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Multiple Human Tracking and Prediction under severe Occlusions using GMM and Kalman Filter

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Abstract

Tracking of objects like cars, suitcases and people is the crucial part in intelligent surveillance systems. So many techniques have sprouted in the last two decades for tracking purposes. In this paper a novel method for tracking is introduced. In addition to the back ground subtraction for detecting the objects in motion, kalman filter is also used for prediction of the object's motion. Results show that by combining the back ground subtraction model with the kalman filter, the algorithm is not only used for tracking the object but also for the purpose of predicting the motion of the tracked object in case of partially occluded of if the object is disappeared in the scene because of full occluded.

Keywords— Gaussian Mixture Model, Kalman filter, Back ground subtraction

I. INTRODUCTION

Automated video surveillance of human objects is an important aspect in intelligent transportation systems. Trajectory data obtained by human tracking serve as the basic input to the studies of pedestrian flows, which can be applied to human traffic prediction, transportation infrastructure design, and evacuation control. Human behavior understanding would be helpful for detecting and predicting abnormal/dangerous activities in transit systems such as airports, subway terminals, and train stations. This paper deals with the multiple-human-tracking problem. Specifically, object tracking in video surveillance aims at extracting objects' spatial–temporal information, which is mandatory for higher level activity recognition. However, it is not trivial due to difficulties such as low figure–ground contrast, changes in object appearance over time, and abrupt motions. Multiple-object tracking is even more challenging as inter object occlusions exist prevalently, which may cause identity switches or immature trajectory terminations [1]. Object tracking approaches can be mainly classified into two types, i.e., the bottom-up category free tracking and the top-down association-based tracking by detection. The first type approaches usually require manual labeling of the region to be tracked in the first frame, whereas the second type approaches associate detection responses of a pretrained object detector based on appearance similarity, motion consistency, etc. Compared with tracking by detection, category free tracking is more reliable and it can effectively avoid the drifting problem caused by accumulated tracking error. In addition, free tracking is robust to occasional detection failures, i.e., isolated false alarms or missed detections are less likely to lead to tracking failures. Therefore, category free tracking is more effective for solving the multiple-object tracking problem [2].

II. RELATED WORK

Okuma *et al.* introduce the detection result into the proposal distribution of the particle filter to deal with multiple-hockey-player tracking, where a particle filter is used to jointly represent a varying number of targets. Cai *et al.* extend Okuma's approach by using independent particle filters for each target. Breitenstein *et al.* use greedy detection–trajectory association to guide the particle filter, taking into account the continuous detection confidence when formulating the observation model. Li *et al.* make compromise between category free tracking and tracking by detection, where each sampling procedure of the proposed cascade particle filter samples a reduced number of particles with a more reliable observation model. Their approach is able to reduce the high computational cost for object detection and meanwhile increase the robustness of visual tracking. For tracking of high-density crowds, in human heads are tracked using particle filters guided by head detections, and a 3-D head plane is estimated online to reduce false alarms. As recursive tracking approaches cannot make use of future evidence, they tend to make mistakes when the information provided by the past and current frames is ambiguous. If a time delay is allowed, global data association approaches are likely to give better performance as many frames are considered at the same time.

The classical multiple hypothesis tracking (MHT) method defers making the trajectory and detection association decision by expanding each of the current trajectory hypotheses to a set of new hypotheses when new detections become available. To avoid the exponentially growing number of hypotheses, a sliding window is used where decision has to be made at the rear end of the window. The disadvantage of MHT is that its complexity limits its window size to be very small. Integer linear programming (ILP) and its related methods have been applied to formulate the global data association problem of multiple target tracking. Jiang *et al.* use detections to construct a graph model, and additional nodes are created to handle occluded objects. Then, the data association problem is formulated into an ILP and solved by linear programming (LP) with relaxation. Zhang *et al.* propose a MAP formulation of multiple people tracking and map it into a cost-flow network, which is solved by iteratively using the minimal cost-flow method. Pirsiavash *et al.* significantly improve the efficiency of by proposing a greedy algorithm to solve the minimal cost-flow problem. Much work has been done towards obtaining the best possible background model which works in real time. Most primitive of these algorithms would be to use a static frame without any foreground object as a base background model and use a simple threshold based frame subtraction to obtain the foreground. This is not suited for real life situations where normally there is a lot of movement through cluttered areas, objects overlapping in the visual field, shadows, lighting changes, effects of moving elements in the scene (e.g. swaying trees), slow-moving objects, and objects being introduced or removed from the scene. Stauffer and Grimson describe method which adaptively models each pixel as a mixture of Gaussian. This method could deal with slow changes in illumination, repeated motion from background clutter and long term scene changes. The results obtained from mixture of gaussian or gaussian mixture model (GMM) method were very noisy. We consider this algorithm to be our baseline for comparing improvements. We introduced kalman filter for estimation of the motion of the object being tracked. GMM tracks the object and the Kalman filter predicts the object's motion whenever there are occlusions either partially or fully in some cases.

