# TARGETING AND TRACKING MOVING OBJECTS IN A CLOSED ENVIRONMENT

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***Abstract*:- In an autonomous real- time video surveillance system, detection of non-rigid moving objects and continuous tracking is an important feature. In this paper, we propose a solution to target and track a person in a closed environment. Real time human target detection and tracking is achieved through image segmentation and filter. To differentiate the target from all other non-rigid objects, we use absolute difference method for background subtraction in Python. Absolute differencing is the module that defines the disparity between the current frame and the modeled background frame.After separating the target, track that object by filter.**

***Keywords:-*** **Background modeling, Background modeling, Contour Extraction, Mapping.**

## 1 INTRODUCTION

Automatic detection and recognition of objects is of prime importance for security systems and video surveillance applications. Automated video surveillance addresses real time observation of people and vehicles within a busy environment. Outdoor surveillance systems must be able to detect and track objects moving in its field of view, classify these objects and detect some of their activities. With the increasing threat of terrorism, the advanced video surveillance system needs to analyze the behaviors of people in order to prevent the occurrence of potentially dangerous situation.

The analysis of behaviors of people requires the human detection and tracking system. Extracting moving objects from video sequence is an extensively studied problem in computer vision leading to several new techniques proposed and studied for image segmentation, object detection, path prediction and correction.

### 1.1 Tracking

Generally tracking is the continuous monitoring of objects (rigid) or human (non rigid) in a specific zone. If any movement is observed in the camera zone, possible variation of parameters likes illumination, light intensity, thermal variation etc., can be observed.

- In the case of thermal measurements an IR camera can observe movement through the thermal variation.
- Another method to observe the variation is Blobs (Binary large objects or basic large) extraction i.e. Continuous matching of blobs in current frame with previous frame .It is performed by matching features of blobs in current frame with the features of blobs in previous frames.

The two basic steps for tracking are

- Detecting of object,
- Filtering/tracking of object in the consecutive frames.

Detecting of an object is achieved by differentiating moving objects in current frame to previous frames. Differencing is a low computationally complex procedure and is most suitable for background subtraction and several algorithms have been proposed to extract moving object.

- Blob matching algorithm,
- Kernel based algorithm,
- Contour tracking,
- Visual feature matching.

### 1.2 Blobs

Binary large objects or basic large objects blobs were originally just amorphous chunk of data. It is a collection of binary data stored as a single entity in DBMS (Database management systems). Blobs are typically images, audio and multimedia objects.

#### 1.2.1 Blob Matching Algorithm

In Blob algorithm the present frame is divided into a matrix of sub blocks or macro blocks. Each sub-block is then compared with a corresponding block and its adjacent neighbors in the previous frame to create a vector that stipulates the movement of a macro block from one location to another in the previous frame. This movement calculated for all the macro blocks comprising a frame, constitutes the motion estimation for the current frame.

Usually the macro block is taken as a square of 16 pixels a side. The macro
block that results in the least cost is the one that matches the closest to current block. There are various cost functions, of which the most popular and less computationally in expensive are

 

Mean Absolute Difference (MAD) method and Mean Squared Error (MSE) given by equation

$$MAD = \frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}|C_{ij} - R_{ij}|$$
$$MSE = \frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{i=0}^{N-1}(C_{ij} - R_{ij})^2 \qquad (1.2)$$

Where,
N is the side of the macro bock,
$C_{ij}$ and $R_{ij}$ are the pixels being compared in current macro block and reference macro block.

**1.2.2 Kernel-Based Tracking Algorithm**

Kernel-based methods for computer vision have received significant attention, these techniques track a target region that is described as a spatially-weighted intensity histogram. An objective function that compares target and candidate kernel densities is formulated using the Bhattacharyya measure, and tracking is achieved by optimizing this objective function using the mean shift algorithm. The objects are tracked by computing the motion of the kernel from one frame to another. Kernel based tracking can be broadly classified as

i. Tracking Using Template and Density-Based Appearance Models
ii. Tracking single objects
iii. Tracking multiple objects
iv. Tracking Using Multi view Appearance Models

