VIDEO ANALYTICS FOR SECURITY SYSTEMS

by

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Declaration

I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.

Signature

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Dated: 17th December 2012

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Summary

This study has been conducted to develop robust event detection and object tracking algorithms that can be implemented in real time video surveillance applications. The aim of the research has been to produce an automated video surveillance system that is able to detect and report potential security risks with minimum human intervention. Since the algorithms are designed to be implemented in real-life scenarios, they must be able to cope with strong illumination changes and occlusions.

The thesis is divided into two major sections. The first section deals with event detection and edge based tracking while the second section describes colour measurement methods developed to track objects in crowded environments.

The event detection methods presented in the thesis mainly focus on detection and tracking of objects that become stationary in the scene. Objects such as baggage left in public places or vehicles parked illegally can cause a serious security threat. A new pixel based classification technique has been developed to detect objects of this type in cluttered scenes. Once detected, edge based object descriptors are obtained and stored as templates for tracking purposes. The consistency of these descriptors is examined using an adaptive edge orientation based technique. Objects are tracked and alarm events are generated if the objects are found to be stationary in the scene after a certain period of time. To evaluate the full capabilities of the pixel based classification and adaptive edge orientation based tracking methods, the model is tested using several hours of real-life video surveillance scenarios recorded at different locations and time of day from our own and publically available databases (*i-LIDS, PETS, MIT, ViSOR*). The performance results demonstrate that the combination of pixel based classification and adaptive edge orientation based tracking gave over 95% success rate. The results obtained also yield better detection and tracking results when compared with the other available state of the art methods.

In the second part of the thesis, colour based techniques are used to track objects in crowded video sequences in circumstances of severe occlusion. A novel Adaptive Sample Count Particle Filter (ASCPF) technique is presented that improves the performance of the standard Sample Importance Resampling Particle Filter by up to 80% in terms of computational cost. An appropriate particle range is obtained for each object and the concept of adaptive samples is introduced to keep the computational cost down. The objective is to keep the number of particles to a minimum and only to increase them up to the maximum, as and when required. Variable standard deviation values for state vector elements have been exploited to cope with heavy occlusion. The technique has been tested on different video surveillance scenarios with variable object motion, strong occlusion and change in object scale. Experimental results show that the proposed method not only tracks the object with comparable accuracy to existing particle filter techniques but is up to five times faster.

Tracking objects in a multi camera environment is discussed in the final part of the thesis. The ASCPF technique is deployed within a multi-camera environment to track objects across different camera views. Such environments can pose difficult challenges such as changes in object scale and colour features as the objects move from one camera view to another. Variable standard deviation values of the ASCPF have been utilized in order to cope with sudden colour and scale changes. As the object moves from one scene to another, the number of particles, together with the spread value, is increased to a maximum to reduce any effects of scale and colour change. Promising results are obtained when the ASCPF technique is tested on live feeds from four different camera views. It was found that not only did the ASCPF method result in the successful tracking of the moving object across different views but also maintained the real time frame rate due to its reduced computational cost thus indicating that the method is a potential practical solution for multi camera tracking applications.

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Finally I would like to employ the knowledge I have gained though this journey for the betterment of my country and in particular, younger generation. This would not have been possible without my inspiration, Imran Khan.

Contents

List of Acronyms and Symbols

Acronyms

ASCPF	Adaptive Sample Count Particle Filter
BAMC	Brooke Army Medical Center
CCTV	Closed Circuit Television
EKF	Extended Kalman Filter
EPF	Energetic Particle Filtering
GMM	Gaussian Mixture Model
GVF-Snake	Gradient Vector Flow Snake
HOSDB	British Home Office Scientific Development Branch
i-LIDS	Imagery Library for Intelligent Detection Systems
I-MCSHR	Incremental Major Colour Spectrum Histogram Representation
KLD-Sampling	Kullback-Leibler Distance Sampling
KLT	Kanade-Lucas-Tomasi Feature Tracker
NCC	Normalized Cross Correlation
POM	Probabilities Occupancy Map
ROI	Region of Interest
SHI	Segmentation History Image
SIFT	Scale Invariant Feature Transform
SIR	Sequential Importance Resampling
SPF	Snake Particle Filter
SVM	Support Vector Machines
VSAM	Video Surveillance and Monitoring

Symbols

N_{active}	Active Particles
A	Adaptive Mask
h	Colour Histogram
Σ	Covariance
r	Detection Rate
N_{eff}	Effective Number of Particles
α	Gaussian Learning Rate
v	Gaussian Noise
G	Gaussian Probability Density Function
Φ	Gradient Direction
D	Histogram Matching Distance
N_{max}	Maximum Number of Particles
μ	Mean
N_{min}	Minimum Number of Particles
I	Monochrome Image Intensity
N_{th}	Particle Filter Threshold
w	Particle weight
p	Probability of Genuine Alarm
Γ	Segmentation History Image Data
Λ	Segmentation History Image Threshold
Ω	Set of Foreground Pixels
σ	Standard Deviation
F	Transition Matrix for Particle Filter State Model
ω	Weight

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Journal Publications

[1] **Waqas Hassan**, Nagachetan Bangalore, Philip Birch, Rupert Young, Chris Chatwin, "An Adaptive Sample Count Particle Filter," Journal of Computer Vision and Image Understanding, vol. 116, issue 12, pp. 1208-1222, December 2012

[2] **Waqas Hassan,** Philip Birch, Rupert Young, Chris Chatwin, "Real-Time Occlusion Tolerant Detection of Illegally Parked Vehicles," International Journal of Control, Automation and Systems, vol. 10, issue 5, pp. 972-981, October 2012.

Conferences Publications

[1] **Waqas Hassan**, Nagachetan Bangalore, Philip Birch, Rupert Young, Chris Chatwin, "Object Tracking in a Multi Camera Environment," IEEE International Conference on Signal and Image Processing Applications *(ICSIPA 2011)*, pp.289-294, doi: 10.1109/ICSIPA.2011.6144137, Kuala Lumpur, November 2011.

[2] Philip Birch, **Waqas Hassan**, Nagachetan Bangalore, Rupert Young, Chris Chatwin, "Stationary Traffic Monitor," 4th International Conference on Imaging for Crime Detection and Prevention *(ICDP-11)*, London, November 2011.

[3] Bhargav Mitra, **Waqas Hassan**, Nagachetan Bangalore, Philip Birch, Rupert Young, Chris Chatwin, "Tracking illegally parked vehicles using correlation of multi-scale difference of Gaussian filtered patches," Proc. SPIE 8055, 805503 (2011); doi:10.1117/12.883821, Orlando, April 2011

[4] **Waqas Hassan**, Bhargav Mitra, Chris Chatwin, Rupert Young, Philip Birch, "Illumination invariant method to detect and track left luggage in public areas," Proc. SPIE 7696, 76961V (2010); doi:10.1117/12.849224, Orlando, April 2010

Chapter 1

Introduction

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INTRODUCTION

Automated video surveillance systems in recent years have generated a great deal of interest from the technical community and security industry around the world. The availability of high-powered computing, low price and high quality video cameras and the escalating need for automated video analysis have engendered an immense interest in the development of security systems that can detect, track and report potential security risks with minimum human intervention. Due to advancement in technology and the introduction of various computer vision techniques, such systems are highly desirable, especially for monitoring public places such as train stations, airports, busy highways or military establishments (see Figure 1.1 for overall surveillance architecture).

However, fully automated surveillance systems are not simple to build. Object detection, tracking and overall video analysis is still an open ended research problem and such systems tend to be highly domain specific. These conclusions can be made from examining one of the first fully automated video surveillance projects: Video Surveillance and Monitoring (VSAM) [1]. Although the main objective of the project was to build a general purpose automated surveillance system, it instead became a collection of algorithms that were switched between different situations. Keeping in view these complexities, an effort has been made in this thesis to develop domain specific robust video analytics software that is deployed to detect, track and report potential security risks in real life scenarios.

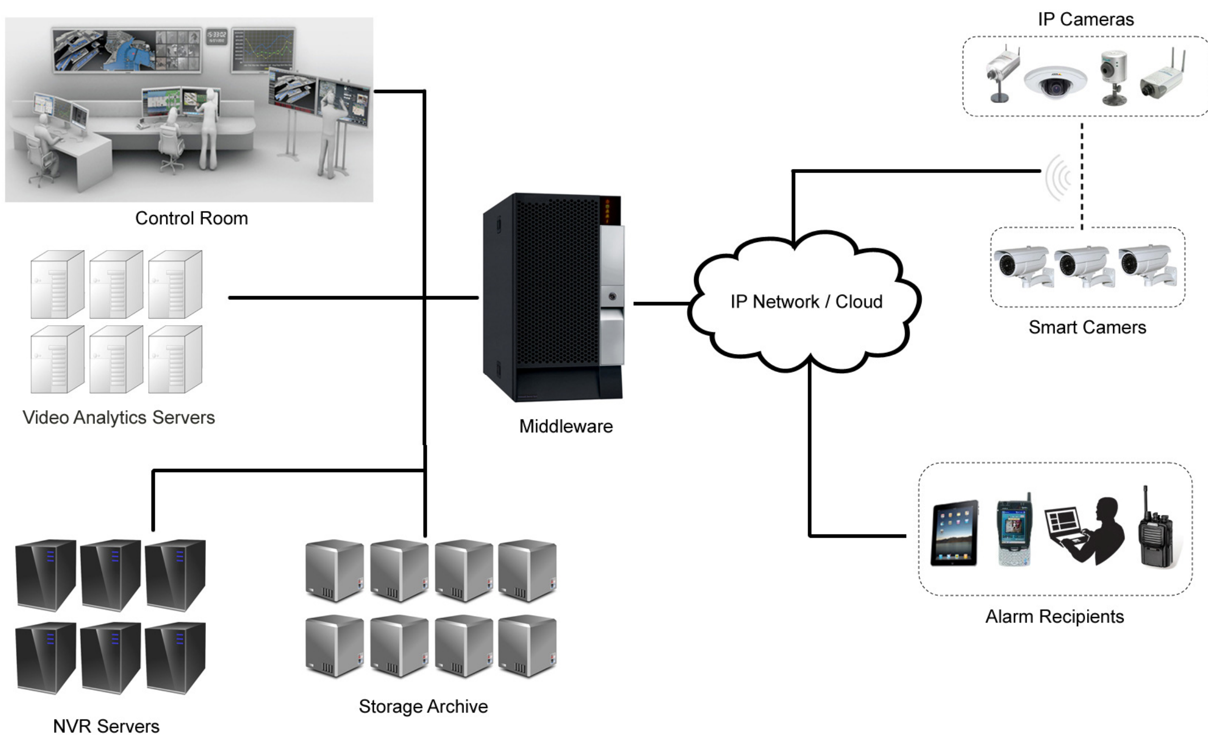


Figure 1.1: Video surveillance system architecture

1.1 Existing Surveillance Systems

The existing surveillance systems can be categorized according to environment (indoor or outdoor) they are designed for, the number of camera feeds they can handle (single or multiple camera systems) and the type of cameras they will involve (moving or stationary cameras). Most of the surveillance systems currently in use share one common feature, i.e. continuous human monitoring, as illustrated in Figure 1.2 [2].

This is the major disadvantage of these systems as the number of cameras in use and the area under surveillance is highly dependent on the number of available human operators. Another weak trait of these systems is the overall performance factor. Since no automated aspects are involved in the development of these systems, their performance is entirely reliant on the vigilance of the person monitoring the system. This is a major concern according to one of the research surveys carried out by the U.S. National Institute of Justice. In their report [3] they showed that the attention of most people falls below an acceptable level after watching security monitors for just 20 minutes. To overcome this issue and avoid people monitoring the security screens for long periods of time, a common practice emerged to record the surveillance videos and later use them as a forensic tool to collect evidence.

Figure 1.2: Human operators monitoring several screens.

The disadvantage of this practice is best illustrated by examining the situation faced by the UK Government when it decided to search through the video recorded by the video surveillance system monitoring the London Underground after the bombings that occurred on the 7th July 2005. Government officials were able to identify the suspects who made the attack, but it required 6,000 man-hours of viewing these videos. A similar situation in the United States, an attempted bombing of Times Square in May 2010, also required law enforcement officers to spend countless hours examining video sequentially. Therefore, citing the high demand and importance of automated surveillance systems, the UK Home Office in 2007 introduced a benchmark dataset Imagery Library for Intelligent Detection Systems (*i-LIDS*) [4] for the development and testing of robust computer vision algorithms that can be used to facilitate law enforcement agencies to identify similar situations more efficiently if encountered again in the future. Since that date, a number of projects are now underway in the vision community, as well as the security industry, to build fully automated surveillance systems.

1.2 Video Analytics

Video analytics generally refers to the software used in video surveillance systems to make notification of different events and activities by matching pixels with predetermined patterns to produce an appropriate response. These are mathematical algorithms used to automatically detect specific objects or behaviours within the video footage. This can, for example, be detection of a person heading towards a secure area or identification of illegally parked vehicle on the road side. The video footage is transformed into meaningful data which is either archived for future analysis or transmitted to the control environment to take further decisions such as gate closure to prevent entry or trigging of an alarm. Video analytics significantly minimizes human intervention in the monitoring of large surveillance areas. One of the major drawbacks of existing surveillance systems, as highlighted in the previous section, is the requirement for continuous human monitoring. Various video analytics software has been developed in this regard to facilitate the operators and improve overall system efficiency. A number of other factors influencing the high demand of video analytics techniques are highlighted in the following points.

Improved Computing Resources: the availability of high-powered computing is playing a vital role in the development of robust surveillance systems. The leading chipmakers such as Texas Instruments, Stretch and Stream, etc. are enabling the camera manufacturers to have more powerful video analytics algorithms running on the network edge by producing hardware that is embeddable on each camera. Although there will always be a need to process the video footage at the network core, such systems can be significant for networks with limited bandwidth.

High-Definition Cameras: high resolution images are always desired for the development of efficient video analytics algorithms. Quality of the video is an important feature and has most effect on the performance of the surveillance system. The availability of high definition cameras has encouraged the vision community to develop more robust solutions that can be implemented in challenging environments.

Fears of Terrorist Attacks: the security market has changed dramatically since the events of 9/11. The attacks on the World Trade Centre twin towers still serve as a reminder of the danger of terrorist attacks. Since then governments around the world have taken strict measures to prevent similar activities by investing huge amounts of money on public security. Airports, train stations, shopping malls and most of other public places are all equipped with Closed Circuit Television (CCTV) cameras. This has increased the demand for intelligent video analysis applications that can be deployed to improve public safety.

IP Networks: the emergence of IP networks has also increased the demand for intelligent video analytics. The fast and easily expandable infrastructure of IP networks is attracting more and more interest in IP surveillance networks. According to the ABI research report "The Video Surveillance Market Hardware and Software Market Trends and Forecasts" published in 2010 [10], by 2012 the number of IP surveillance networks will see a growth of over 45%. This has significantly increased the demand for video analytics.

1.3 Key Marketplaces

Video surveillance systems were originally used by Government departments primarily for policing and transportation. They were then deployed to protect strategic locations such as military establishments, nuclear plants, dams etc. Today surveillance systems are used in almost all public places such as airports, shopping malls, motorways, parking lots, educational institutes and banks. This increase in the use of surveillance systems has also increased the desire to realise fully automated systems. Some of the key areas where automated surveillance systems can be implemented are discussed below:

Governments around the world are investing heavily in the surveillance of key infrastructures. The recent attempted car bombing in New York City in 2010 highlighted the use of video surveillance cameras to fight terrorism. Video surveillance systems are setup to monitor military bases, nuclear plants, borders, prisons etc. Public places such as train stations, bus stops, airports are also monitored for public safety. Although a number of these locations are already equipped with surveillance systems, most of them suffer from the same issues as highlighted in Section 1.1. This is due to the unavailability or unreliability of robust video analytics software. Efficient video analytics software can be built to improve overall security. Intrusion detection algorithms can be deployed to observe sensitive infrastructures or multi camera tracking algorithms can be used to track a particular object or person across different cameras.

Transportation is emerging as one of the most attractive markets for video surveillance systems. The security of places such as airports, busy road/highways and train stations is a critical part of public safety and security. Keeping in view the number of people using the mass transportation systems on a regular basis and the extent of their infrastructures, such places face extraordinary security challenges. Different video surveillance systems are currently available to facilitate the smooth operations of these places, including: intrusion detection systems to monitor controlled areas; illegally parked vehicle detection and tracking systems; unattended baggage detection systems; people counting and number plate recognition systems to monitor access to parking lots. However, these systems face major technical challenges due the environments in which they are deployed. Firstly, such systems are usually used in outdoor environments with unpredictable lighting conditions. This means that the analytics software must be robust enough to work in any illumination environment. Secondly, given the large flow of passengers, these systems must also handle occlusion.

The retail industry is also a growing market for intelligent video analytics. Retail establishments are using video analytics both for crime prevention and behavior analysis. Many stores have found it cost-effective to install between one and five camera systems to monitor for shoplifters. Larger retailers have begun making serious use of analytics. Systems are developed to analyze shopping behaviors and in-store movements for compiling statistics on consumer habits. IBM has introduced “Business Analytics for Retail” [11] software that identifies, reports and analyzes trends in order to respond to consumer buying needs and behavior. The market is currently on the rise and there is need for more intelligent and robust systems that can be used for security as well as identifying shopping patterns.

Intelligent video analytics is also in high demand in the health care market. Automated video surveillance systems are used not only for security purposes but they are also an effective way of patient monitoring. Although the health care market is comparatively new there is some work currently going on in this sector. NICE Systems Ltd have recently announced expansion of their operations in the Brooke Army Medical Center (BAMC) in the US. Video surveillance systems are integrated with an infant protection system, which is now used by the BAMC maternity ward to prevent infant abduction [12]. A number of other different applications can also be developed for patient monitoring e.g. alert generation systems can be developed to identify if a patient is unattended or not. Similarly, entrance monitoring systems can be deployed to identify entrance of unauthorized people into restricted areas of the hospital. Since health care is a reasonably new area for intelligent video analytics, there is much scope for further development.

Education is another sector where video analytics is highly desirable. Since most educational institutes have IP network infrastructures, such systems can easily be integrated in the existing setups. Video surveillance systems are not only used for student and staff safety and protection they are also used again for theft detection, access control, identification of any criminal activity or simply monitoring of inappropriate behavior. According to a report published by the US Department of Education, in 2008, there were about ‘1.2 million victims of nonfatal crimes at school, including 619,000 thefts and 629,800 violent crimes (simple assault and serious violent crime) while in 2009, 8 percent of students reported being threatened or injured with a weapon, such as a gun, knife, or club, on school property’ [13]. This further emphasizes the potential for video analytics in the education sector.

1.4 Challenges and Related Research

Video surveillance has become common for the maintenance of security in a wide variety of applications. However, the increasingly large amounts of data produced from multiple video camera feeds is making it increasingly difficult for human operators to monitor the imagery for activities likely to give rise to threats. This has led to the development of different automated surveillance systems that can detect, track and analyze video sequences both online and offline and report potential security risks. These developments have also raised other important issues such as the communication mechanisms and middleware for surveillance systems as highlighted in [14]. Different studies are currently underway to develop robust solutions that can facilitate the end users to operate efficiently in surveillance environments. The following sections give an overview of some of the solutions that are presented by the research community. It is important to note at this stage that solutions based solely on static camera feeds are discussed in this thesis.

1.4.1 Human Intrusion Detection Systems

Intrusion detection is an important part of automated surveillance systems with its application in different areas which include hospitals, airports and security of sensitive government infrastructures. The intrusion detection systems are primarily based on object detection techniques which can be classified into the two categories of background segmentation based techniques and direct detection techniques that can identify objects based on their features.

Background segmentation based techniques require a pre-processing step of segregating moving foreground objects from a stationary background before classifying moving obejcts as legitimate objects. A mean shift based real-time human detection technique is presented in Beleznai *et al.* [15]. Intensity differences between a current frame and the reference background frame are obtained using a simple frame differencing method. The output of the frame difference step is taken as a two-dimensional distribution map where moving objects are considered to be present at regions with high intensities. Individual objects are classified as human using a simple human model based on three rectangles. An optic flow based object detection method is presented by Elzein *et al.* [16], where optic flow is computed only on regions obtained from frame differencing. A shape based technique is used by Lee *et al.* [17] to identify objects as humans, animals or vehicles. Binary blobs are obtained using a background segmentation technique and objects are classified based on the shape of the boundary contour. A two step object classification model is presented by Zhou and Hoang [18]. Objects are initially segmented using a temporal differencing method before being classified as humans based on the codebook approach. Although the segmentation based methods are simple to implement and computationally less expensive the major drawback of these techniques is that they are only suitable for systems using static cameras. If the cameras are not stationary, more advanced techniques are required for detection objects in the scene.

Shape cues are attractive features to detect a particular object in the scene as they are independent of lighting variations and other object features such as colour. A number of techniques have been presented in the literature to identify objects based on their shapes [19-22]. Although these techniques can efficiently detect objects even in cluttered scenes, they usually require large example shape databases with thousands of shapes. Another way of detecting objects in the scene is by using Haar classifiers [23-25]. A database of predefined objects with various locations, scales, and orientations is matched with the current image to identify the existence of any object in the scene. Although direct detection techniques tend to outperform segmentation based methods, they are usually computationally expensive and therefore require more computational resources to operate in a real time environment. Hence for robust intrusion detection systems both performance in terms of detection rate and computational time are significant.

1.4.2 Stationary Object Detection Systems

Objects such as baggage left unattended in public places or vehicles parked illegally on road sides can pose a serious security threat. Their identification and tracking is one of the most challenging tasks in the development of automated surveillance systems. The number of people using the transportation systems on a regular basis has made the security of airports, train stations and bus stops very critical. Identification of baggage left unattended is one of the key components of the surveillance systems installed at such places. Increase of traffic on the roads on the other hand calls for better automated ways of traffic control management. Stationary vehicles on roads can present security threats or be a danger to drivers. Stopping vehicles could be an indication that somebody is alighting in a restricted zone such as at an airport or it could indicate a parking violation. An automated system provides a clear advantage in these situations as there is no need to constantly monitor each and every camera on the network. If alarms can be generated reliably only these video streams need to be presented to the operator. A comprehensive review of techniques used for intelligent transport systems in urban traffic environments have been presented by Buch *et al.* [26]. The articles highlights the major research being carried out in the area. The authors concluded that for an intelligent transport system to be effective a clear definition of deployment environment is required that will help develop more consistent and efficient application model.

Due to the high demand of automated stationary object detection systems in different sectors, several researchers have attempted different approaches to solve this problem and a general framework has emerged. Objects are initially detected using background segmentation or feature based detection methods. The detected objects are then tracked and alarm events are generated if objects are found to be stationary in the scene for more than a certain period of time. This approach has divided the problem into the two major tasks of detection and tracking. In order to detect the objects accurately, different background segmentation techniques have been utilized [27-32]. One of the most widely used techniques is that proposed by Stauffer *et al.* [27] details of which are discussed later in this thesis. A dual background segmentation method has been proposed by Porikli [28] to specifically segment objects that become stationary in the scene. The method maintains two backgrounds that are updated at different rates to detect static regions. The method copes well with illumination changes and shadows.

Once objects are identified as stationary they are tracked using features such as colour, texture or edge maps. A real time stationary object tracking method has been presented by Tian *et al.* [33]. In this work, region growing techniques were applied on current and background images to classify foreground regions as abandoned or removed objects. Once objects have been identified as abandoned, correlation scores were obtained to keep track of the stationary objects. This research was then extended by the same authors in [34], where tracking information along with human identifiers are used to improve system performance. Another solution based on edge energies is presented by Venetianer *et al.* [35]. The original object background is stored when a new object is identified as stationary. Edge energies for both the current and the background frames are analyzed to determine if the object is still at its static location. Shape based tracking methods have been studied in [36-38] to track rigid objects such as vehicles in traffic management applications. A vehicle and pedestrian classification model in urban traffic scene is present in Buch *et al.* [39]. A 3D model on calibrated cameras is used to perform per frame vehicle detection and classification. Motion segmentation is used to extract the moving objects and identify them as vehicles or pedestrian based on their ground plan location.

Abandoned object detection along with an owner tracking technique has been presented in Ferrando *et al.* [40]. Once objects have been identified as stationary, colour features and object position were utilized to identify the owner. The study has been further improved in Tang *et al.* [41] by deploying a more refined method to distinguish between the owner of the abandoned object and other people moving close by in the scene. However, it has been observed that the system fails to perform if the scene is too crowded. A feature based stationary object detection method has been proposed in Wen *et al.* [42] where pixel variance, edge intensity, edge variance, foreground completeness and histogram contrast with respect to the surrounding background were all considered as object features. Suspected foreground regions were obtained using three different background models along with different shadow removal strategies. Object features were extracted and assembled into classifiers with sigmoid functions using empirical data.

A dual foreground mask based technique was used in Li *et al.* [43] to detect abandoned objects. A Gaussian Mixture Model (GMM) along with an RGB colour space was used to construct two binary foreground masks. The obtained masks were further refined using a radial reach filter method Satoh *et al.* [44] to remove any falsely identified foreground region due to change in illumination conditions. Finally, once objects were identified as stationary, width and height ratio along with a linear Support Vector Machines (SVM) classifier based on the histogram of oriented gradients was utilized to differentiate between left-baggage and a nearby stationary standing person. Another dual foreground mask based technique was proposed in Li *et al.* [45]. Static regions are extracted from a confidence map maintained using a pixel-wise static region detector. Once static regions were obtained, colour histograms of the current and background frames were compared to classify the identified region as an abandoned or removed object. A dual background illegally parked vehicle detection system was presented in Yi Ping *et al.* [46]. The GMM is used to obtain two background models updated at different rates. A rule based approach was then followed and foreground regions identified by each background model were categorized into static and nonstatic regions. Finally the HSV colour space was used to remove shadows from the moving objects. Another dual background segmentation based technique is presented by Evangelio and Sikora [47] to detect static objects in the scene. Pixels are detected using two GMM updated at different learning rates. A finite-state machine is then used to classify these detected pixels as part of the static object. A real time vehicle detection system using a 1-D transformation was proposed in Lee *et al.* [48]. The dimensionality of the image data was reduced from 2-D to 1-D by using image projection techniques which reduced the overall system computational time. Once events were detected, inverse transformation was applied to regenerate the original image. The technique was further improved by the same authors in Lee *et al.* [49].

Different authors have tried to approach this problem with novel methods. However, there are two major challenges faced by these systems, namely, change in illumination and occlusion. Solutions designed for traffic control management systems [50-52] must cope with illumination changes because these systems are deployed in outdoor environments where lighting conditions are unpredictable. So traffic control management systems must be robust enough to work in different lighting conditions. On the other hand, systems designed to detect luggage left unattended in public places are usually deployed in indoor environments such as underground train stations, shopping malls or [53-55]. Although lighting variations do not change much in these situations, due to high number of people using these places on regular basis, the solutions must be robust against occlusion. These two issues make the stationary object detection applications a challenging problem.

1.4.3 Tracking Systems

Tracking moving objects, especially humans in different environments, is an essential part of any video surveillance application. Surveillance systems installed at airports, train stations, military establishments, sensitive infrastructures, borders, shopping malls, retail outlets and many other sectors, all require the capability of tracking human activity and reporting this back to the control environment. This high demand for human tracking applications has led to number of studies being carried out in this domain but due to the nonlinear nature of this problem it is still a challenging task [56-60]. The basic idea of tracking is to associate tracked objects in consecutive video frames by assigning consistent labels as the objects move around in the scene. Difficulties in tracking can arise from several sources. For example: if an object is tracked in the presence of other moving objects with similar characteristics, there is an unexpected change in the motion or direction, an object is partially or completely occluded, the scale of the object changes during tracking or an object as well as the background is in motion at the same time. All these issues make tracking a difficult openended problem.

Numerous approaches have been followed in the past to track objects in these difficult circumstances. Methodologies can be broadly characterized as either region based, active contour based or feature based. Region based tracking techniques often depend on fixed camera views where differences between successive frames are calculated to identify object movement. A region based approach was used by Andrade *et al.* [61] where the image was divided into a series of homogenous regions and detected objects were correlated in consecutive frames for identification. The study identified that the scheme was suitable for scenes with many moving objects. A real-time segmentation and tracking of 3D objects is presented by Prisacariu and Reid [62]. A probabilistic framework is formulated to segment an object using region based segmentation technique while simultaneously performing 2D to 3D pose tracking, using a known 3D model. The experimental results have shown that the proposed tracking method showed robustness to occlusions and motion blur.

A dual tracking algorithm was proposed by Fan-Tung *et al.* [63] to achieve object extraction. Pixelwise and regionwise tracking methods were combined using the Adaboost feature selection technique. K-means clustering was performed to overcome the shortcomings of a pixel wise operation. The masks obtained from both techniques were combined to obtain a final mask for the extracted object. A novel tracking framework (TLD) for long-term tracking tasks is presented in Kalal *et al.* [64]. The framework is divided into Tracking, Learning and Detection. The tracker keeps a track on the object between frames. The detector localizes all appearances that have been observed so far and corrects the tracker if necessary. The learning estimates the detector's errors and updates it to avoid these errors in the future. A significant improvement over the state-of-the-art methods have been reported by the authors of the paper.

Another region based tracking technique was proposed by Marimon and Ebrahimi [65] where matching is divided into two steps, gradient orientation histogram matching followed by template matching using normalized cross correlation (NCC). The rotation between two image patches was estimated using a circular normalized Euclidean distance and image patches were correlated using NCC. It was reported that the method produced accurate matching results, especially for rotated patches.

Active contours are also used for tracking moving objects in scenes. The basic idea of active contours, also known as snakes, is to evolve a curve to detect objects in an image. The detected object can be continuously contoured in each frame based on the previous contour vector which enables it to behave as a tracker. Active contour tracking systems require the solution of two problems, namely, data association and dynamic estimation. The data association is based on *a priori* information and observation. The energy minimization approach used in active contour snakes addresses the issue of dynamic estimation for tracking by Kass *et al.* [66]. Feature based energy minimization techniques solve data association as well as the dynamic estimation issue to perform robust tracking by Chenyang Xu and Prince [67].

An active contour snake usually consists of a set of control points, which are flexibly connected and based on the energy minimization criteria selected. Williams and Shah [61] proposed a fast implementation of the snake model called a "Greedy Snake", which features reduction in computational time. An improved active contour technique to contour an object based on its exterior edges has been proposed by Bangalore *et al.* [69]. Several further approaches to energy minimization have been presented [70-72].

Feature based techniques are the most popular for tracking moving objects in complex environments. Colour, edge and texture are commonly used as features to uniquely identify objects. Incremental major colour spectrum histogram representation (IMCSHR) was proposed by Madden *et al.* [73] to track objects across disjoint camera views. A normalized geometric distance between two points in RGB colour space was calculated to form a major colour histogram and a similarity measure was then estimated between histograms of any two moving objects. The authors reported that matching results obtained using I-MCSHR were more robust as compared to single frame matching.

The Kanade-Lucas-Tomasi Feature Tracker (KLT) is another commonly used feature based tracking method [74]. In this work, features were selected based on good texture quality and tracked by calculating the dissimilarity between the current and first frame. If the dissimilarity measure grows too large, features were abandoned and assumed to be occluded. A multi-target pedestrian tracking technique is presented by Benfold and Reid [75]. A stable head location estimation method has been used to track multiple objects in the scene. A multi-threaded approach has been followed that combines asynchronous Histogram of Oriented Gradients (HOG) detections with simultaneous KLT tracking and Markov-Chain Monte-Carlo Data Association (MCMCDA) to provide guaranteed real-time tracking in high definition video. Experimental results have shown that the proposed method accurately estimated the position of multiple objects in crowded environments.

Feature matching is one of the common problems in vision systems. Matching objects of the same scale and orientation can be performed using simple corner detectors Trajkovic, and Hedley [76]. Dealing with objects of different scale, illumination, viewpoint and orientation requires the use of robust feature matching techniques such as the "Scale invariant feature transform" (SIFT) method by Lowe [77]. SIFT features are invariant against rotation, scale and lighting/contrast and can therefore be utilized in scene modeling, recognition and tracking. SIFT is thus a method to create highly stable feature-vectors from images.

In recent years a number of studies reported in [78-84] have been conducted to propose hybrid tracking methods that make use of both feature and active contour based tracking techniques. One formal way of combining these two approaches is by using particle filters. An Energetic Particle Filtering (EPF) algorithm was proposed by Chun-li and Yu-ning [85] which was combined with a modified Gradient Vector Flow Snake (GVF-Snake) and particle filter to track objects under occlusion. A snake particle filter (SPF) has been proposed by Aksel and Acton [86] with colour as a feature to track objects in video sequences. A snake is used to model the motion model and determine particle weights. A particle filter for geometric active contours is used for tracking deformed objects by Rathi *et al.* [87]. Object features such as rotation, translation, scale and skew, along with the contour vector, were taken as state parameters.

One of the major challenges faced by the particle filter technique is its efficiency in terms of computational cost. The solutions available in the literature only focus on the tracking results and one way of achieving this is by increasing the number of samples or particles. However, a higher number of particles do not come without increased computational cost. Generally if the number of particles are reduced to improve for the computational efficiency, not only are the tracking results compromised but the system also fails to perform under occlusion.

1.4.4 Multi Camera Tracking Systems

Object tracking in multi camera environments is another useful application for video surveillance systems. Due to the high demand for automated surveillance systems, there is a need for a robust tracking method that can track objects across different camera views. These systems can be integrated into any video surveillance environment installed at airports, train stations or shopping malls to ensure public safety and security. Multi camera tracking has recently received added attention from both the scientific community and security organisations and a number of different techniques have been proposed to tackle this problem. A distributed surveillance model was presented by Nguyen *et al.* [88] where objects were tracked in a multi camera environment. Objects were segmented using a simple background segmentation model. Once a segmented object-to-camera distance was obtained, objects were assigned to the appropriate camera based on better visibility and further tracking using a Kalman filter was undertaken. Javed *et al.* [89] proposed a multi camera tracking technique that included both overlapping and non-overlapping camera views.

