Abnormal Event Detection in Video

A Project Report
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Abstract

Video surveillance has gained importance in security, law enforcement and military applications and so is an important computer vision problem. As more and more surveillance cameras are deployed in a facility or area, the demand for automatic methods for video processing is increasing. The operator constantly watching the video footages could miss a potential abnormal event (e.g. bag being abandoned by a person), as the amount of information/data that has to be handled is high. Most often he has to watch the entire video footage offline, to find the person who abandoned the bag.

In this thesis, we present a surveillance system that supports a human operator by automatically detecting abandoned objects and drawing the operator's attention to such events. It consists of three major parts: foreground segmentation based on Gaussian Mixture Models, a tracker based on blob association and a blob-based object classification system to identify abandoned objects. For foreground segmentation, we assume that video sequences of the background shot under different natural settings are available a priori. The tracker uses a single-camera view and it does not differentiate between people and luggage. The classification is done using the shape of detected objects and temporal tracking results, to successfully categorize objects into bag and non-bag(human). If a potentially abandoned object is detected, the operator is notified and the system provides the appropriate key frames for interpreting the incident.

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Chapter 1

Introduction

Video Surveillance can be described as the task of analyzing video sequences to detect *abnormal* or *unusual* activities. Video surveillance activities can be manual, semi-autonomous or fully-autonomous. Manual video surveillance involves analysis of the video content by a human. Such systems are currently in widespread use. Semi-autonomous video surveillance involves some form of video processing but with significant human intervention. Typical examples are systems that perform simple motion detection. Only in the presence of significant motion the video is recorded and sent for analysis by a human expert. By a fully-autonomous system, we mean a system whose only input is the video sequence taken at the scene where surveillance is performed. In such a system there is no human intervention and the system does both the low-level tasks, like motion detection and tracking, and also high-level decision making tasks like abnormal event detection and gesture recognition.

The ultimate goal of the present generation surveillance systems is to allow video data to be used for on-line alarm generation to assist human operators and for offline inspection effectively. The making of video surveillance systems fully-automatic or "smart" requires fast, reliable and robust algorithms for moving object detection, classification, tracking and activity analysis.

Moving object detection is the basic step for further analysis of video. It handles segmentation of moving objects from stationary background objects. Commonly used techniques for object detection are background subtraction, statistical methods, temporal differencing and optical flow. Due to dynamic environmental conditions such as illumination changes, shadows and waving tree branches in the wind, object segmentation is a difficult and significant problem that needs to be handled well for a robust visual surveillance system.

Object classification step categorizes detected objects into predefined classes such as human, vehicle, clutter, etc. It is necessary to distinguish objects from each other in order to track and analyze their actions reliably. There are two major approaches toward moving object classification: shape-based and motion-based methods. Shape-based methods make use of object's 2D spatial information whereas motion-based methods use temporal tracked features of objects for the classification solution.

The next step in the video analysis is tracking, which can simply be defines as the creation of temporal correspondence among detected objects from frame to frame. This procedure provides temporal identification of the segmented regions and generates cohesive information about the objects in the monitored area. The output produced by the tracking step is generally used to support and enhance motion segmentation, object classification and higher level activity analysis. The final step of the fully automatic video surveillance systems is to recognize the behaviors of objects and create high-level semantic descriptions of their actions. The outputs of these algorithms can be used both for providing the human operator with high level data to helm him make the decisions more accurately and in a shorter time, and also for offline indexing and searching stored video data effectively. Below are some scenarios that fully-automated or smart surveillance systems and algorithms might handle:

Public and commercial security:

- Monitoring of banks, department stores, airports, museums, stations, private properties and parking lots for crime prevention and detection
- Patrolling of highways and railways for accident detection
- Surveillance of properties and forests for fire detection
- Observation of the activities of elderly and infirm people for early alarms and measuring effectiveness of medical treatments
- Access control

Smart video data mining:

- Compiling consumer demographics in shopping centers and amusement parks
- Extracting statistics from sport activities

- Counting endangered species
- Logging routine maintenance tasks at nuclear and industrial facilities

Military security:

- Patrolling national borders
- Measuring flow of refugees
- Monitoring peace treaties

The use of smart object detection, tracking and classification algorithms are not limited to video surveillance only. Other application domains also benefit from the advances in the research on these algorithms. Some examples are virtual reality, video compression, human machine interface, augmented reality, video editing and multimedia databases.

1.1 Overview

In this thesis we present an automatic video surveillance system with moving object detection, tracking and classification capabilities.

In the presented system, moving object detection is handled by the use of adaptive background mixture models [20]. In this paper, each pixel is modeled as a mixture of Gaussians and an on-line approximation to update the model is used. Based on the persistence and the variance of each of the Gaussians of the mixture, the Gaussians which correspond to background colors are determined. Pixel values that do not fit the background distributions are considered foreground until there is a Gaussian that includes them with sufficient, consistent evidence supporting it. This system adapts to deal robustly with lightning changes, repetitive motions of scene elements, tracking through cluttered regions, slow-moving objects, and introducing or removing objects from the scene. Slow moving objects take longer to be incorporated into the background, because their color has a larger variance than the background. Also, the repetitive variations are learned, and a model for the background distribution is generally maintained even if it is temporarily replaced by another distribution which leads to faster recovery when objects are removed. The background method consists of two significant parameters - α, the learning constant and T, the proportion of the data that should be accounted for by the background.

After segmenting moving pixels from the static background of the scene, the tracking algorithm tracks the detected objects in successive frames by using a correspondence-based matching scheme. It also handles multi-occlusion cases where some objects might be fully occluded by the others. It uses 2D object features such as position, centroid and size to match corresponding objects from frame to frame. It keeps color histograms of detected objects in order to resolve object identities after a split of an occlusion group. The tracking algorithm doesn't differentiate between objects while tracking, which means the algorithm treats both person and non-person, like a bag, alike.

As the primary objective of this work is to detect bag abandoning event, there should be a classification step. The final stage of this entire automated system is detection of bag, and detection of the abnormal event which is bag abandoning. The classification algorithm incorporated here is the quadratic discriminant analysis. A simple database has been built with detected foreground of 60 images, 30 of bag and 30 of non-bag (person). The features used for classification are aspect ratio and compactness, defined as the ratio of area by perimeter. The classification part, help us in detecting the existence of a bag. From then on, depending on *space contraint* and *time constraint* it is decided whether the bag has been *unattended* or *abandoned*.

1.2 Motivation

Understanding activities of objects in a scene by the use of video is both a challenging scientific problem and a very fertile domain with many promising applications. Thus, it draws attentions of several researchers, institutions and commercial companies [13]. Our motivation in studying this problem is to create a visual surveillance system with real-time moving object detection, classification, tracking and activity analysis capabilities. The presented system handles all the above methods, with few conditions imposed, except activity recognition which will likely be the future step of this work.

1.3 Organization of the Thesis

The remaining part of the thesis is organized as follows. Chapter 2 presents a brief literature survey in foreground segmentation, tracking and classification for video surveillance applications. Our methods for moving object detection and object tracking are explained in chapters 3 and 4 respectively. In the 5th chapter we present our object classification method and the event detection. Each chapter is supplemented with experimental results and summary. Finally, chapter 6 concludes the thesis with the suggestions for future work.

1.4 Summary

In this chapter, we have discussed in brief what is video surveillance, why we require it to be automated and what are its applications. Later, an overview of our work, the motivation for pursuing it and the organization of the thesis has been discussed.

Chapter 2

Smart Video Surveillance

There have been a number of surveys about object detection, classification, tracking and activity analysis in the literature [13, 23, 3]. The survey we present here covers only those work that are in the context as our study. However, for the comprehensive completeness, we also give brief information on some techniques which are used for similar tasks that are not covered in our study.

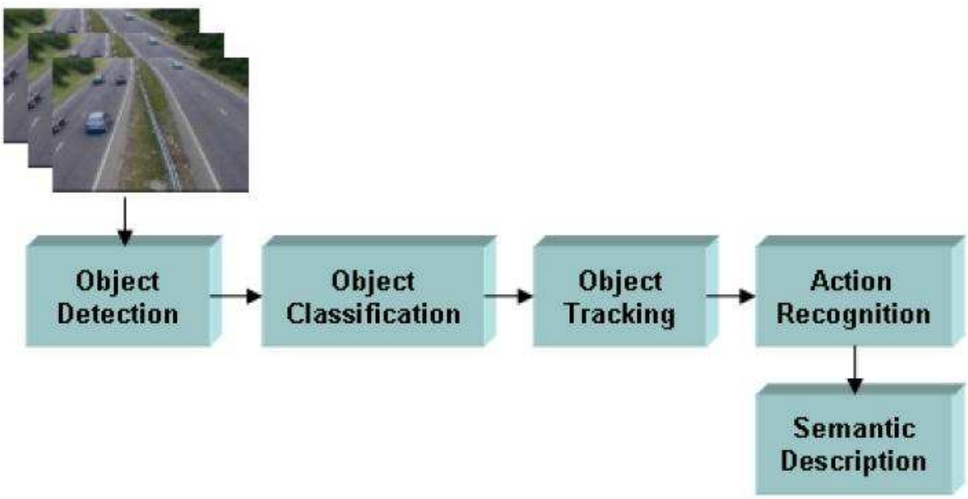


Figure 2.1: A generic framework for smart video processing algorithms.

A generic video processing framework for smart algorithms is shown in fig.(2.1). Although, some steps require interchange of information with other levels, this framework provides a good structure for the discussion throughout this brief survey.

2.1 Moving Object Detection

Each application that benefits from smart video processing has different needs, thus requiring different treatment. However, they have something in common: moving objects. Detecting regions that correspond to moving objects such as people and vehicles in video is the first basic step of almost every vision system since it provides a focus of attention and simplifies the processing on subsequent analysis steps. Due to dynamic changes in natural scenes such as sudden illumination and weather changes, repetitive motions that cause clutter (tree leaves in blowing wind), motion detection is a difficult problem to process reliably. Frequently used techniques for moving object detection are background subtraction, statistical methods, temporal differencing and optical flow whose descriptions are given below.

2.1.1 Background Subtraction

Background subtraction is particularly a commonly used technique for motion segmentation in static scenes [15]. It attempts to detect moving regions by subtracting the current image pixel-by-pixel from a reference background image that is created by averaging images over time in an initialized period. The pixels where the difference is above a threshold are classified as foreground. After creating foreground pixel map, some morphological post processing operations such as erosion, dilation and closing are performed to reduce the effects of noise and enhance the detected regions. The reference background is updated with new images over time to adapt to dynamic scene changes.

There are different approaches to this basic scheme of background subtraction in terms of foreground region detection, background maintenance and post-processing. In [9], Heikkila and Silven used the simple version of this scheme where a pixel location $(\mathbf{x}, \mathbf{y})$ in the current image I_t is marked as foreground if the inequality (2.1) is satisfied,

$$|I_t(x, y) - B_t(x, y)| > \tau \tag{2.1}$$

where τ is a pre-defined threshold. The background image B_t is updated by the use of a first order recursive filter (see Equation (2.2)),

$$B_{t+1} = \alpha I_t + (1 - \alpha)B_t \tag{2.2}$$

where α is an adaptation coefficient. The basic idea is to integrate the new incoming information into the current background image. The larger it is, the faster new changes in the scene are updated to the background frame. However, α cannot be too large because it may cause artificial "tails" to be formed behind the moving objects. The foreground pixel map creation is followed by morphological closing and the elimination of small-sized regions.