III. BACKGROUND SUBTRACTION

Background subtraction is a computational vision process of extracting foreground objects in a particular scene. A foreground object can be described as an object of attention which helps in reducing the amount of data to be processed as well as provide important information to the task under consideration. Often, the foreground object can be thought of as a coherently moving object in a scene. We must emphasize the word coherent here because if a person is walking in front of moving leaves, the person forms the foreground object while leaves though having motion associated with them are considered background due to its repetitive behavior. In some cases, distance of the moving object also forms a basis for it to be considered a background, e.g if in a scene one person is close to the camera while there is a person far away in background, in this case the nearby person is considered as foreground while the person far away is ignored due to its small size and the lack of information that it provides. Identifying moving objects from a video sequence is a fundamental and critical task in many computer-vision applications. A common approach is to perform background subtraction, which identifies moving objects from the portion of video frame that differs from the background model.

Background subtraction is a class of techniques for segmenting out objects of interest in a scene for applications such as surveillance [6,7]. There are many challenges in developing a good background subtraction algorithm. First, it must be robust against changes in illumination. Second, it should avoid detecting non-stationary background objects and shadows cast by moving objects. A good background model should also react quickly to changes in background and adapt itself to accommodate changes occurring in the background such as moving of a stationary chair from one place to another. It should also have a good foreground detection rate and the processing time for background subtraction should be real-time.

A. ***Running Gaussian average***

For this method, Wren Running Gaussian average

For this method, Wren et al. propose fitting a Gaussian probabilistic density function (PDF) on the most recent 'n' frames. In order to avoid fitting the PDF from scratch at each new frame time't', a running (or on-line cumulative) average is computed.

The PDF every pixel is characterized by mean and variance. The following is a possible initial condition (assuming that initially every pixel is background):

$$\mu_0 = I_0 \tag{1}$$

$$\sigma_0^2 = \langle somedefaultvalue \rangle \tag{2}$$

Where I_t is the value of the pixel's intensity at time't'. In order to initialize variance, we can, for example, use the variance in x and y from a small window around each pixel.

Note that background may change over time (e.g. due to illumination changes or non-static background objects). To accommodate for that change, at every frame't', every pixel's mean and variance must be updated, as follows:

$$\begin{aligned} \mu_t &= \rho I_t + (1-\rho)\mu_{t-1} \\ \sigma_t^2 &= d^2\rho + (1-\rho)\sigma_{t-1}^2 \\ d &= |(I_t - \mu_t)| \end{aligned} \tag{3}$$

Where ρ determines the size of the temporal window that is used to fit the PDF (usually ρ=0.001) and'd' is the Euclidean distance between the mean and the value of the pixel.

Gaussian distribution for each pixel.

We can now classify a pixel as background if its current intensity lies within some confidence interval of its distribution's mean:

$$\begin{aligned} \frac{|(I_t - \mu_t)|}{\sigma_t} &> k \rightarrow Foreground \\ \frac{|(I_t - \mu_t)|}{\sigma_t} &\leq k \rightarrow Background \end{aligned} \tag{4}$$

Where the parameter 'k' is a free threshold (usually k=0.25). A larger value for 'k' allows for more dynamic background, while a smaller 'k' increases the probability of a transition from background to foreground due to more subtle changes.