The algorithm tracked objects that were not visible for large periods of time. This was achieved by learning the camera positions and the probability of the path followed by the tracked object using a Parzen window Duda *et al.* [90]. A multi-camera video surveillance system for real-time analysis and reconstruction of soccer game is presented by Ren *et al.* [91]. The technique is divided into a two stage approach, single view and multi-view processing. In the first stage single camera views are used to segment players and ball from the adaptive background while in the second stage the player and the ball position are further refined using multiple observations and overlapping views from multiple cameras.

Occlusion is one of the major issues in tracking. Different authors have made use of multiple views to tackle this issue. A Kalman Filter based multi camera tracking method has been presented by Black and Ellis [92] in which multi camera views were exploited to track objects under occlusion. A background segmentation technique was initially used to segment foreground regions and ground plane information was utilized to obtain viewpoint correspondence. A Kalman filter was then used to track the objects in 3D using global world coordinates. Although the technique was able to track objects under occlusion it was reported by the authors that the tracking of breaks down if objects significantly change their trajectories. A multi-marker tracking algorithm using the Extended Kalman Filter (EKF) for multi-camera tracking systems was proposed by Liu Li *et al.* [93]. The same mapping procedures were applied to estimate global 3D world coordinates from 2D projections. Another occlusion tolerant method to track multiple objects is presented in Fleuret *et al.* [94]. The technique keeps track of up to six people across four camera views using an estimation of the probabilities occupancy map (POM) at the ground plane. The authors reported that the proposed method achieved a processing time of up to six frames per second on a standard PC.

Particle filter techniques have also been used extensively to track objects in multi camera environments. A particle filter based multi camera tracking method was presented by Mohedano and Garcia [95] where a 2D object detection technique was deployed on multiple calibrated cameras whose results were combined by means of a Bayesian association method based on geometry and colour information. Another particle filter based tracking technique was used in [96] to track objects using colour features in two uncalibrated camera views. The tracking results in each camera were evaluated by a dual consistency check and a weighted least-squares method was used to compute the adaptive camera transformation matrix to relocate the estimate if tracking failure occurs. Another robust 3D tracking method using multiple calibrated cameras was presented by Mohedano and Garcia [97]. Objects were tracked in each view using a 2D tracking technique. The tracking results obtained from each camera view were combined using Bayesian association and object position is estimated in 3D using a particle filter. A multi-hypothesis approach to segment and track multiple objects is proposed by Kim and Davis [98]. Objects were segmented using human appearance models and information from ground plane homography. The intersection point from all the cameras on the ground was estimated and a particle filter is used to accurately identify an object's ground point location.

Most of the available multi camera tracking systems discussed above rely on there being over a 50% of overlap between views and calibration information. The problem arises when in a multi camera setup all the cameras were primarily looking at essentially different scenes with as little as a 10% overlap of view. This kind of setup can pose difficult challenges such as a change in the scale of the object as it moves from one camera to another or a change in the object features, such as colour, as the brightness levels can alter across different camera views. Although techniques are available to overcome these issues [99] they were computationally expensive and cannot be deployed for real time systems.

On the other hand, background segmentation plays an important role in most of the available multi camera solutions. Objects were initially segmented using background segmentation techniques and then tracked across the cameras. The process is repeated at each time frame which makes the whole method highly dependent on the output of the background segmentation method. Therefore to overcome these limitations a robust solution is required that can not only keep track objects across different camera views while maintaining video rate processing but also reduce any dependency on background segmentation outputs.

1.5 Achievements

Contributions made in the thesis are highlighted in this section. A new pixel-based classification method is presented to improve the GMM performance under unpredictable lighting, especially to identify objects that become stationary in the scene. The technique also overcomes the occlusion issues faced by such methods and hence does not require an isolated view of the object before identifying it as stationary. The concept of adaptive edge orientation based tracking is introduced where the phase angle of the edge is exploited instead of magnitude to maintain a lock on the position of the objects once detected. The method outperforms existing correlation and colour based methods under variable lighting conditions and gives over 95% matching results even if the tracked object is partially occluded.

In order to track non-rigid objects such as human subjects in crowded scenes, a novel adaptive sample count particle filter (ASCPF) has been proposed. An appropriate particle range for tracking a particular object is initially identified and particles are made to switch between active and inactive states within this identified range. This assists in reducing the overall computational cost as fewer particles are used for tracking. However, simply reducing the number of particles compromised the tracking results in the presence of occlusion. To overcome such situations variable standard deviation values for the state vector elements have been exploited to cope with frequently occluded objects. Experimental results have shown that the proposed particle filter method is up to five times faster as compared to the standard Sequential Importance Resampling (SIR) particle filter.

Tracking objects in a multi-camera environment is a challenging task. A multi-camera tracking solution is proposed in the final part of the thesis. The ASCPF is deployed in the multi-camera environment to track objects across different camera views. The multi-camera environment usually poses challenges such as change in the object scale and features as it moves across different views. Variable standard deviation values of the ASCPF have been utilized in order to cope with sudden colour and scale changes. As the object moves from one scene to another the number of particles, together with the spread value, is increased to a maximum to reduce any effects of scale and colour change. Promising results have been obtained when the ASCPF technique is tested on live camera feeds from four different camera views.

1.6 Thesis Overview

An effort has been made in this thesis to develop robust video surveillance applications that can be deployed in different real life scenarios to facilitate end users to efficiently monitor large surveillance areas. Different video analytics algorithms have been studied in this regard and techniques have been proposed keeping in view the challenges discussed in Section 1.4. The idea is to start with the study of a robust solution to a more constrained object detection and tracking problem and then progressively move on to more complex problems with more relaxed constraints.

The thesis is divided into two sections where both sections deal with real time video surveillance systems. Section 1 deals with stationary object detection systems using edge based techniques, while section 2 deals with object tracking based on colour based methods. A single core 2.66 GHz processor with 3 GB RAM and Windows XP has been used as testing platform throughout the development and testing phases.

Initial object detection and tracking technique is developed in Chapter 2. GMM is used to detect and track moving objects in the scene. The technique has been tested on the *i-LIDS Sterile Zone* dataset. It has been observed that although the overall performance of the method is over 90%, there are certain situations where the algorithm generates a huge number of false alarms mainly due to change in lighting conditions. Another issue that is faced during the testing is loss of the identity of a particular object when two or more objects cross each other. Since no object feature information is available, the technique tends to lose the unique identity of the tracked object. To overcome these two major issues, more robust solutions are presented in the remaining chapters where edge and colour information is utilized to track different types of object in progressively more complex environments.

Chapter 3 of the thesis describes a technique developed to maintain a lock on the position of a detected object in a complex scene by using edge (magnitude) information but still with the constraint of controlled lighting conditions. Since edges tend to alter when an object is in motion this technique is only suitable for maintaining a lock on objects once they have become stationary in the scene. Baggage left unattended in public places is one of the prime examples of such situations. Since this requirement is in high demand, an effort has been made to develop a technique to identify such objects. The method is initially tested on the *PETS 2006* dataset under controlled lighting and produced encouraging results. Problems were faced when testing is carried out in more the complex environments encountered in the *i-LIDS Parked Vehicle* dataset in which lighting is not constrained. It is observed that although the performance of the technique based on the magnitude of edges is better than that of colour based methods in conditions where lighting is not consistent, it fails also beyond a certain level of illumination change. Another issue was faced regarding the occlusion. The proposed technique required an isolated view of the object to identify it as stationary object which is not always possible in real life situations.

In Chapter 4 problems identified in the previous chapter are addressed. A new pixel based classification method is proposed that not only significantly improves the performance of the system in terms of detection rate but also does not require an isolated view of the object to identify it as stationary. This helped detect objects even if they were occluded. Also, improvement was recorded for the tracking part of the problem. Orientation of the edges is utilized instead of magnitude to lock to objects once they become stationary. The improved method is tested on several hours of test sequences from four different datasets and results are compared with the other available state-of-the-art methods.

The second part of the thesis deals with tracking based on colour features. Tracking objects in crowded environments is an important part of a surveillance system and the particle filter is used extensively to solve this problem. Although particle filter based techniques tend to outperform other methods, they are computationally expensive. An Adaptive Sample Count Particle Filter (ASCPF) method is presented in Chapter 5 where particles are switched between active and inactive states based on the proposal distribution. The technique is tested on different scenarios and results are compared with the Sequential Importance Resampling (SIR) particle filter. It was observed that the method produces similar tracking results as compared to the standard SIR particle filter but is up to five times faster.

In Chapter 6, the ASCPF technique discussed in the previous chapter is implemented in a multi-camera environment to track objects across different scenes. Multi camera environments can pose difficult challenges such as a change in the scale of the object as it moves from one camera to another or a change in the object features, such as colour, as the brightness levels can alter across different camera views. A variable standard deviation value of the ASCPF has been utilized in order to cope with sudden colour and scale changes. The technique has been tested on live feeds from four different camera views. It was found that not only did the ASCPF method result in successful tracking of a moving object across different camera views but it also maintained a real time frame rate due to its reduced computational cost.

Chapter 2

Object Segmentation and Tracking Using Gaussian Mixture Model Background Subtraction

Chapter 2

OBJECT SEGMENTATION AND TRACKING USING GAUSSIAN MIXTURE MODEL BACKGROUND SUBTRACTION

2.1 Introduction

Automated detection and tracking of moving objects is of prime importance for video surveillance and security system applications. Tracking objects can simply be defined as accurately assigning unique labels to target objects in consecutive video frames. The process becomes difficult if: an object is tracked in the presence of other moving objects with similar characteristics; there is an unexpected change in the motion or direction; an object is partially or completely occluded; or an object as well as the background is in motion at the same time. However, for situations where the number of objects in the scene is restricted with stationary background and also there is no occlusion, the tracking solution can be reduced from a complex data association process to a simple segmentation problem. A study has been conducted and discussed in this chapter to understand when such systems with restricted scene settings are effectively used in real life situations and what problems they may face if these restrictions are lifted. A simple blob tracking technique has been developed for this purpose where foreground regions are initially segmented using a GMM. These foreground blobs are then tracked and validated if they remain in the scene for a certain period of time. The technique has been tested on over 24 hours of video sequences from the *i-LIDS Sterile Zone* dataset. Experimental results have shown that although the discussed blob tracking technique fails to perform in sudden change in lighting conditions and unable uniquely identify any particular object in the presence of multiple objects, it can be deployed in situations where single object tracking is required.

2.2 Chapter Organization

The chapter is organized as follows. The following section gives a brief overview of the proposed testing environment. Section 2.4 describes the GMM used in this chapter to segment foreground blobs from the background. Section 2.5 explains how the objects are classified and tracked when they are identified in the scene. Results are presented and discussed in Section 2.6 and the study is finally concluded in Section 2.7.

2.3 Overall Testing Environment

In order to identify whether surveillance applications based on basic background segmentation techniques can be deployed in real life scenarios, the *i-LIDS Sterile Zone* scenarios have been studied in this chapter. The Sterile Zone problem is the simplest of the *i-LIDS* scenarios, although it is by no means trivial to provide a robust solution to all the scene variations contained in the dataset. The problem is to detect intruders in a 'sterile zone' region adjacent to a security fence. Potential false alarms can be generated by small animals entering the zone and poor weather conditions such as sleet falling past the camera. Intruders approach the fence in several different ways such as by walking, crawling and rolling, and each of these must be classified. In addition, the lighting conditions vary with some scenes being shot at night under artificial near infra-red illumination.

Initially, a region of interest (ROI), shown in Figure 2.1, is identified from within the camera field of view during manual interactive set-up. All objects appearing within the ROI are automatically segmented from the background and further localized processing on the identified areas of interest is performed to determine whether an alarm should be generated. The incoming frame is initially de-noised using a small kernel convolution based filter (a 3x3 median filter to remove impulse noise) before being fed into the foreground segmentation module. To achieve foreground segmentation, GMM (explained in the following section) is used. Once foreground objects are identified, their width and height are calculated and compared with typical object templates. During set-up, objects are classified according to size which enables the reduction of false alarms which would otherwise be generated by small creatures such as rabbits and birds etc. that enter the ROI in front of the security fence. Objects entering the sterile zone are then tracked and stored in a centralised database. Alarm events are generated if objects are found to be in the scene for certain amount of time.

(a) (b)

Figure 2.1: (a) Typical 'Sterile Zone' scene from the *i-LIDS* dataset. (b) Marked 'Alarm Zone'.

2.4 Gaussian Mixture Model (GMM)

The background segmentation method used to segment foreground regions within this chapter, and more generally in the thesis, is based on the one originally presented in [27]. The algorithm forms a background model for each pixel and if a new pixel fits the existing model it is classified as background; otherwise, it is labelled as foreground (see Appendix A for further details). Figure 2.2 below shows a typical scene from the *i-LIDS* dataset together with the GMM result.

(a) (b)

Figure 2.2: (a) Typical scene from the *i-LIDS* dataset. (b) GMM output.

2.5 Object Classification and Tracking

Once objects are detected entering a scene, or a specified alarm zone, a classification technique based on their shape and position is applied to determine whether the detected object is a distraction, such as small creatures like rabbits or birds etc., or a legitimate human object. More complex human identification methods based on methods such as the calculation of Haar co-efficients are available in the literature [23-25]. Since these techniques require offline training to identify the human form and are more computationally expensive the methods are not covered within the scope of this chapter.

In order to track the detected objects within the scene, the proposed testing approach relies on the assumption that by achieving a higher frame rate (more than 10 frames per second) each foreground blob at time t will overlap some part of its position at time $t-1$. Since the number of moving objects is already limited, this assumption helps objects being tracked accurately while moving in the scene. If objects are moving fast, or a higher frame rate is not achieved, and the tracked object does not overlap its positions between frames, the previous positions are discarded from the database and a new entry is created. Figure 2.3 shows a series of images of a human running towards the fence taken at different frame rates (25 frames per second, 15 frames per second and 10 frames per second). It can be seen that at the higher frame rate (25 frames per second) over 75% of the area overlaps with its area in the previous frame. Similarly, for 15 frames per second, there is over a 25% overlap. However, for a lower frame rate of 10 frames per second less than a 10% overlap has been observed. This illustrates that if a higher frame rate is achieved, even objects moving at higher speeds will overlap some portion of their area between frames.

2.6 Results and Discussion

The proposed testing approach has been evaluated on the Sterile Zone scenario of the *i-LIDS* dataset provided by the British Home Office Scientific Development Branch (HOSDB). It consists of twenty video sequences recorded from two different camera views and different illumination and weather conditions (day, night, snow, fast moving shadows, etc.) with an overall duration of over 24 hours. During each sequence, an intruder enters the scene and tries to break the fence. The system is required to detect the intruder and generate an alarm within 10 seconds. The performance of the algorithm is evaluated by calculating the overall detection rate and the probability of a genuine event [103].

The algorithm, when run on each sequence of the dataset, can result in the following outputs:

- **True positive alarms (a):** System generates alarms in response to a genuine event.
- **False positive alarms (b):** System generates alarms without the presence of a genuine event.
- **False negative alarms (c):** System fails to report a genuine event.

This data allows the following two values to be calculated:

The detection rate:

$$r = \frac{a}{(a+c)} \tag{2.1}$$

and the precision (probability of an alarm being genuine):

$$p = \frac{a}{(a+b)} \tag{2.2}$$

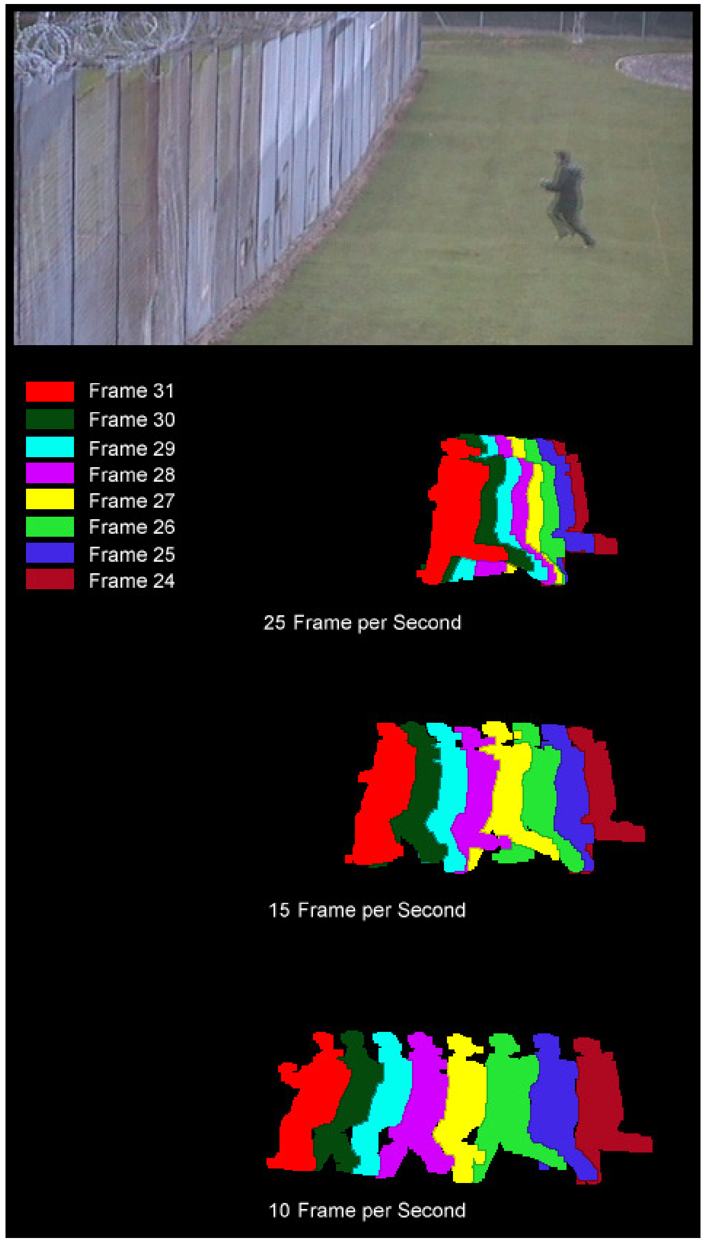


Figure 2.3: Series of images of a human running towards the fence taken at different frame rates (25 frames per second, 15 frames per second and 10 frames per second).

The dataset is divided into two sets of videos: one with genuine alarm events (216 events); and the other with no alarms but distractions caused by small animals such as rabbits, bats and birds etc. Table 2.1 below shows the detailed performance of the proposed algorithm on all the sequences with alarm events following strict *i-LIDS* evaluation guide-lines. It be seen that out of 216 genuine events the simple blob tracking technique successfully detects 197 events (see Figure 2.4 for detection examples) missing only 19 events, giving an overall detection rate of over 91%. On the other hand, it also generated 35 false alarms. It was observed that 15 of those 35 false alarms were generated in one video sequence with no genuine events (SZTEN202a) due to shadows caused by sudden change in illumination conditions, as shown in Figure 2.5. If this sequence is excluded from consideration of the discussed technique, the probability of detecting a genuine event increases from 84.7% to over 90%.

File Name	Duration (hh:mm:ss)	Total Events	True Positive	False Positive	False Negative	Detection Rate (*r*)	Precision (*p*)
SZTEA101a	00:37:11	10	10	1	0	1.000	0.909
SZTEA101b	00:49:46	15	15	0	0	1.000	1.000
SZTEA102a	00:36:39	13	9	0	4	0.692	1.000
SZTEA102b	00:45:56	17	17	0	0	1.000	1.000
SZTEA103a	00:47:14	17	17	0	0	1.000	1.000
SZTEA104a	01:32:18	31	31	1	0	1.000	0.969
SZTEA105a	00:35:28	10	10	1	0	1.000	0.909
SZTEA201a	00:37:11	10	9	0	1	0.900	1.000
SZTEA201b	00:49:46	15	12	4	3	0.824	0.778
SZTEA202a	00:36:37	13	13	3	0	1.000	0.813
SZTEA202b	00:45:38	17	14	1	3	0.824	0.933
SZTEA203a	00:47:10	17	15	0	2	0.882	1.000
SZTEA204a	01:32:12	31	25	4	6	0.806	0.862
Total	**10:53:15**	**216**	**197**	**15**	**19**	**0.912**	**0.908**

Table 2.1: Results from testing the proposed method on videos containing only genuine events from the *Sterile Zone i-LIDS* dataset.

Figure 2.4: Correctly identified alarm events using a simple blob tracking algorithm in different weather and lighting conditions (day, night, snow, fast moving shadows).

From Table 2.1 it can be seen that an overall 90% detection rate can be obtained if number of objects is restricted in the scene and the overall lighting is more or less consistent. The difficulty arises when there is a sudden change in illumination conditions, as shown in Figure 2.5, or the system is required to track multiple objects. Figure 2.6 presents one such scenario when multiple objects are present in the scene. It can be seen that although system keeps track of both objects while they merge and split, it loses object's identity. More robust solutions are available to tackle these problems which are discussed later in the thesis.

Another issue that the algorithm faced was disappearance of the foreground object into the background if it stayed at one particular position for more than a certain period of time. This is due to the update of GMM background model. The update rate is kept high to render the sudden illumination variations ineffective. However, this causes the foreground blob to break up into small regions, as shown in Figure 2.7. On the other hand, if the update rate is kept low to avoid object disappearance into the background, a sudden change in the lighting conditions can cause the false foreground regions to be picked up as moving objects, as shown in Figure 2.5. This shows that, although high detection and precision rates can be achieved in controlled testing environments, a slight change in conditions or the addition of multiple objects in the scene can compromise the overall performance.

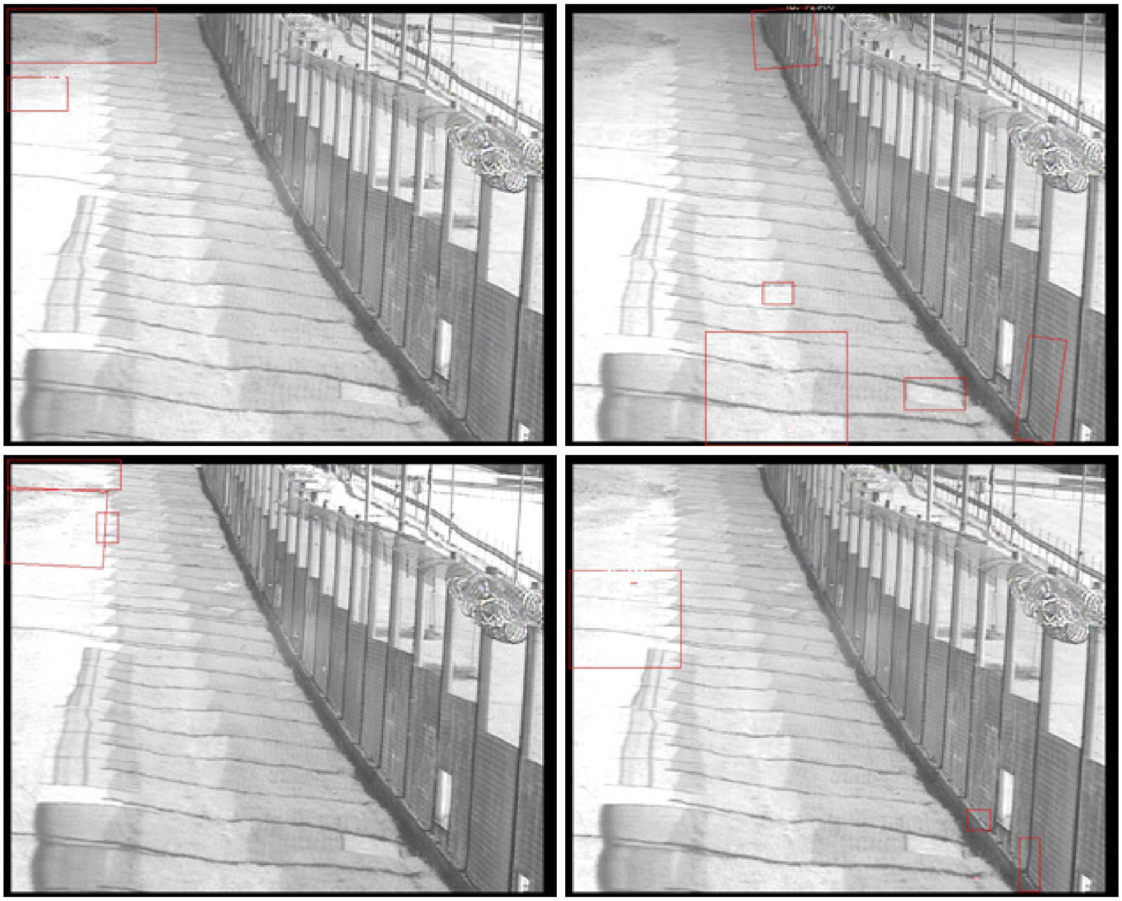


Figure 2.5: False alarm detection due to sudden change in lighting conditions in video sequence SZTEN202a.

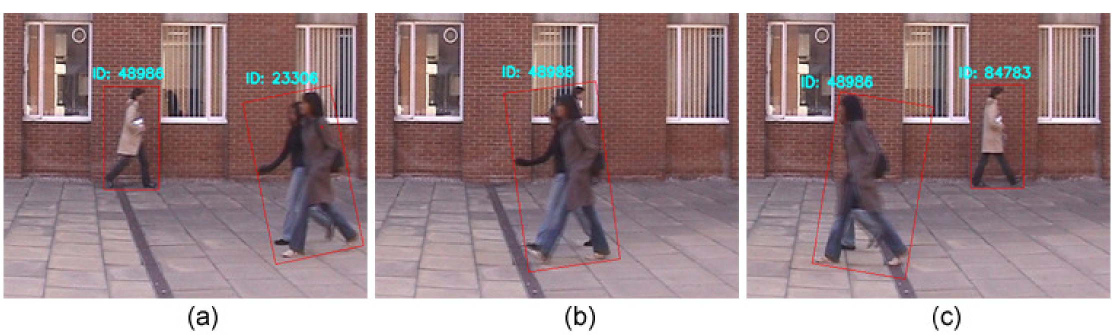


Figure 2.6: A scenario from testing environment where multiple objects cross over and proposed method loses object identity. (a) objects moving towards each other (b) objects merge into a single object (c) objects split up with different identities.

Figure 2.7: Object break-up caused due to higher GMM update rate.

2.7 Conclusion

A simple GMM based blob tracking technique has been assessed in this chapter in order to identify if simple background segmentation based techniques can be implemented in real life scenarios to detect and track moving objects. The technique has been tested on all the video sequences from the *i-LIDS Sterile Zone* dataset and results in terms of detection rate and precision of the method have been obtained.

Experimental results have shown that although the GMM based method gives over a 90% detection and precision score when applied to scenes with relatively constant illumination conditions but it fails to perform well in situations where there is sudden change in lighting conditions as the detection rate falls to 84%. The update rate of the background model plays a significant role in such situations. It has been observed that if the update rate is kept high to minimise the effects of sudden change in illumination conditions this can cause the stationary objects to disappear into the background very quickly. On the other hand if the update rate is kept low, false foreground regions are picked up as moving objects in the scene. Another observation that has been made about background subtraction methods based on GMM is their limitation for tracking multiple objects at any give time. Since no information apart from the object position is available about the foreground blobs, two or more objects crossing each other can cause the method to lose track of the original object.

To overcome these difficulties a more robust solution is required that can not only take care of changing lighting conditions but also track objects of interest in the presence of other moving or stationary objects. A robust edge based technique is presented in Chapters 3 and 4 in which emphasis has been given to maintaining the segmentation of stationary objects under variable lighting conditions.

Chapter 3

Tracking Objects Using Edge Information in Controlled Lighting Conditions

Chapter 3

TRACKING OBJECTS USING EDGE INFORMATION IN CONTROLLED LIGHTING CONDITIONS

3.1 Introduction

Edges are points in an image with sharp changes in intensity. One of the reasons to identify these sharp changes is to capture unique properties of objects within the image. These unique properties are known as object features and can be used for tracking purposes. An important property of edges is that they are less sensitive to change in illumination as compared to colour which makes them a favourable feature for tracking objects. To investigate whether techniques based on edge maps can be used for tracking objects in controlled lighting conditions, a real time edge-based tracking method is studied in this chapter where the magnitude of the edge is used for tracking objects. Although edge maps are robust against gradual change in illumination conditions, they are also very sensitive to the motion of the object. Any change in the object motion can cause the edge map to change which can result in false tracking outputs. Keeping in view these limitations only those objects are considered for tracking which become stationary in the scene. Objects such as baggage unattended in public places are examples of such situations. Since these objects can pose a serious security threat, their identification and tracking is an important part of any video surveillance application. In order to identify and lock on to these objects using edge maps, an edge based tracking technique is deployed within a real time stationary object detection system to keep track of objects identified as stationary. GMM is initially used to generate a binary mask containing all the moving objects in the scene. The binary blobs in the mask are tracked, and those found stationary through the use of a Centroid-Range method are segregated. A Canny edge detector [100] is then applied to the parts of the current frame and the average background frame, encompassed by the stationary blobs, to pick up the high frequency components. These high frequency components constitute an edge map for the tracked object. This resultant edge map is registered and tracked through the use of a correlation based matching process. The technique is tested on indoor scenes from the *Abandoned Baggage* scenarios of *PETS 2006* datasets. Experimental results have shown that the magnitude of the edges does not change in controlled lighting conditions. However further tests on outdoor scenes from *Parked Vehicle* scenario of *i-LIDS* dataset revealed that a sudden alteration in lighting conditions can, nevertheless, cause considerable change in the edge map with consequences for the maintenance of successful tracking.

3.2 Chapter Organization

The chapter is organized as follows. Section 3.3 describes the importance of surveillance systems capable of tracking stationary objects in real life situations and presents a generic framework of how to achieve such systems. Section 3.4 presents the overview of the computational model used to evaluate the performance of an edge-based tracking system; this includes the identification of static objects using the Centroid-Range method (that will filter out all the moving objects and will only keep stationary objects) and edge-based object tracking using the Canny edge detector to obtain the high frequency components encompassed by the identified stationary blobs. In Section 3.5 tests of the proposed system on the *i-LIDS* and *PETS* datasets are conducted and the results discussed. Finally the study is summarized in Section 3.6.

3.3 Algorithm Overview

Identification and tracking of moving objects that become stationary is an important part of any video surveillance application. Due to the increase in the number of camera feeds in surveillance systems around the world, there is a need for robust automated detection and tracking solutions that can identify stationary objects in public places and prohibited zones. Keeping in view the importance of the problem, a number of datasets (*i-LIDS* [4], *PETS* [5], *ViSOR* [6], *MIT* [7], *University of Sussex Traffic Management* [8]) have been introduced to aid the development and testing of computer vision algorithms. Many researchers have attempted different approaches to solving this problem and a general framework has emerged. Moving foreground objects are separated from the static background using one of several background segmentation techniques. These foreground objects are then tracked and alarm-events are generated if the objects are found to be stationary for a prescribed period of time within a designated alarm zone.

This approach divides the problem into two major operations: detection and tracking. In order to detect the objects accurately, different background segmentation techniques have been utilized. The second part of the problem is to deal with the tracking of foreground objects once they have been identified as stationary. Colour is the major feature used for tracking objects, but lighting is again an issue in using colour as a feature for tracking. Since edges are more robust to change in lighting conditions as compared to colour, they have been utilized to track objects in such situations.

Another important aspect of the problem is the handling of regions that are falsely identified as foreground objects. These regions can be formed by temporarily stationary objects leaving the scene, or foreground blobs appearing after initial segmentation due to changes in the illumination conditions.

Keeping the above discussion in view, it is concluded that a robust stationary object detection system must provide solution to the following major challenges:

- The correct identification of objects as stationary
- Temporal tracking of stationary objects in changing lighting conditions
- Temporal tracking of objects under partial or complete occlusion

- The removal of objects falsely identified as stationary from the object database
- The removal of objects from the database when they are no longer stationary

Since the problem discussed in this chapter focuses on investigating the effectiveness of an edge based tracking technique, the first two of the five points listed above are considered in this chapter. The remaining issues are addressed in the following chapter where a more robust system is discussed to tackle the same problem.

3.4 Computational Model

The overall system to evaluate an edge based tracking method is divided into three modules. These are:

- Foreground segmentation
- Identification of stationary objects
- Template registration and tracking stationary objects using an edge base correlation technique.

The Region of Interest (ROI) is identified initially as a binary image. Objects appearing only within the ROI are considered for identification and tracking thus reducing the overall system processing time. Figure 3.1 shows a typical scene from the *PETS 2006* dataset along with the marked ROI. The incoming frame is first de-noised using median filtering before being fed into the foreground segmentation module to get foreground regions. These foreground regions are then checked against a minimum and maximum object size filter to remove objects that are too small or too large. All legitimate objects identified in the foreground segmentation module are then stored in a database for further processing. Objects that are no longer in motion are identified using the Centroid-Range method and tracked using the edge based correlation technique.

3.4.1 Stationary Object Detection

GMM presented in previous chapter has been used to identify any moving objects in the scene. This GMM output is then scanned for any stationary items that may exist in the frame. Each set of connected pixels are separated from the mask and checked for a minimum and maximum object size. The size threshold is determined on the basis of object position in the frame. The position is determined by obtaining the centroid of binary mask encompassing the object. Any objects outside minimum and maximum threshold are discarded.

