

Human Motion tracking using Gaussian Mixture Method and Beta-Likelihood Matching

Michael Kamaraj, Balakrishnan

*Pavendar Bharathidasan College of Engg. & Tech., Tiruchirappalli, Tamil Nadu 620 024.,
e-mail: dmkraaj@gmail.com*

*G.BalaKrishnan is with the Indra Ganesan College of Engg., Tiruchirappalli, Tamil Nadu 620 004,
email: balakrishnan.g@gmail.com*

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. We propose the GMM-Likelihood matching Method of tracking algorithm which integrates the adaptive best background detection, data association, adding new hypothesis update kalman measurement, and 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.

keywords : Real-time visual tracking, Active background estimation, Activity modelling, Data association, Video surveillance and monitoring, Gaussian mixture model, negative log likelihood matching, Kalman filter, Linear Assignment problem.

I. 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 [1] compares the greyscale 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 [2] 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 it is simple, 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 [3]. This algorithm generally provides the most complete characteristic data, works very fast, and meets the requirements of real-time system.

II. 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 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 [5],[6]. W. Grimson and et al. used tracking information in multi-camera calibration, for object detection and classification [7]. Pfinder et al [8] 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 [9] use a Gaussian mixture model that combines color 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 color 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 [10] establish a new moving foreground detection algorithm for dynamic background subtraction by combining pixel spatial information. This approach can foreground in moving screens, however, it does not take pixel time continuity into account, detection errors still exists. Elgammal et al [11] propose a non-parametric Gaussian core model for static scenarios, and divides the background models into long-time background model and short-time background model. Emadeldeen Noureldaim et al [12] proposes 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 [13] propose a novel online sparse Gaussian Process regression model to recover 3-D human motion in monocular videos. Hu Haibo et al [14] proposes a new Gaussian mixture modelling approach which combines the color 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. 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 are vividly described. 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 III, Introduction of the GMM-Likelihood Matching method, Section IV deals the experimental results of tracking of moving human objects which leads to the conclusion in Section V.

III. GMM-LIKELIHOOD MATCHING METHOD

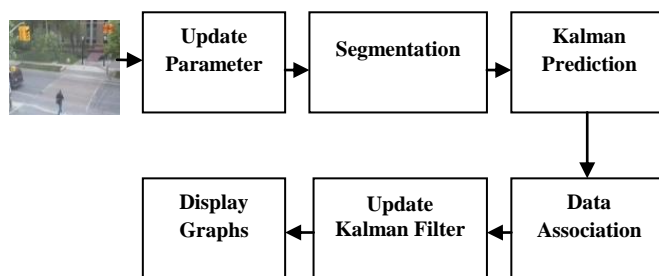


Fig. 1 Flow of the motion tracking Algorithm

Fig 1 represents the flow of the proposed GMM-Likelihood Matching motion tracking algorithm. It loads a sequence of images from the path directory [15]-[17] 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. Association of the observed blob to the tracked object has been done in the data association and the Kalman filter updates the blob association which comes from the data association. Finally, the output generated from the algorithm has been displayed as a graph.

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, $\{X_i, \dots, X_j\}$, is modelled by a mixture of K Gaussian distributions. The probability of observing current pixel value is given by

$$P(X_t) = \sum_{i=0}^K \omega_{i,t} \cdot \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \quad (1)$$

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

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

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 $\Sigma_{i,t} = \text{diag}(\sigma_{i,1}^2, \sigma_{i,2}^2, \dots, \sigma_{i,d}^2)$. 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. We have

$$D_i = \sqrt{D_i} = \sqrt{(X_t - \mu_i)^T \Sigma_i^{-1} (X_t - \mu_i)} \quad (3)$$

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. Apply equation. (3) in equation (2), We get

$$P(X_t) = \frac{1}{(2\pi)^{\frac{d}{2}} |\Sigma_i|^{\frac{1}{2}}} e^{-\frac{1}{2} D_i} \quad (4)$$

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,

$$d_i(X) = \frac{1}{2} D_i + \log P(\omega_i) - \frac{1}{2} \log |\Sigma_i| - \frac{d}{2} \log 2\pi \quad (5)$$

Where ω_i is the estimation of weight and d_i is the distance between Kalman filter predictions and its observations.