In order to gain an understanding of the performance and performance limitations of current kernel-based methods, we use the equivalent SSD form of the original Bhattacharyya metric. We then derive a Newton-style minimization procedure on this measure. The structure of this optimization makes explicit the limitations in kernel-density tracking. These limitations arise from both the structure of the kernel alone and from interactions between the kernel and the image spatial structure. Suppose we are now given a candidate region centered about **c** in a subsequent image acquired at time *t'*, the corresponding empirical feature distribution would be

$$p(c) = p(c, t') = U^t(t')K(c) \qquad (1.3)$$

The location tracking problem can now be stated as follows: given a model distribution, **q**, and a candidate distribution p(c), choose a location **c***that maximizes the similarity between the target distribution and the model distribution.

A single kernel, no matter what its structure, is ultimately limited by two factors:

i. Dimensionality of the histogram (which in turn may be a function of available image structure).
ii. The interaction between its derivative structure and the spatial structure of the image as it is exposed by the histogram.

Thus, the obvious direction to pursue is to somehow increase the dimensionality of the measurement space, and to simultaneously architect the derivative structure of the kernel to be sensitive to desired directions of motion.

(1.1)

**1.2.3 Contour Based Human Tracking**

Contour Based Human tracking is a technique for tracking a super quadric modeled object over a monocular video sequences. The object is currently modeled with a single super quadric. Object's position and orientation in the first frame of the sequence are assumed known. A frame in a sequence is first processed to find object's contour. Contour is determined by extracting edges on the frame in the vicinity of model's contour from the previous frame. The model's relative translation and rotation parameters are then calculated by fitting model's contour to the frame's contour. This fitting is achieved by minimizing the cost function, which is based on model to image mapping.

Labeling each pixel exactly in each frame of a video sequence is a tedious task. The system used in the paper makes use of human assisted layer segmentation, and automatic estimation of optical flow for object contour tracking in order to increase the robustness of the system, the objective functions of flow estimation and flow interpolation.

This module works on the basis of human interaction. The labeling and defining of contour is done by the user in one frame while the rest of the forward and backward tracking is done automatically by the system. The correction of contour can anytime be done by the user in any frame which is then automatically passed to the other frames. Particle filter is used to track the object in the system as real time performance is more important than accuracy.

**1.3 Object Representation**

Outcomes of this project are to monitor parameters that allows us to evaluate of the performance of our tracking system. The parameters for evaluation system are Object position and Object size. The measurements given for the tracking system are compared with the ideal output.

Methods to identify/represent the objects includes

i. Point type representation
ii. Primitive geometric shapes
iii. 2D bounding box
iv. 3D bounding box
v. Articulated shape model
vi. Skeletal mode

**1.3.1 Points**

The object is represented by a point, that is the centroid of the object. In general, the point representation is suitable for tracking objects that occupy small regions in an image.

### 1.3.2 Primitive Geometric Shapes

Object shape may be represented by a rectangle, ellipse, or as a circle. The primitive geometric shapes are more suitable for representing simple rigid objects. However they may also be used to represent non-rigid objects.

### 1.3.3 Object Silhouette and Contour

Contour representation may be used to define the boundary of an object. The region inside the contour is called the silhouette of the object. Silhouette and contour representations are suitable for tracking complex non-rigid shapes or objects.

### 1.3.4 Articulated Shape Models

Articulated objects are composed of body parts with different joints. For example, the human body is an articulated object with torso, legs, hands, head, and feet connected by joints as in figure 1.1. In order to represent an articulated object, one can model that constituent part by integrating different graphical shape like cylinders or ellipses.

### 1.3.5 Skeletal Models

Object skeleton can be extracted by applying medial axis transform to the object silhouette. This model is commonly used as a shape representation for recognizing objects. Skeleton representation can be used to model both articulated and rigid objects.