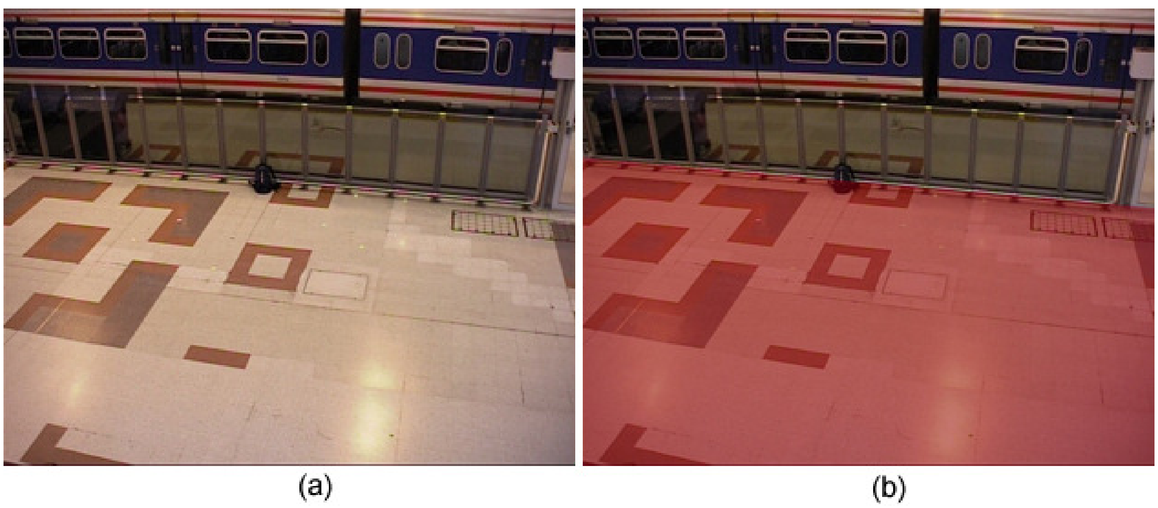


Figure 3.1: (a) Typical scene from *PETS 2006* dataset. (b) Marked alarm zone in red.

The remaining objects are tracked based upon the assumption that they will overlap some part of their position in frame *t-1* (as discussed in Chapter 2). If objects are moving fast and do not overlap their precious positions, their previous positions are discarded from the database and new entry is created.

A Centroid-Range method is applied to each object in the database to determine if they are stationary or not. A dynamic centroid range is calculated for each object depending on its previous positions and kept in the database. If the object centroid at the current frame falls within the generated range consistently for a certain number of frames, the object is considered to be stationary. The concept can be understood better by looking at Figure 3.2. As an object moves in the scene from point *'a'* to *'e'*, its centroid is calculated at each step. If distance *'dist'* between two adjacent centroid positions is greater than the object width, the object is considered to be moving. If that is not the case, then four values; X_{min}, Y_{min} and X_{max}, Y_{max} are kept in the database. These values constitute the centroid range that is used to identify if the object is stationary or not. If the current X and Y position of the centroid is within the minimum and maximum range for a certain number of frames, the object is labeled as stationary. For all non stationary objects, this range will keep on changing thus making this method an effective way of identifying stationary objects.

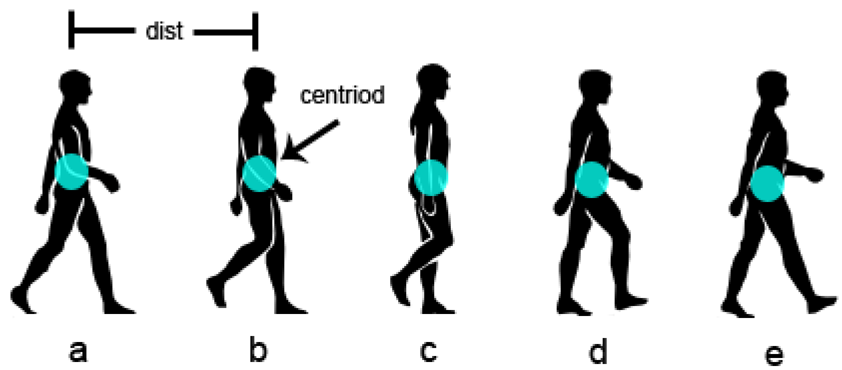


Figure 3.2: Centroid-Range calculation method. The Object centroid is calculated at each step from point 'a' to 'e'. If the current centroid position is within the centroid range for a certain number of frames, the object is considered to be stationary.

3.4.2 Template Registration and Tracking Using Edge Correlation

Once the objects are identified as stationary using the Centroid-Range method, a *Canny* edge detector [100] applied on areas covering the identified stationary object. The *Canny* edge detector is a widely used standard edge detection method that according to different author [101-102] tends to outperform other available edge detection methods such as *LoG*, *Sobel* or *Prewitt*. Figure 3.3 shows steps involved in *Canny* edge detection process (see Appendix A for details).

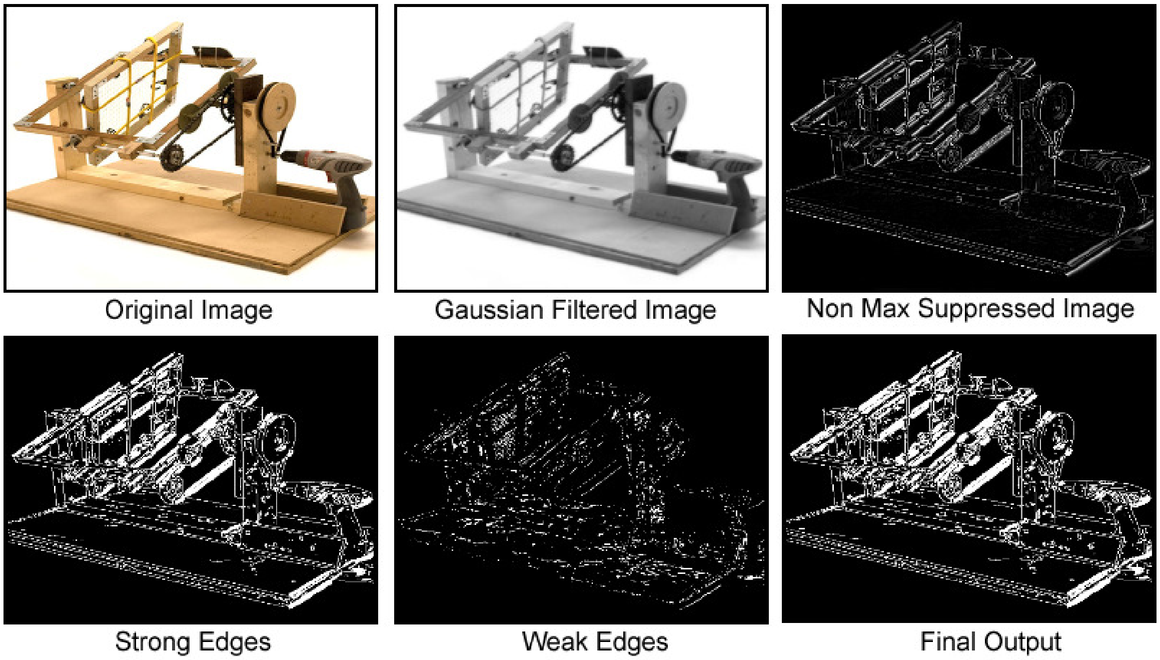


Figure 3.3: Individual outputs obtained after applying steps involved in *Canny* edge detection process.

As a result of applying the *Canny* edge detector to the image, high frequency componen ts are picked up for areas encompassed by the stationary blobs. These high frequency components constitute the object's edge map and are registered in the database as templates to keep track of stationary objects.

Normalized cross correlation has been commonly used to identify objects using template matching. Since only stationary objects are considered for tracking, the correlation technique is best suited for situations discussed in this chapter. A similarity measure is obtained by cross correlating the reference template with the current and energy normalizing using equation 3.1.

$$NCC = \frac{P_{ref}(.,.) * P_{current}(.,.)}{\left\| P_{ref}(.,.) \right\|_2 \left\| P_{current}(.,.) \right\|_2} \tag{3.1}$$

where *NCC* is the normalized cross correlation result obtained after matching the reference patch P_{ref} with current patch $P_{current}$ obtained at time *t*.

In order to track the stationary objects, the *Canny* edge detector is applied to both background and current frame and an edge map is obtained for areas covered by stationary objects. A correlation peak is obtained by correlating the current frame edge map with the reference edge map already stored in the database. For stationary objects, the resultant correlation peak value is higher than the selected threshold value (75% of the autocorrelation peak of the reference edge map). If this value is lower than the selected threshold, then one of the following two possibilities has occurred:

- Object has moved from its position, or
- Some other object is obstructing the camera view

In both cases the background frame edge map is correlated with the current frame edge map to get a second correlation peak and to compare with the selected threshold value. If it is higher than the threshold, the object is considered to be removed; if not, then some other object is obstructing the camera view and the original object it still present at its original position. Figure 3.4 shows a typical abandoned object detection scene from the *PETS* dataset with the corresponding object edge map and correlation peak. (The threshold plane obtained by auto correlating the object's reference edge map is also shown on the correlation plane.)

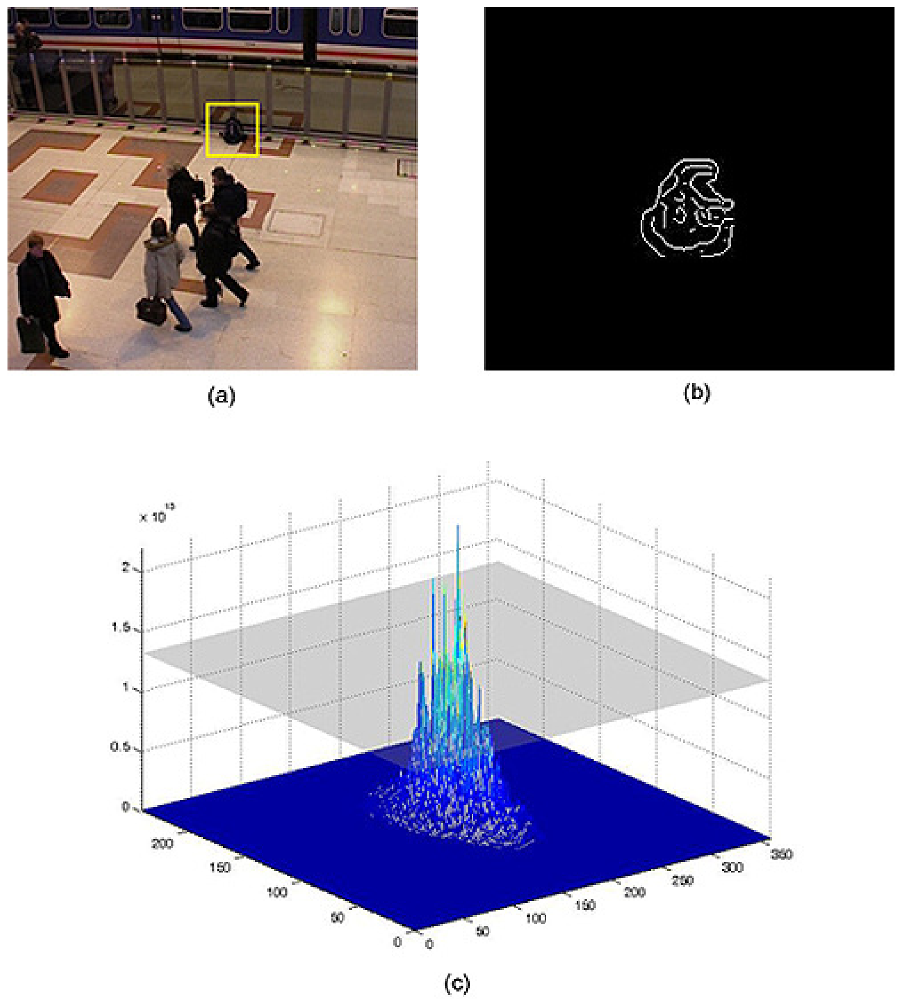


Figure 3.4: (a) A typical abandoned object detection scene from the *PETS* dataset. (b) An object edge map after applying the *Canny* edge detector to the identified object area. (c) Correlation peak along with the threshold value obtained by correlating the reference edge map with the edge map obtained from the current frame. If the correlation peak is higher than the threshold value, the object is considered to be stationary.

3.5 Results and Discussion

The performance of the proposed system has been analyzed from two aspects, namely: a combination of the background segmentation model and the Centroid-Range method to identify stationary objects; and the effectiveness of the edge based technique to keep track of stationary objects. The combined method has been initially evaluated on different indoor sequences from the *PETS* with controlled lighting conditions and then on outdoor video sequences from the *i-LIDS* datasets. The results obtained are compared with the other available methods. Keeping in view the importance of a real time system, the proposed system is designed to run at over 12 frames per second on a single core 2.66 GHz machine.

3.5.1 Object Detection

The combination of a background segmentation technique and the Centroid-Range method is first evaluated using the *PETS 2006* datasets with controlled lighting. The *PETS 2006* dataset has been designed to assess automated video surveillance applications for the detection and tracking of abandoned objects in multi-camera environments [7]. The dataset consists of 7 video sequences taken from 4 different camera views. The ground truth data for all the sequences is also available with the information about the number of people and objects involved and also the relationship between the abandoned object and its owner. Since the proposed system is designed for a single camera environment, it has been tested on one of the four available views. Figure 3.5 shows images from the *PETS 2006* data sequences in which the abandoned object is detected (in scene S3 there are no positive alarms reported in the ground truth data). The overall results of the proposed algorithm, when tested on these sequences, are summarized in Table 3.1 where as Table 3.2 shows the comparisons made with other available state-of-the-art methods. The results presented it Table 3.1 illustrate the overall detection rate of 100%. It also reported 2 false alarms.

Sequence	Abandoned Objects	True Positive	False Positive	Missed Alarm
S1	1	1	0	0
S2	1	1	1	0
S3	0	0	1	0
S4	1	1	0	0
S5	1	1	0	0
S6	1	1	0	0
S7	1	1	0	0

Table 3.1: Results obtained after testing the proposed method on all the sequences from the *PETS 2006* dataset.

Methods	Total Alarms	True Positive	False Positive	False Negative
Proposed Method	6	6	2	0
Tian *et al.* [34]	6	6	1	1
Auvinet *et al.* [55]	6	6	5	0
Chang *et al.* [53]	6	6	0	0
Lv *et al.* [54]	6	6	N/A	0

Table 3.2: Results obtained after testing the proposed method along with other published methods on all the sequences from the *PETS 2006* dataset. N/A: data was not available from the author of the technique.

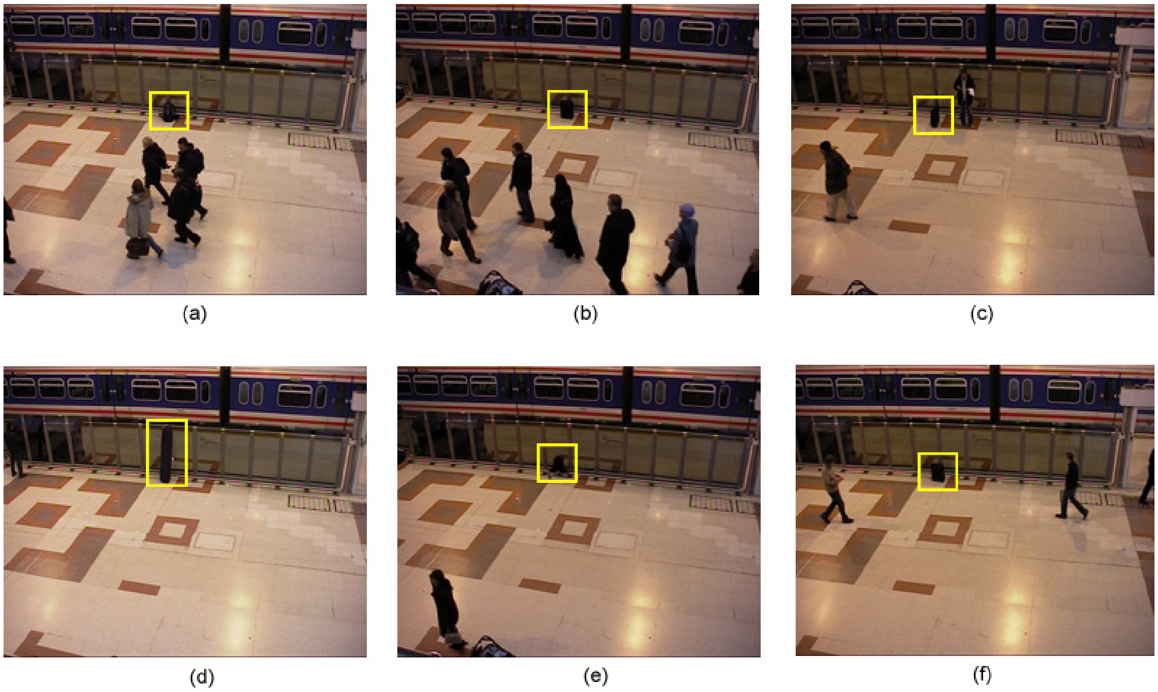


Figure 3.5: Images from the *PETS 2006 Dataset* (a) S1 (b) S2 (c) S4 (d) S5 (e) S6 (f) S7. All events are detected successfully with no false positives. Sequences are available to download from the website given in reference [7].

The technique has also been tested on the outdoor sequences on the *i-LIDS* dataset. The *i-LIDS* video library [4] provides a benchmark to aid in the development and testing of computer vision algorithms. It contains three progressively more demanding video sequences, taken at different times of the day. The dataset consists of long video sequences, containing multiple alarm events, with an overall duration of over 6 hours. Table 3.3 shows the results obtained after testing the proposed system on the *Parked Vehicle* video sequences. Out of 105 genuine events the proposed system picked up 60 events and also reported 56 false events, giving an overall event detection rate of 57%.

False events are generated due to false foreground regions being picked up as stationary objects. These foreground regions appeared due to change in illumination conditions. Figure 3.6 shows images from video sequences listed in Table 3.3 with different camera views and video quality. It has been observed that the main reason behind the low detection rate is that the stationary objects are frequently occluded by other moving objects in the scene. If the stationary objects are occluded consistently, the algorithm fails to pick up them and hence they become part of the background. On the other hand, if the background is not updated frequently enough at a relatively high update rate, change in lighting conditions can cause false foreground regions to be identified as stationary objects, which can further increase the false positives and thus reduce the overall efficiency of the system.

File Name	Duration (hh:mm:ss)	Total Events	True Positive	False Positive	False Negative	Missed Tracks
PVTEA101a	01:21:29	26	13	21	17	4
PVTEA101b	00:24:40	8	2	2	6	0
PVTEA102a	00:51:56	18	9	13	16	7
PVTEA103a	01:03:54	16	15	4	2	1
PVTEA201a	00:18:50	4	2	1	2	0
PVTEA202b	01:05:23	17	11	9	8	2
PVTEA301a	00:15:29	3	1	1	2	0
PVTEA301b	00:28:07	7	4	3	5	2
PVTEA301c	00:27:09	6	3	2	4	1
Total	**06:16:57**	**105**	**60**	**56**	**62**	**17**

Table 3.3: Results from testing the proposed method on videos from the *i-LIDS* dataset of *Parked Vehicle*

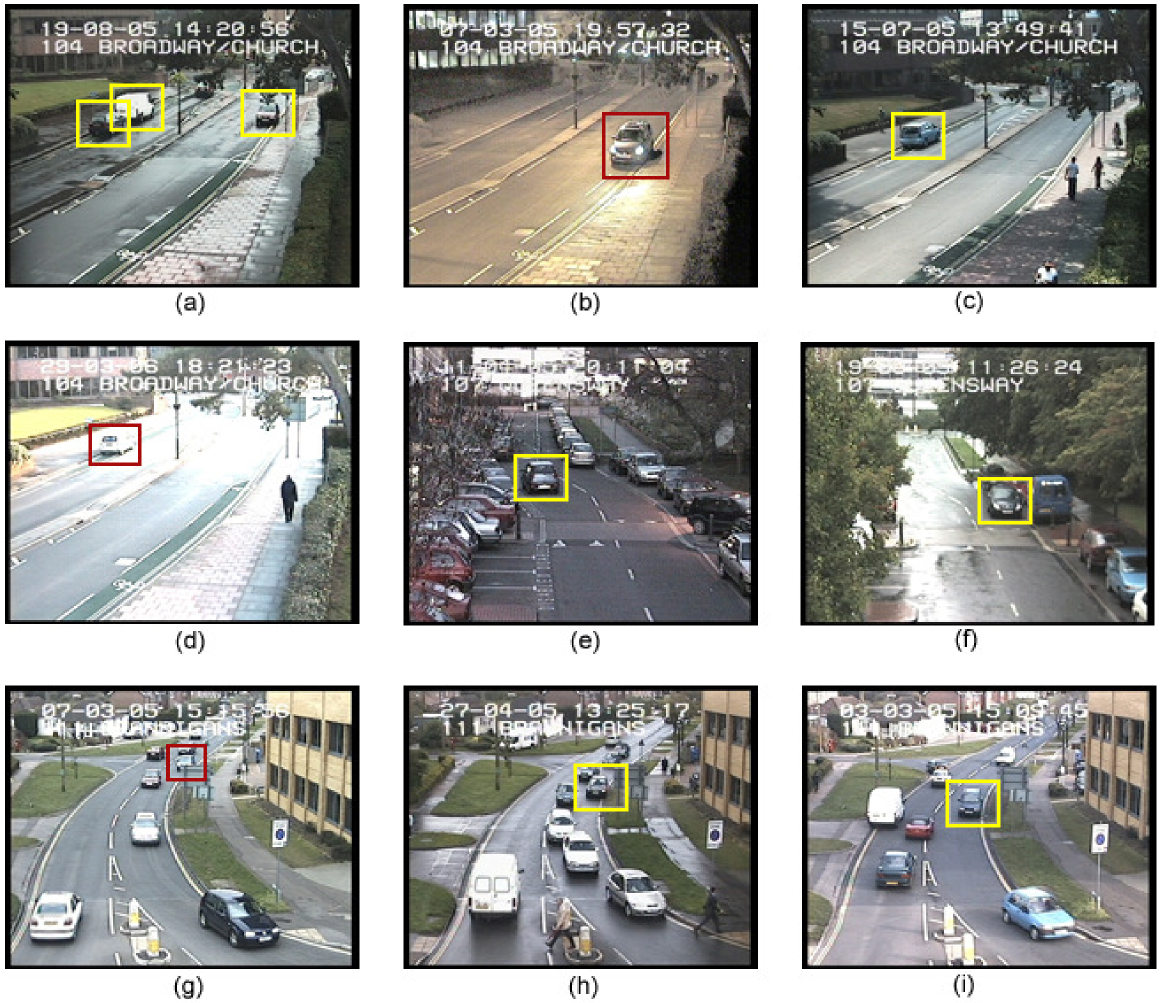


Figure 3.6: Images from the video sequences listed in Table 3.1. (a) PVTEA101a: Level I video, overcast conditions with rain. Video Quality: Good (b) PVTEA101b: Level I video, night video sequence with street lights. Video Quality: Good (c) PVTEA102b: Level I video, day video sequence with changing lighting conditions due to clouds. Video Quality: Good (d) PVTEA103a: Level I video, day video sequence. Video Quality: Poor (e) PVTEA201a: Level II video, overcast conditions with video shot at dusk. Video Quality: Good (f) PVTEA202b: Level II video, overcast with rain. Video Quality: Poor (g) PVTEA301a: Level III video, overcast conditions with video shot at dusk. Video Quality: Good (h) PVTEA301b: Level III video, good conditions. Video Quality: Good but with camera jitter (i) PVTEA301c: Level III video, day video sequence with changing lighting conditions due to clouds. Video Quality: Good.

3.5.2 Edge based Tracking

The second part of the testing process deals with evaluating the performance of the edge based tracking techniques discussed in Section 3.4.2. Edges are an important tracking feature, but since they are sensitive to the motion of the object, they are used to track only stationary objects. Once objects are detected by the background segmentation method and identified as stationary by the Centroid-Range technique, the edge based tracking technique is used to lock on to those stationary objects until they move from their stationary position. In Table 3.1 the results of the proposed method when tested on the *PETS* dataset are presented. All the genuine events were detected without any track being lost by the edge based tracking technique. This is due to the fact that the *PETS* dataset was recorded in an indoor environment with controlled lighting conditions.

On the other hand when same technique was tested on outdoor video sequences, it can be seen from Table 3.3 that out of 60 genuine events detected by the proposed detection model, the tracking technique missed 17 events. The remaining 43 events were tracked successfully. The main reason behind these missed events is a sudden change in illumination conditions. Due to the sudden change in the lighting conditions, the magnitude of the edges changes causing the correlation peak to fall under the selected threshold value. Figure 3.7 shows a series of images with one such situation. The normalized correlation peak values (as defined by equation 3.1) for the tracked object are presented in Figure 3.8. It can be seen that as the lighting changes from frame 900 onwards, the correlation peak value falls. This shows that with a sudden change in lighting conditions, the magnitude of the edges changes thus causing the correlation peak to fall.

Figure 3.7: Data sequence from one of the *i-LIDS* video sequences showing change in illumination conditions.

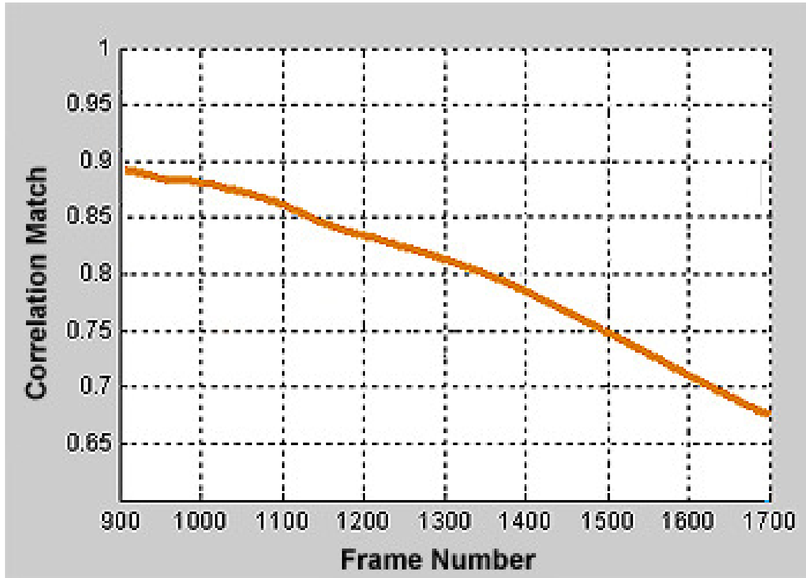


Figure 3.8: The effect of the change in lighting conditions (shown in Figure 3.6) on the correlation results from Frame 900 onwards.

3.6 Conclusion

An edge based tracking technique has been discussed in this chapter where the main focus is to identify whether the magnitude of image edges is a suitable feature with which to track objects in different real world scenarios. Since edge features are very sensitive to the motion of the object, only those objects are considered for tracking that are stationary in the scene. *PETS* and *i-LIDS* datasets are utilized for this purpose, as both datasets provide real world scenarios for identifying abandoned objects on train stations and illegally parked vehicles in no-parking zones. A real time two stage approach is adopted in which binary blobs of foreground objects are initially obtained by using GMM. These blobs of connected pixels are then tracked until they become stationary. Once they are identified as stationary objects, by using the Centroid Range method, their edge-map is obtained and stored in a database for further tracking. In the second stage, an edge-based tracking technique is applied to track these objects. Correlation peaks are obtained for each of the stationary objects by correlating the current edge map with the reference edge map already in the database.

The performance of the proposed system is evaluated from two different aspects. Firstly, the object detection stage is evaluated along with the Centroid Range method to obtain the overall detection rate of the system. The results obtained, indicate an overall detection rate of around 57%. It is observed that main reason behind this low detection rate is that the tracked object is frequently occluded by other moving objects in the scene. As the number moving objects reduces, the detection rate improves. As an example, this is the case when the detection model was tested on the *PETS* dataset, where a 100% detection rate was obtained as compared to only a 57% rate on *i-LIDS* dataset.

In the second stage of the evaluation process, the edge based tracking technique is analyzed. It is observed that in controlled lighting conditions, the magnitude of edge remains consistent where as it changes with sudden alteration in lighting conditions. This change causes the correlation peak to fall under the selected threshold thus resulting in loss of the tracks. Since the *i-LIDS* dataset is shot in an outdoor environment, where changes in lighting conditions are unpredictable, 17 lost tracks were recorded as compare to none in the PETS dataset. Hence it is concluded that in order to track stationary objects in challenging indoor and outdoor environments, a more robust solution is required. This could not only detect stationary objects under occlusion but also be able to track them in changing lighting conditions.

A new pixel based classification technique is discussed in the following chapter that efficiently detects objects under occlusion. Also, the orientation of the edges in an object is studied, and compared to their orientation independent magnitude, to find out if edge orientation is a useful feature to robustly track stationary objects under changing lighting conditions.

Chapter 4

Tracking Objects Using Edge Orientation

Chapter 4

TRACKING OBJECTS USING EDGE ORIENTATION

4.1 Introduction

In the previous chapter it is concluded that, although using the magnitude of edges can perform better than techniques based on colour features, yet in very inconsistent lighting conditions when lighting variations are higher than a certain level its performance is compromised. Such situations can often occur in an environment where the object recognition and tracking system is deployed in an outdoor scene and thus required to keep track of the detected object in variable lighting conditions. In order to develop more intelligent and robust object detection and tracking systems that can be implemented in both indoor and outdoor environments, a pixel-based classification model is presented in this chapter to detect objects that become stationary in the scene. These stationary objects are then tracked using a novel adaptive edge orientation based technique where orientation of the edge is exploited instead of magnitude to keep track of the stationary object. Experimental results have shown that the discussed technique gives more than a 95% detection success rate, even if objects are partially occluded. The technique has been tested on several hours of video sequences recorded at different locations and time of day, both outdoors and indoors. The results obtained are compared with the technique discussed in the previous chapter and also with the other available state-of-the-art methods.

4.2 Chapter Organization

The remaining sections of the chapter are organized as follows: Section 4.3 explains the pixel-based classification method for detection of stationary objects. Tracking is discussed in Section 4.4 along with some experimental results. Object removal is discussed in Section 4.5. The results of tests on different datasets are presented in Section 4.6 and, finally, the study is summarized in the final section.

4.3 Stationary Object Detection

As highlighted in the previous chapter, the overall system is divided into two major sections: detection and tracking. The first stage is to accurately identify stationary objects. There are several assumptions that have been made regarding the data: the stationary objects are initially not part of the scene and come in at a later stage; they must be stationary in the scene for at least 10 seconds before being labelled as stationary and, finally, they must fall within an 'Alarm Zone'. Typical 'Alarm Zones' for different datasets is shown in Figure 4.1.

To identify objects that are newly stationary in the scene the moving objects must first be located and then the tracking stage is triggered when these have become stationary. Stationary objects detection is therefore a two-step process:

- An initial segmentation of the video sequence using a GMM to determine moving objects;
- Formation of SHI using this output of the GMM to filter out transitory motion and determine when an object has become stationary;

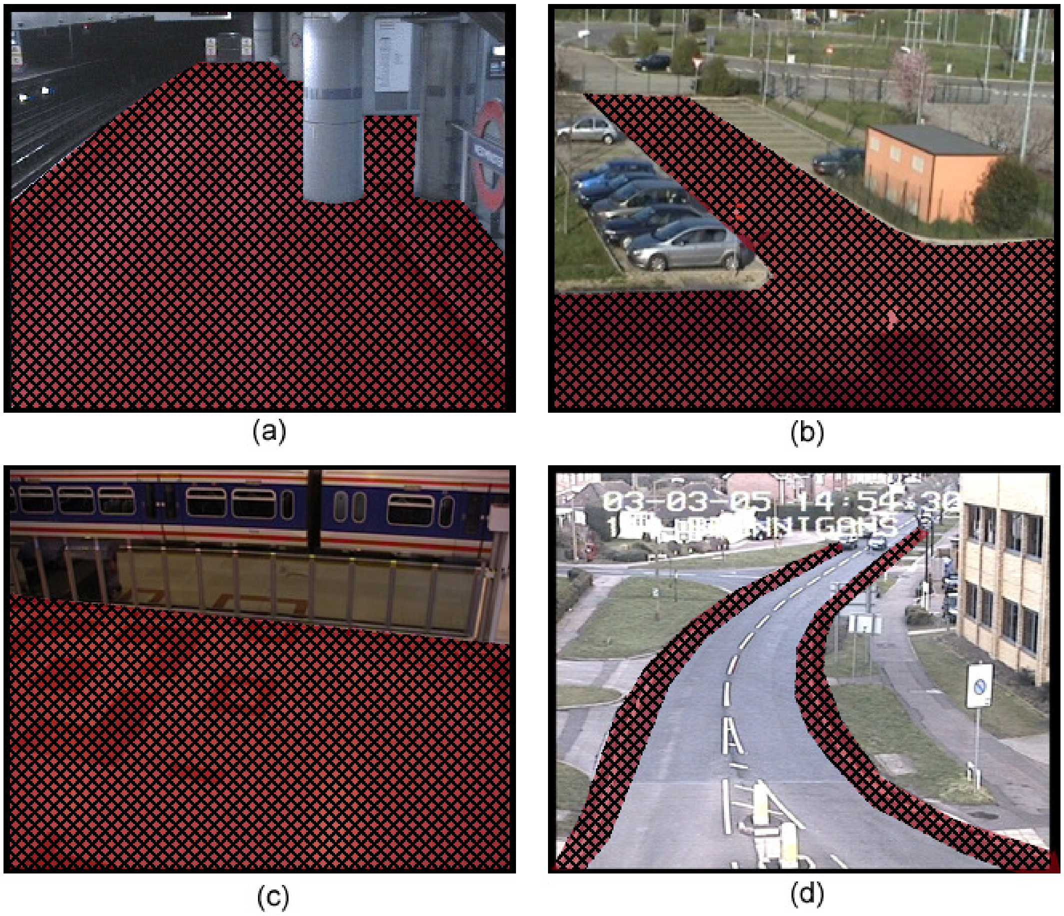


Figure 4.1: Typical Scenes from different datasets (a) *i-LIDS* dataset for Abandoned Baggage (b) ViSOR dataset for Stopped Vehicle Detection (c) *PETS 2006* dataset (d) *i-LIDS* dataset for Illegally Parked Vehicle Detection. The 'Alarm Zones' are marked in red.

