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Surveillance of human tracking using gaussian beta-likelihood matching and kalman filter

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Abstract- Video surveillance is widely used to monitor the place which needs constant security such as Banks, Shopping Malls, Highways, crowded public places, country borders etc. The major disputes include the complex motion behaviours of different human objects, complex scenes with numerous targets, detection of change in human motion. The objective of this paper is to develop a visual detection and tracking system of observing moving objects. The GMM-Likelihood matching method of tracking algorithm is proposed in this paper which integrates the adaptive best background detection, data association, and new hypothesis update kalman measurement, linear assignment problem to minimise the cost of observation of tracking. The experimental result shows that the active background can be extracted accurately and expeditiously, the algorithm is more robust, and can be utilized in the real time tracking applications.

Index Term- Real-time visual tracking, Data association, Video surveillance, Gaussian mixture model, negative log likelihood matching, Kalman filter.

1. Introduction

Tracking and Analysis of any moving object is widely used in the image processing, computer vision, pattern recognition and so on. Designing an effective and efficient tracking algorithm has become an active research topic. Detection of moving objects is the core part of the whole tracking problem and the main approaches are frame difference, optical flow and background subtraction. Frame difference approach [8] compares the grayscale or gradient information between different frames, which has a strong adaptability for dynamic scenarios but it cannot extract the full moving foreground in the cases of slow movement of objects or overlapping of adjacent frames. Optical flow approach [12] has high detection accuracy through combining time and space information, which can detect the moving object even with the movement of camera; still its high computational complexity makes it difficult to realize this algorithm and affects the detection of moving objects. Background subtraction approach carries out statistics for the video sequences and obtains a robust scenario ground truth subtracting background image from current image. On the contrary, the dynamic scenario changes will result in great difference between the extracted moving object and the target. Therefore, the background needs to be updated continuously.

The background subtraction approaches have been extensively researched and widely applied because of its numerous merits like its simplicity, high real-time, etc. In the background subtraction approach, the established background is expected to adapt to light changes, overcome the target occlusion and shadows, capture multiple moving targets, recognize slow-moving targets, and capture the sudden intrusion and loss of the objects. Understanding the activities of objects, especially humans, moving in a scene is both a challenging scientific problem and a very fertile domain with many promising applications. Thus, it draws the attention of several researchers, institutions and commercial companies [15]. This algorithm generally provides the most complete characteristic data, works very fast and meets the requirements of real-time system.

2. Related Works

Object tracking is an important technique used in many systems, especially in the field of image processing. N. Friedman and S. Russell proposed a Gaussian Mixture Model (GMM) for the background subtraction which involves calculating the reference image and labelling the pixels corresponding to the foreground objects [4]. C. Stauffer and W. Grimson developed an algorithm for foreground segmentation based on the Gaussian mixture model [13], [14]. W. Grimson and et al. used tracking information in multi-camera calibration, for object detection and classification [5]. Wren et al [16] used the single Gaussian model to simulate background, and establish tracking system for human beings, where this approach has a very good tracking performance in the indoor scenarios, but it cannot work efficiently in complex multi-peak problems, such as swaying leaves, sparkling lake, waving flags and so on. Javed et al [7] used a Gaussian mixture model that combines colour information and gradient information which obtains contour points of the moving objects through gradient model which fully employs gradient model robustness to noise, and accurately extracts the moving objects through block processing and combining colour information. But it is very complex in computation since it does not consider spatial coherence, and cannot detect effectively where the noise effect still exists. Zhang et al [18] established a new moving foreground detection algorithm for dynamic background subtraction by combining pixel spatial information. This approach con foreground in moving screens, however, it does not take pixel time continuity into account, detection errors still exists. Elgammal et al [2] proposed a non-parametric Gaussian core model for static scenarios, and divides the background models into long-time background