Although background subtraction techniques perform well at extracting most of the relevant pixels of moving regions, they are usually sensitive to dynamic changes when, for instance, stationary objects uncover the background (e.g. a parked car moves out of the parking lot) or sudden illumination changes occur.

2.1.2 Statistical Methods

More advanced methods that make use of the statistical characteristics of individual pixels have been developed to overcome the shortcomings of basic background subtraction methods. These statistical methods are mainly inspired by the background subtraction methods in terms of keeping and dynamically updating statistics of the pixels that belong to the background image process. Foreground pixels are identified by comparing each pixel's statistics with that of the background model. This approach is becoming more popular due to its reliability in scenes that contain noise, illumination changes and shadow [13]. The W4 [10] system uses a statistical background model where each pixel is represented with its minimum *(M)* and maximum *(N)* intensity values and maximum intensity difference *(D)* between any consecutive frames observed during initial training period where the scene contains no moving objects. A pixel in the current image I_t is classified as foreground if it satisfies:

$$|M(x, y) - I_t(x, y)| > D(x, y) \quad or \quad |N(x, y) - I_t(x, y)| > D(x, y) \tag{2.3}$$

After thresholding, a single iteration of morphological erosion is applied to the detected foreground pixels to remove one-pixel thick noise. In order to grow the eroded regions to their original size, a sequence of erosion and dilation is performed on the foreground pixel map. Also, small-sized regions are eliminated after applying connected component labeling to find the regions. The statistics of the background pixels that belong to the non-moving regions of current image are updated with new image data. As another example of statistical methods, Stauffer and Grimson [21] described an adaptive background mixture modeled by a mixture of Gaussians which are updated on-line by incoming image data. In order to detect whether a pixel belongs to a foreground or background process, the Gaussian distributions of the mixture model for that pixel are evaluated. An implementation of this model is used in our system and its details are explained in section (3.1.2).

2.1.3 Temporal Differencing

Temporal differencing attempts to detect moving regions by making use of the pixel-by-pixel difference of consecutive frames (two or three) in a video sequence. This method is highly adaptive to dynamic scene changes, however, it generally fails in detecting whole relevant pixels of some types of moving objects, e.g., possibly generating holes inside moving entities. A sample object for inaccurate motion detection is shown in fig.(2.2). The mono colored region of the human on the left hand side makes the temporal differencing algorithm fail in extracting all pixels of the human's moving region. Also, this method fails to detect stopped objects in the scene. Additional methods need to be adopted in order to detect stopped objects for the success of higher level processing.

Figure 2.2: Temporal differencing sample. Left Image: A sample scene with two moving objects. Right Image: Temporal differencing fails to detect all moving pixels of the right hand side person because of the uniform colored region. The detected moving regions are marked with blue colored pixels

Lipton et al. presented a two-frame differencing scheme where the pixels that satisfy the equation 2.4 are marked as foreground [2].

$$|I_t(x, y) - I_{t-1}(x, y)| > \tau \tag{2.4}$$

In order to overcome disadvantages of two-frame differencing in some cases, three frame differencing can be used. For instance, Collins et al. developed a hybrid method that combines three-frame differencing with an adaptive background subtraction model for their VSAM *(Video Surveillance And Monitoring)* project [17]. The hybrid algorithm successfully segments moving regions in video without the defects of temporal differencing and background subtraction.

2.1.4 Optical Flow

Optical flow methods make use of the flow vectors of moving objects over time to detect moving regions in an image. They can detect motion in video sequences even from a moving camera, however, most of the optical flow methods are computationally complex and cannot be used real-time without specialized hardware [13].

2.2 Object Tracking

Tracking is a significant and difficult problem that arouses interest among computer vision researchers. The objective of tracking is to establish correspondence of objects and object parts between consecutive frames of video. It is a significant test in most of the surveillance applications since it provides cohesive temporal data about moving objects which are used both to enhance lower level processing such as motion segmentation and to enable higher level data extraction such as activity analysis and behavior recognition. Tracking has been a difficult task to apply in congested situations due to inaccurate segmentation of objects. Common problems of erroneous segmentation are shadows, partial and full occlusion of objects with each other and with stationary items in the scene. Thus, dealing with shadows at motion detection level and coping with occlusions both at segmentation level and at tracking level is important for robust tracking.

Tracking in video can be categorized according to the needs of the applications and the methods it uses for its solution. Whole body tracking is generally adequate for outdoor surveillance whereas objects' part tracking is necessary for some indoor surveillance and higher level behavior understanding applications. There is a very good survey on object tracking by Alper et al. Fig.(2.3) gives hierarchical structure of the existing methods in object tracking [3].

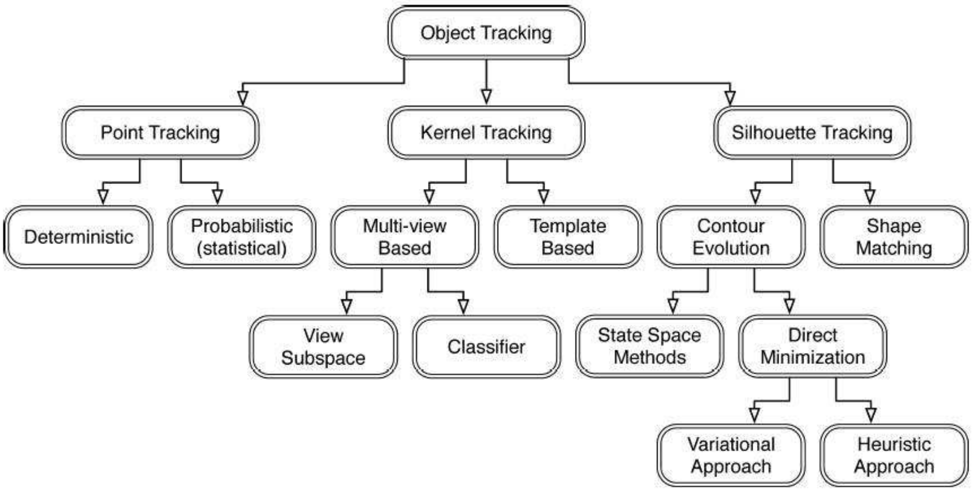


Figure 2.3: Taxonomy of tracking methods [3]

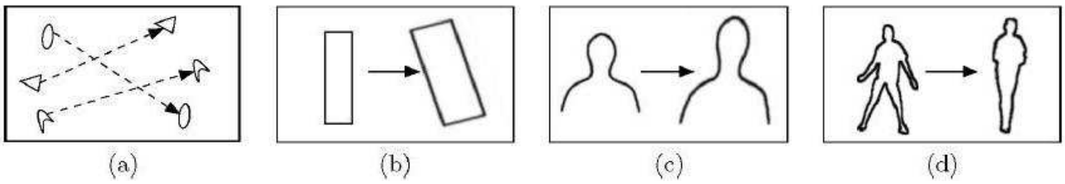


Figure 2.4: Different tracking approaches. (a)Multi-point correspondence, (b)Parametric transformation of a rectangular patch, (c,d) Two examples of contour evolution.

The main tracking categories are *point tracking*, *kernel tracking* and *silhouette tracking*.

- *Point Tracking.* Objects detected in consecutive frames are represented by points, and the association of the points is based on the previous object state which can include object position and motion. This approach requires an external mechanism to detect the objects in every frame. An example of object correspondence is shown in Fig.(2.4(a)). This method can be employed using either deterministic methods [11], or probabilistic methods like kalman filtering technique [4].

- *Kernel Tracking.* Kernel refers to the object shape and appearance. For example, the kernel can be a rectangular template or an elliptic shape with an associated histogram. Objects are tracked by computing the motion of the kernel in consecutive frames(Fig.2.4(b)). This motion is usually in the form of a parametric transformation such as translation, rotation and affine. Mean-shift tracking technique [5] comes under this class of methods.

- *Silhouette Tracking.* Tracking is performed by estimating the object region in each frame. Silhouette tracking methods use the information encoded inside the object region. This information can be in the form of appearance density and shape models which are usually in the form of edge maps. Given the object models, silhouettes are tracked either by shape matching or contour evolution (see Fig.2.4(c),(d)). Variational methods like active contour [14] are used for this kind of tracking.

2.2.1 Feature Selection for Tracking

Selecting the right features play a critical role in tracking. In general, the most desirable property of a visual feature is its uniqueness so that the objects can be easily distinguished in the feature space. Feature selection is closely related to the object representation. For example, color is used as a feature for histogram-based appearance representations, while for contour-based representation object edges are usually used as feature. In general, many tracking algorithms use a combination of these features. Some common visual features are:

- *Color.* The apparent color of an object is influenced primarily by two physical factors, the spectral power distribution of the illuminant and the surface reflectance properties of the object. A variety of color spaces (RGB, L^*u^*v, L^*a^*b, HSV) have been used in tracking.

- *Edges.* Object boundaries usually generate strong changes in image intensities. An important property of edges is that they are less sensitive to illumination changes compared to color features. Algorithms that track the boundary of the objects usually use edges as the representative feature.

- *Optical Flow.* Optical flow is a dense field of displacement vectors which defines the translation of each pixel in a region. This method is commonly used as a feature in motion-based segmentation and tracking applications.

- *Texture.* Texture is measure of the intensity variation of a surface which quantifies properties such as smoothness and regularity. Obtaining texture descriptors requires some processing step. Similar to edge features, the texture features are less sensitive to illumination changes in color.

Among all features, color is one of the most widely used feature for tracking. Despite its popularity, most color bands are sensitive to illumination variation. Hence in scenarios where this effect is inevitable, other features are incorporated to model object appearance.

2.3 Object Classification

Moving regions detected in video may correspond to different objects in real-world such as pedestrians, vehicles, clutter, bags, etc. It is very important to recognize the type of a detected object, as the results here are further analyzed to detect abnormal events. Currently, there are two major approaches towards moving object classification which are shape-based and motion-based methods [13]. Shape-based make use of objects' 2D spatial information whereas motion-based methods use temporally tracked features of objects for the classification solution.

2.3.1 Shape-based Classification

Common features used in shape-based classification schemes are the bounding rectangle, area, silhouette and gradient of detected object regions. The approach presented in [2] makes use of the objects' silhouette contour length and area information to classify detected objects in three groups: human, vehicle and other. The method depends on the assumption that humans are, in general, smaller than vehicles and have complex regions. Dispersedness is used as the classification metric and it is defined in terms of object's area and contour length (perimeter) as follows:

$$Dispersedness = \frac{Perimeter^2}{Area}$$

Classification is performed at each frame and tracking results are used to improve temporal classification consistency. The classification method developed by Collins et al. [17] uses view dependent visual features of detected objects to train a neural network classifier to recognize four classes: human, human group, vehicle and clutter. The inputs to the neural network are the dispersedness, area and aspect ratio of the object region and the camera zoom magnification. Like the previous method, classification is performed at each frame and results are kept in a histogram to improve temporal consistency of classification.