The first step uses a GMM to segment the moving objects within the video sequences. Since the proposed method is required to track the object in real life indoor and outdoor scenarios, there are a number of unpredictable factors. For instance, for application of the algorithm to outdoor scenes to identify illegally parked vehicles, change in the illumination conditions or the starting and stopping of vehicles in busy traffic scenes will cause difficulties. If the background model is updated at a low rate any sudden change in illumination can result in the identification of false foreground areas. If the update rate is higher to cope with the illumination changes, it forces the stationary objects to become part of the background model more quickly resulting in either the partial detection of the moving object or a completely missed object. On the other hand, for indoor environments to detect abandoned objects, partial or complete occlusion is the biggest challenge. Most solutions proposed in the literature require an isolated view of the object before identifying it as abandoned. This requirement is typically difficult to meet, especially in crowded scenes where abandoned objects are frequently occluded.

In the proposed method the update rate is set to be high to cope with rapid lighting variations but Segmentation History Image (SHI) is introduced to post-filter the GMM output and determine when an object has become stationary.

The output of the GMM produces a set, Ω^t, of foreground pixels at time t. The SHI data, Γ, is initially zero then increased by one for every foreground pixel per frame:

$$\Gamma_{\Omega}^{t} = \Gamma_{\Omega}^{t-1} + 1 \tag{4.1}$$

Next the objects in motion are removed whilst keeping stationary pixels. This is achieved by setting the SHI to zero for every pixel not in the current Ω^t:

$$\Gamma_{\overline{\Omega}}^{t} = 0 \tag{4.2}$$

where the bar indicates all pixels not in the current set Ω. This eliminates all those regions that are moving from the SHI, thus leaving only those pixels that belong to the stationary objects.

Finally, a pixel is declared as potentially stationary when its SHI value is greater than some threshold, Λ. Λ is simply the number of frames the system requires to count before declaring a pixel stationary. In the discussed method, it has been set equal to 10 seconds of video. The stationary pixels are described by the set S:

$$S^t = \{a : \Gamma_a > \Lambda\} \tag{4.3}$$

where a is all the possible coordinates in the image.

The SHI effectively acts as a counter to determine when an object has become stationary, but in addition, by the careful selection of the GMM update rate it can filter out false objects due to lighting variations. It is noted that lighting changes are typically much smaller colour changes and often rapid, when compare to vehicles parking. Thus, the update rate of the GMM can be set such that lighting variations have become part of the background or have move and are thus removed from the SHI (via equation 4.2), before the Λ frames have been reached. The choice of the update rate is robust for many different videos and only need changing if Λ is altered. It does not need changing to cope different weather conditions or from switching from day to night time lighting. The process is further elaborated in Figure 4.2 where GMM output is shown in Figure 4.2(a) and the corresponding SHI in Figure 4.2(b).

It can be seen that the pixel identified as foreground region in Frame 1 are initialised each with a value equal to 1. As the object moves in Frame 2, the value of the pixels that overlap a foreground region of the SHI output in the previous frame is increased by 1 where as, pixels of previous SHI that do not overlap the new GMM output are removed from the SHI. The process continues until any pixel of the SHI reaches the threshold, Λ. It is important to note here that the output of the detection technique is based on this threshold value. Only those pixels are included in the final output that reach Λ. Empirical testing (done over several hours of video) has shown that in over 95% of the test sequences the effects of sudden illumination change can be removed if this Λ frames waiting rule is followed.

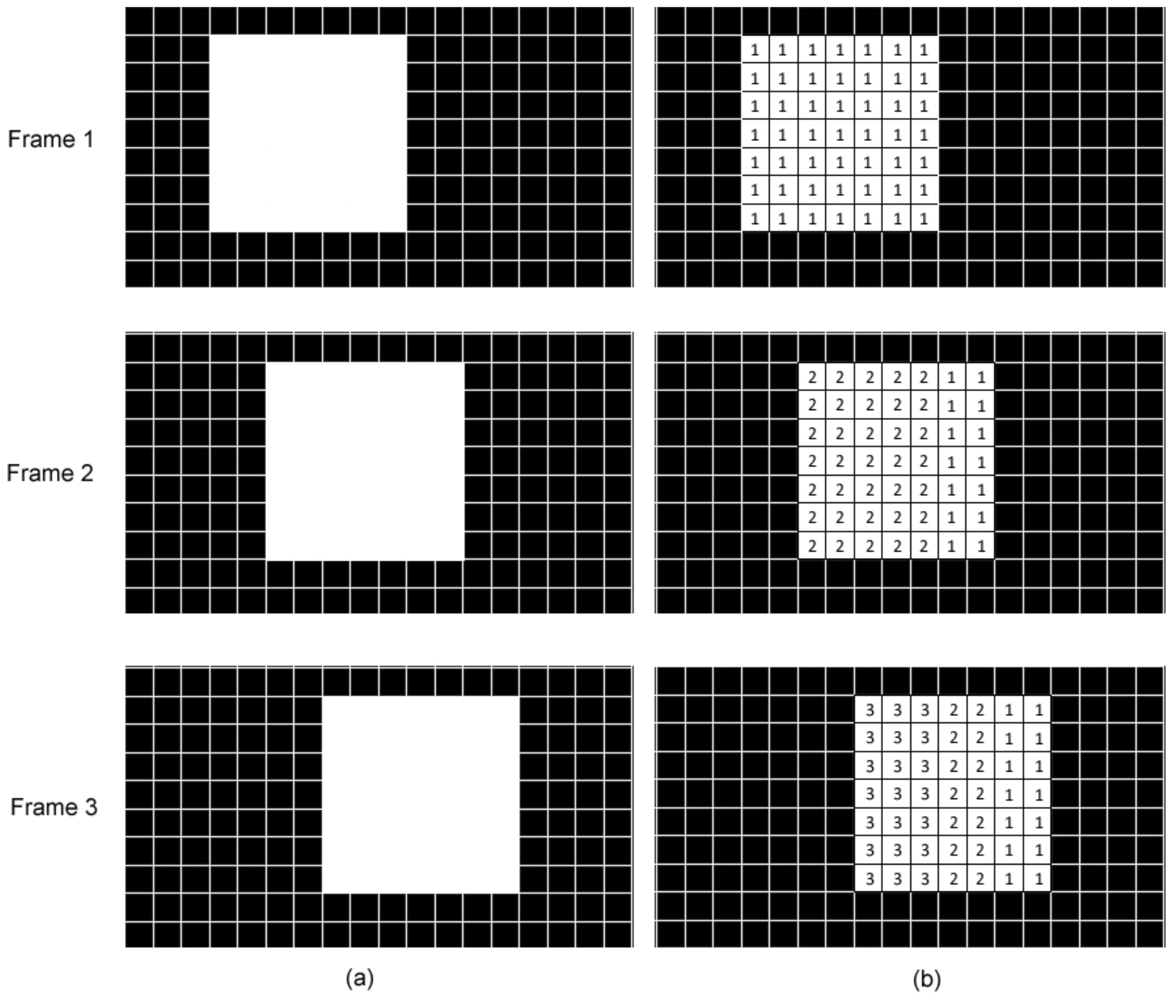


Figure 4.2: (a) GMM output, (b) SHI output.

Figure 4.3 shows a series of images within a typical outdoor scene, the GMM output, SHI and the final output after thresholding. The car shown in Figure 4.3 was initially not part of the scene and become stationary at Frame 108. It can be seen that GMM works almost perfectly if the lighting conditions are consistent (as shown in Frame 108 (b)) and only legitimate foreground regions are picked up (see GMM output Frame 108 (b)). As the lighting condition starts changing (see Figure 4.3 Frame 332 and Frame 409) false regions are picked up as foreground. Frame 409(d) shows the proposed SHI output where pixels only belonging to stationary object are highlighted as legitimate foreground region in the final SHI output.

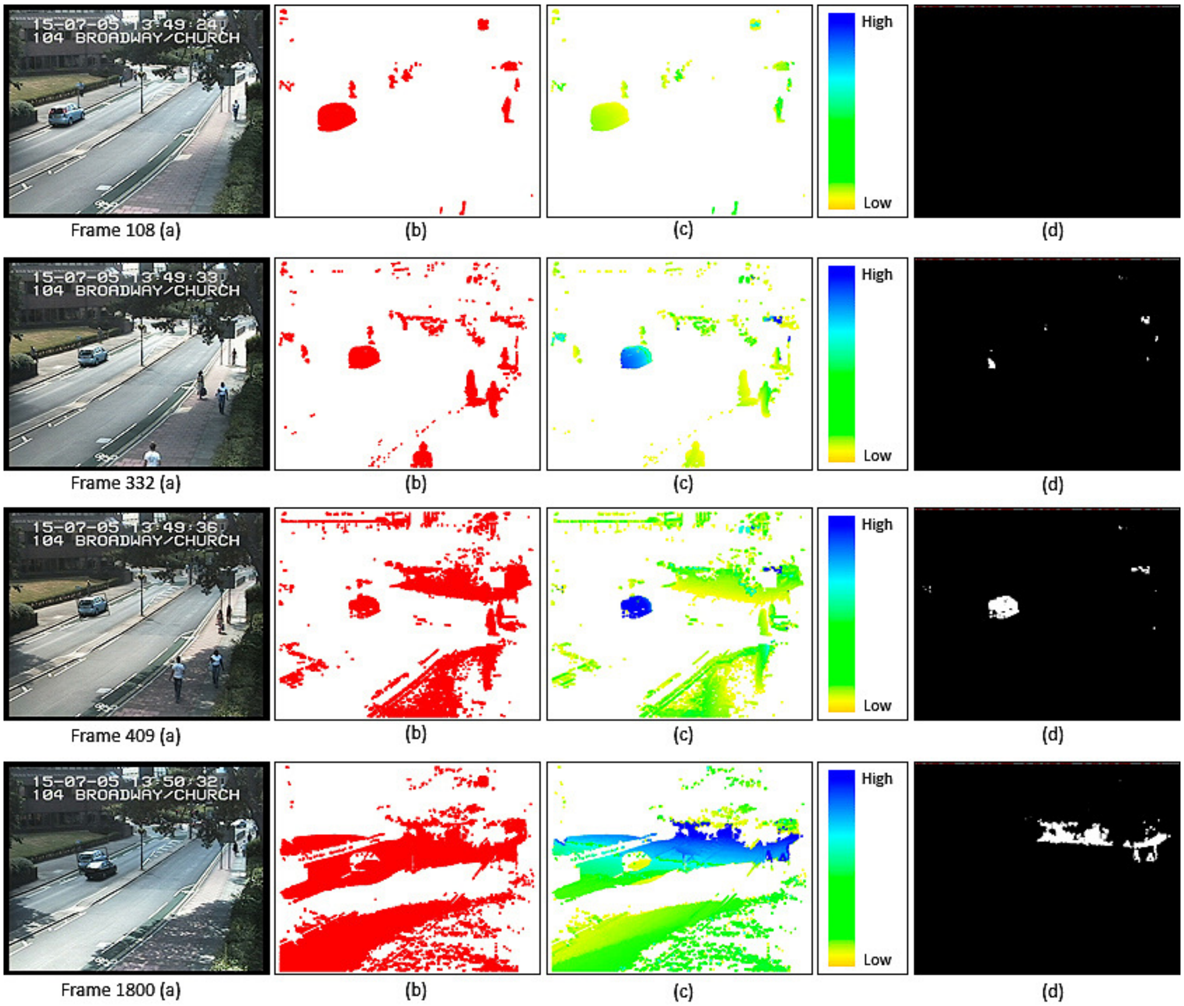


Figure 4.3: Images from the *i-LIDS* dataset for the illegally parked vehicle scenario to illustrate the detection technique. (a) typical frame (b) GMM output (c) SHI (d) SHI after Λ thresholding.

After the detection method, a connected component algorithm is run on the binary image, S^t, to produce objects, Θ_n^t where n is the connected component index and $n \in \{1, \ldots, N\}$ where N is the number of connected components discovered. All the connected foreground pixels are compared against a minimum and maximum object size. Objects that are too small or too large are then removed. The minimum and maximum object size thresholds are selected based on calibration information.

4.4 Stationary Object Tracking

A new adaptive edge orientation based technique is proposed in this section to track objects that are identified as stationary. To maintain the tracking, each object at time t is compared against the object at time T, where T is the time the object is first flagged as stationary by the SHI (equation 4.3). A correlation based method has been developed that uses the direction of the edges to indicate the strength of the match rather than the edge strength alone. A 2-D spatial gradient measure is performed on an image flagged as a stationary object, $I_{\Theta_n}^T$, where I is the monochrome image intensity. This is performed by a 3x3 Sobel convolution operator and is used to find the edges in both the vertical and the horizontal directions. So that the edge directions are well defined, the magnitude of the gradient is then calculated at T. This is done by taking the square root of the sum of the squares of each direction gradient result in Θ_n^T. Finally the output is thresholded to form a subset of coordinates, M_n. A higher threshold is chosen such that most of the edges are preserved.

The direction of the gradient of each member of M_n is then calculated by taking the arctangent of the ratio the vertical and horizontal gradients. It is denoted as $\Phi_{M_n}^T$, where $\Phi_{M_n}^T$ can range between 0 to 360 degree.

The obtained angles are then used to calculate a metric that gives a measure of the degree of correlation between an object at the current time t and the historic time T. . For the n^{th} object this is the real component of:

$$C_n^t = \sum_{M_n} \frac{\exp\left(i\Phi_{M_n}^t\right)\exp\left(-i\Phi_{M_n}^T\right)}{\left|M_n^T\right|} \tag{4.4}$$

where the vertical bars represent the cardinality of the set, and T is the time at which the reference edge mask is produced. The expression obtained above is the generalized correlation equation used in the proposed method for template matching. Since the location of the tracked object is known, the overall computational time is reduced by avoiding the scanning operation on complete image. The problem arises when the tracked object is partially or completely occluded. The occlusion problem is discussed in more detail in the following sub section where improved $\hat{C}_n^t$ is obtained by making use of current GMM segmented object mask, Ω_n^t.

4.4.1 Tracking Under Occlusion

The tracking of objects with occlusion is a major challenge faced by any surveillance application. Tian *et al.* [34] observed that it is very difficult to get high correlation scores when objects are frequently occluded. The proposed technique overcomes this issue by assuming that any current foreground segmented object (from the GMM in stage 1) is a new occluding object and it should be removed from the set of valid pixels used to calculate equation (4.4). The occluded region is removed from the mask, M_n, by subtracting the current GMM segmentation image, Ω_n^t. The adaptive mask for the n^{th} object is a subset of the original mask:

$$A_n^t = M_n - \Omega_n^t \tag{4.5}$$

And the improved correlation result is then:

$$\hat{C}_n^t = \sum_{A_n} \frac{\exp\left(i\Phi_{A_n}^t\right)\exp\left(-i\Phi_{A_n}^T\right)}{\left|A_n^t\right|} \tag{4.6}$$

The object is assumed to be tracked when the correlation is above 80% of the auto-correlation value. The process works efficiently in situations where there is partial occlusion. If object is completely occluded during the tracking process, the proposed method waits for *p* seconds before dropping the object. For situations where a stationary object is occluded by another object that become stationary, the algorithm will drop the previously occluded object and will start tracking the new object.

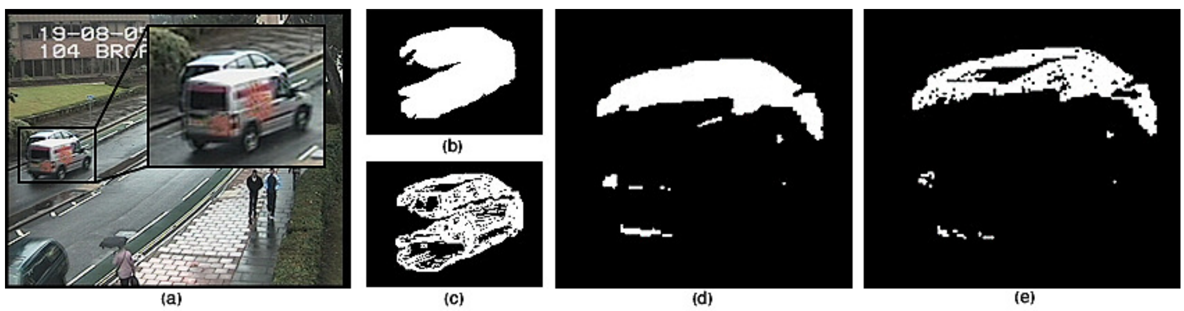


Figure 4.4: Effects of occlusion in a typical Parked Vehicle scenario of the *i-LIDS* dataset; (a) typical scene (b) original object mask at the time the object became stationary (c) original object edge map (d) adaptive binary mask (e) adaptive edge map after applying the proposed technique.

Figure 4.4 shows images highlighting the effects of occlusion and how the proposed technique is used to obtain an adaptive edge map and binary mask for the occluded tracked objects.

Figure 4.5: Frame sequence used to compare results from the adaptive edge orientation based technique with cross correlation as used in Tian *et al.* [34].

The proposed method is tested on the data presented in Figure 4.5. The results obtained are compared with the technique presented by Tian *et al.* [34]. Table 4.1 shows that the adaptive edge orientation based technique gives over 95% matching results even if the object is partially occluded as compared to 52% matching results obtained using the cross-correlation technique, hence demonstrating that proposed method is more reliable for tracking objects under occlusion.

The researcher notes that if the same adaptive approach was to be applied to other cross-correlation based techniques there should also be an improvement in performance over that which has been reported to date.

Frame Number	Adaptive edge orientation match	Cross-correlation match Tian *et al.* [34]
1415	98.29%	94.92%
1500	98.05%	57.78%
1580	97.79%	62.28%
1665	98.08%	52.57%

Table 4.1: Matching results after applying the adaptive edge orientation based technique and the cross- correlation technique to the sequence shown in Figure 4.5.

4.4.2 Tracking under Changing Lighting Conditions

The ability to track objects in changing illumination conditions is another significant characteristic of the proposed method. For surveillance systems deployed in outdoor environments, it is very important to accommodate situations where lighting is not consistent. A change in lighting can not only cause shadows to appear that can falsely classify pixels as members of $\mathbf{\Omega}$**,** but it can also change the apparent colour of a tracked object. This can lead to false tracking results if objects are tracked based on colour features. Techniques based on the energy or magnitude of the edges, e.g. one discussed in the previous chapter, can also suffer from changes in illumination. A change in lighting can cause the magnitude of an edge to change which can result in false tracking outputs. Since the adaptive edge orientation based technique considers the orientation of the edge rather than the intensity, and there is no dependency on colour features, it performs better in conditions where lighting is not consistent, as is now shown in Figure 4.6. The proposed solution is applied to the data sequence shown in Figure 4.6. The results are compared with two other tracking techniques based on colour by Piccardi *et al.* [56] and edge energy, discussed in the previous chapter. The running average variations in matching over 800 frames are presented in Figure 4.7. It can be seen from Table 4.2 that the matching results obtained from the proposed solution are consistently better than the other two techniques throughout the sequence, especially when there is a large change in the illumination conditions.

Figure 4.6: Data sequence showing change in illumination conditions. The tracked object is marked in Frame 900. The same sequence was also used in the previous chapter (Figure 3.7).

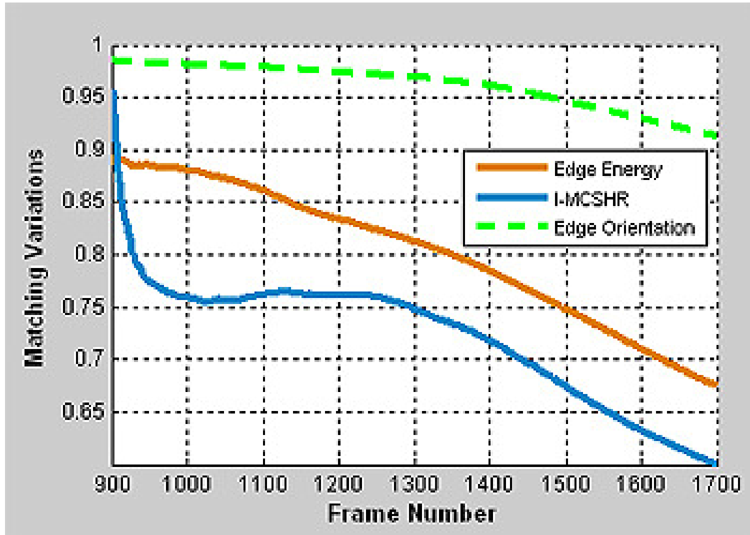


Figure 4.7: Running average variation in matching from frame 900 to frame 1700 for the three tracking techniques indicated. Edge energy values were taken from Chapter 3, Figure 3.8.

Frame Number	**Adaptive edge orientation tracking**	**Edge energy tracking Chapter 3**	**I-MCHSR tracking Piccardi *et al.* [56]**
900	98.53%	88.54%	95.68%
1200	97.40%	83.43%	76.06%
1400	96.08%	78.51%	71.89%
1700	91.30%	67.54%	60.09%

Table 4.2: Running average matching results after applying the adaptive edge orientation based technique; I-MCHSR and edge energy based tracking techniques on data sequence shown in Figure. 4.6.

4.5 Object Removal

The algorithm also deals with the removal of objects that are no longer stationary and with those regions that are falsely identified as static objects. Historic edge maps and tracking results are analyzed for this purpose. Edge maps for the alarm zones are obtained using the technique proposed in Section 4.4 and stored historically. The frequency of this storage process depends on the storage capacity of the system implemented; it has been kept to 15 minutes worth of video sequence in this case. For any foreground regions that are labelled as stationary, edge maps are calculated and matched with the historic edge map database for the exact pixel location.

The idea is that for any legitimate object, the obtained edge map will always be different from edge maps stored in the database for the exact pixel location. Experimental results have shown that although the technique makes the process more computationally expensive, it significantly reduces the number of false alarms.

It can be argued that the system might fail if a similar shape and size object is parked at the same location at a different time. For the proposed system to fail;

- the new object has to exactly match the one parked before
- has to be parked at exactly same pixel location as a slight change in the location will result in a different correlation match
- and finally has to be parked within 15 minutes of the first object left the scene. This is because the historic edge database is progressively refreshed such that the refresh process completes after every 15 minutes

If the above three conditions are met, the proposed method will still detect the stationary object but will fail to track it since it will match the historic edge database.

After the above matching process, regions identified as legitimate foreground objects are tracked using the adaptive edge orientation based technique and the results are compared against a chosen threshold. It is observed that when a stationary object moves, the orientation of the edge map changes and causes matching results to drop below the selected threshold. This can result in two different scenarios; the tracked object has either left its stationary position or is occluded by another object. To differentiate between these two situations, the binary mask overlapping the object's stationary position is obtained from most recent GMM output and analyzed. If the mask is originated from within the area of Θ_n^T in terms of pixel location (ghost object) and its total area is also within the area of the stationary object, the object is assumed to have moved and is no longer tracked. On the other hand if that is not the case, the object is considered to be occluded and the adaptive edge orientation technique is applied to keep track of the stationary object. Object detection and tracking results are discussed in more detail in the following section.

4.6 Results and Discussion

The proposed technique has been tested on four different datasets divided into two scenarios: illegally parked vehicle detection in outdoor scenes and abandoned object detection at train stations. In both cases the alarm events are generated after 60 seconds of the object being left stationary. The update rate was selected such that legitimate foreign objects were categorized as foreground for at least Λ frames before becoming part of the background. This dependency on Λ frames helps the proposed system not only pick up stationary objects efficiently but also reduces any affect of sudden illumination change. An 80% matching threshold was selected in order to track the object using the adaptive edge orientation technique.

This value appeared to work well across all the tested environments with changing lighting conditions and for any video rate and image quality. If the threshold was set too high or too low, the tracking results are compromised on platforms with lower image resolution (like the *ViSOR* dataset) or poor video quality (some sequences from the *i-LIDS* dataset). The thresholds were kept fixed throughout the testing of the proposed system across all four datasets with different video resolution and quality, viewing angles, lighting conditions (day or night) and scene density.

4.6.1 *i-LIDS* Dataset

The algorithm was first evaluated on two sets of *Parked Vehicle* video sequences from the *i-LIDS* dataset, one of which was used in Chapter 3 as well. Both sets contain three progressively more demanding video sequences, taken at different times of the day. The first set consists of long video sequences with multiple alarm events with an overall duration of over 6 hours. The second set contains short video sequences of 2-3 minutes duration with each containing a single alarm event. In both sets the alarm events are generated after 60 seconds of a vehicle being parked in a prohibited parking zone. Table 4.3 shows results obtained from the long video sequences.

Out of 105 alarm events, the method successfully detected 99 events as compared to 60 events detected by the detection technique used in Chapter 3. It also follows the *i-LIDS* requirement to generate the alarm within 10 seconds after the time at which the vehicle has been stationary for 60 seconds. An overall detection rate of over 90% was achieved by the algorithm. However, there were 18 false alarms i.e. 15% of the events. This was due to the fact that no explicit vehicle detection technique has been used to identify whether the detected object is a vehicle or not. It has been observed that, although application of such a technique will decrease the number of false alarms, it will not be without a significant computational cost thus affecting the overall frame rate achievable by the method.

Figure 4.8 shows images from the short video sequences. The proposed method has also been tested on these videos and results are compared with other state of the art techniques as shown in Table 4.4. The average error is calculated by comparing the ground truth start and end times with the acquired results. It can be seen that the system not only runs at over 15 frames/second but also detects illegally parked vehicles more accurately than any other available method.

File Name	Duration (hh:mm:ss)	Total Events	True Positive	False Positive	False Negative	Missed Tracks
PVTEA101a	01:21:29	26	24	4	2	1
PVTEA101b	00:24:40	8	8	0	0	0
PVTEA102a	00:51:56	18	18	6	0	0
PVTEA103a	01:03:54	16	16	1	0	0
PVTEA201a	00:18:50	4	4	1	0	0
PVTEA202b	01:05:23	17	14	2	3	0
PVTEA301a	00:15:29	3	3	2	0	0
PVTEA301b	00:28:07	7	6	1	1	0
PVTEA301c	00:27:09	6	6	1	0	0
Total	**06:16:57**	**105**	**99**	**18**	**6**	**1**

Table 4.3 Results which test the proposed method on videos from the *i-LIDS* dataset of *Parked Vehicle* (also used in Chapter 3).

Method	Sequence	Ground Truth		Duration (sec)	Obtained Results		Duration (sec)	Error (sec)	Average Error (sec)
		Start Time	End Time		Start Time	End Time			
Proposed Method	Easy	02:48	03:15	00:27	02:50	03:17	00:27	4	3.75
	Medium	01:28	01:47	00:19	01:28	01:49	00:21	2	
	Hard	02:12	02:33	00:21	02:16	02:36	00:20	7	
	Night	03:25	03:40	00:15	03:25	03:38	00:13	2	
Bevilacqua and Vaccarri [50]	Easy	02:48	03:15	00:27	N/A	N/A	00:31	4	4.33
	Medium	01:28	01:47	00:19	N/A	N/A	00:24	5	
	Hard	02:12	02:33	00:21	N/A	N/A	00:25	4	
	Night*	03:25	03:40	00:15	N/A	N/A	N/A	-	
Boragno *et al.* [51]	Easy	02:48	03:15	00:27	02:48	03:19	00:31	4	5.25
	Medium	01:28	01:47	00:19	01:28	01:55	00:27	8	
	Hard	02:12	02:33	00:21	02:12	02:36	00:24	3	
	Night	03:25	03:40	00:15	03:27	03:46	00:19	6	
Lee *et at.* [48]	Easy	02:48	03:15	00:27	02:51	03:18	00:27	6	6.25
	Medium	01:28	01:47	00:19	01:33	01:52	00:19	10	
	Hard	02:12	02:33	00:21	02:16	02:34	00:18	5	
	Night	03:25	03:40	00:15	03:25	03:36	00:11	4	
Guler *et al.* [52]	Easy	02:48	03:15	00:27	02:46	03:18	00:32	5	6.75
	Medium	01:28	01:47	00:19	01:28	01:54	00:26	7	
	Hard	02:12	02:33	00:21	02:13	02:36	00:23	4	
	Night	03:25	03:40	00:15	03:28	03:48	00:20	11	
Venetianer *et al.* [35]	Easy	02:48	03:15	00:27	02:52	03:16	00:24	5	9.33
	Medium	01:28	01:47	00:19	01:43	01:47	00:04	15	
	Hard	02:12	02:33	00:21	02:19	02:34	00:15	8	
	Night*	03:25	03:40	00:15	03:34	N/A	N/A	-	
F Porikli [28]	Easy*	02:48	03:15	00:27	N/A	N/A	N/A	-	11
	Medium	01:28	01:47	00:19	01:39	01:47	00:08	11	
	Hard*	02:12	02:33	00:21	N/A	N/A	N/A	-	
	Night*	03:25	03:40	00:15	N/A	N/A	N/A	-	
Lee *et at.* [49]	Easy	02:48	03:15	00:27	02:52	03:19	00:27	8	12.33
	Medium	01:28	01:47	00:19	01:41	01:55	00:14	21	
	Hard	02:12	02:33	00:21	02:08	02:37	00:29	8	
	Night*	03:25	03:40	00:15	N/A	N/A	N/A	-	

Table 4.4 Results of the proposed method, along with other techniques, applied to the *i-LIDS* short videos. *: sequence is not considered for average error calculation. N/A: data was not available from the author of the technique.

Figure 4.8: Images showing detection scenarios from short video sequences (a) PV Easy (b) PV Medium (c) PV Hard (d) PV Night.

The algorithm was also tested on three *Abandoned Baggage* video sequences from the *i-LIDS* dataset. Alarms were generation if the object is left stationary for over 60 seconds irrespective of whether it had been left unattended or not. Individual frames taken from these sequences are shown in Figure 4.9. All the events were successfully detected by the system with a low number of false positives. In order to avoid alarms that can be generated by people standing on the platform and staying stationary for longer durations of time, a minimum-maximum object size filter is applied. The position of the object was calculated and compared with minimum-maximum object size at that perspective position in the frame. Although the technique is simple it removes over 60% of the false alarms generated in such situations. The overall results of the algorithm are shown in Table 4.5. The two false alarms identified in the "hard video" sequence are, in fact, bags on the floor with their owners sitting next to them. Since the proposed method does not associate people with bags, it has been put under the false positive category.

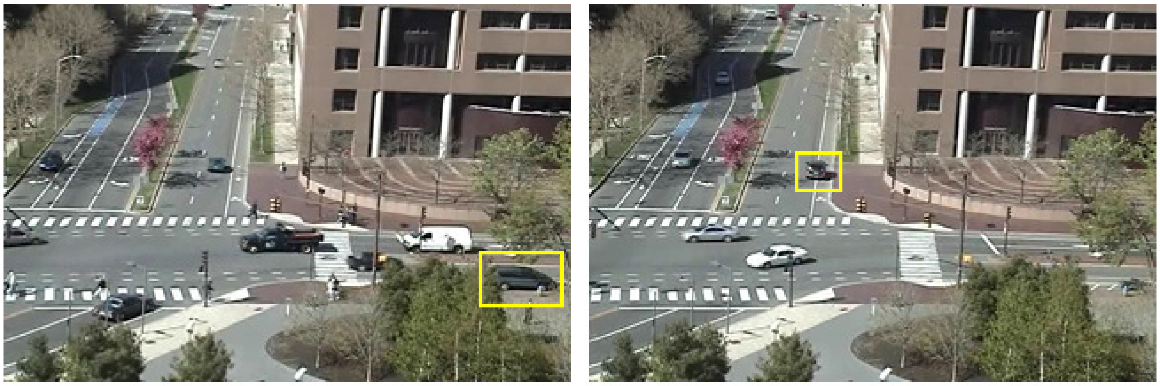
Figure 4.9: Images from *Abandoned Baggage* scenario (a) AB-Easy (b) AB-Medium (c) AB-Hard.

Sequences	True Positive	False Positive	False Negative
AB-Easy	1	0	0
AB-Medium	1	3	0
AB-Hard	1	2	0
Total	**3**	**5**	**0**

Table 4.5 Results obtained after testing the proposed system on *Abandoned Baggage* sequences from the *i-LIDS* dataset.

4.6.2 MIT Dataset

The MIT traffic dataset is a research dataset used to analyze activities in crowded traffic scenes. Although it has not been shot specifically for identifying illegally parked vehicles on the side of road, there are two instances when a car stops on the side of the road. In the first instance the car stays stationary for 4 minutes and 7 seconds and in the second sequence it stays stationary for only 13 seconds. The overall duration of the video is 90 minutes the algorithm has only been tested on the first 10 minutes in which the two relevant events occur. The discussed method successfully detected both events without any false alarms but only generated one alarm (as alarms are only generated if an object is stationary for over 60 seconds). The same threshold values are kept as when tests were carried out on the *i-LIDS* video sequence of *Parked Vehicle*. Figure 4.10 shows images from the MIT Traffic Dataset, highlighting both events that were successfully detected.



(a) (b)

Figure 4.10: Images from the *MIT Traffic Dataset* where events are detected when vehicles are parked on road sides.