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model and short-time background model. Emadeldeen Noureldaim et al [3], [21] proposed the tracking of multiple moving objects, the size and position of the objects along the sequence of their images in dynamic scenes. Xu Zhao et al [17] proposed a novel online sparse Gaussian Process regression model to recover 3-D human motion in monocular videos. Nan Lu et al [19] proposed an improved motion detection algorithm based on double background filtering technique with morphological processing. The Double Background Filter method is used to obtain and maintain a stable background image to cope with the appearance of the moving object, to eliminate the background interference and to separate the foreground moving object. Thi Thi Zin et al [20] proposed an approach based on background modelling technique and an adaptive statistical sequential analysis method to detect any tiny abandoned objects in the low quality videos. Hu Haibo et al [6] proposed a new Gaussian mixture modelling approach which combines the colour and gradient of the spatial information, and integrates the spatial information of the pixel sequences to establish Gaussian mixture background. However, there are few common problems which are still need to resolve such as the accurate background subtraction and unavailability of foreground or illumination changes. Movement of object through cluttered areas, shadows, slow-moving objects and slow processing. In order to overcome the limitations, we have used an alternative approach of a mixture of Gaussian process which can reduce the computational cost and extract the foreground and track the human motion from the frame. Nijad Al-Najdawi et al proposed features extraction of an object in continuous and discontinuous features [10].

In this proposed work, the segmentation of the moving objects is generated by GMM-Likelihood matching method which performs relatively better than the conventional GMM. The GMM-Likelihood Matching method is an extension to GMM which produces precise, apt and obvious features of shape in the scenes and provides good classification of the objects. The tracking of a moving object is then based on applying Kalman Filter on this integrated method. The paper is organized as follows, in the Section 3, Introduction of the GMM-Likelihood Matching method, followed by a brief description of Kalman filtering method is discussed. Section 4 deals the experimental results of tracking of moving human objects and the conclusion is presented in Section 5.

3. Gmm-Likelihood Matching Method

Fig 1. represents the flow of the proposed GMM-Likelihood Matching motion tracking algorithm. It loads a sequence of images from the path directory and converts into a data matrix of images. The tracking algorithm accepts the data matrix with pixel indices, pixel colour component and the time-slice in a consecutive dimension. Mixture parameters of the Gaussian are passed to initialise some global variables and are also used to update the pixel-wise mixtures. The best background component at each pixel and smoothing of the foreground detection has been differentiated in the segment process. The Kalman filter updates and data association produce a good tracking of object. In this paper, a Gaussian Mixture model is independent statistical pixel processes as time series plays a major role in tracking of human movement which is discussed below.

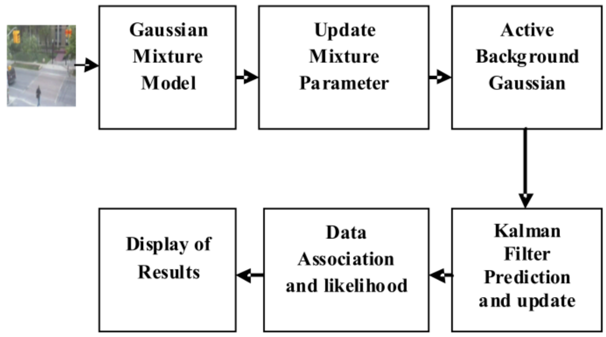

Fig 1. Flow of the GMM-likelihood Algorithm

A. Gaussian Mixture Model

In this model, the values of an individual pixel over time is considered as a "pixel process" and the recent history of each pixel, $\{X_1, \ldots, X_t\}$, is modelled by a mixture of K Gaussian distributions. The probability of observing current pixel value is

$$p(X_t) = \sum_{i=0}^{k} \omega_{i,t} \bullet \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \tag{1}$$

Where $\omega_{i,t}$ is an estimation of the weight of the i th Gaussian in the mixture at time t, $\mu_{i,t}$ is the mean value of *Gaussian* and $\Sigma_{i,t}$ is the covariance matrix of *Gaussian*, K is the number of the components and then η is a Gaussian probability density function is defined as

$$\eta(X_t, \mu_{i,t}, \Sigma_{i,t}) = \frac{1}{(2\pi)^{d/2}\left|\Sigma_{i,t}\right|^{1/2}} e^{-\frac{1}{2}(X_t-\mu_{i,t})^T \Sigma_{i,t}^{-1}(X_t-\mu_{i,t})} \tag{2}$$

Where T is the threshold, d represents the number of dimensions for the vector x, Σ_i^{-1} represents the inverse of the covariance matrix.The covariance matrix can be efficient enough when it is used as a diagonal and isotropic. The covariance may be changed to non-isotropic, but still it remains diagonal. Hence it is defined as $\Sigma_{i,t} = diag(\sigma_{i,1}^2, \sigma_{i,2}^2, \ldots\ldots, \sigma_{i,d}^2)$. On assumption of red, blue, green components being independent, we can define the covariance matrix as a scalar multiple of the identity matrix $\Sigma_{i,t} = \sigma_i^2 I$, where I is the identity matrix.

