section 4 presents the experiment conducted towards the proposed model. The result of the experiment has been presented in Section 5. Finally, Section 6 concludes the chapter along with stating the scope for future works towards the proposed model.

## 2.2 Proposed Model

When a camera network is set-up to identify a subject walking in a given area, the locus of the subject is not known in prior. Hence best positions for camera placement cannot be statically defined. If a most probable path can be estimated based on paths traversed earlier, then camera placement can be done efficiently. Secondly, there can be an effort to find the minimal number of cameras along with their poses to cover the path. However, minimum required number of cameras depends on the nature of path traversed most frequently by the subjects. Number of cameras working together generates large volume of recorded data, which is difficult for storage and processing as well. Minimizing the number of cameras partially resolves the problem. Further reduction in computation is achieved as the camera network works in master-slave mode where awaking, sleeping, and panning of field-cameras is monitored by the overhead-camera.

The proposed model is governed by the fact that the best view of a moving subject for gait recognition, tracking, height measurement and profile face based identification can be done when the line of sight of camera is orthogonal to the movement of the subject. Experiments have been conducted to support the above mentioned fact. The walking pattern of an individual is captured through different cameras, and background subtraction is applied on all the video thus obtained. Background subtraction method separates the moving subject from its stationary background and puts a rectangular boundary over the moving subject. Figure 2.2 shows graphical plots representing the pattern of change in the width of bounding box around the moving subject for three different camera views of the motion of same subject. Figure 2.2(a) represents the plot when camera is capturing the frontal view of the subject making an angle $\sigma = 0$ with the direction of motion, Figure 2.2(b) represents the view captured at $\sigma = \pi/4$, and Figure 2.2(c) represents the view captured at $\sigma = \pi/2$ i.e., camera placed orthogonal to the direction of motion. As $\sigma$ changes from 0 to $\pi/2$, gait cycles becomes gradually detectable. Two of the major gages for gait pattern, heel-strike (when the legs of the moving subject are maximally apart), and mid-swing instant (when the legs are crossing each other) are clearly visible as the peaks and troughs in Figure2.2(c) and are occurring with approximately same frequency. This justifies the necessity of orthogonal placement of camera for capturing gait pattern. A complete gait cycle can be seen in Figure 2.1, that presents a complete gait cycle and subsequent phases in a gait cycle.




(a) $\sigma = 0$ (b) $\sigma = \pi/4$ (c) $\sigma = \pi/2$

Figure 2.2: Change in width of bounding box of moving object with different camera placement angle

The number of field-cameras depends on the curvature of obtained path-band, area under surveillance, and resolution of the cameras used. Proposed model towards solving the above mentioned problem is described in the following sections.

### 2.2.1 Locus Tracking of Subjects' Movement

Movement of people in any area depends upon the type of area, obstacles around the area, entrance point, exit point, shortest distance from entry to exit etc. Hence there is no mechanism to predict the exact path to be travelled by a particular individual. This model proposes to place an overhead camera capturing the top view of the whole surveillance area, albeit of low resolution. It is so away from people that individuals cannot be recognized from the low-resolution images, but various loci of different individuals can be traced by background subtraction and frame-wise connectivity check. This operation takes place during a sufficient span of time to get enough data of the traced paths.

Each frame captured from the surveillance area is divided into grids of size $8 \times 8$ pixels. The overhead-camera captures sufficient set of data of various paths, which makes a visible pattern of movement of individuals in the surveillance region. Figure 2.3 shows the above mentioned scenario in an assumed area under surveillance.

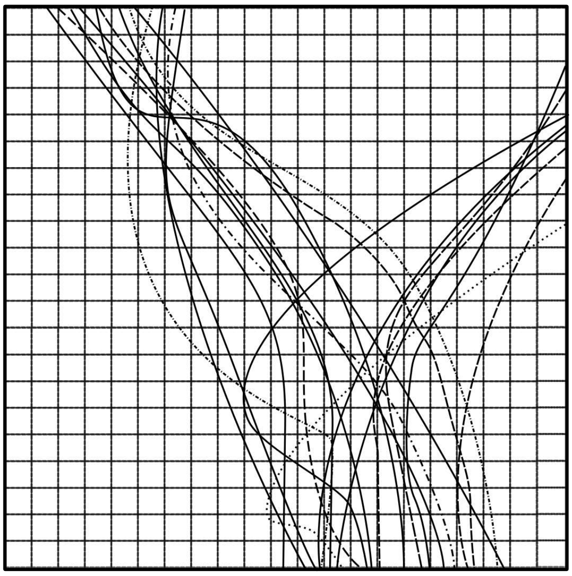


Figure 2.3: Loci of different subjects tracked by the overhead-camera

### 2.2.2 Direction Vector Calculation

In the further sequence of processing, direction of movement of each individual in each grid is studied. The direction of movement is discretized into predefined angles based on the pattern of the pixels of individual motion in each grid. Figure 2.4 shows the pixel patterns and the angle inferred from them. The angle of movement ranges in $[0, \pi]$. The movement is not considered in $[0, 2\pi]$ because the directions: $x$ and $x + \pi$ produce same orthogonal. Histograms of the direction of angles of different traces are plotted with bin-width of $\pi/8$ for each grid blocks. If a single bin in the histogram contains number of traces above a threshold, it signifies existence of prominent maxima indicating a unique direction of movement as shown in Figure 2.5 (a).

If all the bins in the histogram are below a threshold, it implies approximate uniform distribution with no explicit maxima and the grid block is considered to be a chaos region with no specific direction of movement of subjects (an example is shown in Figure 2.5(b)). Hence these kinds of grid blocks are rejected, and no

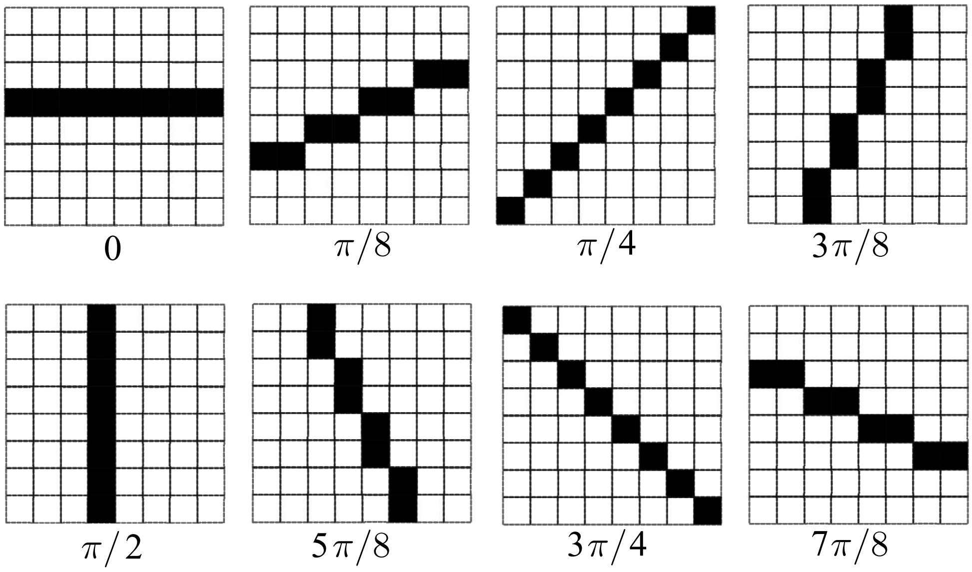



Figure 2.4: Inference of angles from discrete pixel patterns in $8 \times 8$ grid

direction vectors are assigned to them. Direction vectors assigned in such a way yields a collection of grid blocks with respective direction vectors. However, apart from chaos regions and grids with specific direction vectors, there may exist grids owing to such portions of surveillance area where no person traverses. These grids comprise no locus, and hence not considered for further processing (an example is sown in Figure 2.5 (c)).

### 2.2.3 Path-band Estimation

All such grid blocks with explicit maxima will be considered for path-band estimation. Each such direction vector has its bin height (indicating the number of individuals travelled along the particular direction in the grid) as the magnitude of respective direction vectors. These magnitudes are compared and grid block with highest magnitude of its direction vector will get selected first. If more than one magnitude is found to be the maximum then anyone can be selected randomly for further processing. Generally such grid blocks are found at entry or exit points of the surveillance area.