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. And then 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,

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

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

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

$$\sigma_{i,t}^2 = (1 - \rho) \sigma_{i,t-1}^2 + \rho \sum_{i=1}^I \left((X_t - \mu_{i,t})^T (X_t - \mu_{i,t}) \right) \quad (8)$$

Where $\rho = \alpha \eta(X_t | \mu_i, \sigma_i)$ is to accelerate the component mean and covariance.

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 mode 1 allows for a multi-modal background. We can reorder the weights 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,

$$B = \operatorname{argmin}_b \left(\sum_{i=1}^b \omega_k > T \right) \quad (9)$$

Where $1 \leq b \leq k$, 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 to swaying leaves, lake scenarios and so on.

Accumulate the weights in a matrix. When the accumulated weight and component k does not exceed the threshold, the component K+1 must also belong to the background Gaussian. Convert the background Gaussians into an indicator matrix, which indicates the active components which belongs to the background model. Those pixels that have no active background Gaussian are considered as foreground.

D. 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 likelihood L can be expressed as

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

The log likelihood $l = \ln L$ is

$$l_{x_1, \dots, x_n}(\mu, \sigma^2) = -\frac{n}{2} \ln 2\pi\sigma^2 - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 \quad (11)$$

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. Compute the beta probability density of the 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,

$$I_x = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} \quad (12 a)$$

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

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

$$I = I_x \cdot I_y \quad (13)$$

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.

IV. EXPERIMENTAL RESULT

The GMM-Likelihood Matching Algorithm has been implemented using MATLAB. The testing sequences of an image have obtained from the dataset [15][16]. The daria walk is the testing sequence extracted from the Weizmann dataset where it is an avi format file which consists of 84 frames. The size of each frame is 188 x 144 dimensions. The tracking algorithm gets the sequence of frames from the specified folder with the extension and starts running. The algorithm will display the result in a four subplots. The subplot A represents the actual image. The subplot B represents the foreground image. The subplot C represents the best background image. The subplot D represents the object tracked image. The pixel mixture statistics and the pixel mixture graph figure display appears when the pixel coordinate of the debugging pixel takes argument from the figure handle.

The statistics visualisation fig.3 of the image is given below; initially the component is drawn black around it. When the component belongs to the background, the blue frame has been drawn around it. In the case of component being replaced by another component it will be marked as red. The mean and the variance of the R, G, B components are calculated for each frame. It also displays the weight of the components for the each frame.

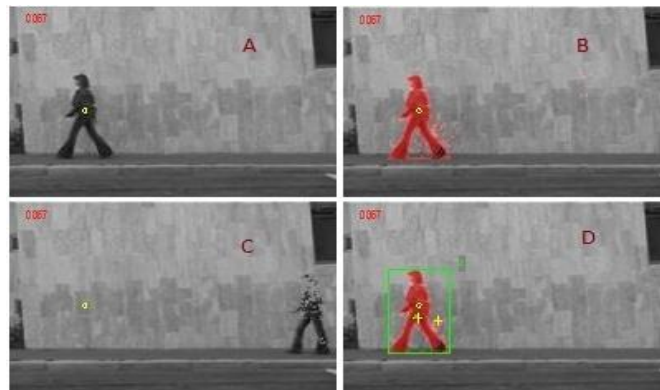


Fig. 2 Display of the tracking of the frame 67 of daria walk.