D_i The Mahalanobis distance is therefore a weighted Euclidean distance where the weighting is determined by the range of variability of the sample point.

$$D_i = \sqrt{D_i} = \sqrt{(X_t-\mu_{i,t})^T \Sigma_{i,t}^{-1}(X_t-\mu_{i,t})} \tag{3}$$

on applying equation **(3)** in equation **(2)**, $P(X_t)$ is obtained as

$$P(X_t) = \frac{1}{(2\pi)^{n/2}\left|\Sigma_{i,t}\right|^{1/2}} e^{-\frac{1}{2}D_i} \tag{4}$$

The negative log probability density of the Gaussian distribution at each point in X yields a matching cost of the observed blob which is given as

$$d_i(X) = \frac{1}{2} D_i + \log P(\omega_i) - \frac{1}{2}\log\left|\sum i,t\right| - \frac{d}{2}\log 2\pi \tag{5}$$

Where $\boldsymbol{\omega_i}$ is the estimation of weight and $\boldsymbol{d_i}$ is the distance between Kalman filter predictions and its observations. The next section will perform the mixture parameter updates.

B. Update Mixture Parameter

The parameters ω, μ, σ for each frame in the mixture are initialized and updated. The mixture of each pixel by reading a new pixel values consecutively and each matching mixture component are updated. The ω for each Gaussian component in the mixture are calculated. When the current pixel value matches none of the distributions, the least likely distribution is updated with the current pixel values which is given by,

$$\omega_{i,t} = (1-\alpha)\omega_{i,t-1} + \alpha(M_{i,t}) \tag{6}$$

where α is the learning rate to update the weighted component. $M_{i,t}$ is the matching variable. At this step some image pixel rows may not sum to unity, since some pixels may not match the mixture component. Hence value 1 has been assigned for the matching component and 0 otherwise, μ and σ will be adjusted for the matching distributions,

$$\mu_{i,t} = (1-\rho)\mu_{i,t-1} + \rho X_t \tag{7}$$

$$\sigma_{i,t}^2 = (1-\rho)\sigma_{i,t-1}^2 + \rho\sum_{i=1}^{I}((Xt-\mu i,t)^T(Xt-\mu i,t)) \tag{8}$$

where $\rho = \alpha\eta(Xt \mid \mu_{i,t}, \sigma_{i,t})$ is to accelerate the component mean and covariance. Depending upon the matching distribution results, the subsequent section will estimate the best background.

C. Active Background Gaussian

In this paper, an active background Gaussian is introduced, the components are those which are either matched or replaced. The ratio ω/σ, the maximum per row has been found and the record indices of those each pixel's component that are most confident in are sorted, so that it can display a single background estimate, where the model allows for a multi-modal background. The weights are recorded according to the ordering of index using linear index and the minimum amount of weights are found so that the background threshold will be exceeded. Large values of ratios are associated with the distributions which have high weight and low variance. The first B distributions chosen under the expression,

$$B = \arg\min_b\left(\sum_{i=1}^{b}\omega_t > T\right) \tag{9}$$

Where 1 ≤ b ≤ k, and T is the background Threshold. When T is too small, the model uses a single distribution and best distribution; where as in the case of T being too large, the model uses the multiple distributions, which is not robust. The weights in a matrix are accumulated. When the accumulated weight and component k does not exceed the threshold, the component K+1 must also belong to the background Gaussian. The background Gaussians are converted into an indicator matrix, which indicates the active components that belongs to the background model. Those pixels that have no active background Gaussian are considered as foreground. The pixel variation of data obtained from these steps is indispensable for the Kalman filter prediction process which is discussed in the later section.