4.6.3 ViSOR Dataset

The algorithm was also tested on the *Stopped Vehicles Detection* scenario of the ViSOR dataset. The dataset consists of four 2-3 minute video sequences each containing multiple events. All four sequences show scenes from a parking lot. The alarm events are generated for vehicles that are stationary for over 60 seconds in places other than those designated for parking. In the first video sequence two vehicles enter the scene. The algorithm picks up both events but does not generate any alarms as the vehicles are parked in the designated parking areas. In the second and third video sequences, an alarm event is generated for each sequence after a vehicle is found stationary for more than 60 seconds in a no parking area. In the final sequence, a single event is detected but no alarms are generated as the stopped vehicle leaves the scene within 60 seconds of being stationary. Figure 4.11 shows images from all four video sequences containing the detected events. The proposed algorithm detected all the events with no false alarms.

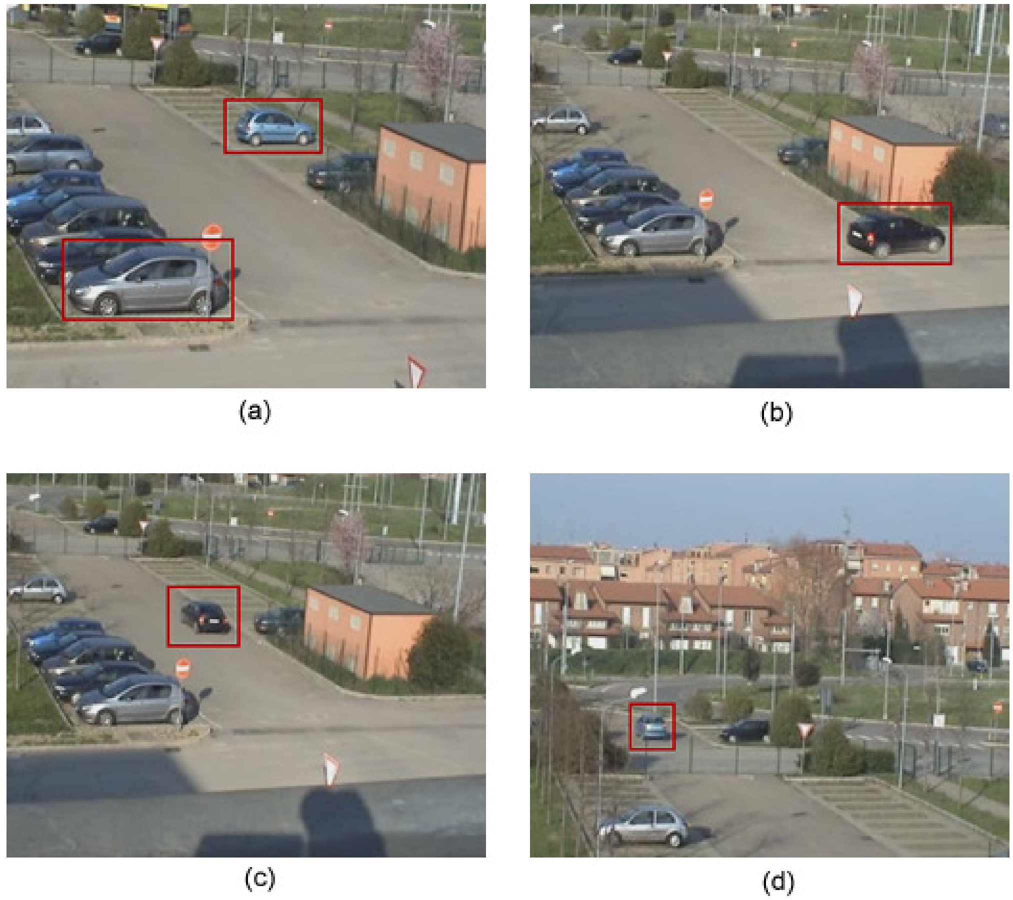


Figure 4.11: Images from the *ViSOR Dataset* (a) Sequence 1 (b) Sequence 2 (c) Sequence 3 (d) Sequence 4. All events are detected with no false positives and alarms are generated for vehicles stationary for over 60 seconds in (b) and (c).

4.6.4 *PETS 2006* Dataset

The overall results of the proposed algorithm when it was tested on the *PETS 2006* dataset are summarized in Table 6. The same sequences were also used in Chapter.3, comparisons being made with the results obtained from Chapter 3 and other available state of the art methods. Table 4.6 shows that the proposed method picks up all the genuine alarms without generating any false alarms. When compared with the other available techniques, it can be seen that the method produces very accurate results (equal to those reported by Chang *et al.*

[53]). Although Lv *et al.* [54] also produced 100% results, no information about false alarms was reported by the authors.

Methods	Total Alarms	True Positive	False Positive	False Negative
Proposed Method	6	6	0	0
Chapter 3 Results	6	6	2	0
Tian *et al.* [34]	6	6	1	1
Auvinet *et al.* [55]	6	6	5	0
Chang *et al.* [53]	6	6	0	0
Lv *et al.* [54]	6	6	N/A	0

Table 4.6: Results obtained after testing the proposed method along with other published methods on all the sequences from the *PETS 2006* dataset. N/A: data was not available from the author of the technique.

4.7 Conclusion

A robust stationary object detection system has been presented in this chapter. Two major concerns faced by such techniques, namely lighting variations and occlusion, are addressed. A new pixel based classification method based on GMM is initially used to detect stationary objects where SHI was utilized to overcome difficulties caused by variable lighting effects. Once objects are identified as stationary, an adaptive edge orientation based tracking technique is applied to track objects under severe lighting conditions and occlusion. The study has demonstrated that the proposed tracking method has an accuracy of over 95% matching results under occlusion as compared to less than 70% accuracy achieved by the other available state of the art methods. Finally, objects that are no longer stationary or are falsely identified as stationary objects are removed by analyzing historic edge maps and tracking results.

The proposed method was tested on four different datasets. Overall over seven hours of video, recorded at different locations and at different times of the day have been used for this purpose. Out of 121 genuine alarms across all the video sequences, the proposed technique picks up 115 alarms, giving an overall detection rate of over 95% as compared to 57% reported in the previous chapter. Also, unlike the technique presented in Chapter 3 where 56 false alarms were recorded, it only produced 23 false alarms i.e. reducing this by a half. This shows that not only is the performance of the proposed method strong but also that it is adaptable to different indoor or outdoor environments. Another important characteristic revealed by the experiments is the reduction in the number of missed tracks. Missed tracks are events that occur when the object is detected but its track is lost by the tracking technique. The adaptive edge orientation based technique misses out only a single object as compared to the magnitude based technique where 17 tracks were lost.

The techniques discussed in this chapter, and also in Chapter 3, are specifically designed to track rigid objects that become stationary in the scene. Keeping in view this implementation environment, edge maps are utilised as they are a useful feature that remains consistent throughout the tracking process. Since edge maps are sensitive to the shape of the object, as soon as an articulated or non-rigid object moves the edge map changes. Thus in order to track non-rigid moving objects, a different approach is required. The following two chapters highlight techniques designed to track such objects in crowded scenes. In that the particle filter has been used and solutions are designed to be implemented in multi-camera environments.

Chapter 5

An Adaptive Sample Count Particle Filter

Chapter 5

AN ADAPTIVE SAMPLE COUNT PARTICLE FILTER

5.1 Introduction

In Chapter 2, colour and edge information was highlighted as two major features used for tracking objects in crowded scenes. Since edge information is sensitive to the motion of the object, it is usually useful to track objects with consistent edge features as shown in Chapter 3 and 4. In order to track non-rigid moving objects such as humans, edges are usually not a practical attribute and colour features are exploited in such situations. Particle filtering techniques have been used extensively over the past few years in this regard. Due to its nonlinear nature and the fact that it does not assume a Gaussian probability density, it tends to outperform other available tracking methods.

A novel adaptive sample count particle filter (ASCPF) tracking method is presented in this chapter for which the main motivation is to accurately track an object in crowded scenes using fewer particles and hence with reduced computational overhead. Instead of taking a fixed number of particles, a particle range technique is used where an upper and lower bound for the range is initially identified. Particles are made to switch between an active and inactive state within this identified range. The idea is to keep the number of active particles to a minimum and only to increase this as and when required. This, together with the variable particle spread, allows a more accurate proposal distribution to be generated while using less computational resource. Experimental results show that the proposed method not only tracks the object with comparable accuracy to existing particle filter techniques but is up to five times faster.

5.2 Chapter Organization

The chapter is organized in the following way. The problem is defined and discussed in Section 5.3. This section highlights the major observations made regarding drawbacks in current particle filtering techniques and outlines an overall framework of how the solution is improved. The in-depth computational model is discussed in Section 5.4, where the modifications proposed at each stage of the particle filter are explained. Results are presented in Section 5.5 where comparisons are made with the standard Sequential Importance Resampling (SIR) particle filter technique followed by a discussion in Section 5.6. The study is finally concluded in Section 5.7.

5.3 Motivation

Tracking moving objects, especially humans in different environments, is an important part of any video surveillance application. Human tracking has been the focus of many studies in the past but due to its nonlinear nature it is still a challenging task. Particle filtering has been used extensively to solve this problem. The basic idea of the particle filter is to estimate the state of the moving object, given previous states and measurements, using Monte Carlo simulations (see Appendix B for details). Samples (particles) are drawn from a proposal distribution and weighted to try to estimate the posterior density. Theoretically, the higher the number of particles the more accurate will be the tracking results. However, this does not work in all situations, as discussed later in the chapter, and also a higher number of particles do not come without computational cost.

It has been observed that in order to design a particle filter for any application, it is the choice of proposal distribution that is critical. The proposal distribution depends on the quality of the particles. Good quality particles or, in other words, particles with higher weights will give a more accurate *a posteriori* density, which will result in a more accurate proposal distribution. However, it is very important to strike a balance between good quality proposal distributions, which in theory can be obtained by a higher number of particles and computational cost.

Another important observation has been made regarding the adoption of particle filters. The solutions proposed so far use a single standard deviation value for each of the state elements to spread the particles [104]. It has been observed that this works well under most conditions but can cause difficulties when the object is frequently occluded.

Motivated by the above findings, an effort has been made to improve the performance of particle filters by taking three important measures:

- Identification of the appropriate particle range for tracking a particular object.
- The concept of adaptive samples is introduced to keep the computational cost down.
- Variable standard deviation (σ) values for state vector elements have been exploited to cope with frequently occluded objects.

The aim is to track an object in crowded scenes to get similar, if not better; tracking results to those reported to date whilst simultaneously using fewer particles and thus keep the computational cost down.

Commonly the techniques proposed in the literature select a fixed number of particles to track objects. In order to keep the computational cost down, the concept of active particles has been introduced. A similar concept was demonstrated by Linzhou *et al.* [106] but the method did not handle any occlusion. Similarly a Kullback-Leibler Distance Sampling (KLD-Sampling) algorithm was presented by Fox *et al.* [107] that adaptively estimated that number of particles. The method was later further improved by Soto *et al.* [108]. Although the improved method provided a self adaptive sampling mechanism with better allocation of particles under the likelihood function, it does not improve the performance of the overall system in terms of computational cost. In the proposed method, particles are made to switch between two states: active (on) and inactive (off). Once the observation is available and particle weights are updated, resampling is performed to solve the degeneracy problem. If the effective number of particles is less than a certain threshold, the particles are resampled and the number of active particles is set to a minimum by eliminating particles with low weights. It has been reported in [105] that typically a minimum of 50 particles are required to effectively represent the shape of the tracked object. Although these findings were obtained from a different perspective (to determine a football player shape and not for tracking), the same criterion is investigated in Section 5.4.1.2 to determine whether it could be used as a minimum number to keep track of a moving object. The remaining particles are made active in the subsequent steps depending on the output of the resampling step. This clearly helps to reduce the computational cost as fewer particles are used to track the object.

To track the moving objects that are frequently occluded in a crowded scene, a variable particle spread method is proposed. As particles are switched between active and inactive states, there can be situations where the number of particles might be less than a desired number, especially when objects are frequently occluded. To minimize the effect of such situations the standard deviation value for the position vector is increased at each step along with the number of active particles. This helps spread the particles to wider areas and effectively minimizes any limitations of using fewer particles. As the resampling threshold is met, the standard deviation value, as well as the active number of particles, is set to a minimum.

5.4 Computational Model

The overall computational model and modifications made to the standard particle filter are presented in this section. The appropriate particle range for tracking a particular object is initially identified. Once the upper and lower limits for this range are obtained, the proposed particle filter technique is applied, discussed later in this section, to track a single object in different environments.

5.4.1 Identification of Particle Range

Although the particle filter has been the focus of many studies in the past decade, not much emphasis has been given to how many particles are appropriate for tracking a particular object. Most techniques proposed in the literature take a fixed number of particles, N, irrespective of the object being tracked. This can result in an additional computational cost if N is higher than required or false tracking outputs if it is too low. A new particle range method is discussed in this section, where the number of particles is switched between an active and inactive state within an identified range.

5.4.1.1 Identification of the Maximum Number of Particles (N_{max})

Theoretically, it has been observed the higher the number of particles the more accurate is the proposal distribution. Different authors have selected different N value for their experiments. It has been observed that although a higher number is desirable, it is not always required as higher number of samples will result in higher computational cost. In the proposed method, this value (upper limit of the particle range N_{max}) is even less important as it is only acting as an upper limit to the number of samples that will be used to track an object. N_{max} for the proposed method is selected as 250. Experiment results presented later in this paper further strength this argument as this upper limit of 250 is not reached even once during the tracking experiments on all 8 sequences.

5.4.1.2 Identification of the Minimum Number of Particles (N_{min})

As particles are switched between active and inactive states, such that $N_{min} \leq N_{active}$ (where $N_{active} \leq N_{max}$), it is very important to identify a reasonable minimum number of particles N_{min} to track the object in different situations. It was reported in [105] that typically a minimum of 50 particles are required to effectively represent the shape of the tracked object. The same observation has been taken into consideration and further tested on four N_{min} value tracks (30, 50, 75 and 100 particles) on the different video sequences shown in Figure 5.1. The complexity of the video sequences is based on scene density as well as frequency with which the tracked object is occluded. The idea is to identify an appropriate minimum number of particles N_{min} such that it not only allows the system to track the object accurately in different surroundings but also keeps the computational cost down. Figure 5.2 shows an average pixel error graph obtained after four N_{min} values are tested and compared against the ground truth data.

The track with 30 particles produces the highest pixel error results for all the sequences, especially where there is frequent occlusion. This is evidently due to the use of fewer particles as compared to other tracks. On the other hand, the remaining three tracks with the N_{min} value equal to 50, 75 and 100, produce almost similar error results with an average pixel error difference of around 2 pixels. This shows that if the number of particles is higher than a certain number (50 in this case) the tracking outputs are almost similar with minimal average pixel error difference. This indicates that it is not the quantity of particles, but their quality that is important for the accuracy of the track produced by the particle filter.

Table 5.1 presents the average computational time along with the average pixel error calculated for the four tracks on all the video sequences. Although the track with 30 particles yields a faster computational time, the corresponding average pixel error is quite high. On the other hand, the track with 100 particles produces almost half the pixel error as compared to the 30 particle track but it is almost four times slower. If track with 50 particles is analyzed , it can be seen that not only is it, on average, around two pixels adrift from the 100 particle track but it is also twice as fast. Hence, 50 particles is an appropriate value for N_{min} for the proposed system due to the resulting accuracy and fast computational time.

Once N_{max} and N_{min} are determined, particles are normally distributed to obtain $\{x_0^{(i)}, w_0^{(i)}\}_{i=1}^{N_{\max}}$, and so form an estimate for $p(x_0)$. Here, $x_0^{(i)}$ is the state vector that includes the x and y Cartesian coordinate position of the object, $w_0^{(i)}$ is the weight assigned to each particle and $i = 1,....., N_{\max}$. Once N_{max} and N_{min} are calculated they are kept fixed throughout the tracking process.

Figure 5.1: Image from four test sequences used to identify appropriate N_{min} value for the proposed system (a) scene with no occlusion (b) scene with low occlusion (c) scene with medium occlusion (d) scene with high occlusion

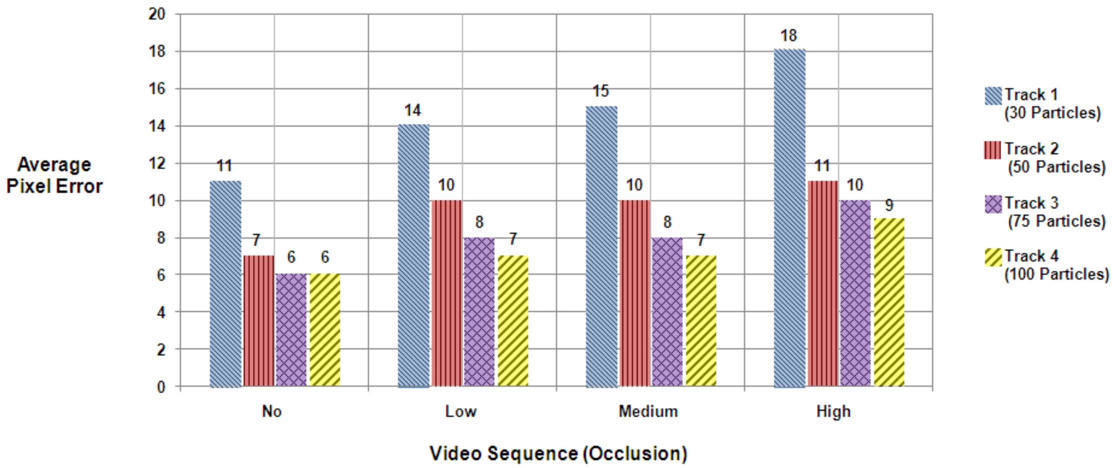


Figure 5.2: Average pixel error graphs obtained after comparing the tracking results with ground truth data on all four video sequences

Sequence (Occlusion)	**Average Pixel Error (in pixels)**			
	Track 1 (30 Particles)	**Track 2 (50 Particles)**	**Track 3 (75 Particles)**	**Track 4 (100 Particles)**
No	11	7	6	6
Low	14	10	8	7
Medium	15	10	8	7
High	18	11	10	9
	Computational Time (in ms)			
	Track 1 (30 Particles)	**Track 2 (50 Particles)**	**Track 3 (75 Particles)**	**Track 4 (100 Particles)**
No	31.4	62.7	94.1	129.2
Low	49	79	124.3	174.4
Medium	37	70.8	102	137
High	32	62.6	97.6	135.1

Table 5.1: The pixel error and computational time results to identify N_{min}

5.4.2 State Model

The state of the object is represented by:

$$x_k = Fx_{k-1} + v_{k-1} \tag{5.1}$$

where, F is the transition matrix and v_{k-1} is the additive white, zero-mean, Gaussian noise, irrespective of the object state and x_k is the state vector.

5.4.3 Prediction Model

It was observed by Dearden and Demiris [104], that the proposal distribution is critical for the design of any particle filter. A good proposal distribution comes with high quality particles. One way of achieving this is by having a good prediction mechanism.
The state information is predicted separately for both x' and y' coordinates:

$$p(x_k^{'} | x_{k-1}) \propto x_k^{'} + v_x \tag{5.2}$$

$$p(y_k^{'} | x_{k-1}) \propto y_k^{'} + v_y \tag{5.3}$$

where v_x and v_y is zero-mean, Gaussian noise with variable standard deviation, σ. The variable σ value allows the particles to spread to wider areas and hence avoid tracking difficulties under occlusion. Since fewer particles are proposed to track the object, there may be situations where the object gets occluded. These situations are often unpredictable. The proposed method in such situations will end up having fewer particles to find the object again (as under no occlusion N_{active} is likely to be near or equal to N_{min}). It has been observed that this is the major limitation of having fewer particles. To overcome this limitation, a new variable particle spread method is introduced which increases the spread of the particles to wider areas as soon as the object gets occluded. Thus when the object is occluded, the spread of the particles is increased to cover more area, so helping overcome any limitation of having fewer particles. During occlusion all the particles end up having similar weights as no particle is able to locate the object.

This results in an increase in the effective sample size, N_{eff}. As N_{eff} increases and reaches a point where it is no longer less than the threshold N_{th} (explained in Section 5.4.5) the number of particles along with their standard deviation is increased to spread the available active particles to a wider area to overcome any limitation of having fewer particles. The usefulness of this method is further elaborated in Section 5.5.2, where to find the effectiveness of the variable standard deviation approach, the results of the adaptive sampling method that incorporates the variable standard deviation are compared with the adaptive sampling method with constant standard deviation.

5.4.4 Update Model

At time k, when the measurement z_k is available, the update step is carried out. A colour based likelihood model is used for this purpose. Although the technique could be used with other metrics, a colour histogram for the tracked object is calculated for each particle using the current frame. Comparison with the reference histogram is used to compute the Bhattacharyya coefficient [115], where $(x'^{(i)}_k, y'^{(i)}_k)$ is considered as the centre of the region. If the likelihood is modelled as a Gaussian distribution for the Bhattacharyya distance, then $p(z_k|x_k)$ is given by:

$$p(z_k|x_k) = \frac{1}{\sqrt{2\pi\sigma'^2}} e^{-\frac{D_k^2}{2\sigma^2}} \qquad (5.4)$$

where the standard deviation, σ', is kept very low, such that if two objects of similar colour cross over, the particles remember their original tracking colour histogram so when the objects separate they follow the correct path. D_k is the Bhattacharyya distance calculated as:

$$D_k = 1 - \sum_{u=0}^{U} \sqrt{h(u)h'(u)} \tag{5.5}$$

where U is the total number of histogram bins and $h(u)$ and $h'(u)$ are the current and reference histograms, respectively.

The weight of each particle is updated according to the observation model and particles with higher likelihood value are assigned higher weights. Finally weights are normalized such that:

$$w_k^i = \frac{w_k^i}{\sum w_k^i} \tag{5.6}$$

5.4.5 Re-sampling

Particles are resampled if the effective number of particles N_{eff} is less than a threshold, N_{th}:

$$N_{eff} = \frac{1}{\sum_i (w_k^i)^2} < N_{th} \tag{5.7}$$

Here $1 \leq N_{eff} \leq N_{active}$, where the upper bound is attained when all particles have the same weight, and the lower bound when all probability mass is at one particle. $N_{eff,}$ the number of effective samples, is a way to measure how well the particles are concentrated on the region of interest. The N_{th} is set to $2N/3$, where N here is equal to N_{active}. This will result in a larger effective sample size which will not only assist in solving the degeneracy problem but will also help the proposed system to achieve accurate tracking results since more particles will be concentrated around the tracked object. N_{th} can be set to a smaller number such as $6N/10$, but since fewer particles are used for tracking it is preferred that majority of the particles are concentrated near the object. Although the selected threshold value will confine the particles to smaller radius around the object, which could affect the tracking results under occlusion, the introduction a variable particle spread technique overcomes this issue, results of which are further highlighted in Section 5.5.2

Once the threshold mentioned in equation (5.7) is met, re-sampling is performed and particles with insignificant weight are removed. Apart from resampling, three other important steps are implemented:

- The number of active particles N_{active} is set to N_{min}. This helps reduce the computational cost. As particles concentrate on the region occupied by the tracked object there is no need to use a higher number of active particles hence N_{active} is set to a minimum. If the condition in equation (5.7) is false, the number of active particles N_{active} is increased from the minimum by a percentage such that N_{eff} is greater than N_{min} (until a limit of N_{max} is reached).
- The x and y standard deviation values of the state vector are reduced to a minimum. If equation (5.7) is false, the value of the standard deviation is increased by 10%. This 10% is a design parameter and can be changed in different environments.

These changes to the resampling step not only reduce the number of active particles and hence reduce the overall computational cost but also help improve the proposal distribution. The overall implementation of the proposed particle filter technique is summarized in Table 5.2.

Proposed Particle Filter Method

1. *Initialization*
   - Manually select the object to be tracked
   - Generate N_{max} samples to obtain $\{x_0^{(i)}, w_0^{(i)}\}_{i=1}^{N\max}$
   - Set *Resampling Flag* to true

2. *For every incoming frame*

   Predict

   - Distribute particles using equation (5.2) and (5.3)

   Update

   For all *active particles*
   - Compute $p(z_k \mid x_k)$ using equation (5.4)
   - Computer independent weights
   - Normalize weights using equation (5.7)

   Resample

   If equation (5.7) is true
   - Resample
   - Obtain mean value for *x* and *y* for all *active particles*
   - Reduce the number of *active particles* to a minimum

   Reduce sigma value for v_x and v_y in equation (5.2) and (5.3) to a minimum Else
   - Obtain mean value for *x* and *y* for all *active particles*
   - Increase *active particles* until N_{max} is reached
   - Increase sigma value for v_x and v_y in equation (5.2) and (5.3) by 10%

3. *Go to Step 2*

Table 5.2: Overview of proposed Adaptive Sample Count Particle Filter method

5.5 Results and Discussion

The performance of the proposed technique is evaluated in terms of computational cost and tracking accuracy by conducting several experiments on the *PETS* [7], *i-LIDS* [4] and *University of Sussex Tracking* [9] datasets. Although both the *PETS* and the *i-LIDS* datasets are designed for tracking objects in multi camera environments, only single camera view is focused in this chapter. In total over 9,000 frames worth of video sequences were used for the evaluation with a single object being tracked in each sequence. These sequences were divided into three categories: sequences with partial and complete occlusion; sequences with change in scale of the tracked object; and sequences with variable target motion. The results obtained are compared with the tracking results of the standard SIR particle filtering method.

The tracking procedure for the proposed method starts with the manual selection of the object to be tracked. Once the object has been selected, the maximum number of particles, N_{max} is set to 250 where as minimum number of particles N_{min} is set to 50 as explained in Section 5.4.1. Finally, the minimum standard deviation value for v_x and v_y in equations (5.3) and (5.4) was set to 0.6.

The results for the SIR particle filtering method are obtained by keeping the N_{min}, N_{max} and N_{active}, equal to 250 and the standard deviation value for v_x and v_y equal to 0.6.

5.5.1 Video Dataset

The datasets used for the evaluation of the proposed technique are selected keeping in mind the complexities of real world scenarios. The *PETS* and *i-LIDS* datasets provide benchmark video sequences for the development of techniques that are robust to real world tracking problems. Although the *PETS* and *i-LIDS* datasets are recorded to track objects in crowded scenes, where there are frequent occlusions, there are certain situations which were not covered by both datasets that were thought useful for inclusion in order to allow further evaluation of the tracking system performance. *University of Sussex Tracking* dataset has been used for this purpose which includes video sequences for scenarios where scale and motion of the target object are not consistent. In total over 9,000 frames worth of data including sequences from the *PETS* and the *i-LIDS* datasets, divided into 3 categories. Comparisons are made with the SIR particle filter method in terms of computational cost and tracking accuracy. The accuracy of the tracking results are analyzed by comparing them with the ground truth, which was obtained by manually clicking the centroid of the target object. The tracking accuracy measure was the pixel error difference between the obtained values and the ground truth x and y locations calculated from:

$$Error = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{5.8}$$

where (x_1, y_1) are the coordinates of ground truth data and (x_2, y_2) are the coordinates of data obtained from each the SIR and the proposed method.
The computational time was obtained by calculating the time taken by both techniques for each frame (in milliseconds).

5.5.2 Frequent Occlusion

Occlusion is one of the major challenges faced by any tracking technique. Particle filtering methods in general tends to out-perform other tracking techniques in such situations due to their adaptive nature, provided occlusion is not 100%. Since fewer particles are proposed in this experiment to track the object, there can be situations where the number of particles is less than the desired number, especially when the tracked object is partially or completely occluded. As particles are gradually increased from N_{min} to N_{max} the increase can cause the computational time to go up and in some cases can still not generate enough particles to get accurate tracking results. To overcome such situations, the use of a variable standard deviation value for x and y position vectors given in equation (5.2) and (5.3) are proposed. This variable standard deviation value not only helps fewer particles to spread to wider regions but can also improve the proposed system's tracking capabilities under occlusion.
To further investigate the proposed method, different video sequences of variable lengths are considered where the tracked object is frequently occluded. The proposed method is tested on these sequences and results in terms of computational time and tracking accuracy

are compared with the standard SIR particle filter method. In order to find the effectiveness of the variable spread method under occlusion, an adaptive sample method is applied without the variable spread approach on the same sequences and compared to the results obtained with those of the proposed technique. This is to verify that the adaptive sampling approach alone is not as effective as when combined with the variable spread technique both in terms of computational cost and tracking accuracies.

Figure 5.3, 5.4 and 5.5 show images along with the tracking results from the three evaluated methods. These three methods are categorized as the proposed method (the proposed method with variable particle spread), the particle filter without variable spread (the method that only incorporates the adaptive sample approach but not the variable spread) and the standard SIR particle filter method.

The top graph shown in Figure 5.3, 5.4 and 5.5 represents the pixel error per frame, calculated by comparing the ground truth data with the x and y position value of the tracked object obtained from the three techniques. The middle graph shows the number of active particles, N_{active}, used by all the three methods; the bottom graph shows the ground truth meta data about the object i.e. whether the object is occluded, not occluded or partially occluded at each frame. Table 5.3 shows the summary of the results obtained from these techniques. It can be seen that the proposed method is the most effective in terms of computational cost. The graphs showing number of active particles (centre graphs) in Figure 5.3, 5.4 and 5.5 support this conclusion as they show that the number of particles used by the proposed method is significantly less than the method without the spread function and also the standard SIR particle filter method (that utilized 250 particles for tracking).

In terms of tracking accuracy the proposed technique is on average less than two pixels adrift from the standard particle filter method but six times faster. If the tracking results for the method without the spread function are compared with the ground truth data, it can be seen that this results in over ten pixels of error, almost five times more than the proposed method.