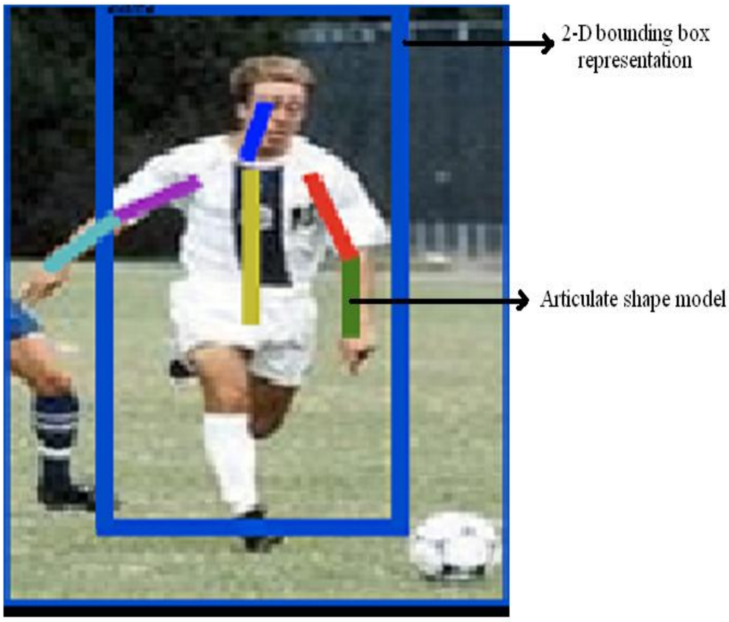


**Figure 1.1** Object Representation articulation of body shape.

### 1.4 Tracking Methods

It is difficult to get a background model from video segued as the background information keeps changing with time due to different factors like illumination, shadows etc. Background subtraction method is used for detecting moving object, as it is able to observe maximum number of moving pixels in a frame.

Object tracking methods usually divided into four groups, they are:

1. Region-based tracking
2. Active-contour-based tracking
3. Feature-based tracking
4. Model-based tracking

Challenge observed during tracking includes, occlusion (i.e. overlapping of moving blobs). Merges, splits, changes in lighting condition, moving camera, shadows and, similarity of people in shape, color and size.

### 1.5 Background Subtraction Methods

There are various background subtraction methods, some of them are listed below:

i. Alpha-beta filter
ii. Kalman filter
iii. Gaussian mixture model
iv. Euclidean algorithm

### 1.5.1 Alpha-Beta Filter

An alpha beta filter is used to measure the data for estimation, data smoothing and control applications. It is similar to Kalman filters and to linear state observers used in control theory. Its principal advantage is that it does not require a detailed system model as it requires only two to three previous samples to predict the gain factor.

 

**1.5.2 Kalman Filter**

Kalman filters use a detailed dynamic system model that is not restricted to two states and is similar to state observer.

A Kalman filter uses covariance noise models for states and observations.

Using these, a time-dependent estimate of state covariance is updated automatically, and from this the Kalman filter matrix terms are calculated. Alpha beta filter gains are manually selected and static.

For certain classes of problems, a Kalman filter is Wiener optimal while alpha beta filtering is in general suboptimal

**1.5.3 Clustering Applied to Multiple Target Tracking Algorithm**

The effectiveness of two Data Association algorithms for Multiple Target Tracking (MTT) based on Global Nearest Neighbor approach are compared. As the time for assignment problem solution increases nonlinearly depending on the problem size, it is useful to divide the whole scenario on small groups of targets called clusters. For each cluster the assignment problem is solved by using Munkres algorithm. Results reveal that the computational time especially for large scenarios decreases significantly when clustering is used.

**1.6 Steps in Tracking an Object**

i. The criterion for selection is the size and position of the different targets in a video segued.
ii. The coordinates of the targets are selected frame by frame by surrounding them with rectangles and taking the upper left corner and lower right corner as locations of our objectives.
iii. The next step is comparing of the ideal trajectories with the detected ones so that a group of parameters can be obtained to analyze the results and determine the quality of our detections.

If imperfect image segmentations appear, They result in multiple blobs potentially generated for a single target. So, blobs must be re-connected before track assignment and updation. This problem might be easily solved in single-target scenarios using a blob-grouping algorithm.

**1.7 Objective and Motivation of this Work**

Surveillance cameras can be used for monitoring a busy and secure environment and to avoid crimes in advance. Especially in public places it is very essential to monitor the behavior of individuals. The theses propose an autonomous system to target and track a human subject in a closed environment. The tracked person’s physical profile is also extracted by using the surveillance camera. When a person to be tracked leaves the camera’s field of view his information is transferred to the next surveillance camera and tracked continuously.