In a variant of the method, a pixel's distribution is only updated if it is classified as background. This is to prevent newly introduced foreground objects from fading into the background. The update formula for the mean is changed accordingly:

$$\mu_t = M\mu_{t-1} + (1-M)(I_t\rho + (1-\rho)\mu_{t-1}) \qquad (5)$$

Where M=1 when I_t is considered foreground and M=0 otherwise. So when M=1, that is, when the pixel is detected as foreground, the mean will stay the same. As a result, a pixel, once it has become foreground, can only become background again when the intensity value gets close to what it was before turning foreground. This method, however, has several issues: It only works if all pixels are initially background pixels (or foreground pixels are annotated as such). Also, it cannot cope with gradual background changes: If a pixel is categorized as foreground for a too long period of time, the background intensity in that location might have changed (because illumination has changed etc.). As a result, once the foreground object is gone, the new background intensity might not be recognized as such anymore.

B. ***Background mixture models***

In this technique, it is assumed that every pixel's intensity values in the video can be modeled using a Gaussian mixture model. A simple heuristic determines which intensities are most probably of the background. Then the pixels which do not match to these are called the foreground pixels. Foreground pixels are grouped using 2D connected component analysis.

At any time t, a particular pixel (x_0,y_0)'s history is

$$X_1,\ldots\ldots,X_t = \{V(x_0,y_0,i) : 1 \le i \le t\} \qquad (6)$$

This history is modeled by a mixture of *K* Gaussian distributions:

$$P(X_t) = \sum_{i=1}^{k} \omega_{i,t} N(X_t | \mu_{i,t}, \Sigma_{i,t}) \qquad (7)$$

Where

$$N(X_t | \mu_{i,t} \Sigma_{i,t}) = \frac{1}{(2\pi)^{D/2}} \frac{1}{|\Sigma_{i,t}|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(X_t - \mu_{i,t})^T \Sigma_{i,t}^{-1} (X_t - \mu_{i,t})\right) \qquad (8)$$

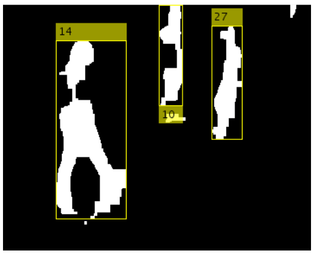
IV. TRACKING OF MULTIPLE HUMANS USING GAUSSIAN MIXTURE MODEL

This is a parametric model of probability density function for object detection. This model is represented in the following way:

GMM is equal to the weighted summation of the so called Gaussian component densities.

This model is used for the probability distribution for taking measurements continuously or for biometric system's features such as tracking an object based on motion in video.

Gaussian Mixture Model can be used as background model. Using video frame this step computes background model. The important motto of this emergence of background model is to withstand the alterations in environment in background.



To get the anticipated outcomes, pixels of frame are removed from necessary video. This background subtraction includes different issues that implicit emerging am algorithm that can used in recognizing the object. it could be capable in responding to different alterations like moving and halt of motion object [1, 2].

Surveillance is basically observing the actions, its behavior or any other altering data. It is often monitored in people. This video surveillance is generally applied in recognizing events and recognizing the humans. However, recognizing any events and tracking them is not a simple task. Various software available that are automated for analyzing video footage. Huge body motions and objects are tracked using this.

A. ***Algorithm of Gaussian Mixture Model:***

To get well aware of algorithm that applied at background subtraction, below steps are studied [1, 2].

Foremost thing to be done is to distinguish every input pixel for mean 'µ' for components. If pixel value is nearer to mean of selected component, that particular component is taken as compatible component. To be a compatible component, the difference of pixel and mean obtained should be less. This is matched with standard deviation with scaling factor of D.

Secondly, Gaussian weight, mean and standard deviation (variance) are updated to replicate the obtained new pixel value. Further components which are non-matched decreases to weight 'w' and the mean and standard deviation won't change. This relied on learning component 'p' to state the instant alterations.

Thirdly, categorize the components which portions of background model. To accomplish this task a threshold value is used as component weights 'w'.

Fourthly, we regulate the pixels of foreground. Here the recognized pixels as foreground will not be suitable with any other components that are firm to the background.

B. ***General formula of Gaussian Mixture Model:***

A Gaussian mixture model can be formulated in general as follows:

$$P(X_t)=\sum_{i=1}^{K}\omega_{i,t}\eta(X_t;\mu_{i,t},\Sigma_{i,t}) \tag{9}$$

Where, obviously,

$$\sum_{i=1}^{K}\omega_{i,t}=1 \tag{10}$$

The mean of such a mixture equals

$$\mu_t=\sum_{i=1}^{K}\omega_{i,t}\mu_{i,t} \tag{11}$$

consider as variable that signifies the present value of pixel in the frame , let K be the number of distributions, while t represents time (i.e., the frame index), represents an estimation of the i^th^ Gaussian weight at time t in the mixture, is the mean value of the i^th^ Gaussian in the mixture at time t, is the covariance matrix of the i^th^ Gaussian in the mixture at time t.