Sequence	No of Frames	Average Pixel Error per Frame (in pixels)			Average Computational Time per Frame (in ms)		
		Proposed Method	Standard Particle Filter Method	Proposed Method without Variable Particle Spread	Proposed Method	Standard Particle Filter Method	Proposed Method with out Variable Particle Spread
I	507	12	11	36	53.6	298.5	77.3
II	1987	12	10	12	67.1	335.3	92.5
III	383	13	9	14	57.6	352.5	74.5

Table 5.3: Average Pixel Error and Computational Cost for each technique when applied on sequences shown in Fig. 5.3, 5.4 and 5.5

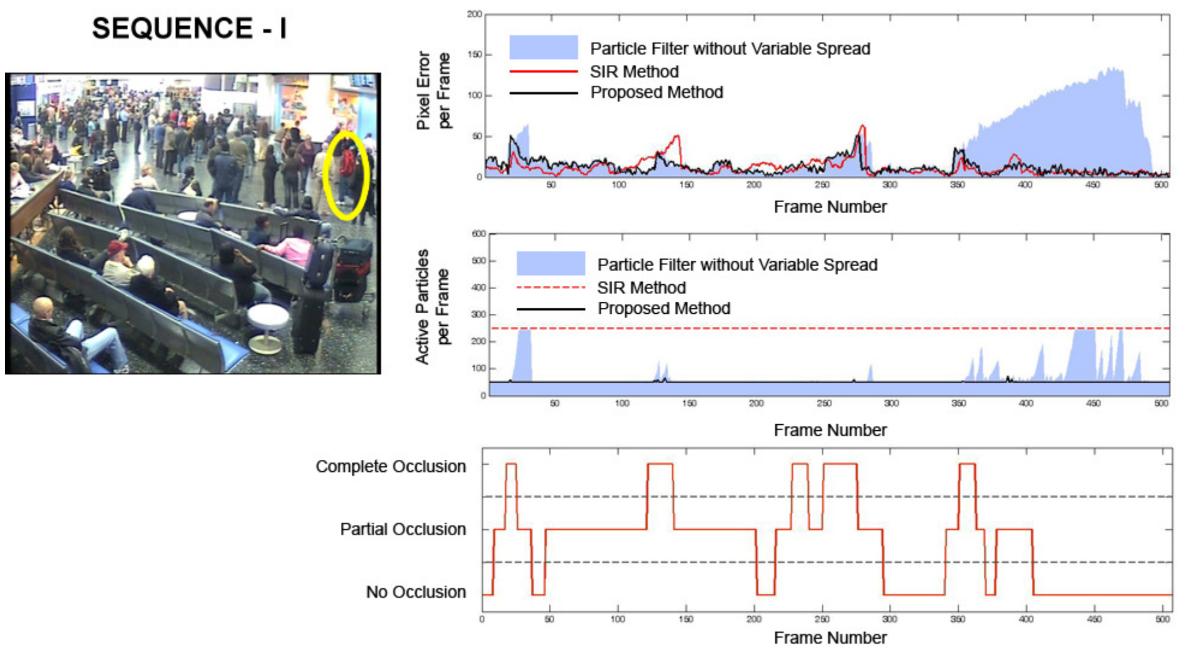


Figure 5.3: Tracking results from the 1st video sequence. The top graph shows the pixel error per frame when compared with ground truth data, the middle graph shows the number of active particles used by the proposed method and the bottom graph shows the state of the tracked object at each frame

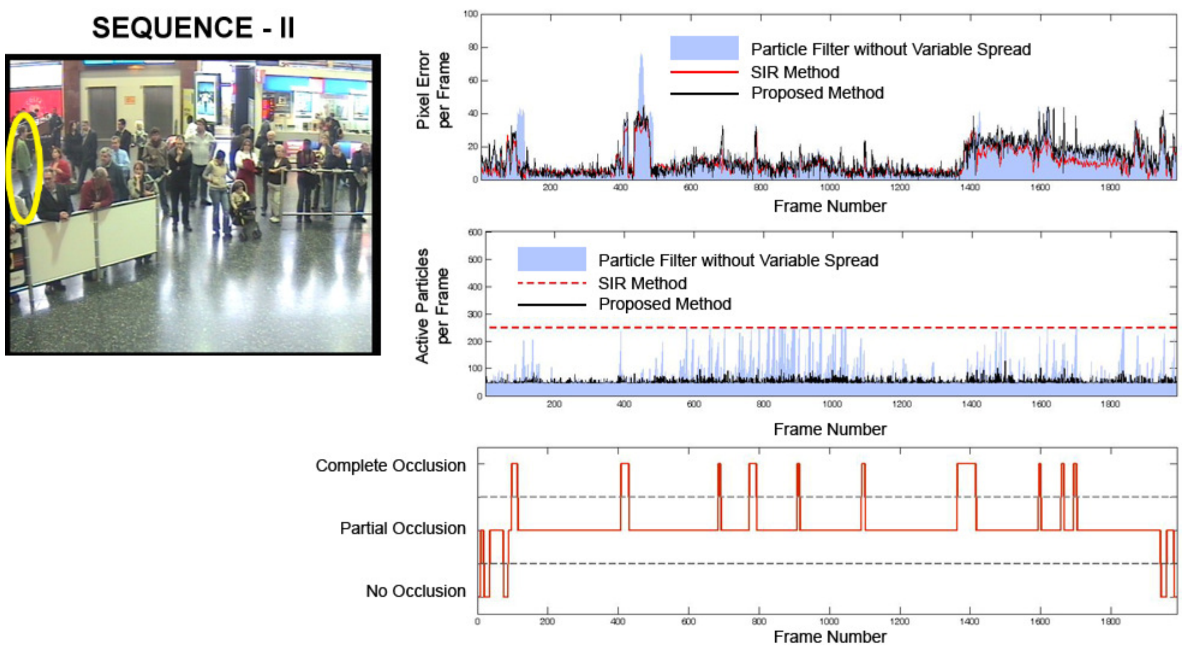


Figure 5.4: Tracking results from the 2nd video sequence where the object is occluded in more than 95% of the frames. The top graph shows the pixel error per frame when compared with ground truth data, the middle graph shows the number of active particles used by the proposed method and the bottom graph shows the state of the tracked object at each frame

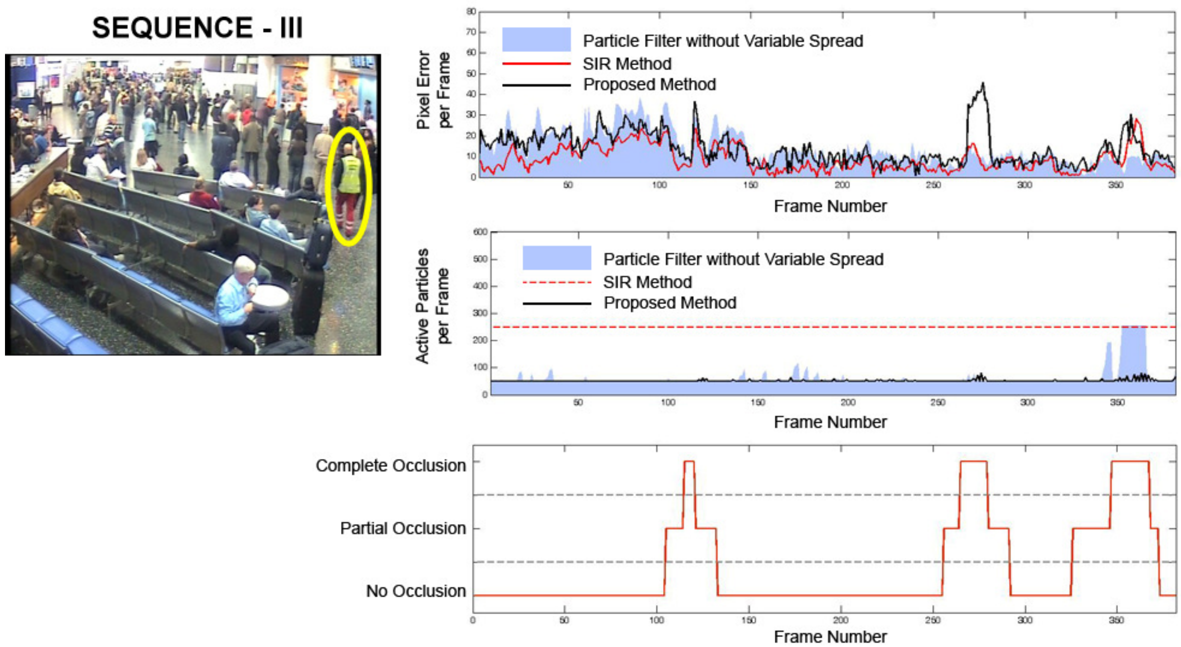


Figure 5.5: Tracking results from the 3rd video sequence where the object is occluded for less than 30% of the frames. The top graph shows the pixel error per frame when compared with ground truth data, the middle graph shows the number of active particles used by the proposed method and the bottom graph shows the state of the tracked object at each frame

5.5.3 Scale Variation

To evaluate the proposed method in situations where the scale of the object in not constant, two video from *University of Sussex Tracking* dataset [9] has been used. The first sequence is approximately 1,200 frames long and the second sequence is approximately 700 frames. The scale of the object changes as it moves away from the camera. Figure 5.6 and 5.7 show images from both sequences to highlight the scale variations. It has been observed that although the scale of the object varies quite considerably during the tracking process, this does not have any significant affect on the tracking accuracy. This is the case for both the proposed method and the SIR particle filter method.

From Figure 5.6 and 5.7 it was observed that on average the proposed method is 12 pixels in error whereas the SIR method is 11 pixels in error with respect to the ground truth data. Although the tracking results for the proposed method are slightly in more error the computational cost on the other hand is considerably less than the standard approach. This highlights the minimal effect of the reduced number of particles on tracking accuracies when the object scale is not constant.

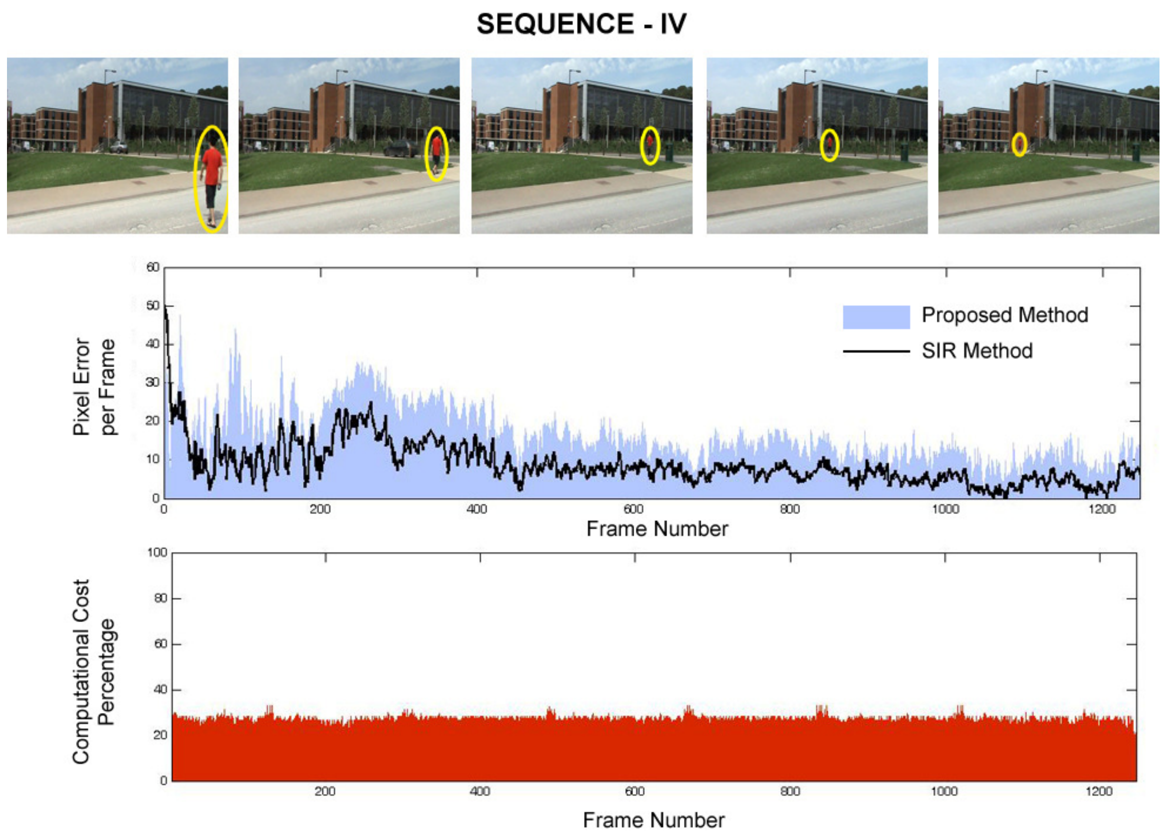


Figure 5.6: Tracking results from the 4th video sequence. The series are images in the top row shows the variation in object scale as it moves away from the camera. The first graph shows the pixel error per frame from the Proposed Method and the Standard SIR Method when compared with ground truth data and the second graph shows the percentage computational time taken by the Proposed Method as compared to the SIR Method

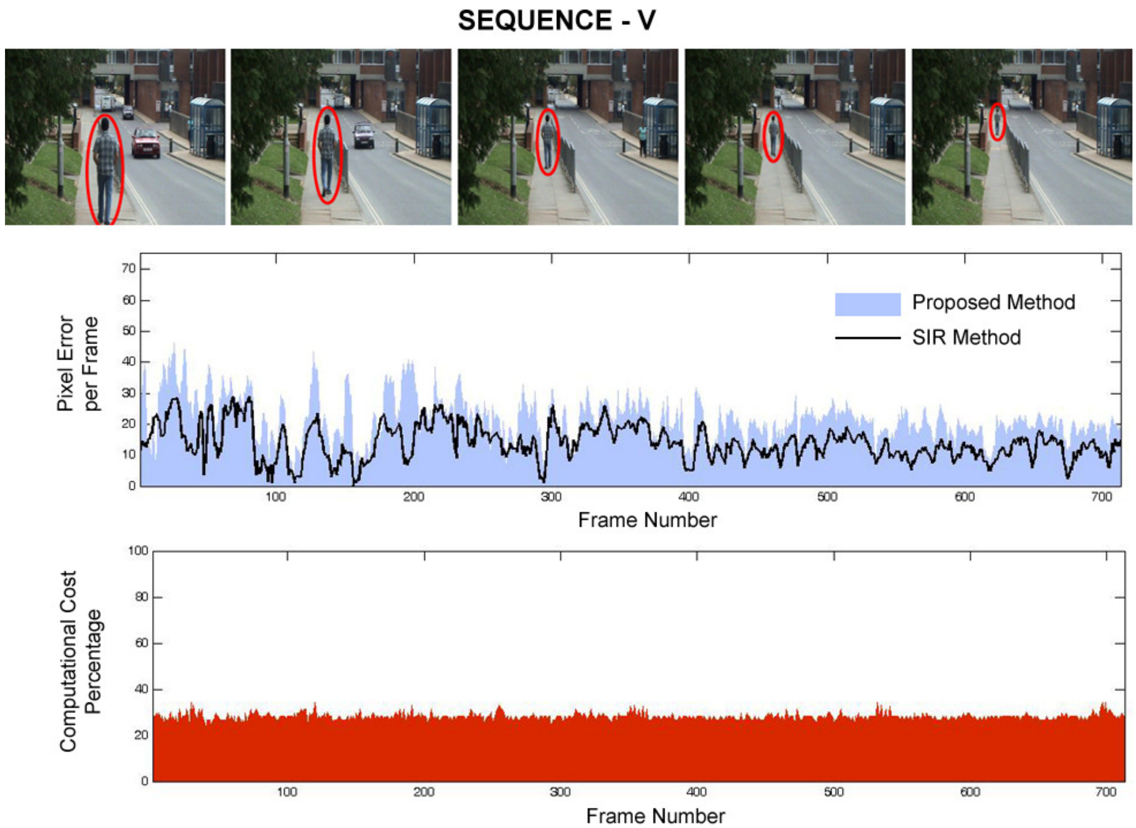


Figure 5.7: Tracking results from the 5th video sequence. The series of images in the top row shows the variation in object scale as it moves away from the camera. The first graph shows the pixel error per frame from the Proposed Method and the Standard SIR Method when compared with ground truth data and the second graph shows the percentage computational time taken by the Proposed Method as compared to the SIR Method

5.5.4 Variable Target Motion (Velocity and Direction)

In this section the affects of variable target motion in terms of object displacement per frame and direction on the proposed method is evaluated. Since in real life scenarios the motion of the tracked object is unpredictable, it is critical that any tracking system keeps track of the object under these circumstances. In order to assess the proposed system performance in such conditions, *University of Sussex Tracking* database has been used where the object motion is not constant. These sequences, along with the tracked object ground truth displacement, are presented in Figure 5.8, 5.9 and 5.10. The purpose now is to assess the proposed method in an environment where the tracked object frequently changes its motion. The proposed technique, together with the SIR method, is tested and results are evaluated in terms of tracking accuracy and computational time. Along with the pixel error and computation cost, the ground truth displacement of the object is shown in the graphs presented in Figure 5.8, 5.9 and 5.10 where the spikes in the middle graphs show the sudden change in object displacement.

It is observed that, similarly to the scale variation tests, variable target motion has no significant affect on the tracking results. The highlight of these tests is the similar tracking results that are obtained using fewer particles as compared to the SIR method. This shows that change in the object velocity does not affect the tracking accuracy of the system and hence fewer particles can be used to get similar tracking results to the SIR method.

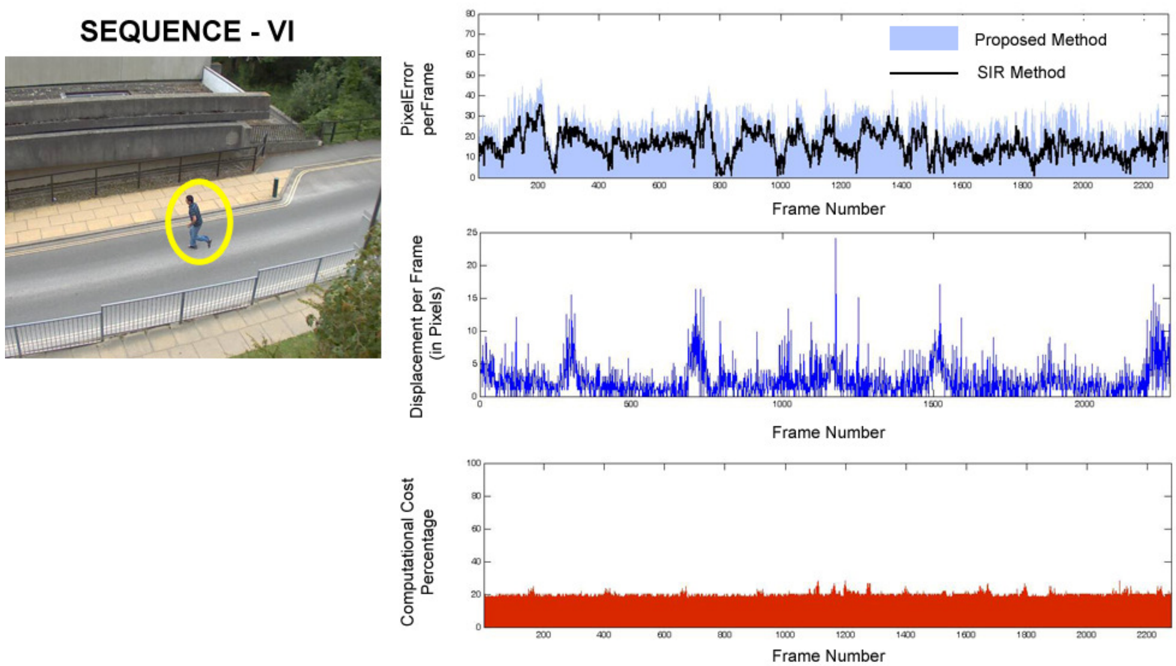


Figure 5.8: Tracking results from the 6th video sequence. The top graph shows the pixel error per frame from the Proposed Method and the Standard SIR Method when compared with ground truth data. The middle graph shows the ground truth displacement of the tracked object where spikes in the graph indicate the change in object acceleration. The bottom graph shows the percentage computational time taken by the Proposed Method as compared to the SIR Method

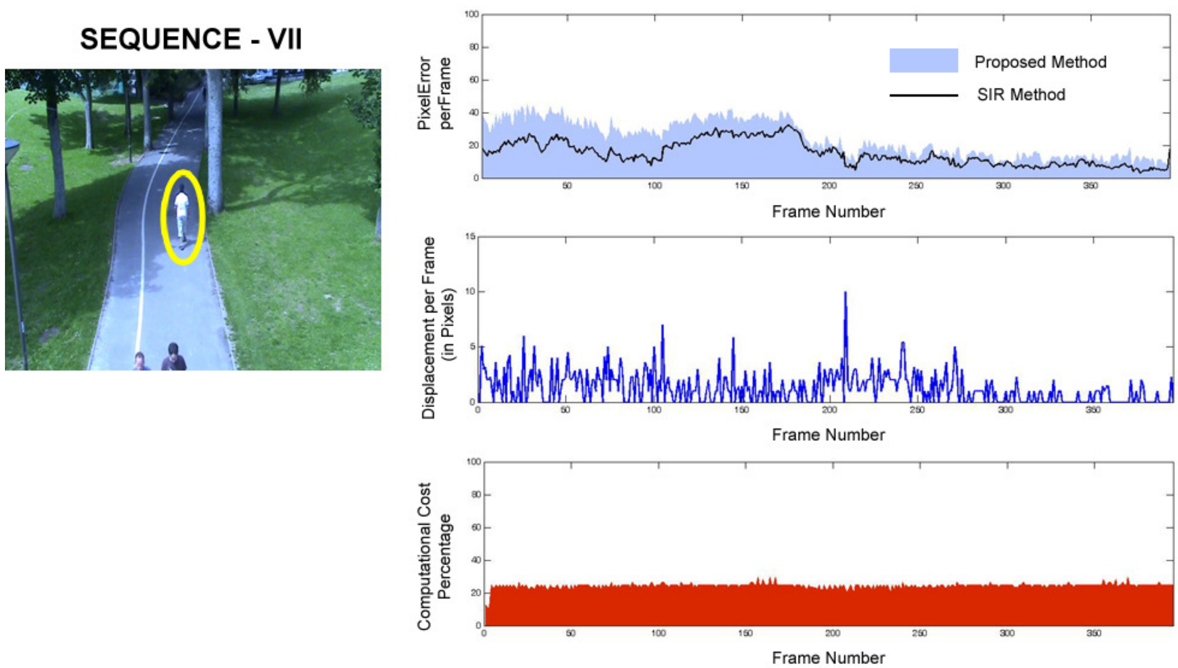


Figure 5.9: Tracking results from the 7th video sequence. The top graph shows the pixel error per frame from the Proposed Method and the Standard SIR Method when compared with ground truth data. The middle graph shows the ground truth displacement of the tracked object where spikes in the graph indicate the change in object acceleration. The bottom graph shows the percentage computational time taken by the Proposed Method as compared to the SIR Method

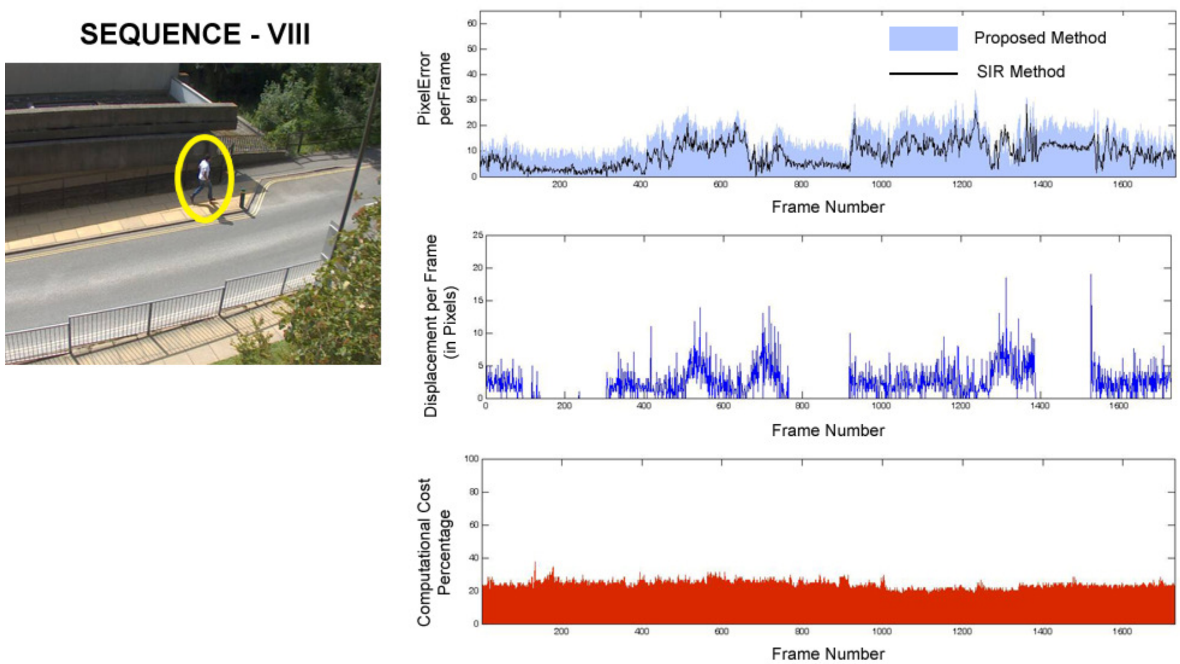


Figure 5.10: Tracking results from the 8th video sequence. The top graph shows the pixel error per frame from the Proposed Method and the Standard SIR Method when compared with ground truth data. The middle graph shows the ground truth displacement of the tracked object where spikes in the graph indicate the change in object acceleration and the empty regions show that object completely stopped at indicated frames. The bottom graph shows the percentage computational time taken by the Proposed Method as compared to the SIR Method

5.6 Discussion

The proposed Adaptive Sample Count Particle Filter method has been evaluated on different real life complex scenarios. The motivation was to develop and test a real time system that will accurately track a moving object in complex scenes using less computational time. Experimental results have shown that the proposed method not only uses fewer particles (and thus reduces the overall system computational cost) but is also very close to getting the same tracking results as a standard SIR particle filter method. A summary of the comparative analyses for the tests conducted is given in Table 5.4.

Sequence	Frames	Video Resolution	Proposed Method		Standard SIR Method	
			Average Pixel Error (in pixels)	Average Computational Time (in ms)	Average Pixel Error (in pixels)	Average Computational Time (in ms)
I	507	720x576	12	53.6	11	298.5
II	1,987	720x576	12	67.1	10	335.3
III	383	720x576	13	57.6	9	352.5
IV	1,247	720x576	12	70.7	9	337.8
V	713	720x576	14	65.1	14	342.7
VI	2,279	640x480	13	48.9	7	243.5
VII	395	720x576	11	69.2	7	312.3
VIII	1,729	640x480	13	62.5	9	286.2

Table 5.4: Summary of results obtained for all eight test sequences. All the sequences, along with the ground truth data, are publically available to download from [9].

The test sequences were selected keeping in mind real life situations such as occlusion, scale changes and variable target motion. Different experiments have shown that although using the adaptive sampling approach alone reduces the computational cost it nevertheless loses tracking accuracy when the object is frequently occluded. A variable particle spread approach is introduced to ameliorate such situations.

The results from first three video sequences where the object was frequently occluded show that the adaptive sampling technique on its own is not as effective as that which also incorporates the variable particle spread method. Not only is the combined approach almost six times faster than the standard particle filter technique but it also produces comparabletracking results.

This shows the effectiveness of the use of the variable standard deviation value for the *x* and *y* position co-ordinates when the tracked object is frequently occluded. Hence it can be concluded that the combination of the adaptive sampling and variable particle spread technique use less computational time as compared to the standard particle filtering method.

Experimental results have also shown that changes in the scale and motion of the tracked object do not have any significant effect on the tracking outputs of the proposed method. If the object scale or motion changes during the tracking process, it is tracked with similar accuracy to the standard method. The major improvement however comes in the computational time, as fewer particles are required by the proposed method.

Another important aspect of this test, as highlighted in the previous sections, is the significance of the quality of particles rather than their quantity. The situation presented in Figures. 5.6-5.10, it can be seen that as long as the object is not occluded and maintains its colour features, the particle filter technique keeps track of the object quite accurately. This can be seen from the pixel error results presented in Figure 5.6-5.10. The results show that the tracking results for both the proposed and standard SIR methods are very similar, hence emphasizing that even if the number of particles is reduced, but they are of good quality, the object will still be tracked with reasonable accuracy.

Overall from results presented in Table 5.4 it was observed that across all the test sequences, the proposed method was not only on average 80% less computationally expensive in comparison to the standard SIR method but also was only on average three pixels more in error than the standard approach.

5.7 Conclusion

An effort has been made in this chapter to accurately track human objects in crowded scenes using a particle filter based on colour features. Since the tracked objects are in constant motion, colour features are given preference over edges. A minimum-maximum particle range is initially identified and particles are switched between active and inactive states to reduce the overall computational cost. However, a reduced number of particles affect the proposal distribution. To overcome this issue an adaptive standard deviation value technique along with a hybrid prediction model has been proposed to get a better proposal distribution with fewer particles.

The overall performance of the proposed method has been evaluated on over 9,000 frames worth of video sequences from the *PETS*, *i-LIDS* and *University of Sussex Tracking* datasets. Experimental results have shown that the proposed system is able to track objects with over 80% reduction in the computational requirements as compared to SIR particle filter methods, making the technique particularly useful for real-time tracking applications.

The solution discussed in this chapter only deals with single camera environments. In order to track the object in multi-camera environment, the discussed technique is deployed in a multi-camera environment. The effectiveness of the ASCPF method in multi-camera environment along with the tracking results are presented in the following chapter.

Chapter 6

Object Tracking in a Multi Camera Environment

Chapter 6

OBJECT TRACKING IN A MULTI CAMERA ENVIRONMENT

6.1 Introduction

Tracking objects in multi camera environments is an important requirement for video surveillance applications. The Adaptive Sample Count Particle Filter (ASCPF) discussed in the previous chapter has been implemented in a multi-camera environment to track objects across different scenes. Such environments can pose difficult challenges such as a change in the scale of the object as it moves from one camera to another or a change in the object features, such as colour, as the brightness levels can alter across different camera views. A variable standard deviation value of ASCPF has been utilized in order to cope with sudden colour and scale changes. As the object moves from one scene to another, the number of particles along with the spread value is increased to a maximum to reduce any effects of scale and colour change. The technique has been tested on live feeds from four different camera views. It was found that not only did the ASCPF method result in successfully tracking the moving object across different views but it also maintained the real time frame rate due to its reduced computational cost.

6.2 Chapter Organization

Section 6.3 presents the challenges faced by multi-camera tracking environments. Section 6.4, 6.5 and 6.6 describe how these challenges are tackled using ASCPF. Tracking results obtained by testing the ASCPF method on up to four camera views are presented in Section 6.7 and the study is finally concluded in Section 6.8.

6.3 Multi-Camera Tracking Challenges

Tracking objects in a multi camera surveillance environment has been the focus of many researchers in the past few years. Most of the techniques presented in the literature to date [94-112] work with the camera setup such that all cameras look at the same scene, with more than a 50% overlap between views. Typically such techniques use calibration and/or feature matching information to keep track of moving objects. A problem arises when in a multi camera setup all the cameras are primarily looking at different scenes with as little as a 10% overlap of view, an example being shown in Figure 6.1(b). This kind of setup can pose difficult challenges since a change in the scale of the object as it moves from one camera to another can occur. Also, as the brightness levels can alter across different camera views changes in an object feature, such as colour, can also occur. Keeping in mind these challenges, a real time multi camera tracking system is proposed. The main motivations behind the work are:

- To develop a real time tracking system that runs at a high frame rate
- Each camera is primarily looking at a different scene with no two camera views overlapping by more than 10%.
- Each camera has a different focal length and exposure setting.

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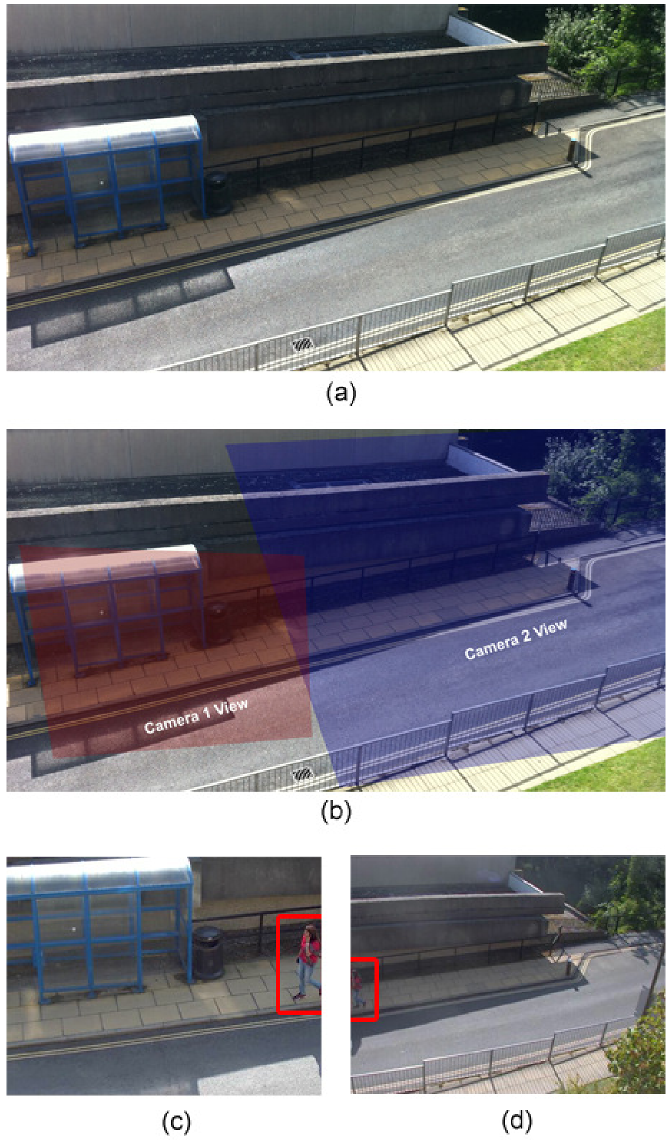


Figure 6.1: Multi-Camera setup for the ASCPF based system. (a) Top View (b) Camera Coverage View (c) Camera 1 View (d) Camera 2 View. The change in scale and brightness is apparent in views (c) and (d)

To develop such a system, the ASCPF is utilized where fewer particles can be used to track the object whilst using a colour histogram as the object feature. These fewer particles help run the system at higher frame rates. In order to track objects as they move from one camera view to another with different focal lengths and brightness parameters, a new approach has been followed where the scale and the colour change is compensated by adjusting the number of active particles and particle spread value. Up to four Axis P1344 Cameras [113] were used to test the ASCPF based system (see Appendix C for camera details). The cameras were setup keeping in mind the above mentioned criteria. Live video feeds were obtained from these cameras and objects were tracked as they move from one camera to another. Figure 6.1 shows the multi camera environment setup. It can be seen that as the object moved from camera 2 to camera 1, there was an increase in the size of the object by more than a half. Also its position and colour information in the new camera view is changed. In order to efficiently track the object across different camera views, it is very important that such situations are handled with minimum error. The ASCPF based technique discussed in this chapter is used to provide solutions to these three fundamental issues and is presented in the following Sections.

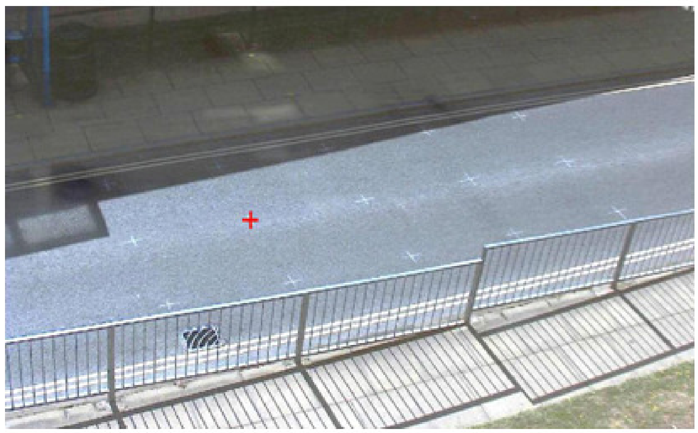
6.4 Object Position

Object position is the most significant feature when tracking objects in a multi camera environment. As the object moves from one view to another, it is very important to get an accurate position in the new scene. In order to obtain object position with minimum error, all the cameras are calibrated. There are a number of techniques proposed in the literature for tackling this problem and these can be broadly categorized as pattern based calibration and self- or auto-calibration.

Pattern based calibration techniques are used in the proposed method. A well known pattern based calibration technique, proposed in [114], was considered to obtain 2D image coordinates.

Once intrinsic and extrinsic parameters were available, 2D image coordinates were converted to 3D world coordinates and vice versa to get the exact object location in different camera views. Fig. 6.2 shows the selected point in one view and the corresponding point in the other camera view after applying the camera calibration technique proposed in [114].

(a)



(b)

Figure 6.2:(a) selected point on Camera 1 (b) corresponding point projected in Camera 2

6.5 Scaling

The second important feature of the proposed system is the capability to cope with the situation where the scale of the object changes as it moves into the new camera view. As shown in Figure 6.1(c) and 6.1(d), as the object moves from one view to another, its scale changes. The number of active particles and particle spread variables, discussed in the previous chapter, are utilized to overcome this situation. When the object position is obtained in the new camera views, the number of active particles along with the particle spread value is increased to a maximum to counter not only the scale change but also any error from the calibration step. This helps the proposed system identify the tracked object with more accuracy in the new view.