**1.8 Organization of the Chapters**

In Section 2 individually lists reference literatures which were reviewed as a part of this work. The various techniques proposed in each literature reviewed is briefly discussed.

In Section 3 the proposed Targeting and tracking method for human intervention in a closed Environment is discussed and results observed.

In Section 4 draws concluding remarks of paper.

## 2. LITERATURE SURVEY

Research outcomes from the academic community have been reported in several peer reviewed journals on the design of a system that can detect and track human subjects in different environments. Listed below are some existing literatures that were referred as part of the paper.

All these papers have proposed their own novel algorithm/methodology which has its own advantages as well as shortcomings which have been discussed below on a paper by paper basis.

Salil P. Banerjee, Kris. Pallipuram proposed **“Multiperson Tracking Using Kalman Filter”[8]** has following features

This paper addresses the problem of implementation of the Kalman filter to track multiple persons in a room.First, an occupancy map of the room has been created using the six cameras which are distributed across the room.Then the Kalman filter has been implemented to track the centroids of the persons detected in the room. The cameras are uncalibrated and need to be calibrated so as to represent the two dimensional image plane into points in the three dimensional world points. The transform *Tn* for each camera’s image space $I[n, c, r]$ to the $(x, y, z)$ world space is given by

$$T_n:\ [n,c,r] \rightarrow (x,y,z) + (i,j,k)d\ d > 0$$

Where d is the distance from the camera to the ground, n is the camera number, c and r are the columns and rows of the image formed in the camera plane respectively.

Next step is to acquire background image B[n,c,r] for each camera while the floorspace to be monitored is empty.After that subtract the observed image and background image, now they got the moving person in the room.The Kalman filter tracks persons even when their blobs merge, providing increased efficieny in tracking multiple persons in the room.

The Kalman filter is an algorithm which smooths the measurements by weighting them against the predicted values by their variances.In other words, the Kalman filter tries to find a balance between predicted values and noisy measurements.The values of the weights are determined by modelling the state equations. The purpose of the Kalman filter is to track the system being measured at discrete intervals of time.

Zhaozhong Wang, Min Liang and Zesheng Tang proposed **"Marker-less Human Body Tracking Using Locally Affine Invariant Contour Matching"** [11] has following features

This paper proposes an affine invariant contour matching method for human body tracking without markers. The contours of human bodies are extracted using image segmentation or background subtraction methods. The matching of contours is based on a locally affine invariant contour descriptor, which can approximate the articulated motion of human bodies. The matching algorithm using the descriptor is simple and fast, wherein an outlier rejection scheme using the geodesic distance along contours is also embedded, making it robust to self-occlusion and viewpoint changes of human poses.

They first discuss affine invariant properties of *n* points in the 2D Euclidean space; all these points may locate on the contour of a human body. The shape *configuration matrix* [17] is given as

$$X := [X_1 \dots X_n]^T \in R^{n*2} \qquad (2.2)$$

So they can find the contour of the human body by using the equation, now they design an articulated contour matching and tracking scheme based on a locally affine invariant descriptor. The proposed method can track articulated human motions with large degree of pose variations; this is superior to many marker-less human tracking algorithms in the literature. their key idea is to use locally affine invariant transformation to approximate the articulated motion of human body. Real world human motion sequences are tested to demonstrate the performance of the method.

Vinu Thomas and Ajoy Kumar Ray proposed **"Fuzzy particle filter for video surveillance"**[10] has following features

Video object tracking is the process of locating one or several moving objects in time by the use of optical cameras.In this paper, an algorithm for object tracking by the use of particle filtering is presented. The algorithm employs fuzzy techniques for feature estimation. The algorithm handles color video image sequences from a stationary camera under changing illumination conditions. The proposed algorithm successfully tracks multiple objects by the use of an adaptive Gaussian mixture model for background modeling and a sequential Monte-Carlo-based tracking algorithm.