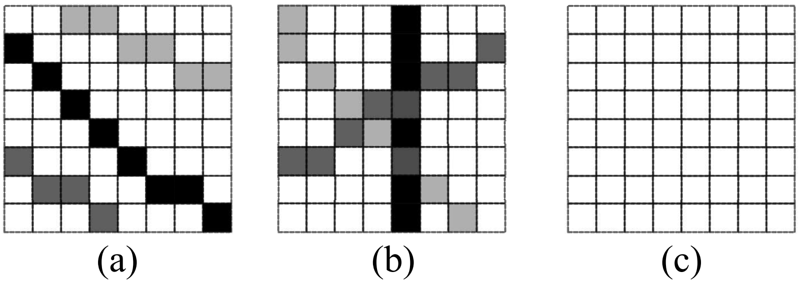


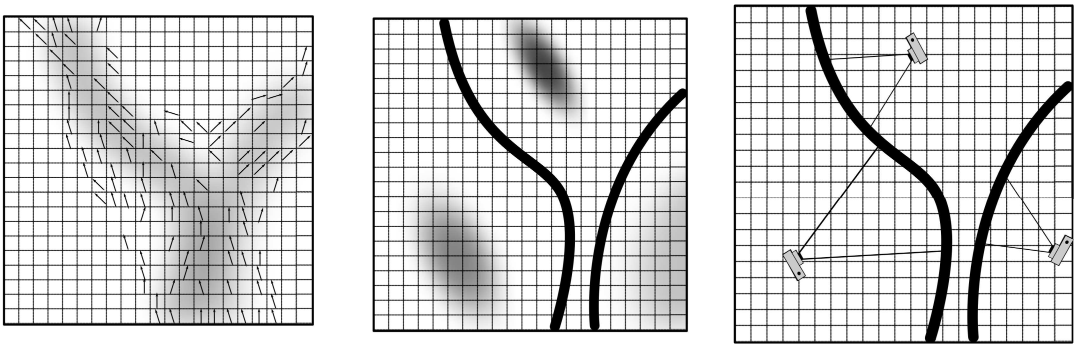

Figure 2.5: (a) Grid indicating unique direction of movement, (b) chaos region, (c) grid with no locus

Further, immediate 8-connected neighbours of the selected grid blocks are compared for contributing to the path band. A few blocks with low magnitude are rejected for further iteration, and rest goes to further processing. Again immediate neighbours of last iteration blocks are compared for rejection. As the iteration goes until the edges are arrived in the grid view of surveillance area, a path-band is formed as a collection of direction vectors. Figure 2.6(a) depicts formation of a path band.

When the number of walks are more, their vectors are high in number. Path-band estimation in such scenario reduces the number of perpendiculars to be drawn, since rather than drawing perpendicular from each vector, now perpendicular has to be drawn only on the thinned path-band. However in the experiment section, with less number of walks, this step has been avoided.

### 2.2.4 Finding Efficient Camera Placement

Perpendicular can be drawn on each direction vector and at each point of the path band. There will be collection of points where more than a certain number of perpendiculars intersect. Voting is done for each pixel of the surveillance region to find how many perpendiculars are passing through a particular point. Number of perpendiculars passing through a point also depends on the number of traced paths considered while training of overhead camera. Collection of these points will form a few potential regions (depicted in Figure 2.6(b)). There may be physical constraints as lack of place for installing cameras, which has to be considered to reject few points from the potential region. Further, out of available points in a region, the one with higher number of intersections may be chosen for camera placement. A sample placement of camera is illustrated in Figure 2.6(c).



(a) Estimated path-band

(b) voted regions for camera-placement with thinned path-band

(c) sample placement of three along field-cameras

Figure 2.6: Finding efficient camera placement

### 2.2.5 Localization and Working of Camera Network

An overhead-camera of fixed type is already placed that has fetched the best probable locations for placing PTZ cameras. PTZ cameras have the ability to pan, tilt and zoom according to the way they are programmed to. Placing PTZ cameras at such points can best utilize the location of its placement since it can pan with the movement of the subject to be tracked, and to capture the gait pattern for longer duration. Since the camera remains approximately orthogonal to the subject with a high probability, it is best-positioned to estimate the height of the subject as well.

Further camera set-up (overhead-camera of fixed type, and field-cameras of PTZ type) can be made to work in master-slave mode [74]. For this, camera set-up should be calibrated and localized. Overhead camera works in master mode and PTZ cameras work in slave mode. Master camera analyses from its top-view that which field camera should remain active and what should be the panning speed to constantly track a subject. This lets the camera-network to be used pro-actively and also optimizes the computational cost. Field-cameras which are not active may go to sleep mode to reduce power consumption and to reduce complexity of calculation. Hence the master camera efficiently manages the mode of slave cameras for optimized use.

## 2.3 Experiment

To verify the proposed work of camera placement, experimental set-up has been done at the corridor of Vikram Sarabhai Hall of Residence, NIT Rourkela. From the top floor, camera has been attempted to be placed over the corridor to get top view and video footages has been taken at different times of the day. Figure 2.7 shows frame sequence of the video footage taken from the top floor of the corridor.

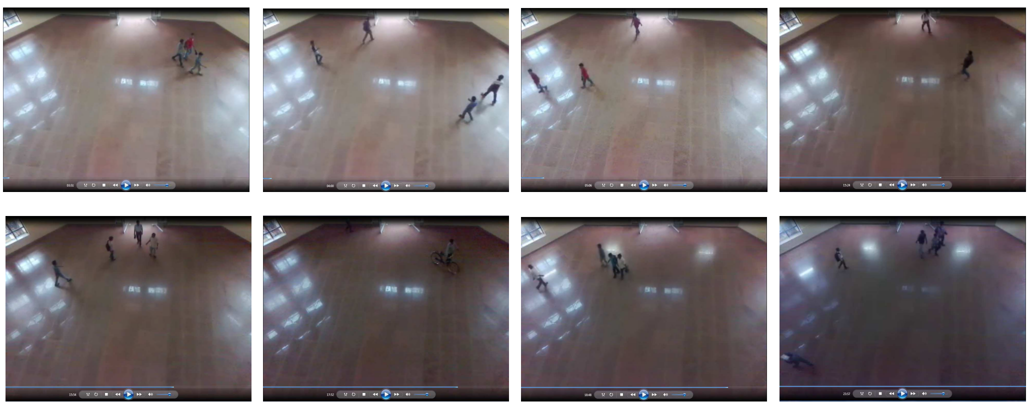
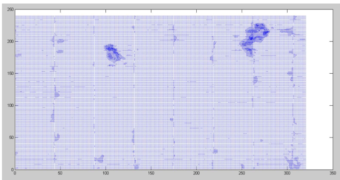


Figure 2.7: Corridor sequence

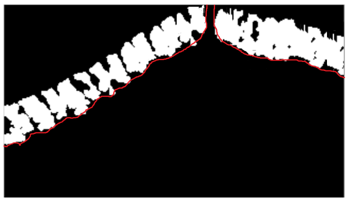
## Trace of The Subject

On the different acquired video footage, Horn and Shunk optical flow method [99] has been applied to obtain optical flow of the subject's movement. Further, binarization of frame sequence and tracing the bottom of the silhouette has been performed over the optical flow to get path-band as traces of all the subjects. Figure 2.8(a) shows a frame of the video where two subjects are found to be walking in the corridor. Its optical flow and binary frame sequence are shown in Figure 2.8 (b) and (c) respectively.

(a) Example Image Sequence



(b) Optical flow of Subjects



(c) Trace in a binary frame sequence

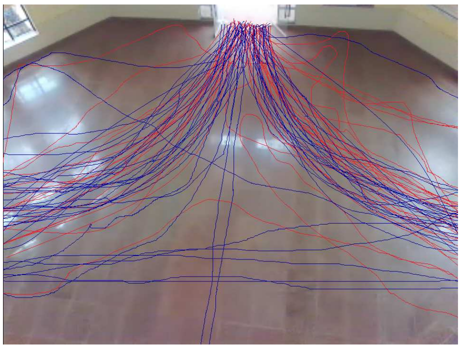
Figure 2.8: Finding trace of the subjects by optical flow

## Mapping on Grid-map

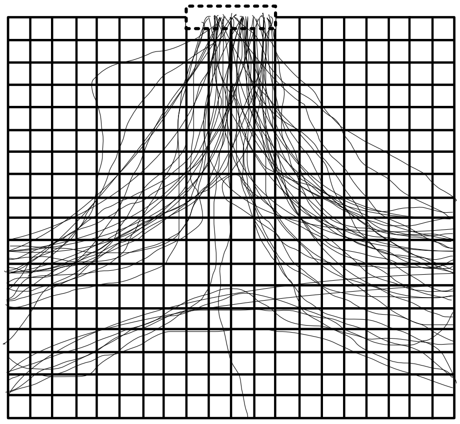
Traces, so far acquired are over camera image, but due to camera placement limitations, overhead camera image is perspective in nature. Thus the method of homography has been applied to achieve point correspondence of the traces over grid-maps. Figure 2.9 shows traces over overhead camera view and corresponding trace over grid-map.

## Direction Vector Estimation

Each grid in the grid-map has $8 \times 8$ pixels. After binning has been done for all the traces in a grid, the bin with maximum height is compared with other bin heights. If apart from nearest neighbour bins any other bin has height at least 0.8 times the



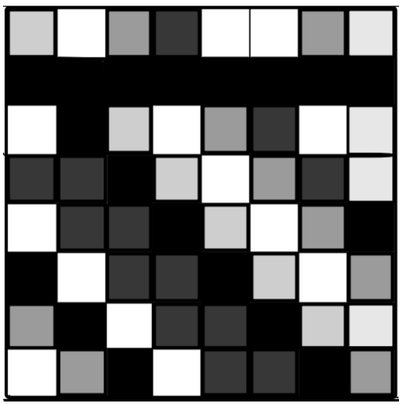
(a) Traces of different subjects



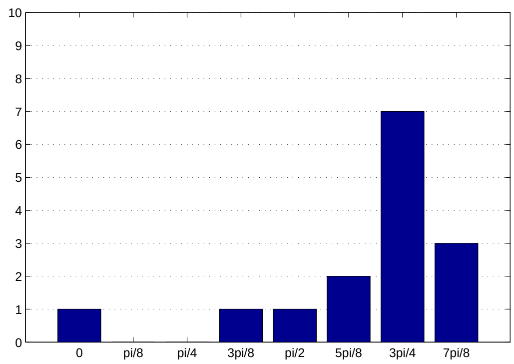
(b) Corresponding traces on grid-map

Figure 2.9: Plotting traces over grid-map from captured images by homography

height of highest bin, then the grid has more than one orientation and such grids are considered to be chaos region. However, if the grid has a specific orientation, that orientation is assigned to it. Performing this operation over the grids gives a path-band of direction vectors. Figure 2.10 shows an example grid with 15 walks and its corresponding plot where there is a proper orientation of subjects movement and hence a direction is assigned to this grid.