2.3.2 Motion-based Classification

Some of the methods in the literature use only temporal motion features of objects in order to recognize their classes. The method proposed in [6] is based on the temporal self-similarity of a moving object. As an object that exhibits periodic motion evolves, its self-self-similarity measure also shows a periodic motion. The methods exploits this clue to categorize moving objects using periodicity.

2.4 Summary

In this chapter, the related work in foreground segmentation, object tracking and object classification has been discussed. Regarding foreground segmentation, we discussed in brief about the frequently used techniques - *background subtraction*, *statistical methods*, *temporal differencing* and *optical flow*. In tracking, we have seen a way of categorizing them into *point tracking*, *kernel tracking* and *silhouette tracking*. We then saw what kind of features could be used for tracking. Finally we end the chapter with object classification, where there were two major approaches - *shape-based* and *motion-based*. In motion-based approach, along with spatial features of objects, temporal motion features of objects were also used to recognize the classes.

Chapter 3

Object Detection

The overview of our video object detection, tracking and classification is shown in fig.(3.1). The presented system is able to distinguish transitory and stopped foreground objects from static background objects in dynamic scenes; detect and distinguish left objects; track objects and generate object information; classify detected objects (into bag and non-bag) in video imagery. In this and following chapters we describe the computational models employed in our approach to reach the goals specified above. The intent of designing these modules is to produce a video-based surveillance system which works in real time environment. The computational complexity and even the constant factors of the algorithms we use are important for real-time performance. Hence, our decisions on selecting the computer vision algorithms for various problems are affected by their computational run time performance as well as quality. Furthermore, our system's use is limited only to stationary cameras and video inputs from PTZ (Pan/Tilt/Zoom) cameras, where the view frustum may change arbitrarily are not supported.

The system is initialized by feeding video imagery from a static camera monitoring a site. The first step of our approach is distinguishing foreground objects from stationary background. To achieve this, we use a combination of adaptive Gaussian mixture models and low-level image post-processing methods to create a foreground pixel map at every frame. We then group the connected regions in the foreground map to extract individual object features such as bounding box, area, perimeter and color histogram.

The object tracking algorithm utilizes extracted object features together with a correspondence matching scheme to track objects from frame to frame. The color

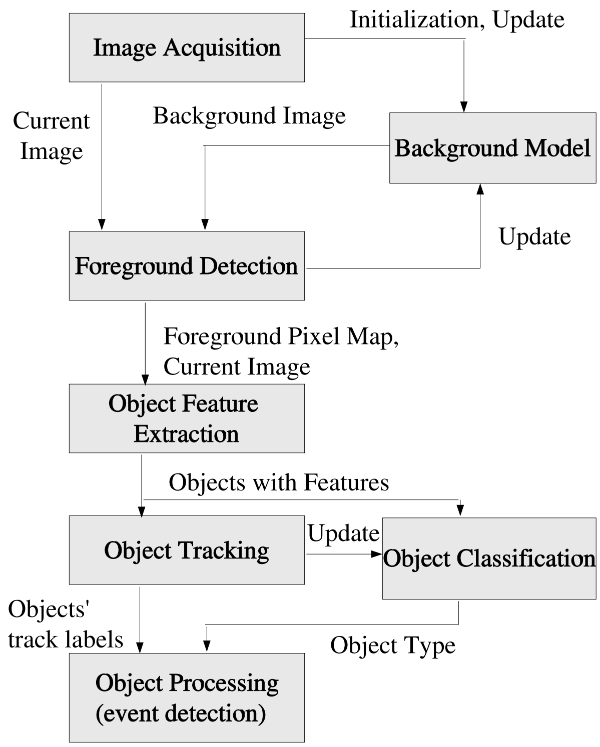


Figure 3.1: The system block diagram.

histogram of an object produced in previous step is used to match the correspondence of objects after an occlusion event. The output of the tracking step is analyzed further for detecting abnormal events, which in our case is *'a bag being abandoned by a person.'*

The remainder of this chapter presents the computational models and methods adopted for object detection. Our tracking and classification approaches are explained in the subsequent chapters.

3.1 Foreground Detection

Distinguishing foreground objects from the stationary background is both a significant and difficult research problem. Almost all of the visual surveillance systems' first step is detecting foreground objects. This creates a focus of attention for higher processing levels such as tracking, classification and behavior understanding and reduces computation time considerably since only pixels belonging to foreground objects need to be dealt with. Short and long term dynamic scene changes such as repetitive motions (e.g. waiving tree leaves), light reflectance, shadows, camera noise and sudden illumination variations make reliable and fast object detection difficult. Hence, it is important to pay necessary attention to object detection step to have reliable, robust and fast visual surveillance system.

The system diagram of the object detection method is shown in fig.(3.2). The method depends on a six stage process to extract objects with their features in video imagery. The first step is the background scene initialization. There are various techniques used to model the background scene in the literature (see section (2.1). We implemented adaptive Gaussian mixture model mainly, but also looked at the results of temporal differencing from performance study point-of-view. The background scene related parts of the system is isolated and its coupling with other modules is kept minimum to let the whole detection system to work flexibly with any one of the background models. Next step in the detection method is detecting the foreground

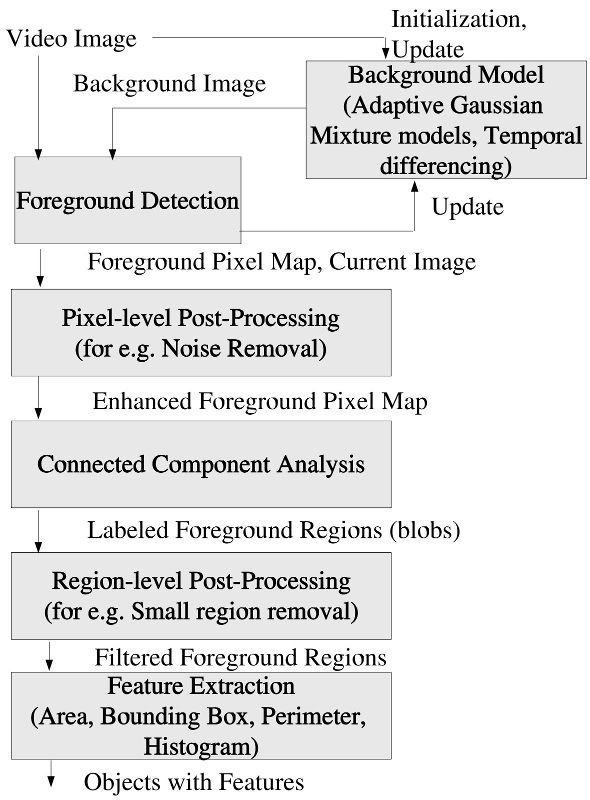


Figure 3.2: The object detection system diagram.

pixels by using the background model and the current image from video. This pixel-level detection process is dependent on the background model in use and it is used to update the background model to adapt to dynamic scene changes. Also, due to camera noise or environmental effects the detected foreground pixel map contains noise. Pixel-level post-processing operations are performed to remove noise in the foreground pixels. Once we get the filtered foreground pixels, in the next step, connected regions are found by using a connected component labeling algorithm and objects' bounding rectangles are calculated. The labeled regions may contain near but disjoint regions due to defects in foreground segmentation process. Hence, some relatively small regions caused by environmental noise are eliminated in the region-level post-processing step. In the final step of the detection process, a number of object features (like area, bounding box, perimeter and color histogram of the regions corresponding to objects) are extracted from current image by using the foreground pixel map. A sample foreground region detection is shown in fig.(3.3). We use a combination of a background

Figure 3.3: Sample foreground detection.

model and low-level image post-processing methods to create a foreground pixel map and extract object features at every video frame. Background models generally have two distinct stages in their process: initialization and update. Following sections describe the initialization and update mechanisms together with foreground region detection methods used.

3.1.1 Temporal Differencing

Temporal differencing makes use of the pixel-wise difference between two or three consecutive frames in video imagery to extract moving regions. It is a highly adaptive approach to dynamic scene changes however, it fails in extracting all relevant pixels of a foreground object especially when the object has uniform texture or moves slowly. When a foreground object stops moving, temporal differencing method fails in detecting a change between consecutive frames and loses the object. Special supportive algorithms are required to detect stopped objects.

We implemented a two-frame temporal differencing method in our system. Let $I_n(x)$ represent the gray-level intensity value at pixel position (x) and at time instance n of video image sequence I, which is in the range [0, 255]. The two-frame temporal differencing scheme suggests that a pixel is moving if it satisfies the following:

$$|I_n(x) - I_{n-1}(x)| > T_n(x) \tag{3.1}$$

Hence, if an object has uniform colored regions, the Equation 3.1 fails to detect some of the pixels inside these regions even if the object moves. The per-pixel threshold, T, is initially set to a pre-determined value and later updated as follows:

$$T_{n+1}(x) = \begin{cases} \alpha T_n(x) + (1-\alpha)(\gamma \times |I_n(x) - I_{n-1}(x)|), & x \in BG \\ T_n(x), & x \in FG \end{cases} \tag{3.2}$$

3.1.2 Adaptive Gaussian Mixture Model

Stauffer and Grimson [20] presented a novel adaptive online background mixture model that can robustly deal with lighting changes, repetitive motions, clutter, introducing or removing objects from the scene and slowly moving objects. Their motivation was that a unimodal background model could not handle image acquisition noise, light change and multiple surfaces for a particular pixel at the same time. Thus, they used a mixture of Gaussian distributions to represent each pixel in the model. Due to its promising features, we implemented and integrated this model in our visual surveillance system.

In this model, the values of an individual pixel (e.g. scalars for gray values and vectors for color images) over time is considered as a "pixel process" and the recent history of each pixel, $X_1, \ldots, X_t$, is modeled by a mixture of K Gaussian distributions. The probability of observing current pixel value then becomes:

$$P(X_t) = \sum_{i=1}^{K} w_{i,t} * \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \tag{3.3}$$

where $w_{i,t}$ is an estimate of the weight (what portion of the data is accounted for this Gaussian) of the i^{th} Gaussian ($G_{i,t}$) in the mixture at time t, $\mu_{i,t}$ is the mean value of $G_{i,t}$ and $\Sigma_{i,t}$ is the covariance matrix of $G_{i,t}$ and η is a Gaussian probability density function:

$$\eta(X,\mu,\Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X-\mu)^T\Sigma^{-1}(X-\mu)} \tag{3.4}$$

Decision on K depends on the available memory and computational power. Also, the covariance matrix is assumed to be of the following form for computational efficiency:

$$\Sigma_{k,t} = \alpha_k^2 I \tag{3.5}$$

which assumes that red, green and blue color components are independent and have the same variance.