Here, the recent history of intensity values of each pixel in an image frame, i.e.,$Xt = I(x, y, t)$, has been considered and modeled by a mix of $k$ Gaussian distributions, and an online approximation is used to update the model. The probability of observing the current pixel value can be denoted as

$$P(X_t) = \sum_{i=1}^{k} w_{i,t}\ \eta\ (X_t\ , m_{i,t}\ , \sum_{i,t}) \qquad (2.3)$$

Various fuzzy distance measures have been applied and compared for the estimation of the object location. For object tracking in a multiple object scenario, fuzzy-based color histogram is used for establishing correlation and one to one correspondence between frames. Once the object is detected, its features such as color histogram, area, centroid, elliptical major axis, and elliptical minor axis are computed.

In the FCH method, the color similarity of each pixel color to all the histogram bins is established through the fuzzy set membership function. The FCH is represented as $F(I) = \{f_1, ,f_2, . . . ,f_j\ \}$, where $,f_j$ is defined as $f_j = \sum_{i=1}^{N} \mu_{i,j}\ , Pi = \frac{1}{N} \sum_{i=1}^{N} \mu_{i,j}$ (2.4)

By using the above equation color difference between the current frame and previous frame is detected so the moving object is detected.

Yasir Salih, Aamir S. Malik proposed **"3d Object Tracking Using Three Kalman Filters"**[4] has following features

Filtering is about attempting to estimate the next state of the system given the previous state and measured observations.The linear and extended Kalman filters are the popular Kalman filters used due to their low computational requirements. Although Kalman is considered as a simple stochastic filter, yet it provides optimal estimation for linear systems that has Gaussian distribution.

$$X_k = Fx_{k-1} + v_k$$
$$Z_k = Hx_k + e_k$$

$v_k$ is the process noise with covariance Q

$e_k$ is the measurement noise with noise covariance R

 

The availability of powerful and cheap computers has contributed to the increasing use of Kalman filter in 3D tracking applications. Kalman filter is an iterative prediction-correction process to estimate the state of the system.The algorithms have been tested on different video sequences and evaluated quantitatively using root mean square error (RMSE).

The accuracy of the estimation is been measured quantitatively using RMSE measure. The RMSE value for the object position is smaller than the one for the size of the bounding box. The size of the bounding box relies on the algorithms ability to extract the full size of the tracked object. In some cases and due to lighting variations the algorithm fails to extract the accurate size of the tracked object.For linear system dynamics, linear Kalman filter provides an optimal estimation using the prediction-correction steps

Jianpeng Zhou and Jack Hoang proposed **“Real Time Robust Human Detection and Tracking System”**[5] has following features

In this paper, they present a real time robust human detection and tracking system for video surveillance which can be used in varying environments. This system consists of human detection, human tracking and false object detection. The human detection utilizes the background subtraction to segment the blob and use codebook to classify human being from other objects. The optimal design algorithm of the codebook is proposed. The tracking is performed at two levels: human classification and individual tracking . In order to describe the procedure of classification based on codebook. they assume $i$ $W$ is the *ith* code vector in code book. $X$ is feature vector of object. N is the number of code vectors in code book. The dimension of code vector is M. So the distortion between $i$ $W$ and $X$ is computed as equation

$$dist_i = \left||W_i - X|\right| = \sum_{j=0}^{M} |W_i^j - X^j| \qquad (2.5)$$

The minimum distortion between $X$ and the code vectors in the code book is defined as equation

$$diss = \min(dist_i)\ i = 0, \dots\dots.., N-1 \qquad (2.6)$$

The color histogram of human body is used as the appearance model to track individuals. In order to reduce the false alarm, the algorithms of the false object detection are also provided.they presented a real time robust human detection and tracking system which can perform in varying environment.

This algorithm has been proved to be robust to varying environment. During the process of human recognition, they introduce the codebook to recognize the human. In order to reduce the false alarm, they proposed the algorithms of false detection. The experiments also proved that the tracking algorithm based on color histogram is robust to partial occlusion of people.

Pavlina Konstantinova, Milen Nikolov, Tzvetan Semerdjiev proposed “**A Study of Clustering Applied to Multiple Target Tracking Algorithm”** [2]has following feature

Clustering is a technique of linking many computers together to act like a single computer. Data cluster an allocation of contiguous storage in databases and file systems.A clustering technique is used to remove improbable candidate associations. When clustering is used instead of one big assignment problem a number of smaller assignment problems have to be solved.