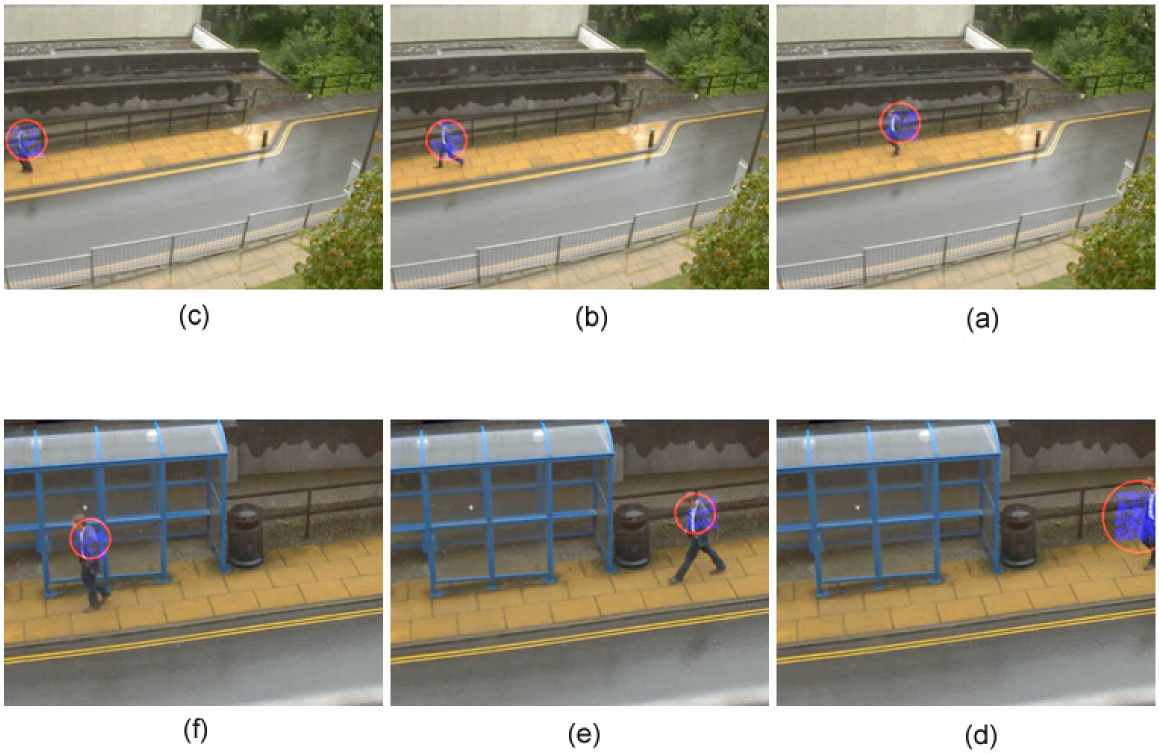


Figure 6.3: Particle spread radius of the object being tracked using the proposed method. The red circle shows the spread radius and the blue spots show the particles. The tracked object moves from Camera 2 to Camera 1. (a) and (b) images are from Camera 2, (d) to (f) images are from Camera 1. The frames run from right to left.

Figure 6.3 shows a series of images, where the object is tracked from Camera 2 to Camera 1 (right to left). It can be seen that as the object moves from one view to another the scale of the object changes. To overcome this situation the number of particles and the spread value are increased. This can be seen clearly from Figure 6.3(b) and 6.3(c) where the spread value increases along with the number of particles as the object moves from Camera 2 (shown in Figure 6.3(a) and 6.3(b)) to Camera 1 (shown in Figure 6.3(c) to 6.3(f)). As the tracking filter adapts to the new camera view, the number of particles and the spread value are again reduced to lower the computational cost, as shown in the Camera 1 images. It can be seen that in the first view the number of active particles is reduced to a minimum due to accurate tracking outputs, but as the object moves into the next view the number of active particles and also the spread value is set to a maximum.

6.6 Colour Features

Object colour was used as a feature to track the object. A reference colour histogram for each of the tracked objects is obtained at the time when it is selected for tracking. In the subsequent frames, the histogram for each particle is obtained and compared with this reference histogram. A Bhattacharyya coefficient was calculated using equation (6.4) to get the matching distance between the two histograms:

$$D_k = 1 - \sum_{u=0}^{U} \sqrt{h(u)h'(u)} \tag{6.4}$$

where U is the total number of histogram bins and $h(u)$ and $h'(u)$ are the current and reference histograms, respectively.

As the object moves from one view to another, due to the change in the scale and brightness parameters, it is important to update its reference histogram. Since with the change in lighting conditions the distance between the reference and the current histogram will increase, which can result in false tracking outputs, a maximum match technique is used to update the reference histogram. As explained in the previous section, the particle spread and number of particles are increased to overcome the scale changes, the same procedure being followed as before. The current histogram for each of the new particles is obtained and the Bhattacharyya coefficient is calculated. The particle with the highest weight is obtained and the colour histogram of the highest weighted particle is then made the reference histogram for the new camera view. This technique helps the ASCPF based method to keep track of the moving object.

6.7 Experimental Results

The ASCPF based tracking method has been tested on live video feeds from up to four Axis cameras. The overall camera setup is shown in Figure 6.1 where no two camera views overlap by no more than 10%. Objects are tracked as they move from one view to another in both directions. The standard deviation value for the particle spread is set to 0.6 whereas for matching the colour histograms it is set to 0.2. The minimum and maximum number of particles was selected according to procedures discussed in the previous chapter. The proposed system has been tested on five progressively more complex data sequences shot in different weather and lighting conditions where the fourth sequence involved up to four camera views. To thoroughly evaluate the performance of the system, comparisons are also made with standard particle filter techniques in terms of computational cost.

Figure 6.3, 6.4 and 6.5 show images from three sequences shot in different weather and lighting conditions used to test the proposed system. Figure 6.6 and 6.7 are from a video sequence with three and four camera views respectively. The camera configuration and setup was slightly different in Figure 6.7 as compared to the other test sequences. The tracked object is manually selected by a mouse click on the initial selection screen. It can be seen that although the scene activity density, weather and lighting conditions are different in all the sequences, the ASCPF method is able to successfully track all the moving objects using a reduced number of particles.

Camera 2

Camera 1

Figure 6.4: Images from one of the test sequences where the object is tracked using the proposed system. The frames run from right to left

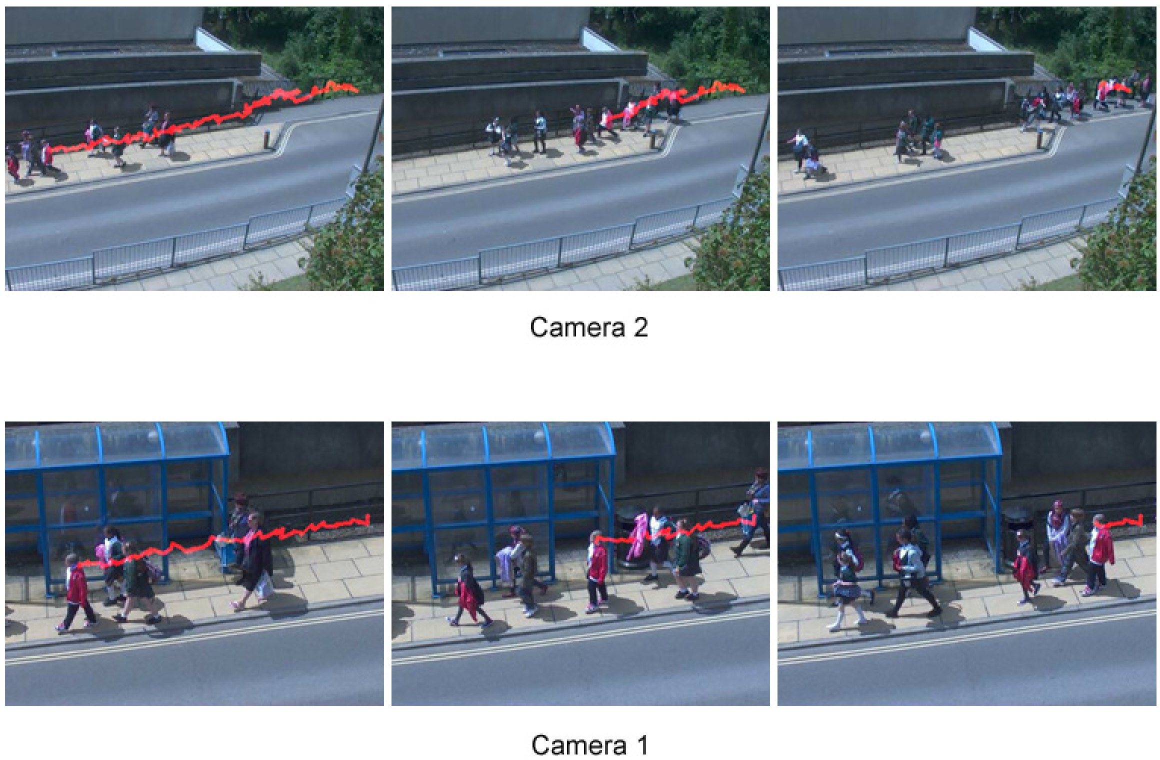


Figure 6.5: Images from a crowded test sequence. The proposed system successfully tracks the object even though it is surrounded by other moving objects in the scene. The frames run from right to left

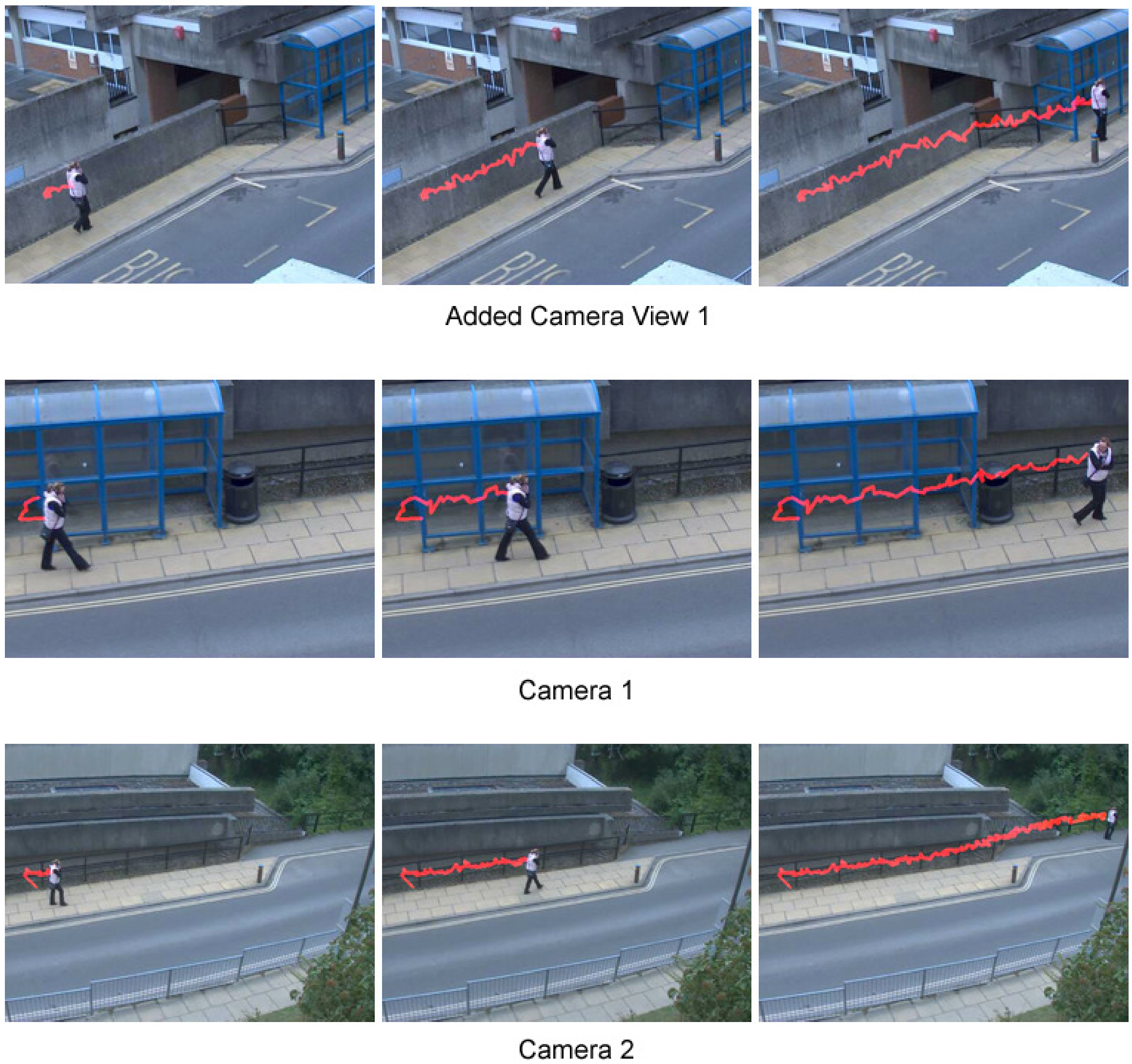
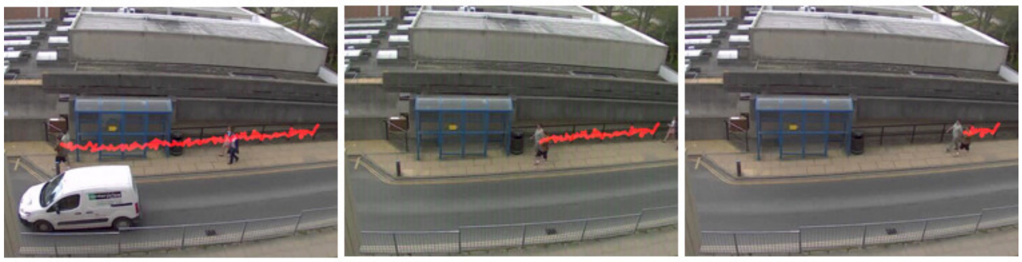


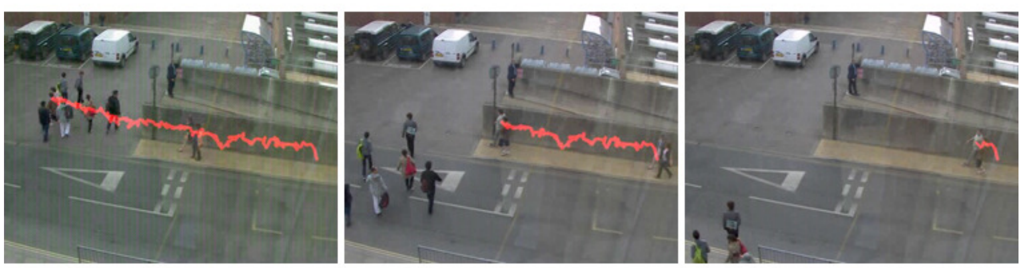
Figure 6.6: Images from an added view video sequence. The added camera is installed on the left of Camera 1. The proposed system successfully tracks the object as it moves from one view to another. The frames run from left to right

Camera 2



Camera 1

Added Camera View 1



Added Camera View 2

Figure 6.7: Images from four camera view video sequence. The added cameras are installed on the left of Camera 2. The camera configuration is slightly different than the previous setup. The ASCPF based tracking system successfully tracks the object as it moves from one view to another. The frames run from right to left where the person enters the scene from the right of Camera 1 and exits from the left of the additional Camera View 2.

6.8 Conclusion

A multi camera tracking system based on ASCPF has been presented in this chapter for which the main focus is to improve the performance of the system in terms of computational cost. Multi camera tracking environments usually pose challenges such as change in the scale and appearance of the tracked objects as they move across different camera views. These challenges are tackled using the ASCPF technique. A well known camera calibration technique is used to map image coordinates from different camera views to global world coordinates. The variable particle spread feature of ASCPF is utilized to minimize any effects of scale change and a reference histogram update technique is deployed to maintain object features across different cameras.

The technique has been tested on progressively complex video sequences from live camera feeds. It has been observed that, due to the adaptive nature of the ASCPF, the ASCPF did not only run faster than video rate but also successfully tracked the objects in all the test sequences.

Chapter 7

Conclusion and Future Work

Chapter 7

CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

An effort has been made in this thesis to study and develop robust event detection and object tracking techniques that can used to track different objects in complex video scenes. Object tracking has been the focus of many studies in the past. Due to the advances in technology in the last decade more powerful systems are now available that are not only used to implement various computer vision techniques requiring the use of complex mathematical models but also maintain video rate processing. These systems have allowed engineers to design more robust and intelligent tracking systems that can be implemented for public safety and surveillance across the world. Keeping in view the importance of the problem, a study has been conducted and is presented in this thesis where the main focus is to track objects in different environments and scene settings whilst maintaining their identity.

The thesis is divided into five progressively more complex problem domains detailed in successive individual chapters. The first chapter presents the putatively straightforward problem of detecting an intruder entering a marked alarm zone under consistent lighting conditions. A simple GMM based background segmentation and tracking technique is used to detect and track objects as they enter the zone. The output of the GMM was used to identify moving pixels in the scene. These pixels are then classified as objects based on their width and height. Alarm events are generated if these objects are found within the marked zone for longer than a certain period of time. Potential false alarms can be generated by small animals entering the zone and poor weather conditions such as sleet falling past the camera. Intruders approach the fence in several different ways such as by walking, crawling and rolling, and each of these must be classified. In addition, the lighting conditions vary with some scenes being shot at night under artificial near infra-red illumination.

The chapter highlights the main issues faced by the surveillance systems when implemented in outdoor environments. It is observed that, although the GMM copes well with a gradual lighting change, its performance is compromised as soon as there is a sudden change in scene illumination. Another observation is made regarding the number of moving objects in the scene. Since no unique object identification technique is applied, the system fails to keep track of the object identity if two or more objects cross each other. Although the proposed method is able to achieve over 90% detection success rate when tested on over 24 hours worth of video sequences with consistent lighting, it fails in more complex situations where the lighting was inconsistent or there are multiple objects in the scene. More robust solutions are presented in the subsequent chapters where edge and colour information is utilised to keep track of the objects in contrast to simple pixel tracking techniques.

Chapter 3 and 4 discuss techniques used to track objects in variable lighting conditions. In both chapters edges are used as the main features to keep track of the objects. Since edges are less sensitive to illumination change, it makes them a favourable feature for tracking. However, on the other hand edges are also very sensitive to motion of the object. Any change in the object motion can cause the edge map to change which can result in false tracking outputs. Keeping in view these limitations only those objects are considered for tracking which become stationary in the scene. Objects such as baggage unattended in public places or vehicles parked illegally on the road side are examples of such situations. Since these objects can pose a serious security threat, their identification and tracking is an important part of any video surveillance application.

Magnitude of edge is used in Chapter 3 mainly in indoor environments to track objects that become stationary in the scene. GMM is initially used to segment moving objects. These objects are then identified as stationary using a Centroid-Range method. The Centroid-Range method requires an isolated view of the objects before identifying them as stationary and thus does not handle any occlusion. Edge maps for the identified objects are obtained using the well known Canny edge detector and stored as templates. The correlation technique is applied to match the stored templates with the edge maps obtained from the area encompassed by the stationary objects from the current frame. The technique is tested on seven different indoor sequences with relatively consistent lighting and achieves 100% success rate.

However, when the same technique was tested in an outdoor environment the success rate came down to around 57%. It is observed from the overall results that there are two major issue that the method fails to address: 1) an isolated view of the object is required before identifying it as stationary. This requirement is typically difficult to meet, especially in crowded scenes where stationary objects might be frequently occluded; 2) though magnitude of edge can perform better than techniques based on colour features in inconsistent lighting conditions, its performance is compromised when lighting variations are higher than a certain level. To address these issues, a more robust object detection and tracking system is studied in the subsequent chapter that can track objects in both indoor and outdoor environments with variable lighting conditions.

In order to develop more robust object detection and tracking system, a pixel based classification model is used in Chapter 4. The proposed detection model not only picks up stationary objects accurately in changing lighting conditions but also handles occlusion. These stationary objects are then tracked using a novel adaptive edge orientation based technique where orientation of the edge is exploited instead of magnitude to keep track of the stationary object. Experimental results have shown that the discussed technique gives more than a 95% detection success rate in both indoor and outdoor environments, even if objects are partially occluded. The technique is tested on several hours of video sequences recorded at different locations and times of day. The results obtained are compared with the other available state-of-the-art methods. Experiment results show that the proposed method significantly improves the performance of the system as compared to the other techniques available in the literature and the one presented in Chapter 3.

As is apparent from the work of Chapter 3 and 4, edge information is sensitive to the motion of the object so methods based on this are usually only used to locate stationary objects with consistent edge features. In order to track non-rigid moving objects such as humans in crowded scenes, edges are usually not a practical attribute and colour features are exploited in such situations. Particle filtering techniques have been used extensively over the past few years in this regard. Due to the nonlinear nature of the particle filter and the fact that it does not assume a Gaussian probability density, it tends to outperform other available tracking methods.

A novel adaptive sample count particle filter (ASCPF) tracking method is presented in Chapter 5 for which the main motivation is to accurately track an object in crowded scenes using fewer particles and hence with reduced computational overhead. Instead of taking a fixed number of particles, a particle range technique is used where an upper and lower bound for the range is initially identified. Particles are made to switch between an active and inactive state within this identified range. The idea is to keep the number of active particles to a minimum and only to increase this as and when required. This, together with the variable particle spread, allows a more accurate proposal distribution to be generated while using less computational resource.

The proposed ASCPF method has been evaluated on different real life complex scenarios. The test sequences were selected keeping in mind real life situations such as occlusion, scale changes and variable target motion. Different experiments have shown that, although using the adaptive sampling approach alone reduces the computational cost, it nevertheless looses tracking accuracy when the object is frequently occluded. A variable particle spread approach is introduced to ameliorate such situations. Experimental results show that the proposed method tracks the object with slightly less accuracy to existing particle filter techniques but is up to five times faster.

The ASCPF technique presented in Chapter 5 has been implemented in a multi-camera environment to track an object across different scenes. Since the technique provided a real time solution to track objects in crowded scenes, it was decided to evaluate its performance in a more complex environment. Multi-camera environments can pose difficult challenges such as the absolute requirement for video rate tracking, change in the scale of the object as it moves from one camera to another or a change in object features, such as colour, since the brightness levels can alter across different camera views. Different ASCPF features are used to overcome each of these challenges. Adaptive samples allowed the ASCPF technique to track an object at video rate. Since fewer particles are used to track the object using the ASCPF technique, fewer resources are required. A variable standard deviation value of the ASCPF is utilized in order to cope with sudden colour and scale changes. As the object moves from one scene to another, the number of particles, along with their spread value, is increased to a maximum to reduce any effects of scale and colour change. It was found that not only did the ASCPF method result in successfully tracking the moving object across different views but it also maintained the real time frame rate due to its reduced computational cost. The ASCPF thus may provide a practical solution for tracking objects in multi-camera environments.

7.2 Future Work

The techniques presented in this thesis can further be improved to try and obtain a fuller scene understanding. The edge based tracking techniques successfully detect and track objects that become stationary in the scene. Although they achieved over 95% detection success rate, there are certain situations where change in lighting can cause false areas to be picked up as stationary objects. Since no object classification is deployed to distinguish between a legitimate stationary object and a false foreground region, a correlation based technique can be applied to ensure that only legitimate objects such as vehicles or baggage are picked up for alarm events. The implementation of such methods might require more computing power since any decisions based on the outcome are required to be made at run time or certainly within seconds. Though such a system might not be available at the time this study has been conducted it could be a step in the right direction.

Establishing the relationship between objects (both moving and stationary) in the scene is another important step towards full scene understanding. Activity recognition has been the focus of many studies in the past and similar techniques will be useful for possible implementation in the unconstrained environments considered in this study. The work conducted as part of this thesis only focuses on detection of stationary objects. There is no method applied to identify if stationary objects have been left unattended or not by an associated supervisory agent. Since unattended baggage or vehicles can cause a serious threat, establishing association between them and other moving objects in the scene can give useful information. For example identifying owner(s) of the luggage left in a public place or of a vehicle parked illegally can be of great importance as this could prevent a serious security threat. Facial recognition techniques can be implemented on high resolution images to identify potential criminals in this regard.

Within the work developed for tracking objects in crowded scenes, despite the encouraging results, there is still much scope for further improvement. The ASCPF technique presented in the thesis works primarily on colour based histogram matching. A problem arises when multiple objects of similar colour make contact with each other. Although the system on most occasions keeps track of the original object, there are still situations where the track is either lost or handed over to the co-located object. A multi-track particle filter could be implemented to solve this problem. Based on the distribution of the particles, the object track can be split into two or more tracks if such situations are encountered. The posterior distribution can be divided into small weighted clusters. If the distance between each cluster is greater than a certain threshold, the track can be split into multiple branches. Similarly, if two or more tracks tend to converge into a single track, the distance threshold can again be used to merge multiple tracks back into a single track. This can help the ASCPF to keep track of multiple objects with similar colour features. Another way of solving this problem would be to increase the particle filter dimensions to cover features other than colour so they can be considered for matching. Through this route it may be possible solve the issue at hand but it will of course require more computation resources.

ASCPF implementation in a multi camera environment is another important feature of this study.

While the ASCPF solution provided encouraging results, there is much room for improvement. The reference histogram update mechanism can further be refined by a more sophisticated approach than the one currently being used. This could help improve the histogram matching results in the new camera view. Another important aspect of the problem is in the setting up of the multi-camera environment. This is currently setup manually and cameras are calibrated using known world coordinates and their corresponding image coordinates. Any change in camera position (zoom, pan or tilt) results in a requirement for recalibration of that particular camera. This would ideally be replaced by self- or auto- calibration techniques but which will, again, require more computational resources.

References

[1] VSAM "Visual Surveillance and Monitoring", Available at http://www-2.cs.cmu.edu/~vsam/ Date of access: 23-04-11

[2] Safer Caerphilly Community Safety Partnership website http://www.caerphilly.gov.uk Date of access: 15-07-2011

[3] M. W. Green, "The Appropriate and Effective Use of Security Technologies in U.S. Schools", A Guide for Schools and Law Enforcement Agencies, Sandia National Laboratories, September 1999, NCJ 178265

[4] *i-LIDS* dataset, United Kingdom Home Office dataset. Available at http://www.homeoffice.gov.uk/science-research/hosdb/*i-LIDS*/ Date of access: 01-06-2010

[5] MIT Traffic dataset, Available at http://www.ee.cuhk.edu.hk/~xgwang/MITtraffic.html Date of access: 18-06-11

[6] ViSOR dataset, Available at http://imagelab.ing.unimore.it/visor/ Date of access: 18-06-11

[7] *PETS 2006* dataset, Available at http://www.cvg.cs.reading.ac.uk/PETS2006/data.html Date of access: 18-06-11

[8] University of Sussex Traffic dataset, Available at http://www.sussex.ac.uk/iims/ Date of access: 28-11-11

[9] University of Sussex Tracking dataset, Available at http://www.sussex.ac.uk/iims/ Date of access: 28-11-11

[10] ABI research report "The Video Surveillance Market Hardware and Software Market Trends and Forecasts", 2010.

[11] IBM "Business Analytics for Retail", available on website http://www-01.ibm.com/software/analytics/retail/ Date of access: 09-10-11

[12] NICE Systems Ltd website http://www.nice.com/video Date of access: 09-10-11

[13] The National Center for Education Statistics (NCES) and Institute of Education Sciences (IES) report "Indicators of School Crime and Safety: 2010" available at http://nces.ed.gov Date of access: 09-10-11

[14] M. Valera, S. A. Velastin, A. Ellis, J. Ferryman, "Communication Mechanisms and Middleware for Distributed Video Surveillance," *IEEE Transactions on Circuits and Systems for Video Technology*,vol.21, no.12, pp.1795-1809, 2011

[15] C. Beleznai, B. Fruhstuck, and H. Bischof, "Human detection in groups using a fast mean shift procedure," *International Conference on Image Processing*, pp. 349–352, 2004

[16] H. Elzein, S. Lakshmanan, and P. Watta, "A motion and shapebased pedestrian detection algorithm," *IEEE Intelligent Vehicles Symposium*, pp. 500–504, 2003

[17] D. J. Lee, P. Zhan, A. Thomas, and R. Schoenberger, "Shape-based human intrusion detection," *SPIE International Symposium on Defense and Security, Visual Information Processing XIII*, 5438: pp. 81–91, 2004

[18] Jianpeng Zhou and Jack Hoang, "Real time robust human detection and tracking system", I*EEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 3: pp. 149 – 149, 2005

[19] D.M. Gavrila, "A Bayesian Exemplar-Based Approach to Hierarchical Shape Matching," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 29, no. 8, pp. 1408-1421, Aug. 2007.

[20] D.M. Gavrila and S. Munder, "Multi-Cue Pedestrian Detection and Tracking from a Moving Vehicle," *International Journal of Computer Vision*, vol. 73, no. 1, pp. 41-59, 2007

[21] B. Stenger, A. Thayananthan, P.H.S. Torr, and R. Cipolla, "ModelBased Hand Tracking Using a Hierarchical Bayesian Filter," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 28, no. 9, pp. 1372-1385, 2006

[22] K. Toyama and A. Blake, "Probabilistic Tracking with Exemplars in a Metric Space," *International Journal of Computer Vision*, vol. 48, no. 1, pp. 9-19, 2002

[23] C. Papageorgiou and T. Poggio, "A Trainable System for Object Detection," *International Journal of Computer Vision*, vol. 38, pp. 15-33, 2000

[24] A. Mohan, C. Papageorgiou, and T. Poggio, "Example-Based Object Detection in Images by Components," *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 23, no. 4, pp. 349-361, 2001

[25] P. Viola, M. Jones, and D. Snow, “Detecting Pedestrians Using Patterns of Motion and Appearance,” *International Journal of Computer Vision*, vol. 63, no. 2, pp. 153-161, 2005

[26] N. Buch, S.A. Velastin, J. Orwell,"A Review of Computer Vision Techniques for the Analysis of Urban Traffic," *IEEE Transactions onIntelligent Transportation Systems*, vol.12, no.3, pp.920-939, 2011

[27] C. Stauffer and W.E.L. Grimson, “Adaptive background mixture models for real-time tracking,” *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 2, 1999

[28] Fatih Porikli, Yuri Ivanov and Tetsuji Haga, “Robust Abandoned Object Detection Using Dual Foregrounds,” *EURASIP Journal on Advances in Signal Processing*, vol. 2008, pp. 1-10, 2008

[29] V. Reddy, C. Sanderson and B.C. Lovell, “Robust Foreground Object Segmentation via Adaptive Region-Based Background Modelling,” *20th International Conference on Pattern Recognition (ICPR)*, pp. 3939-3942, 2010

[30] C. Zhao, X. Wang, W. Cham, "Background Subtraction via Robust Dictionary Learning," *EURASIP Journal on Image and Video Processing*, Volume 2011 , Article ID 972961, 2011

[31] Lu Wang and N.H.C. Yung, “Extraction of Moving Objects From Their Background Based on Multiple Adaptive Thresholds and Boundary Evaluation,” *IEEE Transactions on Intelligent Transportation Systems*, vol.11, no.1, pp. 40-51, 2010

[32] K. Srinivasan, K. Porkumaran and G. Sainarayanan, “Improved background subtraction techniques for security in video applications,” 3rd International Conference on Anti-counterfeiting, Security, and Identification in Communication, pp. 114-117, 2009

[33] Y. Tian, R. S. Feris and A. Hampapur, “Real-time detection of abandoned and removed objects in complex environments,” *IEEE Int. Workshop Visual Surveillance*, 2008

[34] Y. Tian, R. Feris, H. Liu, A. Hampapur and M. Sun, “Robust Detection of Abandoned and Removed Objects in Complex Surveillance Videos,” *IEEE*

Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, vol.41, no.5, pp. 565-576, 2011

[35] P.L. Venetianer, Z. Zhang, W. Yin and A.J. Lipton, "Stationary target detection using the objectvideo surveillance system," *IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 242-247, 2007

[36] F. Ren, J. Huang, R. Jiang, R. Klette, "General traffic sign recognition by feature matching," *24th International Conference Image and Vision Computing New Zealand*, 2009

[37] Y. Yang, C. Yang; X. Wang. "A Detection and Tracing Algorithm of Moving Vehicles," *2nd International Conference on Pervasive Computing and Applications*, 2007

[38] S. H. Jeon, K. Lee, B. Kwon, "Application of template matching method to traffic feature detection using KOMPSAT EOC imagery," *IEEE International Geoscience and Remote Sensing Symposium*, 2005

[39] N. Buch, J. Orwell, S.A. Velastin,"Urban road user detection and classification using 3D wire frame models," *IET Computer Vision*, vol.4, no.2, pp.105-116, 2010

[40] S. Ferrando, G. Gera, M. Massa amd C. Regazzoni, "A New Method for Real Time Abandoned Object Detection and Owner Tracking," *IEEE International Conference on Image Processing*, pp. 3329-3332, 2006

[41] Yiping Tang, Feihu Hu, Guanbao Yang and Bei Lin, "Property protection system based on Omni-Directional Vision Sensors," *3rd International Congress on Image and Signal Processing (CISP)*, pp. 181-184, 2010

[42] Jianting Wen, Haifeng Gong, Xia Zhang and Wenze Hu, "Generative model for abandoned object detection," *16th IEEE International Conference on Image Processing (ICIP)*, pp. 853-856, 2009

[43] Xuli Li, Chao Zhang, and Duo Zhang, "Abandoned Objects Detection Using Double Illumination Invariant Foreground Masks," *20th International Conference on Pattern Recognition (ICPR)*, pp. 436-439, 2010

[44] Y. Satoh, S. Kaneko, Y. Niwa and K. Yamamoto, "Robust object detection using a radial reach filter(rrf)," *Systems and Computers in Japan*, vol. 35, no. 10, pp. 63–73, 2004