(a) sample grid




(b) graphs depicting proper orientation

Figure 2.10: Sample grid and histogram for orientation of movements in the grid

### Camera Placement Regions

An $m \times n$ matrix has been taken where m and n are number of rows and columns of grids in the corridor. Further for each of the grids with proper orientation, an increment of one is done in those corresponding cells in the matrix from where a perpendicular to that orientation will pass. Thus the matrix will be updated for each grid with proper orientation, and the grid from where most of the perpendicular lines pass, their corresponding cell in the matrix will get higher value.

The matrix is finally plotted in a 3D mesh plot where x and y represents the length and width of the corridor and z axis represents the observed number of perpendicular lineson the path of moving subjects as shown in Figure 2.11. The two humps in the plot represent regions with maximum intersection of perpendiculars and hence two probable proximities for camera placement according to this experiment. the result in this plot produces two regions for camera placement and grid locations (4,4) and (5,18) produces highest score in their respective proximity and hence are suggested for camera placement. With more number of walks more precise places of camera can be achieved. In places with relatively less significant walk pattern and fixed number of field cameras available for placement, this algorithm can be inferred for best $n$ places for camera placement, where $n$ is the available number of field cameras.

## 2.4 Concluding Remarks

As the number of subjects walk through the coverage area, there will be more number of locus and hence more data for overhead-camera to refine its calculation. Hence camera placement is refined over the time. At the time of path-band calculation, only those grid blocks are considered where a good number of loci are passing almost parallel, assuring that orthogonal to the direction vector of this block will be orthogonal to most of the locus at this grid block. On the contrary, chaos region

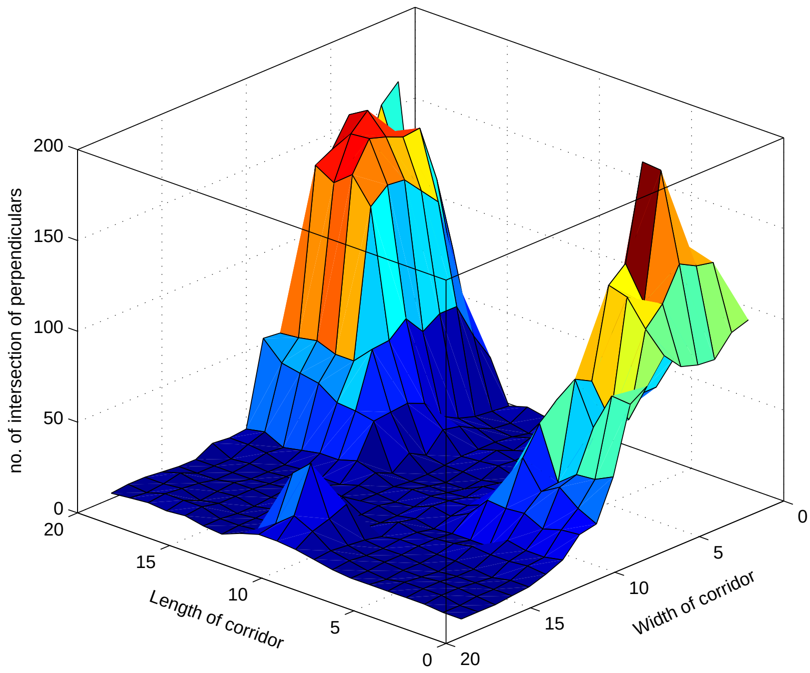



Figure 2.11: 3D mesh plot where two of the humps depicting probable places for camera placement

would not contribute to path-band. This assures maximum orthogonal view of camera from the subject's locus. If the path-band turns out to be a consisting very less curvature, then the region of camera placement is spread through both the sideways of the band, indicating that all the points on both sides of the band are equally potential for placing of field-cameras. Further each field-camera, when calibrated and localized with overhead-camera, optimizes the usage of the camera-network. The accuracy of finding the loci and hence performance of the proposed model severely depends on the resolution of the cameras. Although there are ample theoretic justifications of the model proposed and its simulated verification the proposed model still awaits experimental deployment in some surveillance zones.

# Chapter 3

# Study on Smart Camera Control

Once the cameras are well placed and calibrated in a surveillance zone for a specific task, control flow among the cameras is a crucial stage toward development of a smart MCN based surveillance system. This chapter proposes a smart MCN model which uses the architecture of MCN but avoids its complexities and overheads, by letting single camera to track the subject at any instant of time. The control flow from one camera to another is governed by an occlusion determination algorithm that determines the chances of occlusion, so that with prior knowledge of occlusion, control can be forwarded to such camera that does not encounter any occlusion. This way multiple track of the subject can be avoided (an overhead in MCN based surveillance), at the same time uninterrupted track of the subject (a limitation in single camera based surveillance) can be achieved.

The discussed multi-camera model for visual surveillance works on a single camera which is a part of multi-camera system and instead of handling occlusion; it pre-determines occlusion and avoids its occurrence. The proposed approach analyses the change in the dimension of the subject in camera coordinates as it moves in the 3D world coordinate. It analyses the data to decide the direction of motion and apparent speed of the subject and further determines chances of occlusion and its time and location of occlusion in the camera plane. Based on this, further decision towards avoiding occlusion can be made.

Background subtraction is a reliable method for localization of a foreground with respect to a fixed background. The results of background subtraction are used in this approach for analysis. A few reasonable assumptions are made in our approach while considering motion of subjects, such as eight possible directions of motion and three levels of speed for any subject on move have been considered. This assumption discritizes the approach at both the levels of direction as well as speed. The proposed system can be well described by sub-dividing into following three steps:

(i) Motion analysis

  (a) Direction of motion determination

  (b) Apparent speed determination

(ii) Occlusion determination

(iii) Mitigation of occlusion

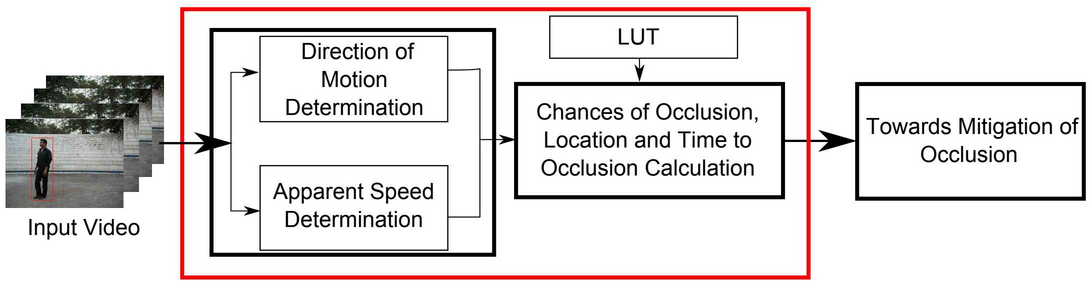



Figure 3.1: Proposed camera control model governed by occlusion determination algorithm

The above three steps are depicted in the form of block diagram in Figure 3.1. Motion analysis of a subject is performed to determine the direction of motion as well as speed of the subject as observed in the image plane. Variation of height and width with respect to frame number of a subject's motion is been exploited to determine the direction of motion. Subject's speed as appear in camera frame vary with distance of subject from camera and hence termed as apparent speed in this context. Apparent speed is determined as displacement of centroid of the subject in few frames. The information of direction and speed is forwarded to the next step for determination of chances of occlusion, and its position and time to occlusion. These two steps of the model have been preformed to achieve prior knowledge of occlusion in a scene. A prior knowledge of occlusion is forwarded further and necessary measures can be taken towards mitigation of occlusion.

Section 3.1 gives brief description of the database used for the experiment. Section 3.2 discusses the motion analysis of the subject. The results of motion analysis i.e. direction and speed information are further utilised for occlusion determination which has been discussed in Section 3.3. Section 3.4 presents the scope towards steps for mitigation of occlusion. Next section presents a few results of occlusion as well as non occlusion. Finally, based on the proposed algorithm and performed experiment, conclusive remarks are presented in Section 3.6.

## 3.1 Database Used

Experiments are performed over both publicly available as well as self acquired databases. Initially experiments are conducted over a set of self acquired database. In order to verify the algorithm over a globally available database, CASIA Dataset A [100] gait database has been used. Since the data is intended for angle invariant gait pattern based subject identification, they are not sufficient for the proposed experiments. For the sake of direction determination, the database is modified and mirror imaged.

CASIA Dataset A is intended for study of gait pattern of different subjects moving at different angles of 0°, 45°, and 90°from the view axis of camera. For our experiments of determining discrete direction, the same database has been modified and mirror image data have been generated to have enough video in all eight directions as needed for this experiment.

The modified database contains 20 subjects making 2 walks in each direction, thereby accumulating 40 videos in each direction, hence a total of 320 videos. These videos have to be classified into 8 directions based on the analysis of pattern of dimensional change in the bounding box of the subject.

Background subtraction method has been used for extracting foreground in self acquired sample videos for system testing, however the investigation results are generated on both self acquired and the CASIA database which is already background separated and algorithm to remove unwanted blobs are subsequently applied to them.

## 3.2 Motion analysis

Motion analysis of the subject gives information about the direction and apparent speed of the subject's movement. This section analyses the motion of the subject to determine direction and speed and presents experimental steps, inferences and results.