The daria walk frames are loaded from the selected directory. The figure handle pick the pixel coordinate (79,42) for the testing, the argument pixel coordinate(x,y) may vary and it depends on the region where the user clicks the image. The fig. 2 shows the result of the daria walk sequence. The moving human image is detected and tracked, where the tracking has been shown within the bounding box. The subplot B shows the foreground detection and the subplot C shows the best background detection.

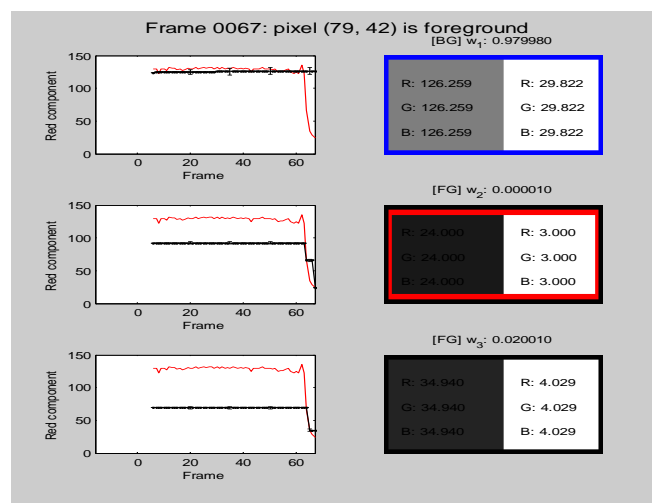


Fig. 3. Display of the red component against frame of the frame 67 sequence of the daria walk.

The fig (3) shows the statistical visualization of the mean and the variance of the pixel coordinates and also it shows the graph of red component against the frame. It plots the red components and the error bar time plot for each and every frame. The updated mean and variance of each frame is processed, and the foreground weight and the background weight for frame 67 are found. From the graph, it is seen that the red component maintain the consistency of the mean value for the frame 1 to 64 and from frame 65 to frame 68 there are abrupt changes in the mean value and from 69 till the end of the frame regains the previous mean value. The pixel coordinate (79, 42) is maintained constant over the frames and it is used to say that pixel of that frame is a foreground pixel or it detected the background pixel. It was also proved statistically with the mean value and the variance.

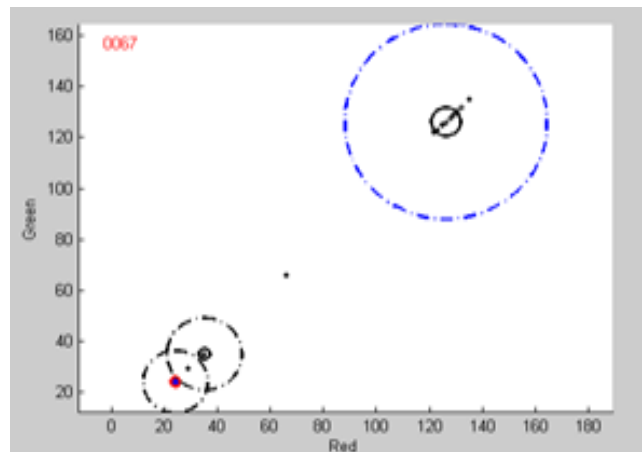


Fig. 4. the Display of the scatter plots of the Green and Red components of the frame 67 of the daria walk.

The fig (4) represents the scatter plots of the first two dimensions of the data and the super impose ellipses indicates the Gaussians. The ellipse for each component of its unit standard deviation has a dotted representation for the matching boundary imposed by standard deviation threshold. By default, the Gaussian will be in black, the replaced Gaussian will be in red whereas the matched Gaussian will be in green and the blue indicates the background boundaries. The unit standard deviation is the square root of the variance. The matching boundary is given in terms of standard deviations; hence each component is multiplied by its own standard deviation to plot a proper ellipse. The fact that the covariance matrix is diagonal has been used. The Table I display the frame wise details of the mean and the variance of the sequence of daria walk. The variation of the mean is same for all the three components; it is obvious that the pixel selected belongs to the background Gaussians. The same pixel positions for the frame 64 & frame 65, is detected as foreground. In this way, this algorithm clearly spots the moving objects in the frame. The mean and the variance are updated for each and every sequence of the frame. The fig (5) shows sequence of the input frame of daria walk. In fig (6) the tracking algorithm image sequence show walking sequence of frames and have been tracked with the bounding box. Henceforth, the GMM-Likelihood Matching motion tracking algorithm method is applied at each level of the algorithm which results in more accurate detection of object.