The input parameters for clustering procedure are the array of the existing tracks and array of received observations for the latest scan. The maximal number of clusters cannot be more than the number of tracked tracks. Track filtering is performed using Converted Measurement Kalman Filter with Interacting Multiple Model including two nested models with different process noise.

$$d_{ij}^2 = \tilde{z}_{ij}^T S^{-1} \tilde{z}_{ij} \qquad (2.7)$$

The above equation is the measurement of normalized distance function, where S is a innovation covariance matrix and $\tilde{z}_{ij}$ is the innovation. $Z_i$ is the measurement prediction vector of track i.

R. Kapoor , A. Dhamija proposed **“ Fast Tracking Algorithm Using Modified Potential Function ”** has following features

Fast tracking techniques are used for both the online and offline captured videos and their motion of the objects is assumed to be non-linear with time and modeled by SDEs. Potential field which controls both the direction and speed of the moving particle and is a real-valued function of location and provides simpler representation of motion.

$$dr(t) = -\Delta V(r(t))dt \qquad (2.8)$$

V(r) s differentiable and Δ denotes the gradient.

$$dr(t) = \mu\big(r(t)\big)dt = \sigma\big(r(t)\big)dB(t) \qquad (2.9)$$

B(t)- p dimensional bivariate Brownian motion,

$\sigma -$ p x p matrix.

For single object, tracking can be done successfully using the location and size estimates of the target, whereas for multiple objects, only the displacement and scaling do not provide enough information and therefore, additional heuristic parameters are required for classification.

Location and size of the object is predicted for every next frame in the form of a rectangle enclosing the object using current and previous ones. The detection of moving objects is done via a pixel level background subtraction algorithm. The algorithm uses Gaussian mixture model (GMM) to describe the intensity value (RGB) of each pixel in the image.

The recursive updating equations automatically discard the Gaussian components corresponding to the old observations; hence, only the most recent data distribution is retained. An accurate estimation of the displacement and scaling of the moving object is essential in order to locate it precisely in successive frames. The accuracy of the system is particularly limited by the foreground segmentation technique. The system can fail only if the segmentation technique fails.

Songhwai Oh, *Member*, *IEEE*, Stuart Russell, and Shankar Sastry, *Fellow*, *IEEE proposed* " **Markov Chain Monte Carlo Data Association for Multi-Target Tracking " [9]**has following features

When the number of targets is fixed, single-scan MCMCDA algorithm provides a fully polynomial randomized approximation scheme for joint probabilistic data association (JPDA). When an unknown number of targets appear and disappear at random times, a multi-scan MCMCDA algorithm Markov chain Monte Carlo data association is used for for solving data association problems and it approximates the optimal Bayesian filter.

Various tracking algorithms like Heuristic approach and Bayesian approach are based on the objective function and single scan , multi scan algorithms are based on which they process the measurement have been studied. In various multi scan algorithms ,Multi Hypothesis Tracking (MHT) algorithm is capable of initiating and terminating a varying number of tracks and is suitable for autonomous surveillance applications. The main disadvantage of MHT in its pure form is its computational complexity since the number of hypotheses grows exponentially over time.

Bayes estimator approaches to solve data association problems are even less tractable than the MAP computation. Joint Probabilistic Data Association (JPDA) is a suboptimal single-scan approximation to the optimal Bayesian filter. JPDA enumerates all possible associations and computes association probabilities.

MCMCDA is a true approximation scheme for the optimal Bayesian filter when run with unlimited resources,it converges to the Bayesian solution. MCMCDA uses Markov chain Monte Carlo (MCMC) sampling instead of enumerating over all possible associations.

When the number of targets is fixed, single-scan MCMCDA is a fully polynomial randomized approximation scheme for JPDA. The proposal distribution for MCMCDA consists of eight moves grouped into five types as follows: (1) birth/death move pair (2) split/merge move pair (3) extension/reduction move pair (4) track update move and (5) track switch move.

The complexity of multi-target tracking problems can be measured by several metrics: (1) the intensity of the false alarm rate ; (2) the detection probability ; and (3) the density of tracks. The problem gets more challenging with increasing ,decreasing , and increasing density of tracks. The performance of the MCMCDA algorithm against multi-scan NNF and MHT has been studied. The simulation results show the remarkable performance of the MCMCDA Algorithm under extreme conditions such as a large number of targets in a dense environment, low detection probabilities, and high false alarm rates.