### 3.2.1 Determination of Direction of Motion

A subject in a plane is free to move in all the directions. Calculation of exact direction of movement is neither a perceptive solution for real time execution nor it is feasible with low resolution video footage. Since the prime motive of direction calculation is to contribute towards occlusion mitigation, the possible direction of subject's motion has been reduced to eight discrete directions as encountered by the camera. Figure 3.2 shows the direction vectors labelled from 1 to 8 with respect to camera. These direction vectors are equidistant and hence distinguishable. However,

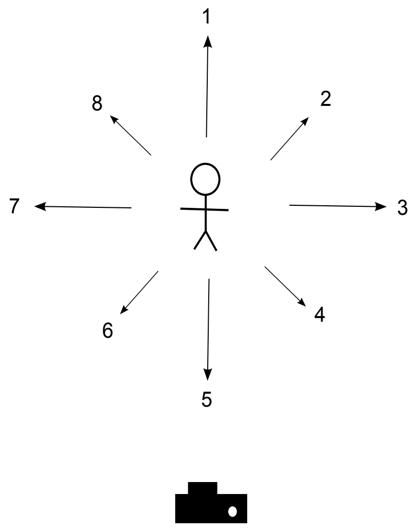



Figure 3.2: Discrete directions of motion with respect to camera

increasing the number of direction vectors decreases the estimation result on low resolution videos and decreasing the number of direction vectors, affects further processing , hence the discretization of eight direction vector is quite justified.

Since the direction of motion has to be utilized for approximating the chances of occlusion, discrete direction can be applied. The discrete direction will also provide faster computation which is needed for real time processing. To realize the direction of motion of a subject, change in the width, height, and location co-ordinates of the bounding box of the subject is studied. The pattern change in the subsequent frames of sample video during the motion in the perspective view of camera is shown in Fig. 3.3. The change in the dimension as well as location in the camera frame of a subject together make a unique pattern for each of the direction. Variations of height and width with respect to frame number for four different direction of motion of a subject are plotted in Figures 3.4 and 3.5. This gives the pattern based on which the direction of motion can be explained.

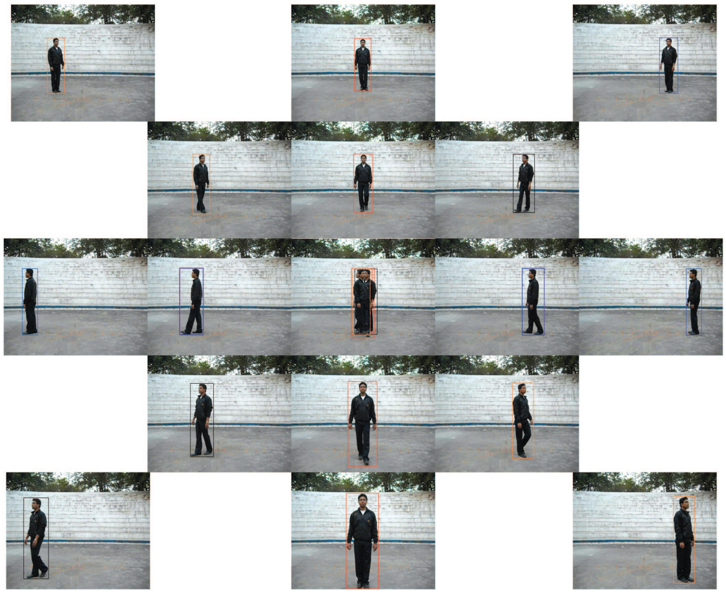


Figure 3.3: Pattern change in the dimension of subject

**Study of Frames and Inferences**

Fig. 3.4 and 3.5 show change of pattern in height and width of the subjects as it moves along different directions. When the subject is moving orthogonal to the view axis (i.e. along direction vector 3 or 6), the cyclic pattern is visible in regular interval in the width graph, however height remains constant as can be seen in the height graph. When the subject is moving along the view axis (i.e. along direction vector 1 or 5), then the subject appears to be growing in width and height from vanishing point and vice versa for opposite motion. Hence it is very obvious that the width and height has some pattern distinguishing them from another and a smart mechanism is needed to identify them. Next section of this chapter presents various steps taken towards direction estimation of moving subject and its further implementation.

**Experiment**

The aim of the experiment is to generate a phase or phase band of the graph that represents the direction of motion of the subject.

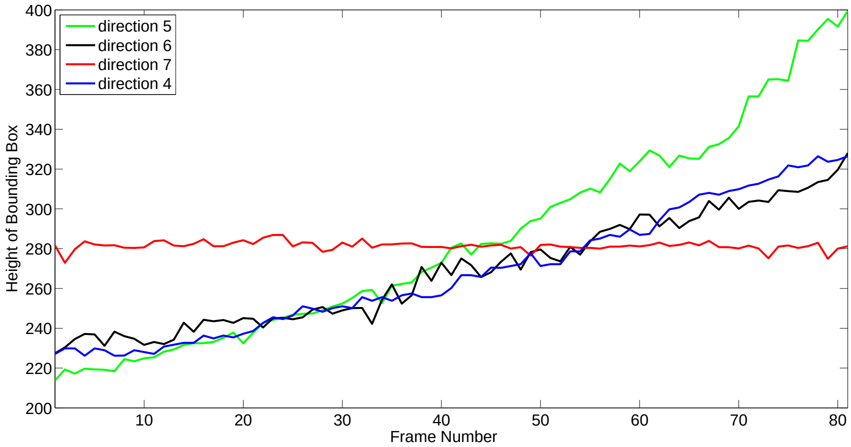



Figure 3.4: Variation of height with respect to frame number for four different direction of subject's motion

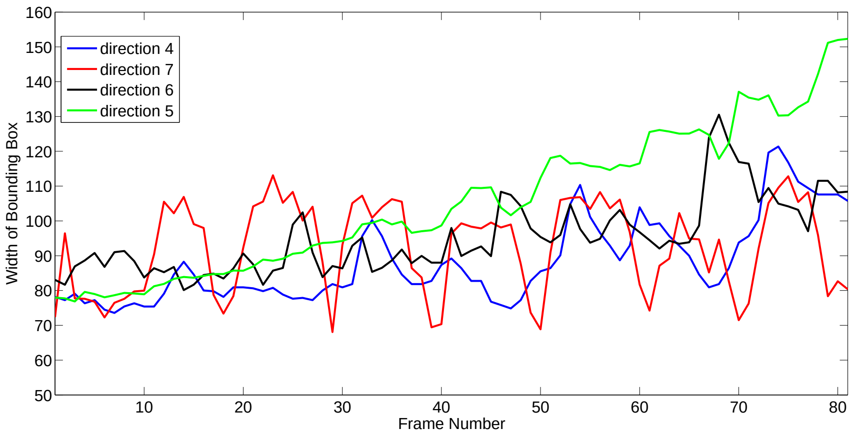



Figure 3.5: Plot of width for different direction

**Challenges** In order to generate a unique phase or phase band for motion in a particular direction, a system is required to be robust towards many issues that has been listed here:

- Low resolution database.
- Static occlusion causing foreground to be unavailable for few frames.

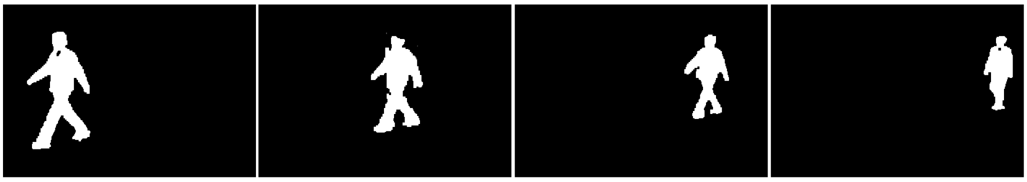
- Improper segmentation.
- Variable speed during the walk.
- Direction of motions being approximate rather than exact.
- Different distances of subject with respect to camera.
- Different amount of distances covered or different number of gait cycles of walk available for analysis.

In order to meet above mentioned challenges, following stages are performed towards achieving a unique phase band for each direction. The following paragraphs elucidates each of these stages in sequence.

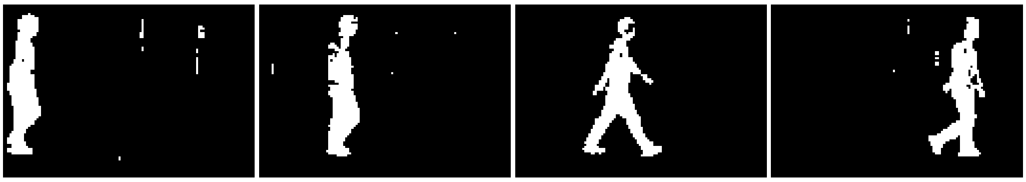
**(a) Frame Rectification and Removal of Undesired Blobs** The frame sequence provided in the database are segmented and are converted to binary image sequences. Frame contains unwanted blobs due to improper segmentation, presence of noise and partial occlusion. Unwanted foregrounds are deleted by selecting of largest connected component. Optical flow based methods are applied for rectification of improper segmentation. Figure 3.6 shows, few frames from two video sequences and their rectified forms after unwanted blob removal.