V. KALMAN FILTER

The Kalman filtering equations provide an estimate of the state $\hat{x}_{k|k}$ and its error covariance $P_{k|k}$ recursively. The estimate and its quality depend on the system parameters and the noise statistics fed as inputs to the estimator. This section analyzes the effect of uncertainties [3] in the statistical inputs to the filter. In the absence of reliable statistics or the true values of noise covariance matrices Q_k and R_k, the expression no longer provides the actual error covariance. In other words,

$$\begin{aligned} P_{k|k} &= (I-K_kH_k)P_{k|k-1}(I-K_kH_k)^T+K_kR_kK_k^T \\ P_{k|k} &\neq E\left[(x_k-\hat{x}_{k|k})(x_k-\hat{x}_{k|k})^T\right] \end{aligned} \tag{12}$$

In most real time applications the covariance matrices that are used in designing the Kalman filter are different from the actual (true) noise covariances matrices. This sensitivity analysis describes the behavior of the estimation error covariance when the noise covariances as well as the system matrices F_k and H_k that are fed as inputs to the filter are incorrect. Thus, the sensitivity analysis describes the robustness (or sensitivity) of the estimator to misspecified statistical and parametric inputs to the estimator [4].

This discussion is limited to the error sensitivity analysis for the case of statistical uncertainties. Here the actual noise covariances are denoted by Q_k^a and R_k^a respectively, whereas the design values used in the estimator are Q_k and R_k respectively. The actual error covariance is denoted by $P_{k|k}^a$ and $P_{k|k}$ as computed by the Kalman filter is referred to as the Riccati variable. When $Q_{k|k}^a \equiv Q_{k|k}$ and $R_{k|k}^a \equiv R_{k|k}$, this means that $P_{k|k}^a = P_{k|k}$. While computing the actual error covariance using $P_{k|k}^a = E\left[(x_k - \hat{x}_{k|k})(x_k - \hat{x}_{k|k})^T\right]$, substituting for $\hat{x}_{k|k}$ and using the fact that $E\left[w_k w_k^T\right] = Q_k^a$ and $E\left[v_k v_k^T\right] = R_k^a$, results in the following recursive equations for $P_{k|k}^a$:

$$P_{k|k-1}^a = F_k P_{k-1|k-1}^a F_k^T + Q_k^a \tag{13}$$

and

$$P_{k|k}^a = (I - K_k H_k) P_{k|k-1}^a (I - K_k H_k)^T + K_k R_k^a K_k^T \tag{14}$$

While computing $P_{k|k}$, by design the filter implicitly assumes that $E\left[w_k w_k^T\right] = Q_k$ and $E\left[v_k v_k^T\right] = R_k$ [5]. Note that the recursive expressions for $P_{k|k}^a$ and $P_{k|k}$ are identical except for the presence of Q_k^a and R_k^a in place of the design values Q_k and R_k respectively.

VI. PREDICTION OF MULTIPLE HUMANS USING GMM AND KALMAN FILTER

In addition to the Gaussian Mixture Model, Kalman filter is used for the purpose of continuously tracking the object in the case of partial or full occlusion of the object being tracked. Ones the object is detected by the GMM, the kalman filter produces the estimates of the current state variables along with their uncertainties. In the case of failure of tracking by the GMM, the outcome of the next measurement is observed and these estimates are updated using weighted average with more weight being given to the estimates with high certainty. In the case of occlusion of the object being tracked, the kalman filter estimates and predicts the path of the occluded object [8]. The prediction by the kalman filter is more useful when the GMM fails completely in tracking the object. For example when the object size is becoming less than the threshold of the blob area, the object is no longer detected and tracked by the GMM. The Kalman filter helps the Gaussian Mixture Model in tracking the object by prediction till the object restores its size which is sufficiently larger than the threshold of the blob area.

6 video clips each of length around 3minutes are taken for conducting experiments.