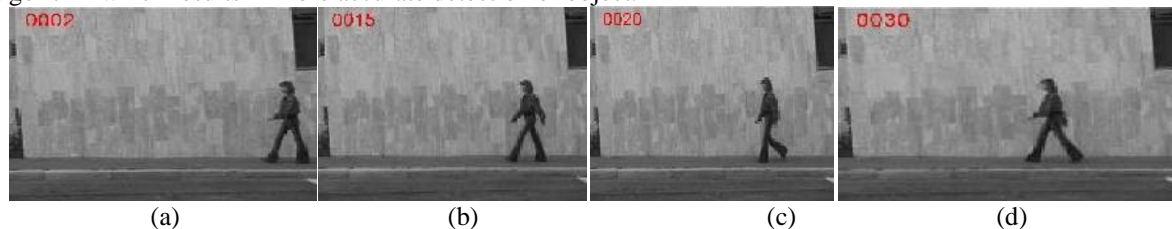




Fig 5. (a)-(e) The sequence of the input frame of daria walk

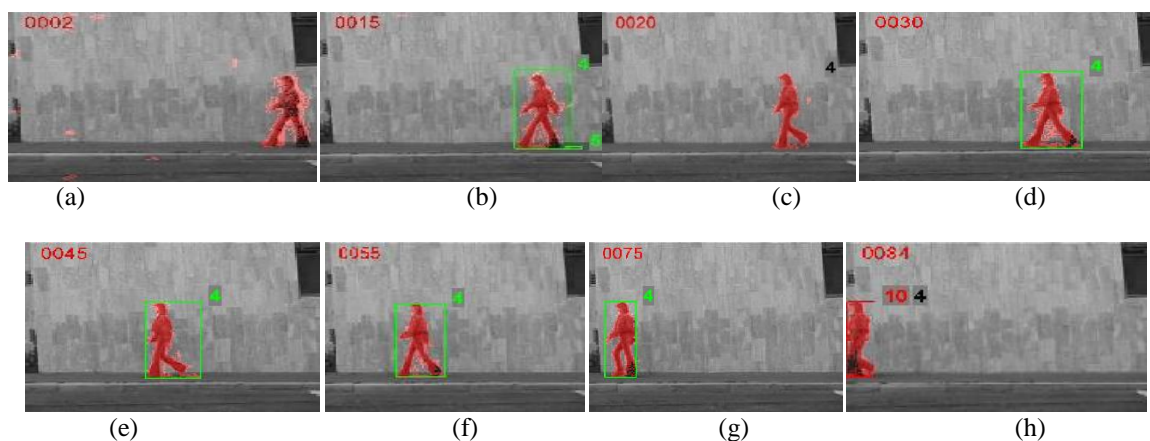


Fig 6. (a)-(e) The sequence of the output frame of daria walk

Table I Frame-Wise Mean And Variance Of R, G, B Components For The Selected Pixel Coordinate (79,42) Of Daria Walk