**(b) Morphological Operations and Tracking the Subject** On the rectified frame sequence, moving subject is identified and rectangular bounding box is fitted over them to get the track of the moving subject. Further, the subjects are tracked where the pattern of change in the dimensions of the subject are recorded for further reference. In the perspective view, the dimensions of the subject are varying, and this fact has been exploited to differentiate between the subjects that are moving in different directions. The pattern in the temporal change of width as well as height are plotted, and different plots for height and width are obtained which have been utilised for two way analysis for estimating the direction of motion of the subject

(a) Frame sequence 1 with noise



(b) Frame sequence 1 after noise removal



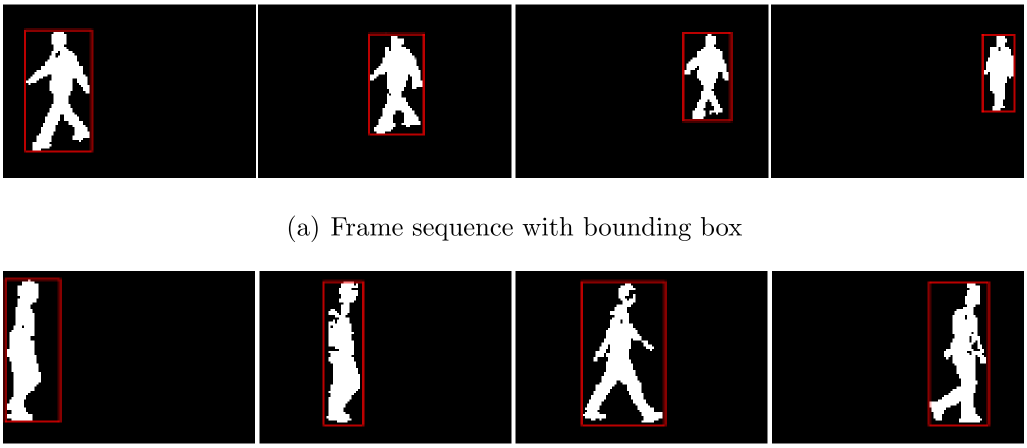
(c) Frame sequence 2 with noise

(d) Frame sequence 2 after noise removal

Figure 3.6: Frame rectification and unwanted blob removal

under study. In the Fig. 3.7, a frame sequence with direction vector 6 is shown after noise removal and morphological operations.

**(c) Extrema Detection and Putting Envelop Over the Plot** After getting the plots of the frame sequence, next objective is to distinctively identify the plots such that plots of same direction of motion should come under same identifier. Subjects may be observed nearer or farther from the camera and hence the graph in both the cases may look different although there may be similarity in the pattern of the graph. Thus to achieve distance invariance, and to overcome a few of the



(a) Frame sequence with bounding box

(b) Frame sequence with bounding box

Figure 3.7: Morphological operations and tracking of subject

improper segmentation, graphs have been proposed to be presented in terms of linear regression of the extrema boundaries of the graph. This step has been elaborated and divided into following sub-steps for better understanding:

- **Covering envelope over the plots** The prime objective of finding the envelope is to process the envelope further to boil down the graph into a line of the form $y = mx + c$,

  However, the span of the envelope i.e. the difference between $m1$ and $m2$ (as shown in Fig. 3.8 ) and the area covered by envelop, can be used to study the distance of the subject from camera in particular cases as well. Higher the area covered, closer the subject is from camera. Upper envelope has been made from a set of local maxima points representing the maximum width or height of the subject recorded in a gait cycle while capturing subject's movement.

- **Soft Extrema Elimination** The envelope has been made over local maxima and minima points in the graph, but improper segmentation of videos has resulted into some trough regions formed at upper fragment of the graph and certain crests are formed at lower fragment of the graph. Due to this, a few minima points exist in the maxima region and vice versa. This can be seen

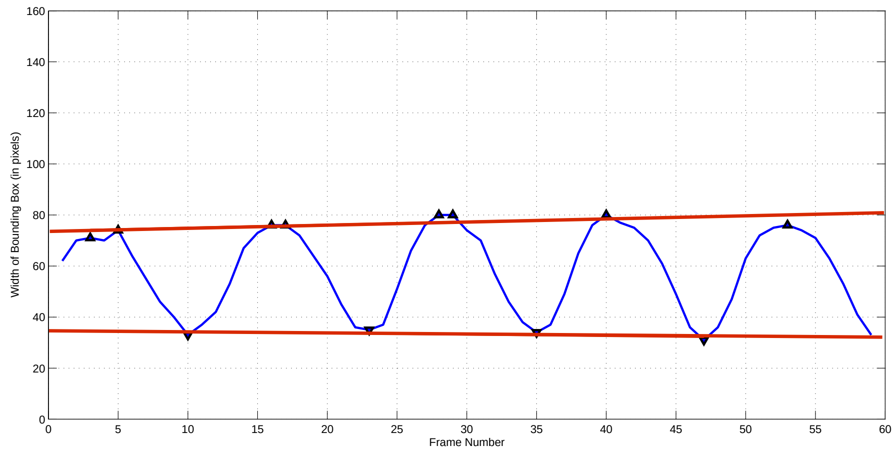
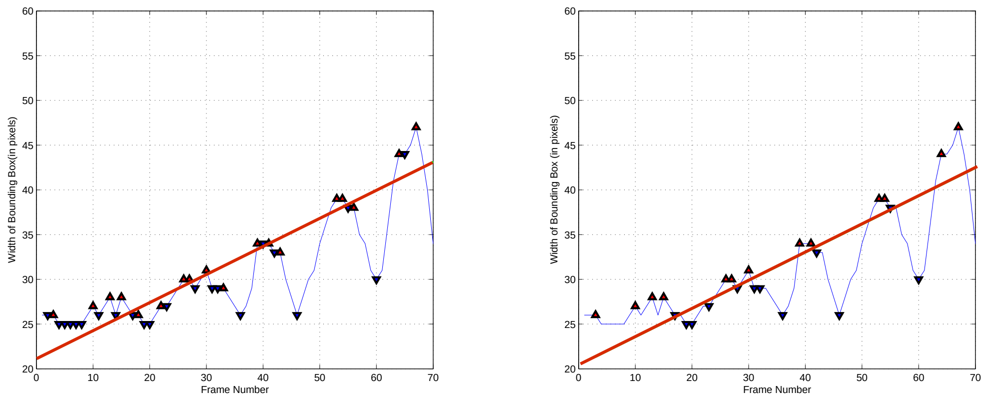



Figure 3.8: Envelop over the plot

in Fig. 3.9, which is a graph of a particular subject in CASIA Dataset A) walking at an angle of 45° with respect to camera. Such misplaced extremas are eliminated before calculation for putting envelop. A linear fitting is done over the curve to decide whether an extrema is correctly placed or not.




(a) Extrema points including soft extremas (b) Extrema points after excluding soft extremas

Figure 3.9: Detection and removal of soft extremas

Linear regression is a statistical analysis for association between two variables.

It is used to find the relation between them. In the context of the proposed work, our objective is to eliminate erroneous data that could contribute in constructing envelop over the graph. To identify such points, a linear regression function has been cast-off, where 2-tuple variable point's co-ordinates are,
$(x, y)$ = (dimension, frame number) where dimension: length or width in different graphs
The linear regression relationship between $x$ and $y$ is given in the slope-intercept straight line equation form as:
$y = mx + c$
where,

$$m = \frac{n\sum y - (\sum x)(\sum y)}{n(\sum x^2 - (\sum x)^2)}$$

and,

$$c = \frac{(\sum y)(\sum x^2) - (\sum x)(\sum xy)}{n(\sum x^2) - (\sum x)^2}$$

and, $n$ = number of variable pairs to be regressed, in this case they are the number of readings for each walk i.e. the number of frames in the video under study.
The resulted regression line $y = mx + c$ is plotted on both the graph types i.e. width vs frame number and height vs frame number. Maxima points are always expected to lie above this line and minima are below this line. Those points that do not satisfy these criteria are named soft extremas in this context and they have to be eliminated. After elimination of such points, the envelop generated are represented by these two equations
$y = m_1x + c_1$
$y = m_2x + c_2$
Finally, a line as average of these two lines are plotted, which is represented as
$y = mx + c$
where, $m = \frac{(m_1+m_2)}{2}$

and, $c = \frac{(c_1+c_2)}{2}$

Fig. 3.10(a), shows envelop drawn by the regression lines of the extremas after removal of soft extremas. Later, the average of the two lines has been taken are drawn as phase and shown in Fig. 3.10(a)

**(d) Study of Phase of the Line** The line represented as $y = mx + c$ carries the information of phase i.e. direction of motion of the subject and its distance from the camera. Thus we have distance invariant, phase information of the motion of the subject with respect to the studies of width and height of the subject.

Thus two different equations obtained from different graphs are

$y = m_h + c_h$ from the study of change in height

$y = m_w + c_w$ from the study of change in width

Where

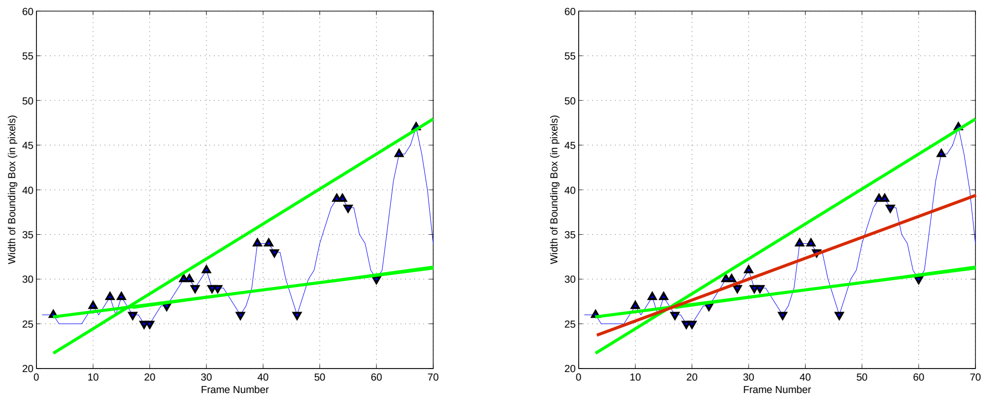
$m_h$ : Phase representing subjects direction of motion with respect to height

$m_w$ : Phase representing subjects direction of motion with respect to width

$c_w$ : Representing subjects distance from camera with respect to width

Subjects may be moving nearer to or farther from the camera; however the phase of the subject does not alter with the distance of the subject. Fig. 3.11(a) and 3.11(b) represent subject moving in the direction 3 but at different distances from the camera. Distance from the camera affects the span of the graph generated, however the phase of the subject in both the cases are nearly same thus bringing distance invariance in the system.