The procedure for detecting foreground pixels is as follows. At the beginning of the system, the K Gaussian distributions for a pixel are initialized with predefined mean, high variance and low prior weight. When a new pixel is observed in the image sequence, to determine its type, its RGB vector is checked against K Gaussians, until a match is found. A match is defined as a pixel value within γ (=2.5) standard deviations of a distribution. Next, the prior weights of the K distributions at time $t(w_{k,t})$, are updated as follows:

$$w_{k,t} = (1-\alpha)w_{k,t-1} + \alpha(M_{k,t}) \tag{3.6}$$

where α is the learning rate and $M(k,t)$ is 1 for the matching Gaussian distribution and 0 for the remaining distributions. After this step the prior weights of the distributions are normalized with the new observation as follows:

$$\mu_t = (1-\rho)\mu_{t-1} + \rho(X_t) \tag{3.7}$$

$$\sigma_t^2 = (1-\rho)\sigma_{t-1}^2 + \rho(X_t-\mu_t)^T(X_t-\mu_t) \tag{3.8}$$

where

$$\rho = \alpha\eta(X_t|\mu_{t-1},\sigma_{t-1}). \tag{3.9}$$

If no match is found for the new observed pixel, the Gaussian distribution with the least probability is replaced with new distribution with the current pixel values as its mean value, an initially high variance and low prior weight.

In order to detect the type (foreground or background) of the new pixel, the K Gaussian distributions are sorted by the value w/σ. This ordered list of distributions reflect the most probable background from top to bottom since by Equation (3.6) background pixel processes make the corresponding Gaussian distribution have larger prior weight and less variance. Then the first B distributions are chosen as the background model, where

$$B = arg \min_b (\sum_{k=1}^{b} w_k > T) \tag{3.10}$$

and T is the minimum portion of the pixel data that should be accounted for by the background. If a small value is chosen for T, the background is generally unimodal. Fig.(3.4) shows the foreground pixel map without any enhancements and in the subsequent sections we see how this initial foreground is enhanced.

Figure 3.4: Initial foreground pixel map (without any enhancements)

3.2 Pixel Level Post-Processing

The outputs of foreground region detection algorithms we explained in the previous section generally contain noise and therefore are not appropriate for further processing without special post-processing. There are various factors that cause the noise in foreground detection such as:

- **Camera noise**: This is the noise caused by the camera's image acquisition components. The intensity of a pixel that corresponds to an edge between two different colored objects in the scene may be set to one of the object's color in one frame and to other's color in the next frame.
- **Reflectance noise**: When a source of light (for instance sun) moves, it makes

some parts in the background scene to reflect light. This phenomenon makes the foreground detection algorithms fail and detect reflectance as foreground regions.

- **Background colored object noise**: Some parts of the objects may have the same color as the reference background behind them. This resemblance causes some of the algorithms to detect the corresponding pixels as non-foreground and objects to be segmented inaccurately.

Morphological operations, erosion and dilation [8], are applied to the foreground pixel map in order to remove noise that is caused by the items listed above. Our aim in applying these operations is removing noisy foreground pixels that do not correspond to actual foreground regions, and to remove the noisy background pixels near and inside object regions that are actually foreground pixels. Erosion, as its name implies, erodes one-unit thick boundary pixels of foreground regions. Dilation is the reverse of erosion and expands the foreground region boundaries with one-unit thick pixels. The subtle point in applying these morphological filters is deciding the order and amounts of these operations. The order of these operations affects the quality and the amount affects both the quality and the computational complexity of noise removal.

For instance, if we apply dilation followed by erosion we cannot get rid of one-pixel thick isolated noise regions, since the dilation operation would expand their boundaries with one pixel and the erosion will remove these extra pixels leaving the original noisy pixels. On the other hand, this order will successfully eliminate some of the non-background noise inside object regions. In case we apply these operations in reverse order, which is erosion followed by dilation, we would eliminate one-pixel thick isolated noise regions but this time we would not be able to close holes inside object. To solve this problem, we move one step further by filling these holes using the morphological operation *"fill"*:
'fill' fills isolated interior pixels (individual 0's that are surrounded by 1's), such as the center pixel in this pattern:

1	1	1
1	0	1
1	1	1

Fig.(3.5) shows the result of pixel-level post-processing of the initial foreground pixel map, shown in fig.(3.4).

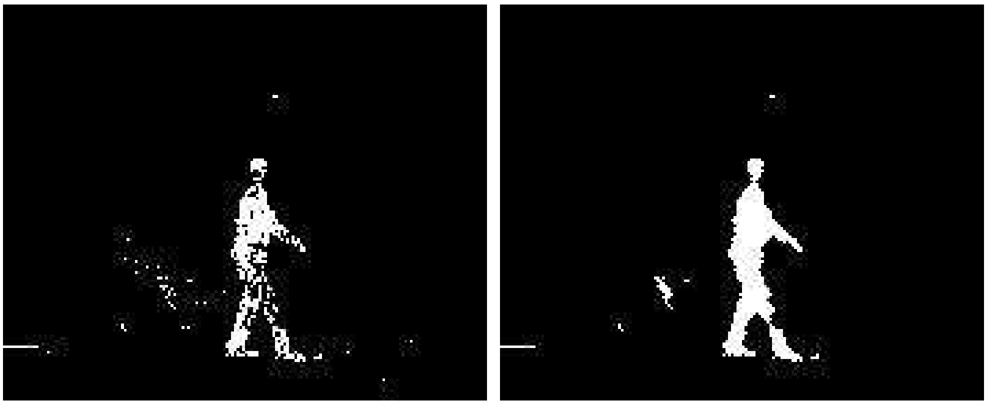


Figure 3.5: Foreground pixel map before and after pixel-level post-processing

3.3 Detecting Connected Regions

After detecting foreground regions and applying post-processing operations to remove noise and shadow regions, the filtered foreground pixels are grouped into connected regions (blobs) and labeled by using connected component labeling algorithm [8]. After finding individual blobs that correspond to objects, the bounding boxes of these regions are calculated. Fig.(3.6) shows sample foreground regions after region connecting and labeling.

Figure 3.6: Foreground pixel map before and after connected component analysis. Different connected components are shown in different colors in the right image

3.4 Region Level Post-Processing

Even after removing pixel-level noise, some artificial small regions remain due to inaccurate object segmentation. In order to eliminate this type of regions, regions that have a smaller sizes than a pre-defined threshold are deleted from the foreground pixel map. Fig.(3.7) shows the result of applying region level post-processing to the image obtained after connected component analysis (see fig.(3.6)).

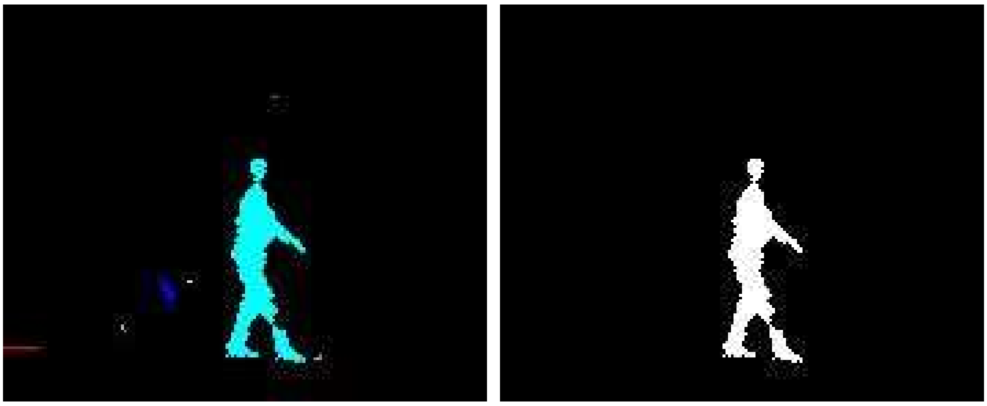


Figure 3.7: Final foreground pixel map, before and after region-level post-processing

3.5 Extracting Object Features

Once we have segmented regions we extract features of the corresponding objects from the current image. These features are size (S), center-of-mass or just centroid (C_m) and color histogram (H_c). Calculating the size of the object is trivial and we just count the number of foreground pixels that are contained in the bounding box of the object. In order to calculate the center-of-mass point, $C_m = (x_{C_m}, y_{C_m})$, of an object O, we use the following equation:

$$x_{C_m} = \frac{\sum_i^n x_i}{n}, \quad y_{C_m} = \frac{\sum_i^n y_i}{n} \tag{3.11}$$

where n is the number of pixels in O.

The color histogram, H_c, is calculated over RGB intensity values of object pixels in current image. In order to reduce computational complexity of operations that use H_c, the color values are quantized. Let N be the number of bins in the histogram, then every bin covers $\frac{255}{N}$ color values. The color histogram is calculated by iterating over pixels of O and incrementing the stored value of the corresponding color bin in the histogram, H_c. So for an object O the color histogram is updated as follows:

$$H_c(\frac{c_i}{N}, \frac{c_j}{N}, \frac{c_k}{N}) = H_c(\frac{c_i}{N}, \frac{c_j}{N}, \frac{c_k}{N}) + 1 \quad \forall c (= (c_i, c_j, c_k)), \in O \tag{3.12}$$

where c represents the color value of $(i, j, k)^{th}$ pixel. In the above equation i, j and k are the variables indexing into three color channels. In the next step the color histogram is normalized to enable appropriate comparison with other histograms in later steps. The normalized histogram $\hat{H}_c$ is calculated as follows:

$$\hat{H}_c[i][j][k] = \frac{H_c[i][j][k]}{\sum_{ijk}^{N} H_c[i][j][k]} \tag{3.13}$$

Finally, the histogram obtained would be a 3D matrix $(N \times N \times N)$ where N, as defined before, is the number of bins.

One more blob feature, which would come to use for us in the classification step is *'compactness(C)'* [16] which is defined below in equation 3.14.

$$C = \frac{area}{perimeter} \tag{3.14}$$

This feature represents how *"stretched out"* a shape is. The perimeter is the number of pixels that are part of an object and have atleast one 4-connected neighbor that is not in the object. For example, circle has the minimum perimeter for a given area, hence exhibits highest compactness. Fig.(3.8) shows some features, for instance, which were obtained from the final enhanced foreground pixel map.

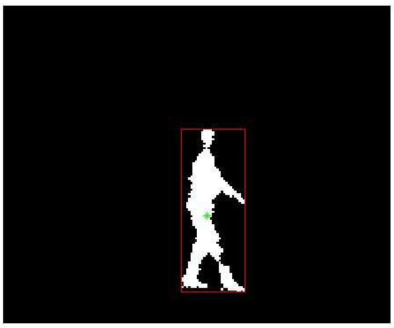


Figure 3.8: Bounding Box and Centroid features

3.6 Results

The foreground detection process using Gaussian mixture models was computationally intensive, and so we had to get the results off-line. To give exact figures, the average amount of time it took to process a frame is 0.18 seconds which amounts to 5-6 frames per second(fps). We tested the detection process on 10 different videos, out of which it failed to segment moving objects accurately for one video. This is because of the quick illumination changes in the video. For the rest, the segmentation results were accurate without any tuning of parameters. Some results from different videos, were shown in figs.(3.9, 3.10, 3.11). The foreground pixel map in these images look smaller than the original because of the way they were obtained in matlab (using "print" command).