D. Kalman Filter Prediction and Update

The Kalman filter is applied to estimate the state parameters of the linear system of Gaussian distribution. The measurements of the each blob give the updated mean and variance which is required for the Kalman filters prediction. The matched object will set a counter where each and every time the counter value is incremented for the matched object and the bounding box around the human motion is computed. The unmatched objects are propagated and a new track has been added for it. The filter is considered to be finished when it propagates several times and the predicted objects will match the feedback into the update of the Kalman filter. When the object is destroyed, the filter updates can be used to determine the condition of object trajectory. The Kalman filter predictive outcome will be used in the likelihood matching of the data association and to calculate the Kalman cost, which is explained below.

E. Data association and likelihood Matching

Data association is to associate the observed blobs with the tracked objects and to compute the kalman costs based on the predictive observation distribution. From these features, new observations are created and evaluated using negative log probability density from each and every observation.

The likehood L can be expressed as

$$L_{x_1,\ldots,x_n}(\mu,\sigma^2) = \prod_{i=1}^{n}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x_1-\mu)^2}{2\sigma^2}\times\ldots\times}\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x_n-\mu)^2}{2\sigma^2}} \tag{10}$$

The log likelihood $l = \ln L$ is

$$L_{x_1,\ldots,x_n}(\mu,\sigma^2) = -\frac{n}{2}\ln 2\pi\sigma^2 - \frac{1}{2\sigma^2}\sum_{i=1}^{I}(Xt-\mu i,t)^2 \tag{11}$$

This likelihood is mapped onto the dimensions of the frame of an image. It has high values around the corners, but low values in the middle. The beta probability density is computed for respective image. The corresponding points are mapped into the interval [0, 1] and the independent joint likelihood of the set of points is expressed as a vector as follows,

$$l_x = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}X^{\alpha-1}(1-X)^{\beta-1} \tag{12a}$$

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$$l_y = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} Y^{\alpha-1}(1-Y)^{\beta-1} \quad (12b)$$

The beta distributions are the functions of the two parameters, α and β. Where $0 \le x \le 1$. $\alpha, \beta > 0$, Γ denotes the gamma function. The joint likelihood I, is written as

$$l = l_x \bullet l_y \quad (13)$$

A new hypothesis is added which uses the given binary indicator matrix of assignments to label all the matched observations. A new track is added to the unmatched observations. The cost of matching is the product of beta likelihood and the squared distance. The Matlab implementation of the tracking algorithm using the Linear Assignment Problem ensures a minimum cost matching.

4. Experimental Result

In order to evaluate the accuracy of the proposed method, experiment is conducted using video sequence taken from KTH, Weizmann, PETS 2000, PETS 2001, and Stgeorge dataset. In performing experiments, no restriction has been imposed on the background scenes. More than 50 video sequences have been taken in environment like vehicle passing and the swaying of the tree leaves. In addition the scenes of person walking at various patterns are also included. These scenarios can be found in our daily life of real world environment. This type of realistic condition has not been taken into account in other existing methods. The frames used here have 180 X 144 resolutions. The algorithm was coded in Mat lab 2008b and run on Intel 2.66 GHz CPU.

The video sequences of jogging, walking and running are taken from the KTH action dataset in this proposed work. It consists of 84 frames, in which each frame is of size 180 X 144 and the sample rate is of 25 fps. In the detection and tracking system adapted in this study, there are many parameters. The so called parameters are component number k whose value is 3, Initial variance for newly placed component whose value is 3, component threshold whose value is 10. These values are kept constant for all video sequences from the dataset except few parameters. α determines the speed of the component weights, ρ determines the speed of the component mean and covariance. The standard deviation threshold, the other parameter is used to find the matching and non matching component and the mixture parameter of background threshold is used to indicate the percentage of weight accounted for the background model. Similarly for the Weizmann, PETS2000, PETS2001 and Stgeorge dataset studies, these parameter values are slightly modified as shown in Table I to adapt the situation.

The result obtained from running the video sequence as shown in Fig 2 which comprises of four frames that shows the detection result for the daria walk sequence from KTH dataset. The first frame shows the original image, second frame shows the Gaussian mixture foreground image which is marked in red, and the third frame shows the groundtruth image. Finally the image tracking of the human movement is shown in the fourth frame. In the proposed work, the beta likelihood method is responsible for the good matching of the human movement in the frame. During iteration of the video sequences, the new hypothesis function will assign label number to each matching component. This is tracked in each frame and the label value will continue till the information about that component gets lost from the frame. The non matching component is ignored.