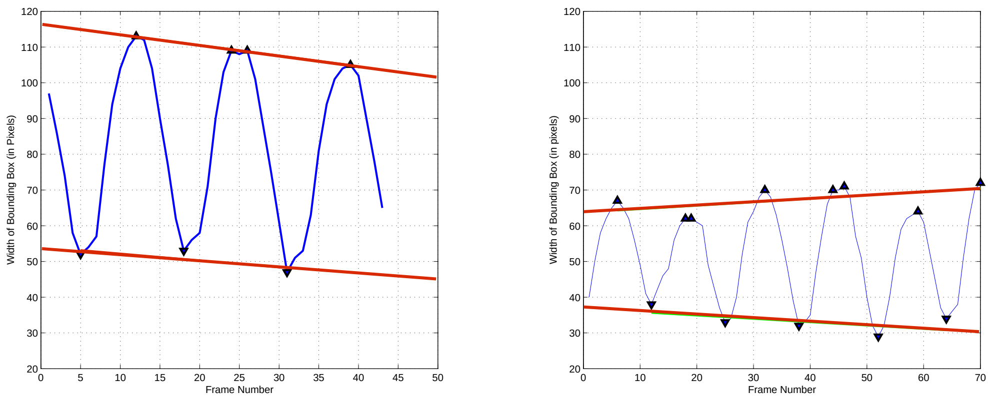
**(e) Plotting of Phase and Determination of Direction of Motion** For each sample video, we have its phase information with respect to height and width. All these values are plotted and two separate graphs are obtained having all $m_h$ and $m_w$ information. The $m_h$ and $m_w$ of the subjects moving in the same direction (i.e. the in-phase videos) are shown as connected points in separate graphs in the next section. Thus the phase information has been exploited to estimate the direction of




(a) Regression line on extremas as envelop to the graph (b) Average line depicting phase of the graph

Figure 3.10: Envelop and average line drawn based on envelop

motion of the subject.




(a) Subject moving closer to the camera (b) Subject moving farther to the camera

Figure 3.11: Distance invariant direction of motion estimation through phase

### Results

The direction of the subject has been estimated based on the height and width information of the moving subject. Fig. 3.12 and 3.13 shows the results in graphical representation where connected points in the graph represents the phase of the subject moving in the same direction. Out of 8 discrete directions, direction 2 & 8, and 4 & 6 overlap, since the videos are mirror image and mod of slopes are plotted in the graph. They are presented with different markers attached with them, as shown in corresponding legend chart. Further best fitting linear separator is applied on the curves to minimize misclassification and achieving best accuracy. The system has an overall good estimation accuracy as follows:

- height based accuracy is 93.75%
- width based accuracy is 83.75%

Also, the algorithm copes well with diverse situations like presence of noise and occlusion, variable speed, inexact direction of motion, variable distances of subject and low resolution videos. However, with better segmentation the results can be further improved.

Further, that algorithm has been run on 320 different videos for 400 times on a system for estimating its suitability in terms of time consumption. The algorithm has been tested over following simulation platform: It has Intel Xeon processor with 4 parallel processing core of frequency 2.4 GHz each and 8 threads. It has 8 GB of RAM and 12 MB of cache memory and runs on 64 bit instruction set. The average time taken for direction estimation is 1.04 sec. with a maximum and minimum time consumptions of 1.97 sec and 0.62 sec.

### 3.2.2 Apparent Speed Determination

Determination of speed is done in parallel to direction calculation. The speed calculated here is in terms of pixel displacement as observed after a fixed number of frames. A subject closer to the camera may appear faster while the one which is far from the camera may appear slower. Hence it is apparent speed and not the actual speed. Like direction, speed is also discretized to three levels, high ($v_3$), medium ($v_2$), and low ($v_1$). Once the subjects are determined, their centroids are known,

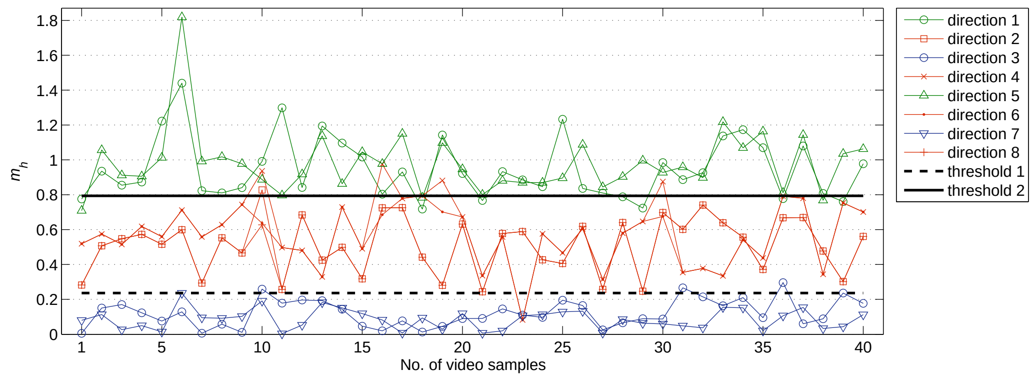



Figure 3.12: Direction estimation result based on height of the subject

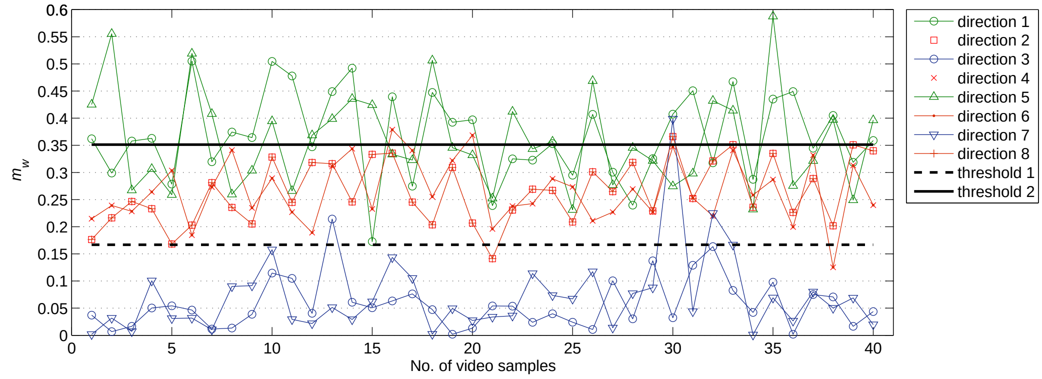



Figure 3.13: Direction estimation result based on width of the subject

and the displacement of these centroids are calculated in terms of pixels. Depending upon the frame width of the frame sequence, a subject is assigned with any of these speeds:

$v_3$ : if $p > 5\%$ of width of frame

$v_2$ : if $1\%$ of width of frame $< p \leq 5\%$ of width of frame

$v_1$ : if $p \leq 1\%$ of width of frame Where is $p$ is the pixel displacement of the subject in fixed number of frames.

Occlusion occurs due to mutual motion of the subject. With respect to image sequence at 2D camera co-ordinate, the mutual motion gives two separate information

- Change in the dimension of the subject, that eventually gives the direction of motion of subject
- Change in the location of subject that gives the speed and present location of the subject

Both of these information are already estimated by the approaches proposed in the earlier section. Next section describes the application of these information in determining the proximity of occlusion.

## 3.3 Occlusion Determination

Successful calculation of direction and apparent speed of a moving subject takes the work to the next level where based on the above results, chances of occlusion of a subject is determined. The direction of motion and speed informations are used in lookup table generation. Further, based on the lookup table chances of occlusion and its location and time to occlusion are calculated. This section presents some pre-calculations, and steps for developing lookup table. Once the lookup table is generated, it can be referenced for determination of chances of occlusion, and in cases of occlusion determination of time and position of occlusion in camera frame. Further, related calculations are presented in this section.

**Pre-calculations** : Given the first $f$ frames

* **Locations**: Centroid of both the subjects $S_p$ and $S_q$ represented as their locations as
$L(S_p) : (x_p, y_p)$
$L(S_q) : (x_q, y_q)$.

* **Deciding $S_1$ and $S_2$** : With the location information of both the subjects, the one with lesser abscissa is said to be Subject 1 ($S_1$) and the other subject becomes Subject 2 ($S_2$). This has been described in the algorithm 1.