Figure 3.9: Left: Background image. Middle: Current image. Right: Foreground with Bounding Box and Centroid features

Figure 3.10: Left: Background image. Middle: Current image. Right: Foreground with Bounding Box and Centroid features

Figure 3.11: Left: Background image. Middle: Current image. Right: Foreground with Bounding Box and Centroid features

3.7 Summary

In this chapter we have discussed on how a moving object can be segmented from a video image. We have seen two methods - *temporal differencing* and *Gaussian mixture models* in this regard. Temporal differencing method fails in detecting stopped objects and moving objects which are uniformly colored. The Gaussian mixture model technique was dealt in detail and would result in an initial foreground pixel map. The resultant foreground map was then subjected to various levels of post-processing operations - *pixel-level post-processing*, *connected component labeling*, and *region-level post-processing*. These operations resulted in the final foreground pixel map, from which features like centroid, bounding box, perimeter and histogram were extracted. Each of these levels were supplemented with a running example image, taken from a sample video.

Chapter 4

Object Tracking

The aim of object tracking is to establish a correspondence between objects or object parts in consecutive frames and to extract temporal information about objects such as trajectory, posture, speed and direction. Tracking detected objects frame by frame in video is a significant and difficult task. It is a crucial part of smart surveillance systems since without object tracking, the system could not extract cohesive temporal information about objects and higher level behavior analysis steps would not be possible. On the other hand, inaccurate foreground object segmentation due to shadows, reflectance and occlusions makes tracking a difficult research problem.

We used an object level tracking algorithm in our system. That is, we do not track object parts, such as limbs of a human, but we track objects as a whole from frame to frame. The information extracted by this level of tracking is adequate for most of the smart surveillance applications.

The tracking algorithm we developed is inspired by the ideas presented in [12], though the methods adopted are entirely different. In short, there it is probabilistic method, whereas we used deterministic methodology. Our approach makes use of the object features such as size, center-of-mass, bounding box, color histogram and compactness, which are extracted in previous steps to establish a matching between objects in consecutive frames. Furthermore, our tracking algorithm detects object occlusion and distinguishes object identities after the split of occluded objects.

The system diagram for our tracking method is shown in the fig.(4.1). The first step in our object tracking algorithm is matching the objects in previous image (I_{n-1}) to the new objects detected in the current image (I_n). We now explain the correspondence-based object matching part in detail.

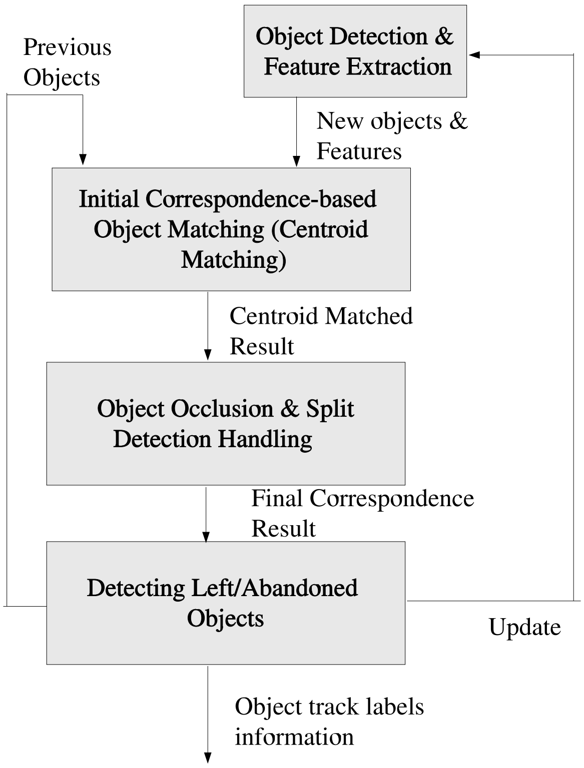


Figure 4.1: The object tracking system diagram

4.1 Correspondence-based Object Matching

The idea here is to iterate over the list of objects in the previous frame and those in present frame, and match the pairs which are "close enough". To give a meaning to this "close enough", we need a distance metric as well as a threshold.

The criterion for closeness is defined as the distance between the center-of-mass points being smaller than a pre-defined constant. This check is inspired by the fact that the displacement of an object between consecutive images should be small. In other words, two objects (say O_p and O_i) with center-of-mass points (c_p and c_i, respectively) are close to each other if the following inequality is satisfied:

$$Dist(c_p, c_i) < \tau \tag{4.1}$$

where τ is pre-defined threshold and $Dist()$ function is defined as the Euclidean distance between two points, which is given by:

$$Dist(c_p, c_i) = \sqrt{(x_{c_p} - x_{c_i})^2 + (y_{c_p} - y_{c_i})^2} \tag{4.2}$$

Let I_{n-1} and I_n denote the previous and current frames. And let L_{n-1} and L_n be the number of blobs/objects in these frames, respectively. The obvious three case which arise are:

$$\begin{aligned} L_n &> L_{n-1} \\ L_n &< L_{n-1} \\ L_n &= L_{n-1} \end{aligned} \tag{4.3}$$

For simplicity of explanation, lets assume that the absolute difference between the number of blobs of any two consecutive frames is atmost *one*. In that case, the equations in (4.3) turn out to be

$$\begin{aligned} L_n &= L_{n-1} + 1 \\ L_n &= L_{n-1} - 1 \\ L_n &= L_{n-1} \end{aligned} \tag{4.4}$$

Before we go further, we need to keep a note that every *merge* and *split* related information is stored and maintained. Detecting the case of *merge* and *split* would be discussed later. Information is stored as a structure, say *sstruct* and *mstruct*, the basic member variables of which are given below:

$$\begin{array}{l} sstruct \\ \{ \\ \qquad parent \\ \qquad children \\ \qquad keyframe \\ \} \end{array}$$

where, the object which splits is termed as *parent*, which it splits into are termed as *children* and the frame in which this split takes place is termed as *keyframe*. similarly, for merge structure ...

$$
\begin{array}{l}
mstruct \\
\{ \\
\qquad parents \\
\qquad child \\
\qquad keyframe \\
\}
\end{array}
$$

where the objects which merge together are termed as *parents*, which they are merged into is termed as *child* and the frame in which this merge takes place is termed as *keyframe*. Split-structure (sstruct) has some more member variables which will be dealt with in next chapter. With this brief background, we will now discuss in detail the cases defined in Equation 4.4.

Case I

This case would arise because of two reasons, namely *split* or *entry*. Without any loss of generality, let us assume that the number of objects in I_{n-1} is 3 (so, 4 in I_n) and $\{1,2,3\}$ as their track labels. Before any kind of matching the situation is simply the one shown in the fig.(4.2).

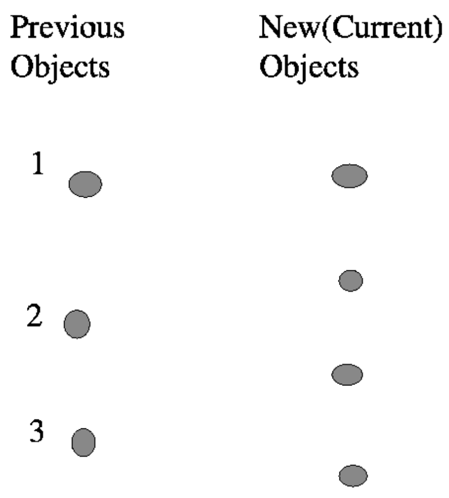


Figure 4.2: Before any matching

We first iterate over the lists of objects in the previous and current frames, and find *centroid match* (see Inequality (4.1)) which we have already discussed. After the centroid match, either of the two cases as depicted in fig.(4.3) would happen:

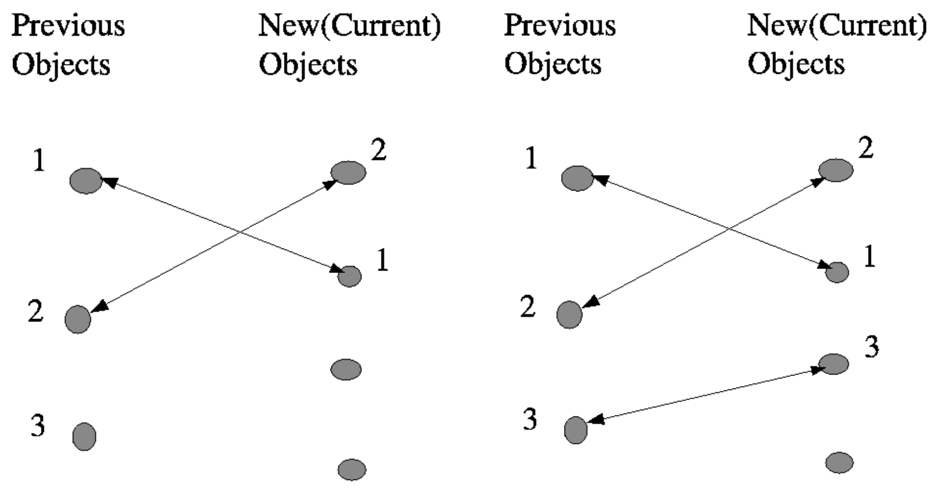


Figure 4.3: After Centroid Matching. Left: Case of split. Right: Case of entry.

If there were n-1 matches, then it is the case of *entry* else it is the case of *split*. If it is an entry a new track label, in the assumed case 4, is assigned to the unmatched new object.

Split Case : In the case of split, first the split-structure is updated by storing the unmatched previous object as the *parent*. We then assign track labels to the 2 unmatched new objects depending on whether there were any merge cases before. In case there were merge cases already, we iterate over the list of merge structure (mstruct) and check for 'any matches' with the *parents* member.

How do we check for this kind of matches??

In order to match the unmatched new objects to the children pairs in merge structure, we make use of the stored pre-occlusion color histograms of tracking objects and color histograms of new objects. We perform a matching scheme similar to the initial object matching methods explained before. However since we cannot match objects based on their position, using distance is not feasible in this case. Hence, to compare correspondence of objects, we use *battacharya coefficient*. The battacharya coefficient between two normalized color histogram, say H_a and H_b with N bins are calculated using the following formula:

$$\rho(H_a, H_b) = \rho(h_a, h_b) = \sum_i \sqrt{h_{a_i} h_{b_i}} \tag{4.5}$$

where h_a and h_b are vectorized versions of H_a and H_b respectively. To keep the information complete, battacharya distance is define using the following formula:

$$d(H_a, H_b) = d(h_a, h_b) = \sqrt{1 - \rho(h_a, h_b)} \tag{4.6}$$

Higher the battacharya coefficient, more is the correspondence between the objects. This can be checked out from the Equation (4.5) that the battacharya coefficient between two same histograms is 1. As always is the case, we pre-define a threshold for match saying that if the battacharya coefficient between 2 objects satisfies the Inequality (4.7), then they are matching pairs.

$$\rho(H_a, H_b) > Th1 \tag{4.7}$$

Finding a match need not mean that the parent (left-over previous object) and the parent corresponding to matching children are same, as the track label would have changed due to some segmentation errors. And, in case there are no merge cases, new track labels were assigned to the two unmatched new objects. Whatever be the case, the new track labels of the two objects were stored in split structure as *children*. Fig.(4.4) shows a case, where the split objects are actually the objects which merged previously and is handled by the method explained above.