The MCMCDA algorithm is flexible and can easily incorporate domain specific knowledge to make it more efficient. The efficiency of MCMCDA has been demonstrated as part of of the real-time control system developed for solving multi-agent pursuit-evasion game using a large-scale outdoor wireless sensor network.

S.-W. Lee, J. Kang, J. Shin and J. Paik proposed **"Hierarchical active shape model with motion prediction for real-time tracking of non-rigid objects"** has following features

Video tracking systems generally deal with non-rigid objects with various shapes and sizes. This often results in a poor match of an initial model with the actual input shape, and consequently causes the failure of tracking. The robustness of the active shape model (ASM) enables video tracking systems to deal with such unpredictable inputs.The proposed tracking system adopts a hierarchical approach to reduce computational loads and increase immunity to noise.

The proposed framework significantly reduces computational overhead in the iterative fitting process by starting the process with lower-resolution images and predicting the initial shape and location of the object in the next frame using block matching and Kalman filtering.

OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code.

## 3.TARGETING COLOURED OBJECT

In this chapter we have discussed about targeting a colored object. We have used Python and Opencv tools to do this work. This chosen problem is no way related our proposed work, even then we have chosen this in order to get familiar with the tools usage. Let us now see how to target a particular color.

### 3.1 Targeting Colored Object:

A sample image (figure 3.1) was taken with yellow colored object in it.


Figure 3.1 Original image with yellow color

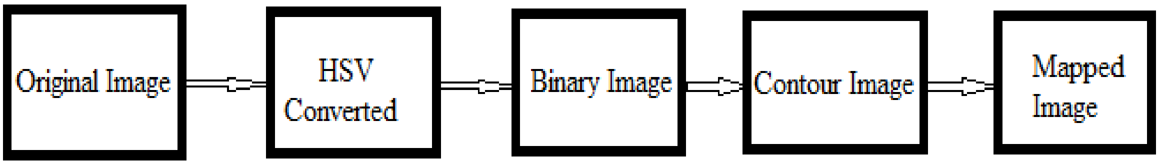


**Figure 3.2** Block Diagram for Finding Colored Object

Block diagram (Figure 3.2) describes the procedure for finding a contour for a detected object. Original image with yellow color is taken this image is transformed into Hue Saturation Value (HSV) image and yellow color is extracted from it. Extracted yellow color is represented as binary image contours are drawn and mapped on the original image. The algorithm for detecting colored object is described below

### 3.2 Steps for Color Tracking in an Image:

1. *Original image is converted to HSV image.*

   In this process the original image with yellow colored object is converted into HSV image (figure 3.3) this is done to distinguish the color differences in the image.

 

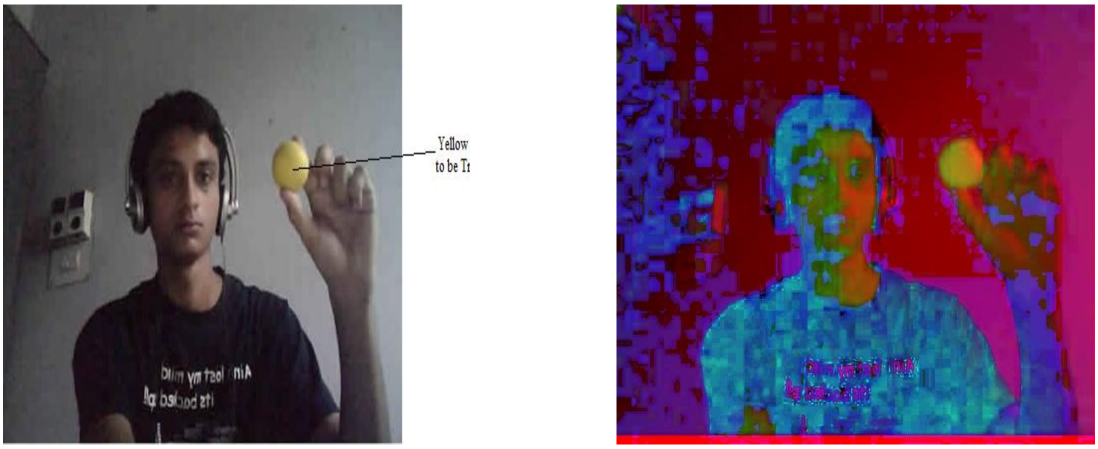


Figure 3.3 Original image to HSV image conversion

2. *Yellow color is tracked by finding threshold values.*

Here the HSV image is filtered with the threshold values of yellow color this filtered image is represented as binary image with yellow color in white and the remaining in black is shown in figure 3.3.