S.No	Frame	Pixel Coordinate	Mean(μ)			Variance(σ^2)			Weight	Region
			Red	Green	Blue	Red	Green	Blue		
1.	6	79,42	124.197	92.018	69.198	5.225	3.00	3.00	1.000000	Background
			124.197	6.823	198.476	5.225	3.00	3.00	0.000000	
			124.197	237.044	121.380	5.225	3.00	3.00	0.000000	
2.	22	79,42	124.934	92.018	69.198	16.147	3.00	3.00	1.000000	Background
			124.934	6.823	198.476	16.147	3.00	3.00	0.000000	
			124.934	237.044	121.380	16.147	3.00	3.00	0.000000	
3.	47	79,42	126.148	92.018	69.198	29.486	3.00	3.00	1.000000	Background
			126.148	6.823	198.476	29.486	3.00	3.00	0.000000	
			126.148	237.044	121.380	29.486	3.00	3.00	0.000000	
4.	64	79,42	126.259	66.000	69.198	29.822	3.00	3.00	1.000000	Foreground
			126.259	66.000	198.476	29.822	3.00	3.00	0.000000	
			126.259	66.000	121.380	29.822	3.00	3.00	0.000000	
5.	65	79,42	126.259	66.000	35.000	29.822	3.00	3.00	0.999980	Foreground
			126.259	66.000	35.000	29.822	3.00	3.00	0.000010	
			126.259	66.000	35.000	29.822	3.00	3.00	0.000010	
6.	68	79,42	126.259	47.000	35.000	29.822	3.00	4.029	0.999980	Background
			126.259	47.000	35.000	29.822	3.00	4.029	0.000010	
			126.259	47.000	35.000	29.822	3.00	4.029	0.000010	
7.	71	79,42	126.194	59.000	35.000	29.901	3.00	4.029	0.980773	Background
			126.194	59.000	35.000	29.901	3.00	4.029	0.000010	
			126.194	59.000	35.000	29.901	3.00	4.029	0.019218	
8.	84	79,42	126.074	59.000	35.000	27.842	3.00	4.029	0.985214	Background
			126.074	59.000	35.000	27.842	3.00	4.029	0.000008	
			126.074	59.000	35.000	27.842	3.00	4.029	0.014779	

V. CONCLUSION

The GMM-Likelihood Matching motion tracking algorithm is simple, fast, and consistent with the real-time tracking requirements in video surveillance systems and other practical applications with the integrated

combined segmentation of foreground and best background. The tracking results based on the routine loop of detecting the objects by using data association function and the new hypotheses function in Kalman Filter algorithm, beta likelihood matching provides a better result. The GMM-Likelihood Matching motion tracking algorithm effectively solves the influence of the lighting change, multi-target movements, the disappearing, mixing and shading of moving objects to the tracking effects. Application of the experimental results has proved the effectiveness and robustness of the algorithm. In future the motion detection and tracking achieved by our framework can further be used to find the trajectory of the motion, suspicious behaviour analysis and irregular motion detection.