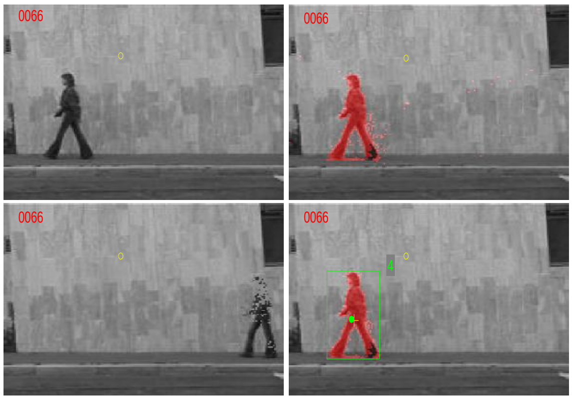


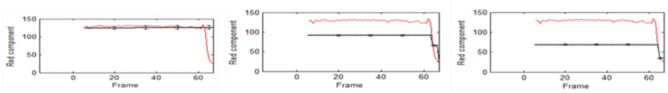
Fig. 2. The Tracking of the frame 66 of daria walk.

Table I Video Sequences And Parameter Values

Parameters	Datasets			
	KTH	PETS2000	PETS2001	Stgeorge
α	0.02	0.005	0.005	0.01
ρ	0.01	0.005	0.005	0.01
Standard deviation Threshold	49	50	67.46	49
Background Threshold	0.9	0.8	0.8	0.8

The Table II shows the mean and the standard deviation of the image sequences. In this Table II, the average mean pixel value of the 84 frame is 124.19 for the specific pixel coordinates. Similarly the average standard deviation is 28.13 which distinguish between the foreground and the background region of the frame. The mean deviation from the average indicates change in the frame. Similar case is studied and the values are tabulated in Table III by keeping the frame constant and varying the pixel coordinates.

The Fig 3 shows the plot for the mean value of the red component and the variance of the 84 frames. It is observed that the mean value of the red component at the pixel varies from 124.19 to 126.0.These variations are used as main parameters to update the mixture and kalman filter prediction to match the object.



(a) (b) (c)

Fig. 3. Mean and variance of the red component

The Fig 4 is the 2D scatter plot of the first two dimensions of the data and superimpose ellipse indicating the best background Gaussian. A plot in which a little bit of noise added to make the density become visible despite the discreteness of data. An ellipse of its unit standard deviation and also plot of dotted representation of the matching boundary for each component are imposed by standard deviation threshold.

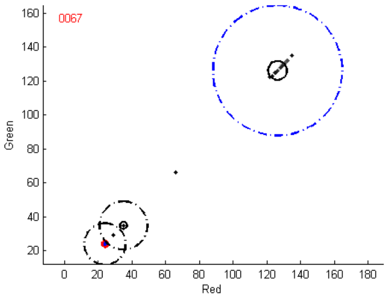


Fig. 4. Scatter plots of Red component

Some detection results have been presented by using video sequences taken from PET2000, PET2001 and Stgeorge dataset. Few sample image frames are show in Fig 5 and Fig 6. In these images, it can be seen that there are significant amount of varying backgrounds. This causes the more complex detection problems. By using the proposed method, such kind of problems can be overcome and the moving object alone can be detected accurately.