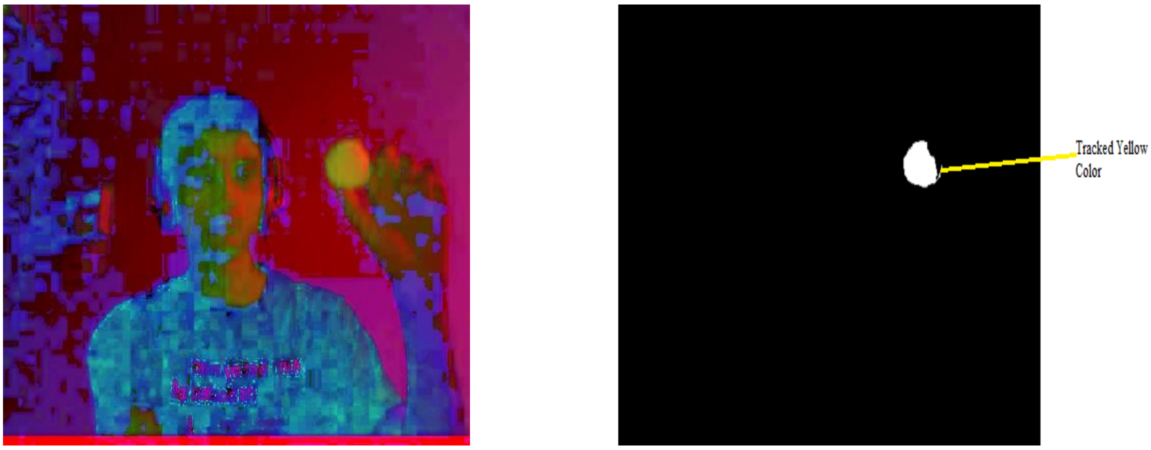


Figure 3.4 HSV to binary image conversion

3. *Contours are found for tracked object.*

In this binary image where yellow color represented as white is applied with contours. This is done by finding the boundary between white and black color in the binary image.

4. *Colors are filled on contour and mapped on original video.*

This enveloped contour is filled with red color and masked on the original image which is shown in figure 3.5.


Figure 3.5 Contours are found for binary image and mapped onto Original image

 

**3.3 Python Code for Targeting Yellow object**

The Python code for targeting yellow color is shown below and explained with comments.

**Code:**

```
# OpenCV libraries are imported to Python
import cv
#image is extracted from file location
img=cv.LoadImage("yellow.jpg")
#image size is created for HSV image to be saved
hsv_img = cv.CreateImage(cv.GetSize(img), 8, 3)
#original image is converted from RGB to HSV
cv.CvtColor(img, hsv_img, cv.CV_BGR2HSV)
#image size is created for Threshold image to be saved
thresholded_img =  cv.CreateImage(cv.GetSize(hsv_img), 8, 1)
#Yellow color is extracted by using its threshold values
cv.InRangeS(hsv_img, (20, 100, 100), (30, 255, 255),
 thresholded_img)
#Contours are found for threshold image
contour=cv.FindContours(img2,storage,cv.CV_RETR_CCOMP,cv.C
 V_CHAIN_APPROX_SIMPLE)
#Red colored contour are drawn for the found contour
cv.DrawContours(frame, contour, cv.RGB(255, 0, 0), cv.RGB(0, 255,
 1, 3, 8, (0,0) )
```

## 4. CONCLUSION

### 4.1 Conclusion

Targeting and tracking a human intervention in a closed environment was the main objective of this paper. Since targeting and tracking a person in a closed environment is completed by importing OpenCV into Python tool.

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