[45] Qiujie Li, Yaobin Mao, Zhiquan Wang and Wenbo Xiang, “Robust Real-Time Detection of Abandoned and Removed Objects,” *Fifth International Conference on Image and Graphics*, pp. 156-161, 2009

[46] Tang Yi Ping and Chen Yao Yu, “Illegally Parked Vehicles Detection Based on Omnidirectional Computer Vision,” *2nd International Congress on Image and Signal Processing*, pp. 1-5, 2009

[47] R. H. Evangelio, T. Sikora, "Static Object Detection Based on a Dual Background Model and a Finite-State Machine," *EURASIP Journal on Image and Video Processing*, Volume 2011 , Article ID 858502, 2011

[48] Jong Taek Lee, M.S. Ryoo, M. Riley and J.K. Aggarwal, “Real-time detection of illegally parked vehicles using 1-D transformation,” *IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 254-259, 2007

[49] J.T. Lee, M.S. Ryoo, M. Riley and J.K. Aggarwal, “Real-Time Illegal Parking Detection in Outdoor Environments Using 1-D Transformation,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol.19, no.7, pp. 1014-1024, 2009

[50] A. Bevilacqua and S. Vaccari, “Real time detection of stopped vehicles in traffic scenes,” *IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 266-270, 2007

[51] S. Boragno, B. Boghossian, J. Black, D. Makris and S. Velastin, “A DSP-based system for the detection of vehicles parked in prohibited areas,” *IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 260-265, 2007

[52] S. Guler, J.A. Silverstein and I.H. Pushee, “Stationary objects in multiple object tracking,” *IEEE Conference on Advanced Video and Signal Based Surveillance*, pp. 248-253, 2007

[53] Jing-Ying Chang, Huei-Hung Liao and Liang-Gee Chen, “Localized Detection of Abandoned Luggage,” *EURASIP Journal on Advances in Signal Processing*, vol. 2010, Article ID 675784, 9 pages, 2010

[54] F. Lv, X. Song, B. Wu, V. K. Singh and R. Nevatia, “Left luggage detection using bayesian inference,” *9th IEEE International Workshop on Performance Evaluation in Tracking and Surveillance (PETS '06)*, pp. 83-90, 2006

[55] E. Auvinet, E. Grossmann, C. Rougier, M. Dahmane and J. Meunier, "Left-luggage detection using homographies and simple heuristics," *IEEE International Workshop on PETS*, pp. 51–58, 2006

[56] M. Piccardi and E.D. Cheng, "Multi-Frame Moving Object Track Matching Based on an Incremental Major Color Spectrum Histogram Matching Algorithm," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*, pp. 19-19, 2005

[57] S.M. Khan and M. Shah, "Tracking Multiple Occluding People by Localizing on Multiple Scene Planes, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.31, no.3, pp. 505-519, 2009

[58] F. Jialue, X. Wei, W. Ying, G. Yihong, "Human Tracking Using Convolutional Neural Networks," *IEEE Transactions on Neural Networks*, vol.21, no.10, pp.1610-1623, 2010

[59] J. Berclaz, F. Fleuret, E. Türetken, Pascal Fua, "Multiple Object Tracking Using K-Shortest Paths Optimization," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 9, pp. 1806-1819, 2011

[60] H. Kjellstrom, D. Kragic, M. J. Black, "Tracking people interacting with objects," *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 747-754, 2010

[61] E. L. Andrade, J. C. Woods, E. Khan, M. Ghanbari, "Region-based analysis and retrieval for tracking of semantic objects and provision of augmented information in interactive sport scenes," *IEEE Transactions on Multimedia*, vol. 7, no. 6, pp. 1084-1096, 2005

[62] V. A. Prisacariu, I. D. Reid, "PWP3D: Real-Time Segmentation and Tracking of 3D Objects," *International Journal of Computer Vision*, pp. 1-20, 2012

[63] W. Fan-Tung, C. Sheng-Ting, L. Chia-Wen, A region-based object tracking scheme using Adaboos-based feature selection, *IEEE International Symposium on Circuits and Systems, ISCAS 2008*, pp. 2753-2756, 2008

[64] Z. Kalal, K. Mikolajczyk, J. Matas, "Tracking-Learning-Detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.PP, no.99, pp.1, 2011

[65] D. Marimon, T. Ebrahimi, "Orientation histogram-based matching for region tracking," *Eighth International Workshop on Image Analysis for Multimedia Interactive Services*, pp.8, 2007

[66] Michael Kass, Andrew Witkin, Demetri Terzopoulos, "Snakes: Active Contour," Models, *International Journal of Computer Vision*, vol 1, pp. 321-331, 1998

[67] Chenyang Xu, Jerry L. Prince, "Snakes, Shapes, and Gradient Vector flow," *IEEE Transactions on Image processing*, vol.7, no 3, pp. 359-369, 1998

[68] D.J. Williams, M. Shah, "A fast algorithm for active contours," *Third International conference on Computer Vision*, pp. 592-595, 1990

[69] N. Bangalore, R.C.D. Young, P.M. Birch, C.R. Chatwin, "Tracking Moving Objects Using Bandpass Filter Enhanced Localisation and Automated Initialisation of Active Contour Snakes," *ICGST International Journal on Graphics, Vision and Image Processing, GVIP*, vol. 10, pp. 1-8, 2010

[70] S. Lefevre, J.G. Gerard, A. Piron, N. Vincent, "An Extended Snake model for Real-time multiple Object tracking," *International workshop on Advanced concepts for Intelligent vision systems*, pp.268-275, 2002

[71] T. Chan, L. Vese, "Active contour without edges," *IEEE transactions on Image processing*, vol.10, no.2, pp. 266-277, 2001

[72] Min Hu, Xijian Ping, Yihong Ding, "Automated Cell Nucleus Segmentation using Improved Snake," *International Conference on Image Processing*, Volume 4, pp. 2737–2740, 2004

[73] C. Madden, E. Cheng, M. Piccardi, "Tracking people across disjoint camera views by an illumination-tolerant appearance representation," *Machine Vision and Applications*, vol. 18, no. 3, pp. 233–247, 2007

[74] Jianbo Shi, Carlo Tomasi, Good Features to Track*, IEEE Conference on Computer Vision and Pattern Recognition*, pp. 593-600., 1994

[75] B. Benfold, I. Reid, "Stable multi-target tracking in real-time surveillance video," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp.3457-3464, 2011

[76] Miroslav Trajkovic, Mark Hedley, "Fast corner detection," *Image and Vision Computing*, vol 16, issue 2, pp. 75-87, 1998

[77] David G. Lowe, “Object recognition from local Scale-Invariant features,” *Seventh international conference on Computer Vision (ICCV 99)*, vol 2, pp.1150, 1999

[78] G.I. Chiou, Jenq-Neng Hwang, “A neural network-based stochastic active contour model (NNS-SNAKE) for contour finding of distinct features,” *IEEE Transactions on Image Processing*, vol.4, no.10, pp. 1407-1416, 1995

[79] M. Gastaud, M. Barlaud, G. Aubert, “Combining shape prior and statistical features for active contour segmentation,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol.14, no.5, pp. 726- 734, 2004

[80] O. Michailovich, Y. Rathi, A. Tannenbaum, “Image Segmentation Using Active Contours Driven by the Bhattacharyya Gradient Flow,” *IEEE Transactions on Image Processing*, vol.16, no.11, pp. 2787-2801, 2007

[81] K. Somkantha, N. Theera-Umpon, S. Auephanwiriyakul, “Boundary Detection in Medical Images Using Edge Following Algorithm Based on Intensity Gradient and Texture Gradient Features,” *IEEE Transactions on Biomedical Engineering*, vol.58, no.3, pp. 567-573, 2011

[82] S. Sun, D. R. Haynor, Y. Kim, “Semiautomatic video object segmentation using VSnakes,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 13, no. 1, pp. 75–82, 2003

[83] Q. Chen, Q. S. Sun, P. A. Heng, D. S. Xia, “Parametric active contours for object tracking based on matching degree image of object contour points,” *Pattern Recognition Letters*, vol. 29, no. 2, pp.126–141, 2008

[84] N. Paragios, R. Deriche, Geodesic active regions for motion estimation and tracking, *Seventh IEEE International Conference on Computer Vision*, 1999., vol.1, pp. 688-694, 1999

[85] D. Chun-li, D. Yu-ning, A Novel Algorithm for Object Tracking with Particle Filtering and GVF-Snake, *Eighth International Conference on Intelligent Systems Design and Applications*, 2008, vol.2, pp. 8-13, 2008

[86] A. Aksel, S.T. Acton, “Target tracking using the snake particle filter,” *IEEE Southwest Symposium on Image Analysis & Interpretatio*, pp. 33-36, 2010

[87] Y. Rathi, N. Vaswani, A.Tannenbaum, A. Yezzi, “Tracking Deforming Objects Using Particle Filtering for Geometric Active Contours,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, pp. 1470-1475, 2007

[88] N. T. Nguyen, S. Venkatesh, G. West, and H. H. Bui, “Multiple camera coordination in a surveillance system,” *ACTA Automatica Sinica*, vol. 29, no. 3, pp. 408-421, 2003

[89] O. Javed, Z. Rasheed, K. Shafique, and M. Shah, “Tracking across multiple cameras with disjoint views,” *IEEE International Conference on Computer Vision*, vol. 1, pp.952-957, 2003

[90] R. O. Duda, P. E. Hart, and D. G. Stork, “Pattern Classification,” *Wiley-Interscience, 2nd edition*, pp. 164-173, 2000

[91] J. Ren, M. Xu, J. Orwell, G.A. Jones, Graeme A., "Multi-camera video surveillance for real-time analysis and reconstruction of soccer games," *Machine Vision and Applications*, vol. 21(6), pp. 855-863, 2010

[92] J. Black and T. Ellis, “Multi-camera image tracking,” *Image and Vision Computing*, vol. 24(11), pp. 1256–1267, 2006

[93] Liu Li, Sun Bo, Wei Ning, Chao Hu, M.Q.H. Meng, ”A Novel Marker Tracking Method Based on Extended Kalman Filter for Multi-Camera Optical Tracking Systems,” *5th International Conference on Bioinformatics and Biomedical Engineering, (iCBBE) 2011*, pp.1-5,2011

[94] F. Fleuret, J. Berclaz, R. Lengagne, and P. Fua, “Multi-camera people tracking with a probabilistic occupancy map,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.30, no.2, pp.267-282, 2008

[95] R. Mohedano and N. Garcia, “Robust multi-camera tracking from schematic descriptions,” *17th IEEE International Conference on Image Processing (ICIP)*, pp.3949-3952, 2010

[96] Yifan Zhou, J. Benois-Pineau, and H. Nicolas, “A multi-resolution particle filter tracking with a dual consistency check for model update in a multi-camera environment,” *11th International Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS)*, pp.1-4, 2010

[97] R. Mohedano and N. Garcia, “Robust multi-camera 3D tracking from mono-camera 2d tracking using Bayesian Association,” *IEEE Transactions on Consumer Electronics*,vol.56, no.1, pp.1-8, 2010

[98] K. Kim and L.S. Davis, “Multi-camera tracking and segmentation of occluded people on ground plane using search guided particle filtering,” *European Conference on Computer Vision*, pp. 98-109, 2006

[99] G. D. Finlayson and S. D. Hordley, "Color constancy at a pixel," *Journal of the Optical Society of America A: Optics, Image Science, and Vision*, vol. 18, issue 2, pp. 253-264 2001

[100] J. Canny, “A Computational Approach to Edge Detection,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.PAMI-8, no.6, pp.679-698, 1986

[101] M. Roushdy, “Comparative Study of Edge Detection Algorithms Applying on the Grayscale Noisy Image Using Morphological Filter”, *ICGST International Journal on Graphics, Vision and Image Processing*, Volume 6, Issue 4, 2006

[102] M. Juneja and P. S. Sandhu, “Performance Evaluation of Edge Detection Techniques for Images in Spatial Domain,” *International Journal of Computer Theory and Engineering*, vol. 1, No. 5, 2009

[103] *i-LIDS* Team, “Imagery Library for Intelligent Detection Systems (*i-LIDS*); A Standard for Testing Video Based Detection Systems,” *40th Annual IEEE International Carnahan Conferences Security Technology*, pp.75-80, 2006

[104] A. Dearden and Y. Demiris, “Tracking football player movement from a single moving camera using particle filters,” *3rd European Conference on Visual Media Production*, pp. 29–37, 2006

[105] X. Xinyu and L. Baoxin, “Adaptive Rao–Blackwellized Particle Filter and Its Evaluation for Tracking in Surveillance,” *IEEE Transactions on Image Processing*, vol.16, no.3, pp. 838-849, 2007

[106] Xu Linzhou, Zhang Xin-hua, Yang Shao-qing and Fan Wen-tao, “An efficient particle filter with variable number of particles for bearings-only tracking,” *IEEE 10th International Conference on Signal Processing (ICSP)*, pp. 2395-2398, 2010

[107] D. Fox, “KLD-Sampling: Adaptive Particle Filters,” *In Advances in Neural Information Processing Systems*, vol. 14, pp. 713–720, 2001

[108] A. Soto, "Self adaptive particle filter," *International Joint Conference on Artificial Intelligence*, pp. 1398–140, 2005

[109] D. Comaniciu, V. Ramesh and P. Meer, "Real-time tracking of non-rigid objects using mean shift," *IEEE Conference on Computer Vision Pattern Recognition*, pp. 142–149, 2000

[110] M. Taj and A. Cavallaro, "Multi-camera track-before-detect," *ACM/IEEE International Conference on Distributed Smart Cameras*, 2009.

[111] A. Sundaresan and R. Chellappa, "Multi-camera tracking of articulated human motion using motion and shape cues," *IEEE Transactions on Image Processing*, vol. 18, issue 9, pp. 2114--2126, 2009.

[112] V. I. Morariu and O. I. Camps, "Modeling correspondences for multi-camera tracking using nonlinear manifold learning and target dynamics," *Computer Vision and Pattern Recognition*, vol. 1, pages 545–552, 2006.

[113] The Axis website. [Online]. Available: http://www.axis.com

[114] J. Heikkila, "Geometric camera calibration using circular control points," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, issue. 10, pp. 1066-1077, 2000

[115] A. Bhattacharyya, "On a measure of divergence between two statistical populations defined by their probability distributions," Bulletin of the Calcutta Mathematical Society 35, pp. 99–109.

APPENDIX A

Gaussian Mixture Model (GMM)

The foreground/background pixel segmentation is formed using a GMM on a per pixel basis with *K* Gaussian distributions for each pixel. Each Gaussian distribution has a mean μ, a standard deviation σ and a weight ω. The robustness of the segmentation is dependent on the value of *K*. If it is kept large, segmentation results improve but at the cost of slow system performance. It has been observed that three to five Gaussians provide sufficiently robust segmentation, whilst still maintaining real-time performance.

At a given time *t*, the Gaussian probability density function, *G*, for the k^{th} Gaussian distribution, with covariance $\Sigma_{k,t}$ and a mean μ is given as:

$$G(x_t, \mu_{k,t}, \Sigma_{k,t}) = \frac{1}{\sqrt{2\pi|\Sigma_{k,t}|}} e^{-\frac{1}{2}(x_t-\mu_{k,t})^T \Sigma_{k,t}^{-1}(x_t-\mu_{k,t})} \tag{A.1}$$

Therefore the probability that the pixel x_t belongs to this Gaussian distribution is given as:

$$P(x_t) = \sum_{k=1}^{K} \omega_{k,t} \times G(x_t, \mu_{k,t}, \Sigma_{k,t}) \tag{A.2}$$

where $\omega_{k,t}$ is an estimate of the weight of the i^{th} Gaussian initialized as *1/K*. The weight on each distribution represents the probability that the colour of the image pixel remains the same, i.e. is part of the background.

A three step matching, update and decision is carried out for each pixel. A pixel is considered to part of the background model if its value appears inside a confidence interval of 2.5 standard deviations from the mean. If this is the case then the corresponding distribution is updated using the following three equations:

$$\mu_{k,t} = (1-\alpha)\mu_{k,t-1} + \alpha x_t \quad \text{(A.3)}$$

$$\sigma_{k,t}^2 = (1-\alpha)\sigma_{k,t}^2 + \alpha x_t \quad \text{(A.4)}$$

$$\omega_{k,t} = (1-\alpha)\omega_{k,t-1} + \alpha x_t \quad \text{(A.5)}$$

α here is a learning rate and plays an important role in the over all detection. A higher α value will adapt quickly to global illumination change where as a low α value is useful for the detection of slow moving objects. The importance of this learning rate and its effects on real time surveillance systems is further highlighted in the results section.

Next a decision is made as to whether the new pixel value is foreground or background. This is achieved using equation A.2 to compute the probability that a given pixel intensity is background. The background models are classified with respect to their weights and a thresholding mechanism is used identify if a pixel belongs to the background or foreground. GMM relies on the assumption that the background is visible more frequently than any foreground region. If a certain pixel value occurs repeatedly, the weight of the corresponding model is increased and the pixel is considered to be part of the background.

If no match is found, the Gaussian distribution with the lowest weight is replaced by a new one with the value of the pixel as the mean and with a initially high standard deviation, σ_0, and a low weight, ω_0. The matched distributions are then updated by calculating a new mean, μ, and variance σ^2.

Canny Edge Detector

Canny is a multi-stage process in which the image is initially smoothed using 1D Gaussian convolution both in the *x* and *y* direction.

$$g(m,n) = G_\sigma(m,n) * f(m,n) \quad \text{(A.6)}$$

where

$$G_\sigma \quad = \quad \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{m^2+n^2}{2\sigma^2}\right] \qquad \text{(A.7)}$$

It then finds the image gradient in both x and y direction using the *Sobel-operator* to highlight changes in intensity, which indicates the presence of edges.

$$M(m,n) \quad = \quad \sqrt{g_m^2(m,n) + g_n^2(m,n)} \qquad \text{(A.8)}$$

and

$$\theta(m,n) \quad = \quad \tan^{-1}\left[g_n(m,n) / g_m(m,n)\right] \qquad \text{(A.9)}$$

where $g_m^2(m,n)$ is the gradient in the x direction and $g_n^2(m,n)$ is the gradient in the y direction obtained after applying the *Sobel-operator*.

Since edges will occur at points where the gradient is at a maximum, the algorithm then tracks along these regions and suppresses any pixel that is not at the maximum, a process known as *non-maximal suppression.*

After the *non-maximum suppression* step the remaining edge-pixels are labelled as *strong* or *weak* based on their strength. Although the majority of these will probably be true edges, some may be caused due to the presence of noise or colour variations. Thresholding is the simplest technique used to identify true edges in which only those edges are preserved that are stronger then a certain value. The *Canny* edge detection algorithm classifies these edges into two categories, *strong* and *weak*, by using double thresholding. A high and a low threshold value is selected. Edge-pixels stronger than the high threshold are labelled as *strong*; edge pixels weaker than the low threshold are removed where as edge-pixels between the two thresholds are marked as *weak*. S*trong* edges are considered as certain edges and are included in the final output where as pixels marked as *weak* are included if and only if they are connected to the *strong* edge-pixel.

APPENDIX B

Nonlinear Bayesian Tracking

Tracking can be defined as a process of evolving state sequence x_k given by equation:

$$x_k = Fx_{k-1} + v_{k-1} \tag{B.1}$$

where *F* is possibly a nonlinear function of the state x_{k-1} and v_{k-1} is the process noise.

The main objective here is to recursively estimate x_k given the measurement

$$z_k = hx_k + n_k \tag{B.2}$$

where *h* is possibly a nonlinear function and n_k is the measurement noise.

From a Bayesian point of view, tracking is the recursive estimation of x_k with some degree of confidence at time *'k'* given the measurements $z_{1:k}$ up to time *k*. Thus, it is requires to construct a probability density function $p(x_k|z_{1:k})$. Since it is assumed that the prior $p(x_0|z_0)$ is available, the required pdf $p(x_k|z_{1:k})$ is recursively obtained from a two step prediction and update model.

If the required *pdf* $p(x_{k-1}|z_{k-1})$ is available at $k-1$, the prior *pdf* of the state at time *k* is obtained using equation

$$p(x_k|z_{k-1}) = \int p(x_k|x_{k-1})\, p(x_{k-1}|z_{k-1})dx_{k-1} \tag{B.3}$$

where $p(x_{k-1}|z_{k-1})$ is the previous *a posteriori* distribution and $p(x_k|x_{k-1})$, obtained from equation (B.1), is the predictive conditional transition distribution of the current state, given the previous state and all previous observations.

At time *k*, when measurement z_k becomes available the prior can be updated using Bayes' rule

$$p(x_k|z_k) = \frac{p(z_k|x_k)\,p(x_k|z_{k-1})}{p(z_k|z_{k-1})} \tag{B.4}$$

Depending on the measurement z_k, the prior density is updated using equation (B.4) to obtain the posterior density of the current state.

Particle Filtering

Let $\{x_k^i, w_k^i\}$ be random samples that characterize the posterior pdf $p(x_k|x_k)$ *where i=0 to N* and w_k^i are the weights associated of each sample. Weights are chosen on the basis of importance sampling such that

$$w_k^i \propto \frac{p(x_k|z_k)}{q(x_k|z_k)} \tag{B.5}$$

where $q(x)$ are the samples easily generated from the proposal density using equation

$$q(x_k|z_k) = q(x_k|x_{k-1}, z_k)q(x_{k-1}|z_k) \tag{B.6}$$

From equation B.4,

$$p(x_k|z_k) = \frac{p(z_k|x_k \mid z_{k-1})\,p(x_k|x_{k-1}|z_{k-1})}{p(z_k|z_{k-1})} \times p(x_{k-1}|z_{k-1}) \tag{B.7}$$

$$= \frac{p(z_k|x_k)\,p(x_k|x_{k-1})}{p(z_k|z_{k-1})}\,p(x_{k-1}|z_{k-1})$$

$$\propto p(z_k|x_k)\,p(x_k|x_{k-1})\,p(x_{k-1}|z_{k-1}) \tag{B.8}$$

By substituting (B.6) and (B.8) in (B.5), the weight update equation can be shown to be

$$w_k^i \propto \frac{p(z_k|x_k)\,p(x_k|x_{k-1})\,p(x_{k-1}|z_{k-1})}{q(x_k|x_{k-1}, z_k)\,q(x_{k-1}|z_k)} \tag{B.9}$$

$$= w_{k-1}^i \frac{p(z_k|x_k)\,p(x_k|x_{k-1})}{q(x_k|x_{k-1}, z_k)} \tag{B.10}$$

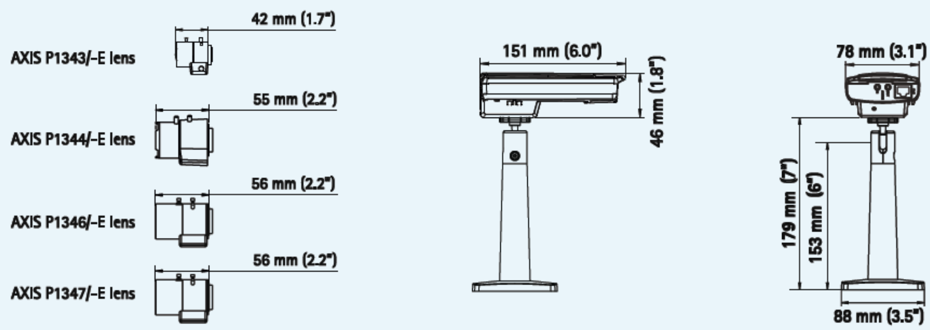
APPENDIX C

Axis Camera Datasheet

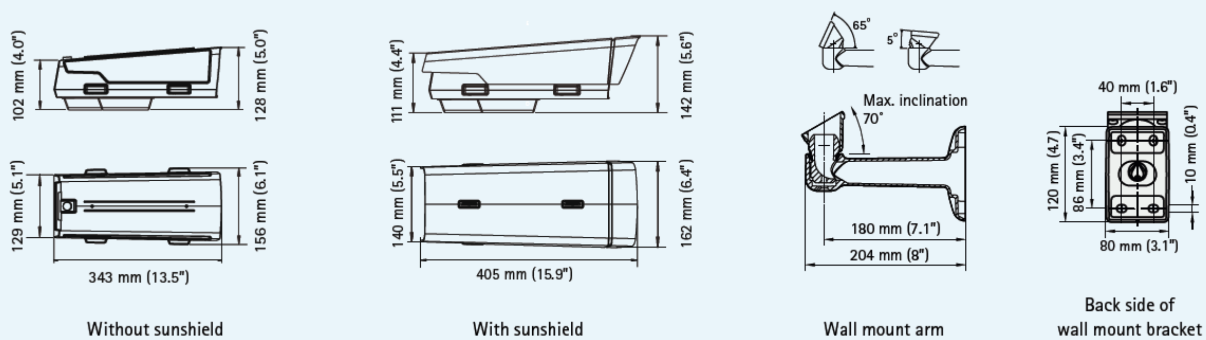
Camera	
Models: indoor	**AXIS P1343:** SVGA resolution, day and night **AXIS P1344:** 1 MP/HDTV 720p, day and night **AXIS P1346:** 3 MP/HDTV 1080p, day and night **AXIS P1347:** 5 MP, day and night
Models: outdoor	**AXIS P1343-E:** SVGA resolution, day and night **AXIS P1344-E:** 1 MP/HDTV 720p, day and night **AXIS P1346-E:** 3 MP/HDTV 1080p, day and night **AXIS P1347-E:** 5 MP, day and night
Image sensor	**AXIS P1343/-E:** Progressive scan RGB CMOS 1/4" **AXIS P1344/-E:** Progressive scan RGB CMOS 1/4" **AXIS P1346/-E**, Progressive scan RGB CMOS 1/3" (effective) **AXIS P1347/-E:** Progressive scan RGB CMOS 1/2.5"
Lens	All AXIS P13 cameras use IR-corrected, CS-mount lens **AXIS P1343/-E:** Varifocal 3-8 mm: 61° - 21° view*, F1.0, DC-iris **AXIS P1344/-E:** Varifocal 3-8 mm: 66° - 27° view*, F1.2, DC-iris **AXIS P1346/-E:** Varifocal 3.5-10 mm: 72° - 27° view*, F1.6, P-Iris; DC-iris lenses also supported **AXIS P1347/-E:** Varifocal 3.5-10 mm: 89° - 33° view*, F1.6, P-Iris; DC-iris lenses also supported *horizontal angle of view
Day and night	Automatically removable infrared-cut filter
Minimum illumination	**AXIS P1343/-E:** Color: 0.2 lux, B/W: 0.05 lux, F1.0 **AXIS P1344/-E:** Color: 0.3 lux, B/W: 0.05 lux, F1.2 **AXIS P1346/-E:** Color: 0.5 lux, B/W: 0.08 lux, F1.6 **AXIS P1347/-E:** Color: 0.5 lux, B/W: 0.08 lux, F1.6
Shutter time	**AXIS P1343/-E, AXIS P1344/-E:** 1/24500 s to 1/6 s **AXIS P1346/-E:** 1/35500 s to 1/6 s **AXIS P1347/-E:** 1/25500 s to 1/6 s
Video	
Video compression	H.264 (MPEG-4 Part 10/AVC) Motion JPEG
Resolutions	**AXIS P1343/-E:** 800x600 (SVGA) to 160x90 **AXIS P1344/-E:** 1280x800* (1 MP) to 160x90 **AXIS P1346/-E:** 2048x1536 (3 MP) to 160x90 **AXIS P1347/-E:** 2560x1920 (5 MP) **to** 160x90 *1440x900 (1.3 MP) scaled resolution available via VAPIX®
Frame rate H.264/ Motion JPEG	**AXIS P1343/-E, AXIS P1344/-E:** 30 fps in all resolutions **AXIS P1346/-E, AXIS P1347/-E:** 3 MP mode: 20 fps in all resolutions; HDTV 1080p (1920x1080) mode and 2 MP 4:3 (1600x1200) mode: 30 fps in all resolutions **AXIS P1347/-E:** 5 MP mode: 12 fps in all resolutions
Video streaming	Multiple, individually configurable streams in H.264 and Motion JPEG Controllable frame rate and bandwidth VBR/CBR H.264
Multi-view streaming	**AXIS P1346/-E:** Up to 8 individually cropped out view areas. When streaming 5 view areas in VGA resolution, the rate is 20 fps per stream in H.264/Motion JPEG (3 MP capture mode) **AXIS P1347/-E:** Up to 8 individually cropped out view areas. When streaming 4 view areas in VGA resolution, the rate is 12 fps per stream in H.264/Motion JPEG (5 MP capture mode)
Pan/Tilt/Zoom	Digital PTZ, preset positions, guard tour
Image settings	Compression, color, brightness, sharpness, contrast, white balance, exposure control, exposure zones, backlight compensation, fine tuning of behavior at low light, rotation, mirroring of images, wide dynamic range - dynamic contrast Text and image overlay, privacy mask **AXIS P1343/P1344/P1346/P1347:** Corridor Format
Audio	
Audio streaming	Two-way
Audio compression	AAC LC 8/16 kHz, G.711 PCM 8 kHz, G.726 ADPCM 8 kHz Configurable bit rate
Audio input/ output	External microphone input or line input, line output **AXIS P1343/P1344/P1346/P1347:** Built-in microphone

Network	
Security	Password protection, IP address filtering, digest authentication, HTTPS encryption**, IEEE 802.1X network access control**, user access log
Supported protocols	IPv4/v6, HTTP, HTTPS**, QoS Layer 3 DiffServ, FTP, SMTP, Bonjour, UPnP, SNMPv1/v2c/v3(MIB-II), DNS, DynDNS, NTP, RTSP, RTP, TCP, UDP, IGMP, RTCP, ICMP, DHCP, ARP, SOCKS
System integration	
Application Programming Interface	Open API for software integration, including VAPIX® and AXIS Camera Application Platform from Axis Communications, available at www.axis.com ONVIF, specification available at www.onvif.org AXIS Video Hosting System (AVHS) with One-Click Camera connection
Intelligent video	Video motion detection, active tampering alarm, audio detection Support for AXIS Camera Application Platform enabling installation of additional applications
Event triggers	Intelligent video, external input
Event actions	File upload via FTP, HTTP and email; notification via email, HTTP and TCP; external output activation; video and audio recording to edge storage; pre- and post-alarm video buffering
Installation aids	Focus assistant, pixel counter, remote back focus
General	
Casing	Camera: Metal (zinc) **AXIS P1343-E/P1344-E/P1346-E/P1347-E:** IP66- and NEMA 4X-rated, IK10 impact-resistant aluminum enclosure with integrated dehumidifying membrane Color: white NCS S 1002-B
Processor and memory	**AXIS P1343/-E, AXIS P1344/-E:** ARTPEC-3, 128 MB RAM, 128 MB Flash **AXIS P1346/-E, AXIS P1347/-E:** ARTPEC-3, 256 MB RAM, 128 MB Flash
Power	**AXIS P1343/P1344/P1346/P1347:** 8-20 V DC or Power over Ethernet (PoE) IEEE 802.3af **AXIS P1343/P1344:** max. 6.4 W, PoE Class 2 **AXIS P1346:** max. 9.6 W, PoE Class 3 **AXIS P1347:** max. 9.0 W, PoE Class 3 **AXIS P1343-E/P1344-E/P1346-E/P1347-E:** PoE IEEE 802.3af max. 12.95 W or High PoE max 25.5 W
Connectors	RJ-45 10BASE-T/100BASE-TX PoE; 3.5 mm mic/line in, 3.5 mm line out; terminal blocks for power, 1 alarm input and 1 output
Edge storage	SD/SDHC memory card slot (card not included) Support for recording to network share (network-attached storage or file server) - available in firmware version 5.40 and up
Operating conditions	**AXIS P1343/P1344/P1346/P1347:** Humidity 20 - 80% RH (non-condensing); 0 °C to 50 °C (32 °F to 122 °F) **AXIS P1343-E/P1344-E/P1346-E/P1347-E:** -30 °C to 50 °C (-22 °F to 122 °F) with PoE; down to -40 °C (-40 °F) with High PoE
Approvals	EN 55022, EN 55024, EN 60950-1, EN 61000-6-1, EN 61000-6-2, FCC Part 15 Subpart B Class B, VCCI Class B, C-tick AS/NZS CISPR 22, ICES-003 Class B **AXIS P1343/P1344/P1346/P1347:** EN 61000-3-2, EN 61000-3-3 **AXIS P1343-E/P1344-E/P1346-E/P1347-E:** EN 50121-4/IEC 62236, EN 60950-22, IEC 60068-2-6, IEC 60068-2-27, IEC 60529 IP66, NEMA 250 Type 4X, IEC 62262 IK10 **AXIS P1346/-E:** KCC Class B
Weight	**AXIS P1343/P1344/P1346/P1347:** 0.6 kg (1.3 lb.) **AXIS P1343-E/P1344-E/P1346-E/P1347-E:** 3.1 kg (6.8 lb.)
Included accessories	Stand, connector kit, Installation Guide, CD with installation tools, recording software and User's Manual, Windows decoder 1-user license **AXIS P1343-E/P1344-E/P1346-E/P1347-E:** Wall mount bracket, sunshield, cable glands

Dimensions: AXIS P13 Network Cameras



Dimensions: AXIS P13-E Network Cameras and wall mount bracket with internal cable channel



Optional accessories

AXIS PoE Midspan 1-port

AXIS T8123 High PoE 30 W Midspan 1-port

AXIS T90A Illuminators

Lenses

AXIS T8414 Installation Display

For information on AXIS Camera Station and video management software from Axis' Application Development Partners, see www.axis.com/products/video/software/

Optional mounting accessories for outdoor models

Wall bracket accessories

Adapter plate

Pole mount

Corner mount

Ceiling brackets with ball joint

Column mount with ball joint