* **Distance**: Apparent distance between the subjects can be calculated in terms of pixels as
  $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$

* **Directions**: Direction of a subject $S_1$
  given by $D(S_1)$ is the discrete direction of a subject as determined in the Section 3.2.1
  Such that,
  $D(S_1) \in \{1, 2, 3, 4, 5, 6, 7, 8\}$
  $D(S_2) \in \{1, 2, 3, 4, 5, 6, 7, 8\}$

* **Speeds**: In the first $f$ input frames, the pixel displacement of the subject's centroid gives apparent speed of the subject, which is categorized to three levels as fast ($V_3$), medium ($V_2$) and slow ($V_1$). This has been discussed in Section 3.2.2. The speed is in terms of pixel displacement in $f$ frames and while calculations in the next section, $V(S_1)$ and $V(S_2)$ are presented as $p_1$ and $p_2$ respectively.
  Such that,
  $V(S_1) \in \{V_1, V_2, V_3\}$
  $V(S_2) \in \{V_1, V_2, V_3\}$

### 3.3.1 Lookup table generation

The direction of mutual motion of the subjects mostly determines the chances of occlusion, hence estimation is not only dependent on 8 discrete directions of a subject but on the mutual combinations of motion of the subject. Hence, chances of occlusion due to direction of motion of any pair of potential occluder are best represented with an $8 \times 8$ matrix. Further, with each pair of direction of the subjects their

**Algorithm 1:** Algorithm for deciding $S_1$ and $S_2$

**Data**: $L(S_p) = (x_p, y_p)$

$L(S_q) = (x_q, y_q)$

**Result**: $S_1$ and $S_2$

**if** $x_p = x_q$ **then**
  No different subjects identified
**end**
**if** $x_p \leq x_q$ **then**
  $S_1 = S_p$
**else**
  $S_1 = S_q$
**end**

three possible levels of speed, hence a two level lookup table is designed to infer the chances of occlusion.

At the first level, the mutual direction of the subjects are exploited and an $8 \times 8$ matrix depicting 64 possible mutual pair of directions are presented. Following inferences can be made from the direction information of the subject:

- If the subjects are approaching each other i.e. if (D($S_1$)=(1 || 2 || 3 || 4 || 5) & D($S_2$)=(1 || 5 || 6 || 7 || 8))−(D($S_1$)=(1 || 5) & D($S_2$)=(1 || 5))
  then, there must be an occlusion. These cases with certain occlusion are given a value of 1 in the lookup table. Further, in such cases finding the proximity of occlusion is the task i.e. finding the time and location of occlusion in the frame. This has been elaborated in the next section.

- If the subjects are departing or stationary with respect to each other i.e. if D($S_1$)=(1 || 5 || 6 || 7 || 8) & D($S_2$)=(1 || 2 || 3 || 4 || 5)
  Then, there are no chances of occlusion and no further calculation towards occlusion handling is required. These cases with no occlusion are given a value

0 in the lookup table.

- If both the subjects are moving in the same direction i.e. if D($S_1$)=(2 || 3 || 4 ) & D($S_2$)= ( 2 || 3 || 4 ) || D($S_1$)=(6 || 7 || 8) & D($S_2$)= (6 || 7 || 8)
  In such situation direction information is not sufficient and the apparent relative speed between the subjects is required. Speed dependent cases in the first level of lookup table are detailed for three levels of speed in the second level. At this level of lookup table, each 0 represents that either subject's apparent speeds are identical or the difference is very low to encounter occlusion within the frame. However, in other cases, speed, direction of motion and mutual distance is exploited to calculate whether occlusion will be encountered within the frame or not. Table 3.1 represents lookup table, where speed dependent occlusion cases are not presented. In Table 3.1 $P(O|S)$ presents the speed dependent cases. Each such cases can be further detailed for three levels of speed represented with $3 \times 3$ matrix. If both the subjects are moving in the direction (2||3||4), then Table 3.2 represents the matrix to be substituted for each occurrence of $P(O|S)$. If subjects are moving in the direction (6||7||8), then Table 3.3 represents the same. Here Table 3.2 and 3.3 when substituted to Table 3.1 adds another dimension for speed in the chances of occlusion calculation. The occurrence of $C$ in the Table 3.2 and 3.3 represents that no analogical determination of chances of occlusion is possible and the results can be drawn based on calculation as given in Equations 4.5 and 4.6.

### 3.3.2 Time and Location of Occlusion Calculation

Time and location of occlusion i.e. the location and time of occlusion is required to be calculated in cases when occlusion between two subjects are certain. On the other hand, there are other set of cases when both the subjects are moving in the same

Table 3.1: Matrix for direction based occlusion probability estimation

| | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 |
|---|---|---|---|---|---|---|---|---|
| D1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| D2 | 1 | $P(O\|S)$ | $P(O\|S)$ | $P(O\|S)$ | 1 | 1 | 1 | 1 |
| D3 | 1 | $P(O\|S)$ | $P(O\|S)$ | $P(O\|S)$ | 1 | 1 | 1 | 1 |
| D4 | 1 | $P(O\|S)$ | $P(O\|S)$ | $P(O\|S)$ | 1 | 1 | 1 | 1 |
| D5 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| D6 | 0 | 0 | 0 | 0 | 0 | $P(O\|S)$ | $P(O\|S)$ | $P(O\|S)$ |
| D7 | 0 | 0 | 0 | 0 | 0 | $P(O\|S)$ | $P(O\|S)$ | $P(O\|S)$ |
| D8 | 0 | 0 | 0 | 0 | 0 | $P(O\|S)$ | $P(O\|S)$ | $P(O\|S)$ |

Table 3.2: Matrix for speed based occlusion determination with directions $(D_i, D_j)|(i, j) \in \{2, 3, 4\}$

| | V1 | V2 | V3 |
|---|---|---|---|
| V1 | 0 | 0 | 0 |
| V2 | C | 0 | 0 |
| V3 | C | C | 0 |

Table 3.3: Matrix for speed based occlusion determination with directions $(D_i, D_j)|(i, j) \in \{6, 7, 8\}$

| | V1 | V2 | V3 |
|---|---|---|---|
| V1 | 0 | C | C |
| V2 | 0 | 0 | C |
| V3 | 0 | 0 | 0 |

direction and whether their occlusion will be encountered in the current camera or not is the issue. This section discusses the calculation involved in both the cases one by one.

**When the subjects are approaching each other** Motion analysis of the subject determines the direction of their movement, based on which lookup table has been generated that indicates the chances of occlusion. If the subjects are found to be approaching towards each other, then the occlusion is certain and next task is to calculate its proximity i.e. its time and location of encountering occlusion. Let
$p_1$ : apparent speed of $S_1$
i.e. $p_1$ pixels travelled in $f$ frames (1 second)
$p_2$ : apparent speed of $S_2$
i.e. $p_2$ pixels travelled in $f$ frames (1 second)
if subjects are approaching each other
then, relative speed between subjects=$(p_1 + p_2)$
i.e.$(p_1 + p_2)$ pixels would be covered in $f$ frames
then, $d$ pixels would be covered in $\frac{d}{p_1+p_2}$ seconds
therefore time to occlusion is given by

$$\frac{d}{p_1 + p_2} \tag{3.1}$$

and, frame number of occlusion is given by $(\frac{d}{p_1+p_2}) \times f$
if $(x, y)$ be the point of occlusion, then
equating the distance equation between two points and distance as product of time and speed

$$(\frac{dp_1}{p_1 + p_2})^2 = (D_1)^2 = (x - x_1)^2 + (y - y_1)^2 \tag{3.2}$$

$$(\frac{dp_2}{p_1 + p_2})^2 = (D_2)^2 = (x - x_2)^2 + (y - y_2)^2 \tag{3.3}$$

also, considering the relation between $(x, y)$ and $(x_1, y_1)$

$$\frac{(y - y_1)}{(x - x_1)} = m \tag{3.4}$$

where $m$ being the slope of motion direction of $S_1$

Using Equations 3.2,3.3 and 3.4, the location of occlusion is given by

$$x = \frac{2(mx_1 - y_1)(y_1 - y_2) - ((D_1)^2 - (D_2)^2) + ((x_1)^2 - (x_2)^2) + ((y_1)^2 - (y_2)^2)}{2m(y_1 - y_2) + 2(x_1 - x_2)} \tag{3.5}$$

and

$$y = -mx_1 + y_1 + mx \tag{3.6}$$

The apparent location of occlusion is thus given by $(x,y)$.

**When the subjects are moving in the same direction** Direction of motion of the subjects are not sufficient to determine the chances of occlusion in some cases. These are the cases when both the subjects are moving in the same direction and any chance of occlusion depends upon the relative speed between the subjects. Considering the same variables if subjects are departing each other,

relative speed between subjects=$(|p_1 - p_2|)$

$d$ pixels would be covered in $\frac{d}{|p_1 - p_2|}$ seconds

Now, using same distance Equations 3.2, 3.3 and 3.4, the co-ordinates of location of occlusion can be determined. However, in this case if the co-ordinates $(x, y)$ are within the frame range, then occlusion will be encountered in the view of this camera, otherwise no occlusion will be observed.

## 3.4 Mitigation of Occlusion

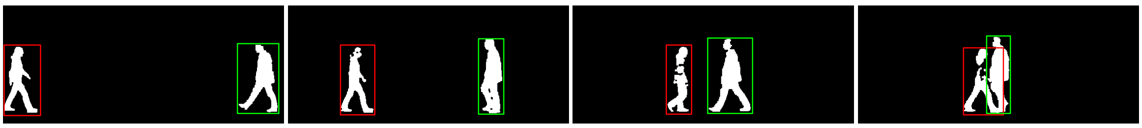
Based on the direction of motion and speed of the subjects, their probability and proximity of occlusion are determined. Up to this level, the system acts as a single camera system. After a conclusion is drawn about the proximity of occlusion, then steps towards mitigation of occlusion takes place. Multiple cameras in the systems are precalibrated and localized. Hence the poses of cameras are known to each other. In case of any possible occlusion, the active camera selects minimal number of cameras in the network that is not expected to encounter occlusion at the same time. This camera will awake those set of cameras and they start further tracking of subject. This will not only let the continuous tracking of subjects possible but also let the cameras to work efficiently in terms of energy and avoids processing complexity.