Fig 1: Mall Video frame

Fig 2: Lab Video frame

Fig 3: Corridor Video frame

Fig 4: Stair case Video frame

Fig 5: Car shed Video frame

Fig 6: Street Video frame

VII. RESULTS

Different videos of length around 3 minutes are taken. Video samples taken are 1. Mall, 2. Laboratory, 3. Corridor, 4. Staircase, 5. Car parking and a 6. Street video. In all these videos the people are detected. To identify the person, the person is bounded with a bounding box with number. The yellow box is the envelope of the person and the number over top or bottom is the count of the person.

1) ***Tracking of humans:***

Gaussian Mixture Model is used for back ground subtraction. The moving object is detected by subtracting the frame N with frame N+1. For all these 6 video clips the detected. The results are shown in the figures from fig. 7 to fig. fig. 11.

2) ***Prediction of motion of humans:***

Along with the Gaussian Mixture Model for tracking purpose, kalman filter is also used for predicting the motion of the tracked human.

In the case of the human being tracked is occluded, still because of the estimator kalman filter, the object is still being tracked.

Case:1 (human being tracked is fully occluded)

In case of the human being tracked is partially occluded, the human is tracked based on the prediction algorithm based on the kalman filter. The example of street video clip is showing how this algorithm is predicting the path of the occluded human and reinstating the human detecting when the occlusion is removed. Fig. 17 shows how the human is detected though the person is fully occluded by another person.

Case:2 (human being tracked is going far away from the camera (object becoming small in size))

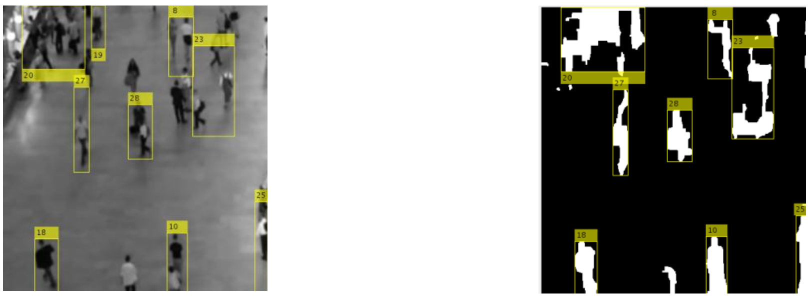
The example of stair case video shows that when the human being tracked is going far away from the camera, though the human supposed to be neglected by the tracker because of the small size; still the motion of the human is being tracked by the algorithm because of the estimation by kalman filter. Fig. 15 shows how the object is detected though the object is becoming small, going far from the camera.

Case: 3 (human being tracked is partially occluded)

The example of mall video clip is showing better results for this. Although the person being tracked is occluded because of some object, still the estimator could be able to track the person. Fig. 12 shows various examples of partial occlusions. In all these cases, the person is detected by the kalman filter.

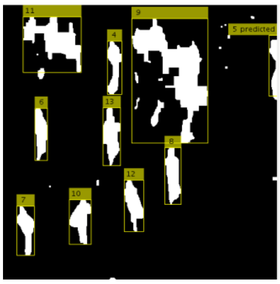
<u>Tracking of Humans:</u>

1) ***Mall VideoFrames***



(a) **(b)**

(c)



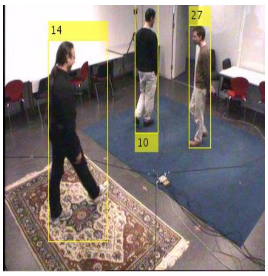
(d)

(e)

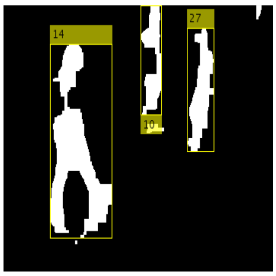
(f)

Fig: 7(a), (c), (e) are the mall video frames with frame numbers 359, 73 and 410 respectively showing the human detection and (b), (d), (f) showing their binary images

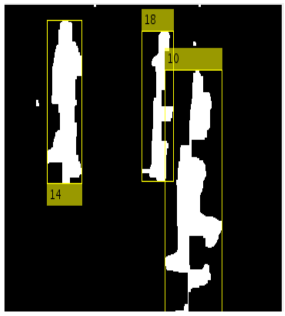
2) ***LabVideo Frames***



(a)



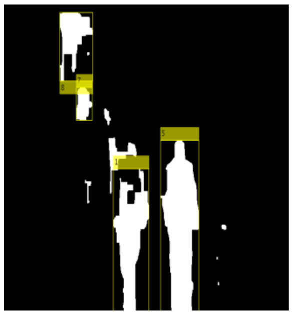
(b)