Case II

This case would arise because of two situations, namely *merge* and *exit*. Following similar reasoning as in the $CaseI$, before any kind of matching the situation is simply the one shown in fig.(4.5)

After the centroid matching, as explained previously, the resulting situations would look like that shown in fig.(4.6). If there were n-1 matches, then it is the case of *exit* else it is the case of *merge*. If it is an exit, then there is nothing to do and we go ahead with next set of consecutive frames.

Merge Case : On the other hand, in the case of merge, first the merge-structure

Figure 4.4: Occlusion handling(split case). Top Left: Before merge (left/right object bounded by red/green box). Top Right: After merge. Bottom Left: Before split. Bottom Right: After split (left/right object bounded by green/red box)

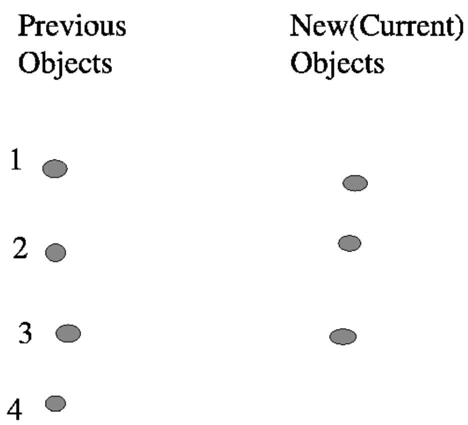


Figure 4.5: Before any matching

is updated by storing the unmatched previous two objects as the *parents*. We then assign track label to the unmatched new object depending on whether there were any split cases before. In case there were split cases already, we iterate over the list of split structure (sstruct) and check for any matches with the *parent* member. The matching procedure is the same, as defined previously while dealing with *Case I*. Track label is assigned to the unmatched new object accordingly, and is stored in merge structure

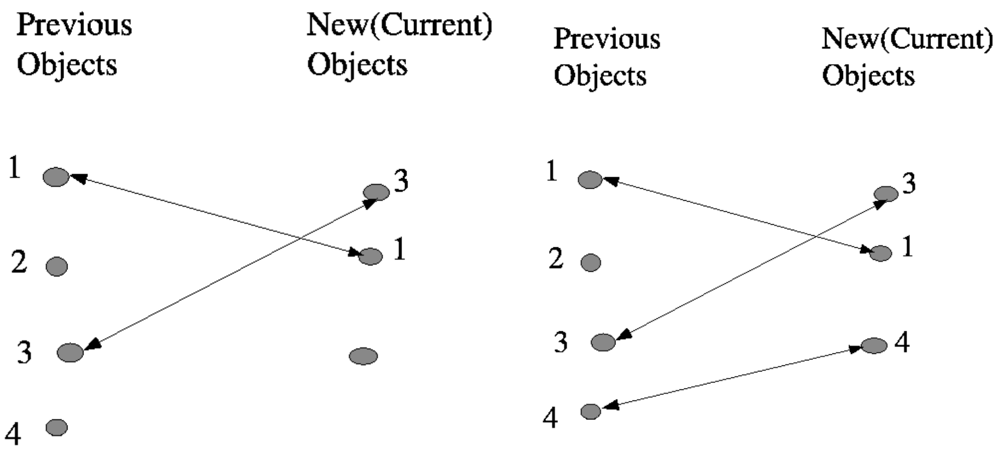


Figure 4.6: After Centroid Matching : Left figure is the case of merge and the right one is the case of exit

as *child*. Fig.(4.7) explains a case, where the merged object is actually the one which split previously and is handled by the method explained.

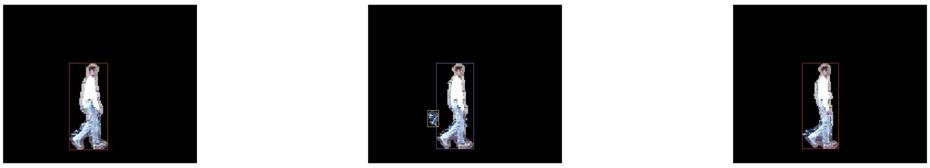


Figure 4.7: Occlusion handling(merge case). Left: Before split. Middle: Before merge. Right: After merge.

Case III

This is a case where the number of objects in the previous and current frames is same, which means there are no splits or merges. We are avoiding the rare cases where there is *split as well as exit* and *merge as well entry* which would also fall into this category. Considering these cases would be one of the issues of our future work. With this assumption, direct centroid match gives us the correspondence. Pictorially, the situation before and after centroid match would look like that shown in fig.(4.8). This case doesn't require any histogram matches.

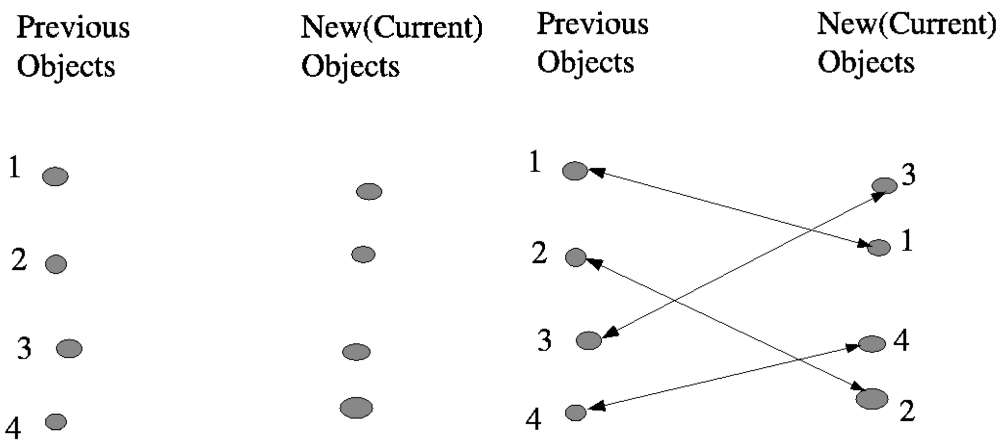


Figure 4.8: Before and after centroid matching

4.2 Results

We tested the whole-body object tracking algorithm presented in this chapter on some simple applications and it is evident from the results that the nearest neighbor matching scheme gives promising results. Fig.(4.9) shows an example of a simple video where a person enters the scene and abandons a bag. The moment person leaves the bag, a split is detected in the video and new track labels were assigned to the bag and the person. Due to some segmentation errors in the foreground detection system, an object could split momentarily for a frame and merge in the next frame. Cases like these were also handled by our algorithm, and an example for this is shown in the fig.(4.10). We were able to handle simple object occlusions using the histogram-based correspondence based approach, an example of which is shown in the fig.(4.11).

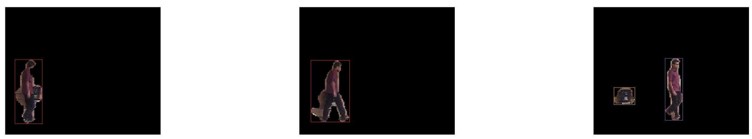


Figure 4.9: Case of split

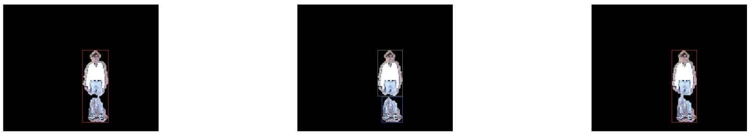


Figure 4.10: Case of split and merge

Figure 4.11: Occlusion handling

4.3 Summary

In this chapter we presented a whole-body object level tracking system which successfully tracks objects in consecutive frames. The approach we followed is a deterministic one, and it makes use of features like size, center of mass, bounding box and histogram. We first associate objects between the previous frame and current frame using centroid matching technique, where Euclidean distance between the centroids of objects is considered. To handle simple object occlusions, we incorporated histogram-based correspondence matching approach in object association. Using this approach, the identity of objects entered into an occlusion could be recognized after a split. The same approach comes in handy to recover from segmentation errors like “momentary splits”, where an object is split into two in a frame and then merge in the next frame. The tracking information, track labels, obtained from the tracking phase is then used by the classification and abnormality detection phase for further processing.

Chapter 5

Object Classification and Event Detection

The ultimate aim of different smart visual surveillance applications is to extract semantics from video to be used in higher level activity analysis tasks. Categorizing the type of a detected video object is a crucial step in achieving this goal. With the help of object type information, more specific and accurate methods can be developed to recognize higher level actions of video objects. The information obtained during classification along with tracking results is then used for *abnormal event detection* like anomalous behavior in parking lots, object removal, object abandon, fire detection, etc. Here, we present a video object classification method based on object shape similarity as part of our visual surveillance system. And, instead of keeping the abnormal event detection as an abstract goal we pre-define an abnormal event and detect that event in the video. In our case, the abnormal event is *'abandoning of a luggage/bag by a person'*.

5.1 Object Classification

Typically in high-level computer vision applications, like that of behavioral study, classification step comes before tracking. That is, each and every object in each and every frame are classified before feeding to the tracking module. Which means that the tracking module knows beforehand what object it is tracking. Support Vector Machines (SVMs) are popularly used for classification of objects. In [18] Sijun Lu et al. provide a novel approach to detect unattended packages in public venues. In this paper, they provided an efficient method to online categorize moving objects into the pre-defined classes using the *eigen-features* and the *support vector machines*. In [17] Collins et al. developed a classification method which uses view dependent visual features of detected objects to train a neural network classifier to recognize four classes: human, human group, vehicle and clutter. The inputs to the neural network are the dispersedness, area and aspect ratio of the object region and the camera zoom magnification. Like the previous method, classification is performed at each frame. In the later part of this chapter, we will see that unlike these methods classification is performed only on a limited number of objects and in a limited number of frames.

5.1.1 Bayes Classifier

Bayes classifier is a statistical technique to classify objects into mutually exclusive and exhaustive groups based on a set of measurable object's features. In general, we assign an object to one of a number of predetermined groups based on observations made on the object. As this topic is well-known to everybody, we keep this subsection short and clear. Since we will be dealing with 2-category classification, namely bag and non-bag, we discuss the theory in brief assuming there are two categories. So, consider a two-category classification problem :

$$\mathcal{D} = \{x_i, y_i\} \; where \; x_i \in R^n \; and \; y_i \in \{-1, +1\} \tag{5.1}$$

Let +1 resemble class c_1 and -1 resemble class c_2, and say $p(c_1)$ and $p(c_2)$ are their prior probabilities respectively. After observing a data point, say x, Bayes classifier just says the following:

$$if \; p(c_1|x) > p(c_2|x) \; then \; x \in R1 \; else \; x \in R2 \tag{5.2}$$

where R1 and R2 are the regions of c_1 and c_2 respectively in R^n. Though Bayes classifier is defined as in Equation (5.2), this form is not used directly when classifying. Bayes theorem relates the conditional and marginal probabilities of two events A and B by the Equation (5.3).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{5.3}$$

where

- $P(A)$ is the *prior probability* or *marginal probability* of A.
- $P(A|B)$ s the *conditional/posterior probability* of A, given B.
- $P(B|A)$ s the *conditional/posterior probability* of B, given A.
- $P(B)$ is the *prior/marginal probability* of B.