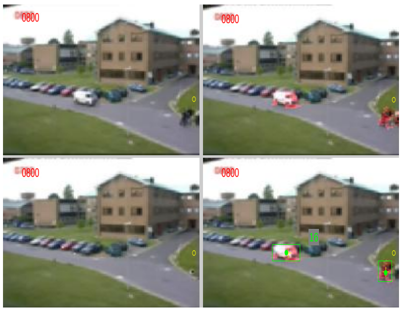


Fig 5.The Stgeorge video sequences

Fig 6. The street crossing frame sequences

Table IV presents some comparative results of the proposed method with the groundtruth (GT) results. The experiment finding shows that the frame consists of a static background and a single person movement for the dataset [11], [1]. In that the accuracy of the proposed algorithm is 100%, when the algorithm is applied for the PETS2000 and PETS2001 the accuracy of the tracking is 98.5% which is a better result compared to the existing methods. When the Stgeorge Street crossing dataset [9] of 8 fps and 25 fps is applied, the accuracy percentage is 98.7% which is a significant improved result for the complex background. It is observed from this experimental study that the algorithm performance and its accuracy are increased as the number of frames is more than 1000. So, this method is useful for surveillance applications even though the pure background image is not available. The Fig 7 shows the bar chart for the proposed method for dataset with respect to the ground truth. It is seen that accuracy of the proposed method varies from 98% to 100% while averaging those values obtained about 98.72% accuracy of image tracking.

Table II Comparison Results Of Mean And Standard Deviation Of Red Components For The Selected Pixel Coordinate

Frame	Pixel Coordinate	Mean(μ)			Standard deviation(σ)			Weight	Region
		Red	Green	Blue	Red	Green	Blue		
6	79,42	124.197 124.197 124.197	92.018 6.823 237.044	69.198 198.476 121.380	5.225 5.225 5.225	3.00 3.00 3.00	3.00 3.00 3.00	1.000000 0.000000 0.000000	Background
22	79,42	124.934 124.934 124.934	92.018 6.823 237.044	69.198 198.476 121.380	16.147 16.147 16.147	3.00 3.00 3.00	3.00 3.00 3.00	1.000000 0.000000 0.000000	Background
47	79,42	126.148 126.148 126.148	92.018 6.823 237.044	69.198 198.476 121.380	29.486 29.486 29.486	3.00 3.00 3.00	3.00 3.00 3.00	1.000000 0.000000 0.000000	Background
64	79,42	126.259 126.259 126.259	66.000 66.000 66.000	69.198 198.476 121.380	29.822 29.822 29.822	3.00 3.00 3.00	3.00 3.00 3.00	1.000000 0.000000 0.000000	Foreground
65	79,42	126.259 126.259 126.259	66.000 66.000 66.000	35.000 35.000 35.000	29.822 29.822 29.822	3.00 3.00 3.00	3.00 3.00 3.00	0.999980 0.000010 0.000010	Foreground
68	79,42	126.259 126.259 126.259	47.000 47.000 47.000	35.000 35.000 35.000	29.822 29.822 29.822	3.00 3.00 3.00	4.029 4.029 4.029	0.999980 0.000010 0.000010	Background
71	79,42	126.194 126.194 126.194	59.000 59.000 59.000	35.000 35.000 35.000	29.901 29.901 29.901	3.00 3.00 3.00	4.029 4.029 4.029	0.980773 0.000010 0.019218	Background
84	79,42	126.074 126.074 126.074	59.000 59.000 59.000	35.000 35.000 35.000	27.842 27.842 27.842	3.00 3.00 3.00	4.029 4.029 4.029	0.985214 0.000008 0.014779	Background

Table III Comparison Results Of Mean And Standard Deviation Of Red Channels Of Various Pixels Coordinate