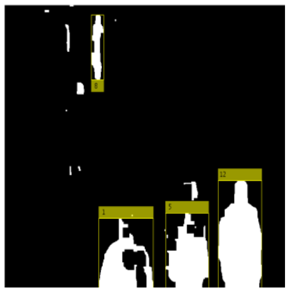
(c) **(d)**

Fig: 8(a), (c) are the Lab video frames with frame numbers 925, 1079 respectively showing the human detection and (b), (d) showing their binary images

3) Corridor Video Frames



(a) **(b)**



(c) **(d)**

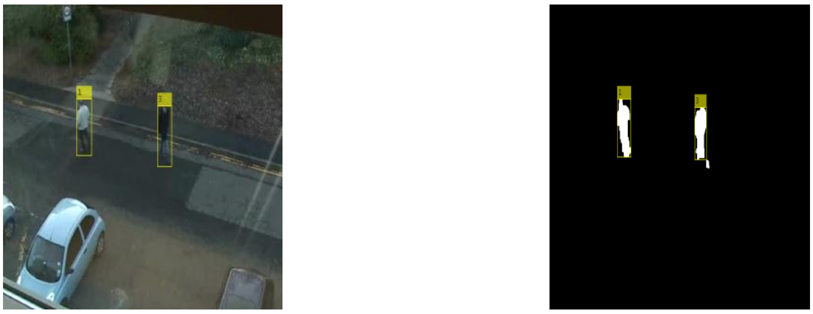
Fig: 8(a), (c) are the Corridor video frames with frame numbers 155, 245 respectively showing the human detection and (b), (d) showing their binary images

4) ***Staircase Video Frames***

(a) **(b)**

Fig: 9(a) is the stair case video frame with frame number 345 showing the human detection and (b) showing their binary image

5) ***Car Parking Video Frames***



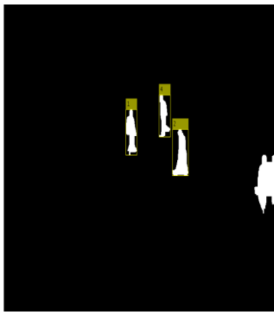
(a) **(b)**

Fig: 10(a) is the car parking video frame with frame number 253 showing the human detection and (b) showing their binary image

6) ***Street Video Frames***

(a) **(b)**

(c)



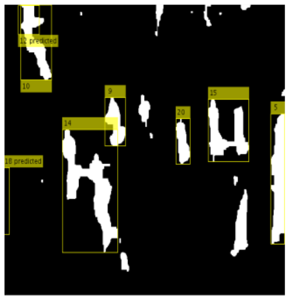
(d)

Fig: 11(a), (c) are the street video frames with frame numbers 71, 16 respectively showing the human detection and (b), (d) showing their binary images

<u>Prediction of motion of humans</u>:

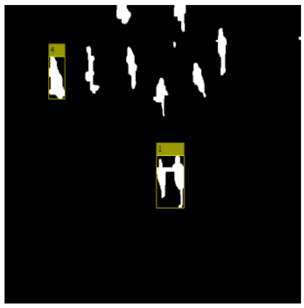
1) ***Mall VideoFrames***

(a)

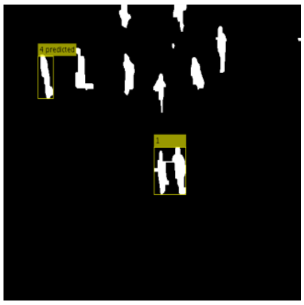


(b)

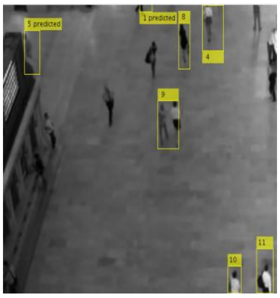
(c)



(d)