Applying Bayes rule (5.3) to Bayes classifier (5.2), and assuming $P(x)$ non-zero, Bayes classifier can be restated as defined in (5.4).

$$if\ p(x|c_1)p(c_1) > p(x|c_2)p(c_2)\ then\ x \in R1\ else\ x \in R2 \tag{5.4}$$

Most of the standard probability densities assume exponential form, which inspire to state Bayes classifier using *logarithm* function. Finally, we define a function $f(x)$ as in Equation (5.5) using which we restate the Bayes-classifier as defined in (5.6).

$$f(x) = \log \frac{p(x|c_1)}{p(x|c_2)} - \log \frac{p(c_1)}{p(c_2)} \tag{5.5}$$

$$if\ f(x) > 0\ then\ x \in c_1\ else\ x \in x_2 \tag{5.6}$$

5.1.2 Quadratic Discriminant Analysis

Discriminant analysis involves the predicting of a categorical dependent variable by one or more continuous or binary independent variables. It is useful in determining whether a set of variables is effective in predicting category membership. Quadratic discriminant analysis (QDA) is one type of discriminant analysis, where it is assumed that there are only two classes of points, and that the measurements are *normally distributed* (see Equation (5.7)).

$$\eta(X, \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X-\mu)^T \Sigma^{-1} (X-\mu)} \tag{5.7}$$

Assuming (μ_1, Σ_1) and (μ_2, Σ_2) as the respective parameters for classes c_1 and c_2, and also prior probabilities, $p(c_1)$ and $p(c_2)$, to be equal $f(x)$ as defined in Equation (5.5) would be

$$f(X) = \log \frac{\frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X-\mu_1)^T \Sigma_1^{-1} (X-\mu_1)}}{\frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X-\mu_2)^T \Sigma_2^{-1} (X-\mu_2)}} \tag{5.8}$$

Simplifying $f(X) = 0$ with the condition, $p(c_1) = p(c_2)$, imposed we get Equation (5.9).

$$\begin{aligned} g(X) &= X^T(\Sigma_2^{-1} - \Sigma_1^{-1})X + 2 * X^T(\Sigma_1^{-1}\mu_1 - \Sigma_2^{-1}\mu_2) \\ &+\mu_2^T\Sigma_2^{-1}\mu_2 - \mu_1^T\Sigma_1^{-1}\mu_1 = 0 \end{aligned} \tag{5.9}$$

Finally, we will be using the following classifier :

$$if\ g(X) > 0\ then\ X \in c_1\ else\ X \in c_2 \tag{5.10}$$

5.1.3 Learning Phase

During any classification problem, we look for two things :

- What is the *classification rule* to separate the groups?
- Which set of features determine group membership of the object?

We looked into first aspect in the previous section. The features which we would be using for the classification are :

- Aspect Ratio
- Compactness (see Equation (3.14))

We have chosen these features keeping in mind that they have to be *scale invariant* and *translation invariant*. We have not built a detailed and elaborate database, but a small one with 30 bags and 30 non-bags (people-single and group) and this proved to be sufficient for our work. This is because we are not taking decisions based on this classification result alone, but consider them as potential candidates. We have taken 5 different types of bags and took their images from 2 different distances at 2 different angles. For instance fig.(5.1) shows few bags and their blobs, which were extracted using image processing techniques.

Fig. (5.2) shows some of the people blobs with their original images, which were obtained using adaptive Gaussian mixture models discussed in third chapter. The features obtained from these blobs are then used to obtain *mean* and *variance* by the

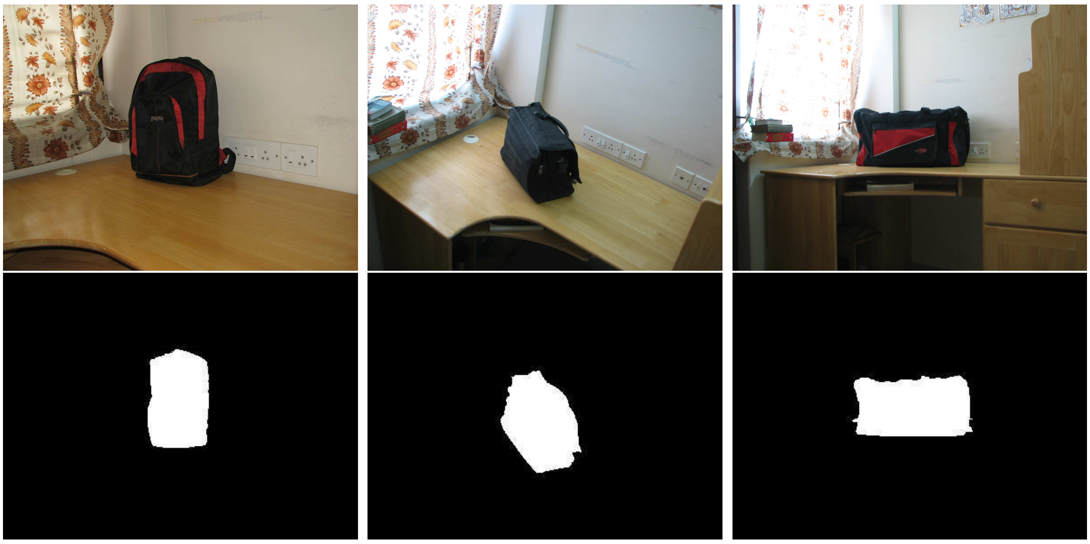


Figure 5.1: First Row: Bags. Second Row: Corresponding blobs.

following equations :

$$mean = \overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \tag{5.11}$$

$$variance = \Sigma = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X})(X_i - \overline{X})' \tag{5.12}$$

where each X_i is the feature vector and n is the number of data available. Now, given a new object its feature vector, Y, is obtained which is then fed to Equation (5.10) and classified accordingly.

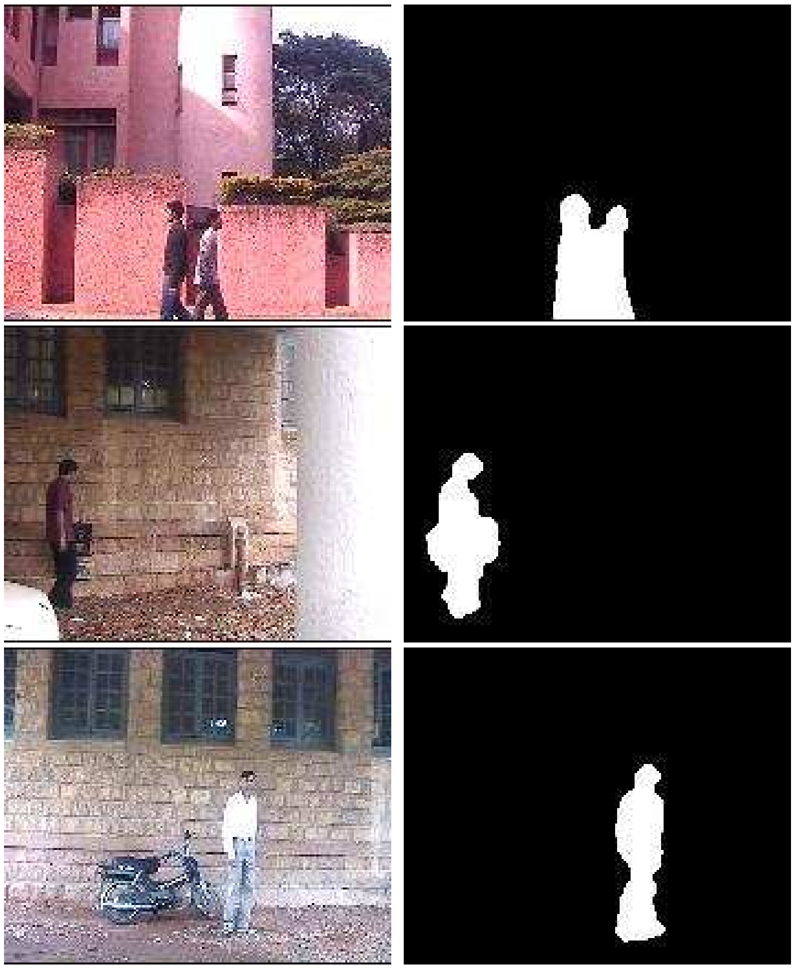


Figure 5.2: Left Column: Non-bags(mostly people). Right Column: Corresponding blobs.

5.2 Event Detection

Event detection is the phrase used in a very abstract way, in the sense that there is no specification of what event to be detected. It could either be an application in *sports video* [7], where the event could be *goal* in soccer or *try* in rugby. It could also be an application in the area of surveillance like accident detection through traffic surveillance video or abandoning of bag/luggage in airport or railway station [12]. Or, it could even be a general application like *fire detection* [24]. All the above mentioned cases fall in what is called as *pre-defined event detection*, i.e. what event to be detected is known before hand. There is also work in the literature where no pre-defined event is assumed [22]. In this paper, stochastic models were developed to characterize the normal activities in a scene. Given video sequences of normal activity, probabilistic models are learnt to describe the normal motion at the scene. For any new video sequences, motion trajectories are extracted and evaluated using these probabilistic models to identify if they are abnormal or not.

Our objective is to detect the event *'abandoning of a bag by a person'* in video which is a very critical surveillance application. The ninth International Workshop on Performance Evaluation of Tracking and Surveillance (PETS2006) is conducted in New York in June 2006, where the theme is detection of abandoning of bag [1]. Lots of details regarding this kind of work can be found in this site. One of the recent work in this area, which is being published in *Pattern Recognition* journal in August 2007 is also on the detection of this event. In this paper, an efficient method is provided to online categorize moving objects into the predefined classes using the eigen-features and the support vector machines. Then, utilizing the classification results a method is developed to recognize human activities with hidden Markov models and decide the package ownership. Finally the unattended package detection is achieved by analyzing the multiple object relationships: package ownership, spatial and temporal distance relationships.

5.2.1 Bag Detection

Since we are dealing with bag abandoning event, we just need to focus on *object splits*. *Bag removal* is another abnormal event which is one of the issues of our future work, in which case *object merges* need to be considered. In previous chapter, we stated three members of our split structure *(sstruct)*, namely *parent, children, and keyframe*. There are some other members like *class_count*, *child1[]*, *child2[]*, *is_bag*, *bag_owner[]* which hold classification and decision results.

In general, to classify an object it is not easy or right to decide on it's class by performing classification only once (in just one frame). In our work, from the time of split we perform classification over the "split objects" for the next 25 (1 sec) frames and then classify the object by voting scheme. Three kinds of splits are possible :

- Bag-Person (possibly an abnormal event)
- Person-Person (normal event)
- "Momentary split"

The first two cases don't need any explanation. They are the probable cases of bag abandoning event for which classification is performed for the next 25 frames. If the split is of "bag-person" type, then that person is decided as the *owner* of the bag.

The third case is a kind of split which arises due to segmentation error and would be discarded eventually. Such cases arise due to bad segmentation, where an object would split into two objects and in the next frame merge again (see fig.(4.10)).