REFERENCE

- [1]. A. Lipton, H. Fujiyoshi and R. Patil, "Moving target classification and tracking from real-time video," in Proc. of IEEE Workshop Application of Computer Vision, Los Alamitos, CA, Oct. 1998.
- [2]. A. Shafie, F. Hafiz, and M. Ali, "Motion detection techniques using optical flow," World Academy of Science, Engineering and Technology, 2009, vol.56, pp.559-561
- [3]. L. Wang, W. Hu, and T. Tan. Recent developments in human motion analysis. Pattern Recognition, 36(3):585-601, March 2003.
- [4]. N. Friedman and S. Russell, "Image Segmentation in Video Sequences: The 13th Conference on Uncertainty in Artificial Intelligence, Brown University, Rhode Island, Morgan Kaufmann Publishers, Inc., San Francisco, 1997, pp. 175-181.
- [5]. C. Stauffer and W. Grimson "Adaptive Background Mixture Models for Real-Time Tracking," Proceedings of IEEE Computer Vision and Pattern Recognition, Vol. 2, 1999, pp. 246-252.
- [6]. C. Stauffer and W. Grimson, "Learning Patterns of Activity Using Real-Time Tracking" IEEE Transactions on Pattern Analysis & Machine Intelligence, Vol. 22, No. 8, 2000, pp. 747-757.
- [7]. W. Grimson, C. Stauffer, R. Romano and L. Lee, "Using Adaptive Tracking to Classify and Monitor Activity in a Site," Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1998, pp. 22-29.
- [8]. Wren, R. Christopher, A. Azarbajejani, T. Darrell and A. Pentland, "Pfinder: real-time tracking of the human body", IEEE Transactions on Pattern Analysis and Machine Intelligence, 1997, 19(7), pp.780-785.
- [9]. O. Javed, K. Shafique and M. Shah. "A hierarchical approach to robust background subtraction using color and gradient information". in Proc. Of IEEE Workshop Motion Video Computing, Dec. 2002, pp.22-27.
- [10]. S. Zhang et al, "Dynamic background modeling and subtraction using spatio-temporal local binary patterns," in Proc. of IEEE Int. Conf. On Image Processing, 2008, pp.1556-1559.
- [11]. A. Elgammal, D. Harwood and L. Davis, "Non-parametric model for background subtraction," ECCV 2000 in computer vision, 2000,pp.751-767.
- [12]. Emadeldeen Noureldaim, Mohamed Jedra, Nouredine Zahid, "Multiple Tracking of Moving Objects with Kalman Filtering and PCA-GMM Method",in Scientific Research Intelligent Information Management, 2013,Vol 5,pp 42-47.
- [13]. Xu Zhao, Yun Fu, and Yuncai Liu, "Human Motion Tracking by Temporal-Spatial Local Gaussian Process Experts", IEEE transaction on image processing, Vol. 20, NO. 4, APRIL 2011,pp 1141-1151
- [14]. Hu Haibo, Zhao Hong, "Real-time Tracking in Image Sequences based-on Parameters Updating with Temporal and Spatial Neighbourhoods Mixture Gaussian Model", World Academy of Science, Engineering and Technology, 2010, Vol. 43, pp 754-759.
- [15]. <http://www.nada.kth.se/cvap/actions>.
- [16]. www.wisdom.weizmann.ac.il/~vision/SpaceTimeActions.html.
- [17]. <http://www.cs.berkeley.edu/~flw/tracker/stgeorge.html>.
- [18]. Mohamed F. Abdelkader, Rama Chellappa, Qinfen Zheng, "Integrated Motion Detection and Tracking for Visual Surveillance", Proceedings of the Fourth IEEE International Conference on Computer Vision Systems (ICVS 2006), 0-7695-2506-7/06
- [19]. Yafeng Yin, Hong Man, Jing Wang, Guang Yang, "Human Motion Change Detection by Hierarchical Gaussian Process Dynamical Model with Particle Filter", Seventh IEEE International Conference on Advanced Video and Signal Based Surveillance, 2010,pp 307-314.



Michael Kamaraj received the B.Sc. (Electronics) degree in 1997 and MCA degree in 2000 both from Bharathidasan University, Tiruchirappalli, Tamil Nadu, India. He is currently pursuing the Ph.D. degree at the Bharathiar university, Coimbatore, Tamil Nadu, India. He worked as a Assistant Professor at the various colleges from 2000 to 2008. In June 2008, he joined Pavendar Bharathidasan College of Engg. & Tech. as a Assistant Professor and Head. His research interest includes video analysis of human motion, image processing, pattern recognition, video surveillance.



Dr. G. Balakrishnan, M.E., Ph.D., is the Director, Indra Ganesan College of Engineering. He completed his B.E.(CSE) from Bharathidasan University, Trichy, M.E., (CSE) from PSG College of Technology, Coimbatore and Ph.D., (Image Processing) from University Malaysia Sabah, Malaysia. He has more than 10 years of Academic and Industrial experience. He has more than 40 publications in various international journals and conferences. His research interests are in image processing and computer vision, stereo image matching, pattern recognition, video surveillance.