Frame	Pixel Coordinate	Mean(μ) Red	Mean(μ) Green	Mean(μ) Blue	Standard deviation(σ) Red	Standard deviation(σ) Green	Standard deviation(σ) Blue	Weight	Region
41	80,93	139.533	33.040	42.00	7.790	3.000	3.000	0.979980	Foreground
		139.533	33.040	42.00	7.790	3.000	3.000	0.020010	
		139.533	33.040	42.00	7.790	3.000	3.000	0.000010	
41	35,115	152.270	159.905	177.605	4.552	5.394	3.000	0.679851	Background
		152.270	159.905	89.727	4.552	5.394	3.000	0.320149	
		152.270	159.905	33.219	4.552	5.394	3.000	0.000000	
41	81,121	125.318	37.060	28.020	14.046	4.029	3.088	0.968602	Background
		125.318	37.060	28.020	14.046	4.029	3.088	0.015702	
		125.318	37.060	28.020	14.046	4.029	3.088	0.015696	
41	84,91	127.240	53.000	38.000	7.362	3.000	3.000	0.999980	Foreground
		127.240	53.000	38.000	7.362	3.000	3.000	0.000010	
		127.240	53.000	38.000	7.362	3.000	3.000	0.000010	
41	115,99	89.025	44.050	53.980	4.330	3.316	3.057	0.883681	Foreground
		89.025	44.050	53.980	4.330	3.316	3.057	0.039218	
		89.025	44.050	53.980	4.330	3.316	3.057	0.077102	
41	51,78	156.670	64.693	58.956	20.537	3.000	3.000	1.000000	Background
		156.670	104.927	86.030	20.537	3.000	3.000	0.000000	
		156.670	127.074	127.443	20.537	3.000	3.000	0.000000	
41	31,66	158.550	80.075	27.549	6.711	3.000	3.000	1.000000	Background
		158.550	180.701	98.956	6.711	3.000	3.000	0.000000	
		158.550	18.128	8.767	6.711	3.000	3.000	0.000000	
41	60,93	156.963	74.000	60.970	16.680	3.000	3.235	0.979980	Foreground
		156.963	74.000	60.970	16.680	3.000	3.235	0.000010	
		156.963	74.000	60.970	16.680	3.000	3.235	0.020010	

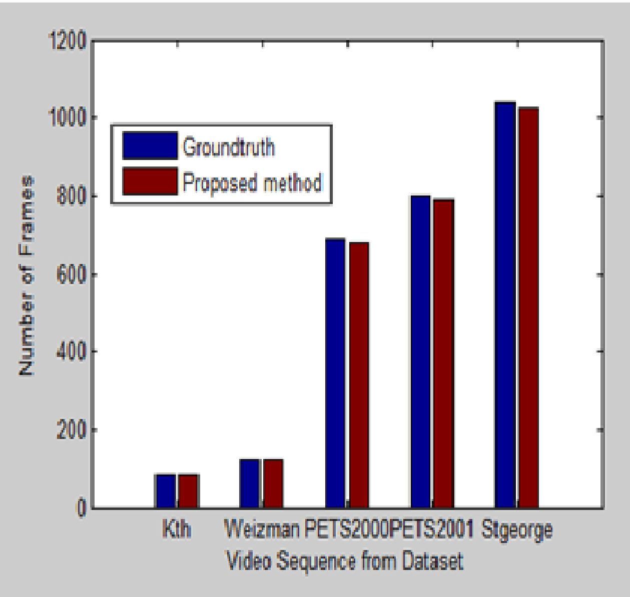


Fig 7. Detection of moving human frame with the ground truth

Table IV Accuracy of Proposed Method

Frames from dataset	GT	Our Proposed method	Accuracy
KTH [11]	84	84	100%
Weizman[1]	124	124	100%
PETS 2000 [9]	690	680	98.5%
PETS 2001 [9]	800	788	98.5%
Stgeorge 8fps & 25 fps[9]	1040	1027	98.7%
Average	2738	2703	98.72%

Table V Comparative Results

Methods	Accuracy
KLT featured Detection[10]	96.3%
PCA-GMM-KF[3]	97%
Space-time Neighbourhood method for GMM with Kalman Filter[6]	97.2%
2DPCA-GMM-KF[21]	98%
Our Proposed Method	98.72%

When compared with the existing methods as show in Table V. It is observed that the maximum percentage 98.72% of accuracy of image tracking is possible with the proposed system. This proves that the proposed system is better when compared to the other existing methods.

5. Conclusion

In this paper, the effectiveness of the GMM-likelihood matching algorithm for the human motion tracking has been investigated. An algorithm is designed which involves segmentation, Gaussian background detection, likelihood matching and kalman filter. As a result, the image of human movement is tracked correctly and firmly. The experiment results validate the effectiveness of this algorithm. This proposed method achieve 98.72 % overall. This presents fast and robust motion detection and tracking algorithm the experiments indicated that the algorithm can detect moving objects precisely, including slow moving or tiny objects. The model effectively solved the influence of the lighting change, multi-target movement and the disappearing, mixing and shading of movement objects to the tracking effects. The new algorithm is simple, fast, and consistent with the real-time tracking requirements in video surveillance systems and other practical applications. Experimental results prove the effectiveness and robustness of the algorithm.

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