There could be situation similar to the third case above, where due to segmentation error an object would split into two and remain that way without merging for some time. In such scenario, performing classification for 25 frames and deciding on voting scheme may result in classifying both the split objects as bags. To avoid such rare cases, we take into account object velocities in the form of *centroid variances*. An abandoned object will always have centroid variance almost zero, which is not the case with moving objects. This criterion alone might be sufficient if our objective is to detect any new motionless object. But, our objective is to detect bag/luggage abandoning which then requires both criteria. There is some work in literature where classification is not performed at all for this kind of abnormal event detection, but some heuristics were used. For instance, in [12] left-luggage detection process relies on three critical assumptions about the properties of a bag :

- Bags probably don't move.
- Bags probably appear smaller than people.
- Bags must have an owner.

In [16] detection of abandoned package is done by considering characteristics like *lack of motion, minimum distance from nearest person, etc.* In [19] an object is classified as abandoned, depending on factors like *minimum extent, sufficiently high probability of being foreground, no humans nearby a still object, etc.*

5.2.2 Alarm Criteria

In this section, we see what are the constraints depending on which an alarm should be set notifying the operator of a possible abnormal event. We impose two constraints before deciding that a bag has been abandoned:

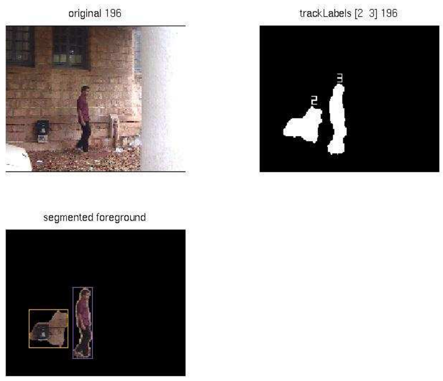
Space constraint :

We enclose the bag, once it is detected for 25 frames from the time of split, with a circle and the person with an ellipse. We have defined two regions, namely "unattended" region and "abandoned region". Each region is defined by a radius and the bag is enclosed with the circle corresponding to that radius. The decision of whether the person is within a particular region is taken by checking if the ellipse (which encloses the person) and the corresponding circle (which encloses the bag) intersect. One more way of imposing space constraint, which we have not explored, is done by 3D modeling. In [18] the authors have used revised ray-tracing method which converts a given pixel location on screen into a three-dimensional location in the real-world. If ground-truth data is available, then using *homography* the pixel distance on screen can be converted to the actual distance [12].

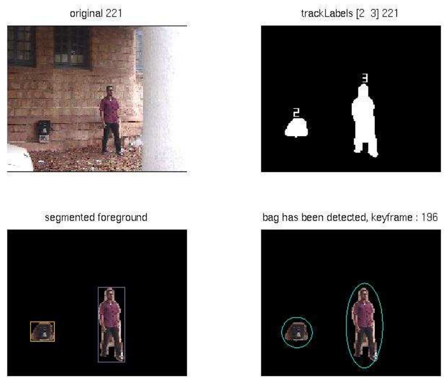
Time Constraint :
Once the bag has been detected, we wait for t_1 seconds and by that time if the owner is beyond the unattended region then we say that the bag has been unattended. Then we wait for t_2 seconds more, and by that time if the person is beyond the abandoned region then we say that the bag has been abandoned. Bag being unattended is like a caution to the operator, of a possible abnormal event. Alarm would be set if the person is beyond the unattended region for a considerable amount of time, which is a pre-defined setting.

5.3 Results

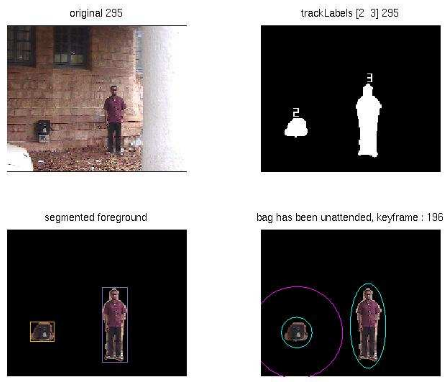
Classification results using quadratic discriminant analysis were found to be quite accurate. We used a very small training set of 60 cases, where 30 of them belong to one class - bag, and the rest belong to the second class - non-bag(people). Using a test set of 50 cases, gave us an accuracy of 95%. Few examples of the extracted blobs were shown in figs.(5.1,5.2). The classification rule which we used, though simple, gave good results because of the right selection of features as well as the second level confirmation done using centroid variances. Once the objects were classified, time constraint and distance constraint were imposed to detect the abnormal event. Figs.(5.3,5.4,5.5) show three examples where a bag has been abandoned.



(a)



(b)



(c)

Figure 5.3: Abnormal Event I. (a) Bag-Owner split. (b) Bag detected. (c) Bag unattended

(a)

(b)

(c)

Figure 5.4: Abnormal Event II. (a) Bag-Owner split. (b) Bag detected. (c) Bag unattended.

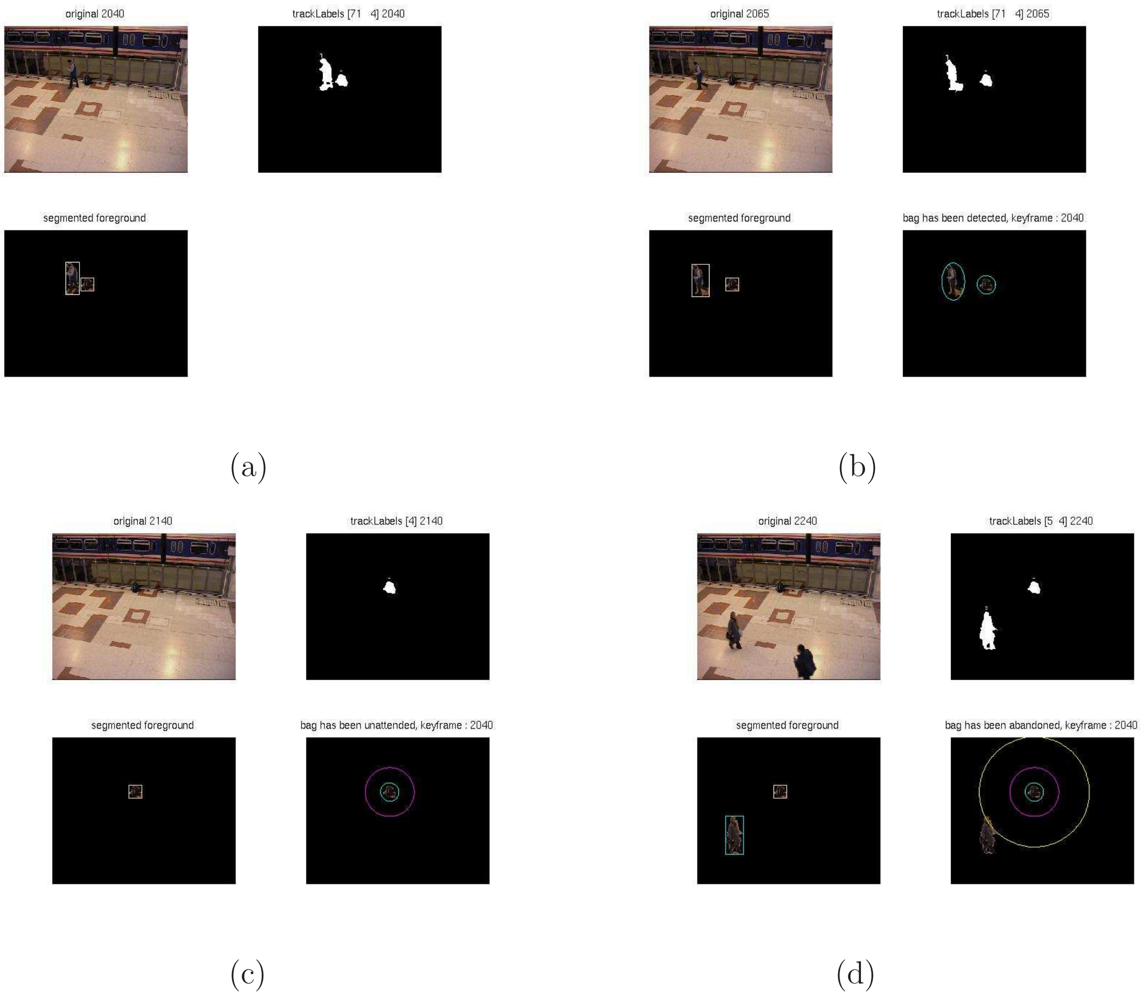


Figure 5.5: Abnormal Event III, (a) Bag-Owner split. (b) Bag detected. (c) Bag unattended. (d) Bag abandoned.

5.4 Summary

In this chapter we have discussed a methodology to classify objects into bag and non-bag(people). Unlike most of the work in literature where all objects are classified in all the frames, we are not performing classification in that manner. We classify only those objects which were result of some split case, and even this we do it only for the next 25 frames (1sec). We have discussed the classification rule, quadratic discriminant analysis, in detail and the learning phase from which we get the required parameters for the discriminant. We then saw the criteria and constraints based on which the events 'bag unattended' and 'bag abandoned' were detected.

Chapter 6

Conclusion and Future work

In this thesis we presented a set of methods and tools for a "smart" visual surveillance system. We divided the work into three stages: *object detection*, *object tracking* and *object classification*; and *event detection* comes as part of classification step.

We implemented two different object detection algorithms, namely *temporal differencing* and *adaptive Gaussian mixture models*. The adaptive Gaussian mixture models gave us the most promising results in terms of detection quality. However, no object detection algorithm is perfect, so is this method since it needs improvements in handling darker shadows, sudden illumination changes and partial object occlusions. Higher level semantic extraction steps would be used to support object detection step to enhance its results and eliminate inaccurate segmentation.

The presented whole-body object tracking algorithm successfully tracks objects in consecutive frames. Our tests in sample videos show that using nearest neighbor matching scheme gives promising results and no complicated methods are necessary for whole-body tracking of objects. Also, in handling object occlusions (object merges and object splits), the histogram-based correspondence matching approach recognizes the identities of objects entered into an occlusion successfully after a split. However, due to the nature of the heuristic we use, the occlusion handling algorithm would fail in distinguishing occluding objects if they are of the same color. Also, in crowded scenes handling occlusions becomes infeasible with such an approach, thus a pixel-based method, like optical flow is required to identify object segments accurately.

The object classification part along with event detection, presented in fourth chapter works well in detecting abandoning of bag. The classification rule which we used is very simple, but it did give good results because of the features we selected as well as the second level confirmation done using centroid variances. Although the method gives promising results in categorizing object types, it has one drawback: the method is view dependent. View-dependent problems can be solved by developing the above modules from multi-camera perspective.

The main intent of "smart" visual surveillance systems is that they should be working not only with minimal errors but also in real-time. Out of the three modules we presented in our thesis, the last two work in real-time but the object detection results had to be obtained off-line. The system specifications, on which we tested our programs on different videos are given below:

- Intel Pentium 4
- 3.00 GHz
- 1MB Cache
- 1GB RAM
- MATLAB-7.1

Though the detection process had to be done offline, converting the modules to *c code* might result in real-time setup. Apart from scope in improving the presented modules, which were discussed above, there are two applications for which the framework presented in our thesis is extendible:

1) Bag Removal (e.g. surveillance in museums)
2) People Counting (e.g. crowd control)

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