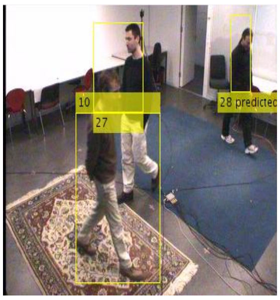
(e) **(f)**

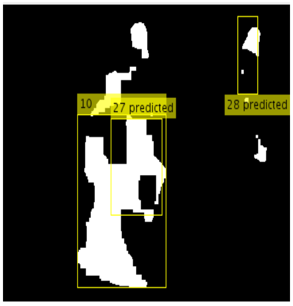


(g) **(h)**

Fig: 12(a), (c), (e), (g) are the Mall video frames with frame numbers 342, 50, 58, 97 respectively showing the human detection and (b), (d), (f), (h) showing their binary images

2) ***LabVideo Frames***



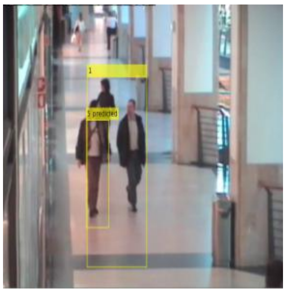


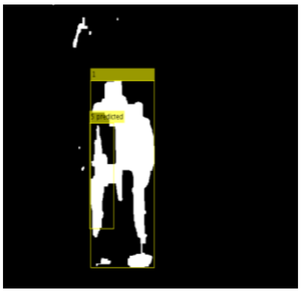
(a) **(b)**

(c) **(d)**

Fig: 13(a), (c) are the Lab frames with frame numbers1079, 512 respectively showing the human detection and (b), (d) showing their binary images

3) Corridor Video Frames

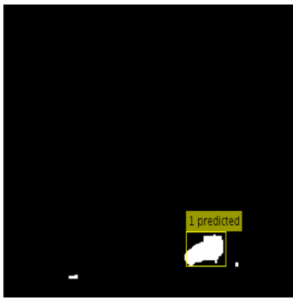




(a) **(b)**

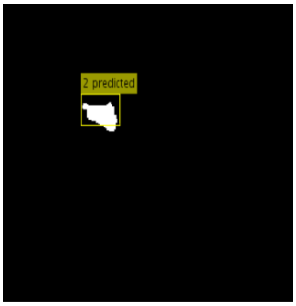
Fig: 14(a) is the corridor video frame with frame number 63 showing the human detection and (b) showing its binary image

4) Staircase Video Frames



(a) **(b)**

(c)

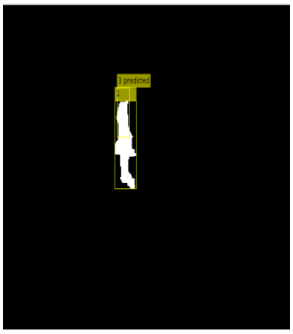


(d)

Fig: 15(a), (c) are the staircase video frames with frame numbers 202, 406 respectively showing the human detection and (b), (d) showing their binary images

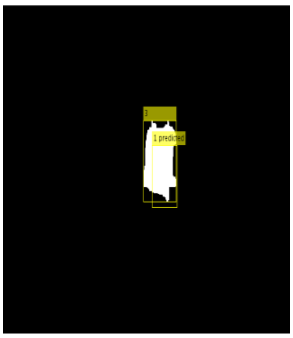
5) ***Car Parking Video Frames***

(a)



(b)

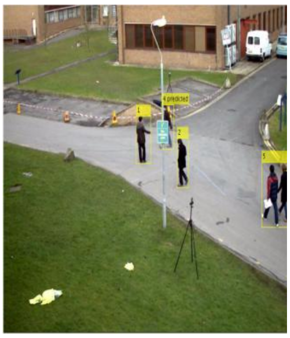
(c)



(d)

Fig: 16(a), (c) are theCar parking video frames with frame numbers 209, 424 respectively showing the human detection and (b), (d) showing their binary images

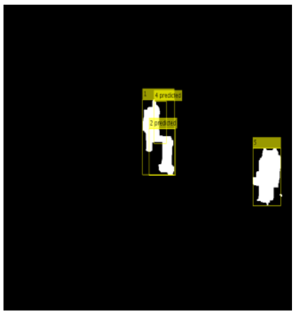
6) ***Street Video Frames***



(a)

(b)

(c)



(d)

Fig: 17(a), (c) are the street video frames with frame numbers respectively 18, 23 howing the human detection and (b), (d) showing their binary images

VIII. CONCLUSIONS

From the results we can see that by using the Gaussian Mixture Model, the human can be tracked. And by combining the kalman filter Gaussian mixture model the human not only being tracked but also very well predicted in the case of occlusion either partially or fully.

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