To justify the proposed approach towards occlusion determination, different cases are experimented. Sample videos are captured with various possible motions in different directions depicting the scenario of occlusion and non-occlusion. CASIA Dataset A database which contains gait pattern of different subjects and captured from different camera angles are modified to get eight different directions of motion and are added in such a way to get variety of cases of occlusion. During the motion, subject may be nearer to or far from the camera and hence may appear larger or smaller in size, but the characteristics of the graph remains unchanged irrespective of its appearance (as seen in the Fig.3.11). The next section presents various cases of encountering occlusion and the cases of non occlusion observed over CASIA database as well as self acquired database.

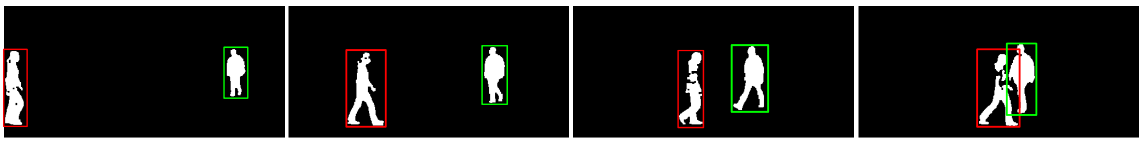
## 3.5 Results

The earlier sections of this chapter presents our novel approach towards achieving uninterrupted track of the subject in an MCN environment that optimally utilises the camera resources. In order to test the proposed approach, CASIA Dataset A for gait patterns are used. Section 3.2 show the results of morphological operations, tracking of the subject and direction determination in different paragraphs. Utilising these results as input to the proposed algorithm, occlusion estimation tests has been performed. The results are carried over modified CASIA database where the frames from two different frame sequences are concatenated to achieve desired conditions of occlusion and non occlusion.

The result of experiment over the modified and concatenated CASIA database has been presented in the figure 3.14. Figure 3.14(a) and 3.14(b) shows the image sequence from modified CASIA dataset with successful determination of chances of occlusion where in first case subjects are moving in directions 3 and 7 respectively with speeds $v_3$ each. In another case the subjects are moving in the directions 3 and 6 with speeds $v_3$ each.



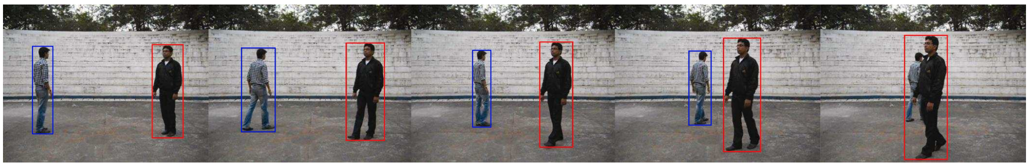
(a) Occlusion predicted with subjects directions as 3 and 7 and speed levels as 3 and 3



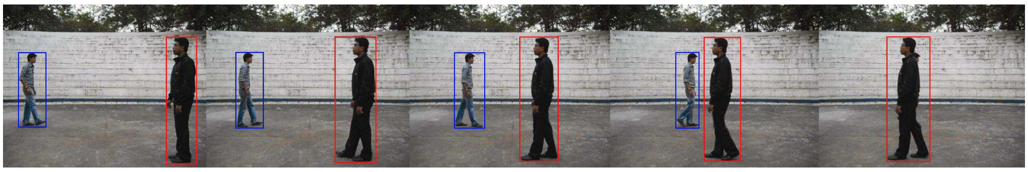
(b) Occlusion predicted with subjects directions as 3 and 6 and speed levels as 3 and 3

Figure 3.14: Test cases depicting occlusion over CASIA Dataset A

Experiments conducted over self acquired databases also illustrates encouraging results. Figure 3.15(a) and Figure 3.15(b) shows sequence of frames where the directions of two subjects are estimated based on earlier mentioned method. On that basis their chances of occlusion are successfully determined. However occlusion also depends on subjects speed. Figure 3.15(c) and Figure 3.15(d) shows two frame sequences in which the direction of subjects are same but Figure 3.15(c) resulting occlusion while Figure 3.15(d) avoids occlusion. The direction in both the cases is found to be direction 3. The difference in the subject's speed level is found zero in Figure 3.15(c) resulting non-occlusion while the speed level difference is found to be two in Figure 3.15(d) resulting occlusion.



(a) Occlusion predicted with subjects directions as 2 and 6



(b) Occlusion predicted with subjects directions as 3 and 7

(c) Occlusion predicted with subjects directions as 3 and 3 but speed levels as 3 and 1

(d) No occlusion predicted with subjects directions as 3 and 3 but speed levels as 1 and 1

Figure 3.15: Test cases depicting occlusion and non occlusion

## 3.6 Concluding Remarks

The proposed work shows efficient and effective way for determining occlusion and avoiding it in a multi-camera network. The proposed camera network works in single camera mode avoiding complexity and higher operation cost as long as tracking is possible from one camera. It awake one or more cameras in case of any occlusion and does not compromise in losing the track of the subject. It finds its implementation in places like dedicated roads, office corridor, passage in railway station, airports, subways, shopping malls and other places where multiple cameras can be installed.

# Chapter 4

# Conclusion

With ever increasing demand of surveillance and rapidly advancing camera technology, mankind has landed into the era of visual surveillance. Over the time, dependency and necessity over visual surveillance is growing rapidly and so is the research in the domain. The tracking and recognition over single camera has been elaborated and the multi-camera network (MCN) has emerged as a solution to overcome the limitations of single camera-based visual surveillance. This thesis explores the trade-offs of single as well as multi-camera based surveillance and attempts to optimize multi-camera set-up as in single camera system yet not compromising the benefits of multi-camera based surveillance system.

With different chapters, different levels of multi-camera development model have been explored, and survey, proposals, experiments and results are presented that lead to a model for an efficient surveillance system.

The necessity and advancement of calibration and localization of multi-camera network has been studied and presented in chapter 1. The chapter elaborates the complexity as well as necessity of a calibrated multi-camera network. The chapter explores different research challenges in the domain of multi-camera network. Effective utilization of camera is a major issue in MCN, this has been resolved with research on effective placement of camera. Chapter 2 discusses various camera placement techniques and presents a novel approach towards task specific efficient placement of field cameras in the proposed model. With the aim of capturing gait patterns of moving subjects, a novel camera placement technique has been proposed that places the camera so as to stay orthogonal to the direction of movement of the subject. The proposed model has been experimentally tested over a corridor sequence taken at Vikram Sarabhai Hall of Residence at NIT Rourkela and based on the number of walks of different subjects, suitable camera placement results are presented. With cameras placed efficiently, the camera control is also an important issue in MCN based surveillance. Chapter 3 presents research on camera control. To justify the scope of the model, a brief comparison of single and multi-camera based surveillance and their benefits and trade-offs are presented in chapter 1. A three step model has been proposed that lets most of the cameras to stay in sleep mode while minimal cameras are tracking the subject. Direction and apparent speed of the subjects are determined and with their results, chances of occlusion are calculated. In case of any chances of occlusion, the time and placement of occlusion is also determined. A prior knowledge of occlusion will let the system to take necessary action towards mitigation of occlusion. These experiments are performed on existing database, CASIA Dataset A for gait and its modified versions.

## Scope for future research

The experiment conducted towards the proposed model has produced motivating results. It achieves good accuracy in challenging situations as

- Changing speed of the subject within video.
- Different velocity of subject in different video.
- Different distances of the subject from the camera.
- Presence of noise and partial occlusion.

- Direction of motion of subject being not accurate.
- Varying direction of subject while motion.
- Low resolution video.

Many challenges have been identified and expected. Even though ample justification has been given towards the efficient placement of camera work, and experimental results over self acquired data has been produced, it still awaits experimental justification in complex surveillance zone. Further scope towards implementation of the proposed work lies in developing algorithms that can decide the control flow from one camera to another. Mitigation of occlusion can be done when a robust algorithm can utilize the pose (position with orientation) information of pre-localized and calibrated cameras, and based on these values, it can awake the camera which does not encounter occlusion at all. Since the algorithm works in real time environment and finds its implementation in vital issue as surveillance, fast and optimized working along with high accuracy is a concern that can always be explored.

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# Dissemination

1. **Rahul Raman**, Pankaj K Sa, and Banshidhar Majhi, "Occlusion Prediction Algorithm for Multi-camera Network", in the Proceedings of *Sixth ACM/IEEE International Conference on Distributed Smart Cameras (ICDSC 2012)*, ACM/IEEE2012 ,Hong Kong, 2012.
2. **Rahul Raman**, Pankaj K Sa, Sambit Bakshi and Banshidhar Majhi, "Towards Optimized Placement of Cameras for Gait Pattern Recognition ", in the Proceedings of *2nd International Conference on Communication, Computing & Security (ICCCS 2012)*, Elsevier, India, 2012.
3. **Rahul Raman**, Sambit Bakshi, and Pankaj K Sa, "Multi-camera Localisation: A Review", in *International Journal of Machine Intelligence and Sensory Signal Processing (IJMISSP)*, Inderscience Publishers, Published, 2013.

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