ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, Vol 10(10), DOI: 10.17485/ijst/2017/v10i10/109692, March 2017 ISSN (Online) : 0974-5645

Improved Algorithm for Object Tracking in Video Camera Network

Mukesh Tiwari and Rakesh Singhai

Department of Electronics and Communication, Rajiv Gandhi Technical University, Bhopal – 462033, Madhya Pradesh, India; mukeshtiwari_79@yahoo.co.in, rksinghai@gmail.com

Abstract

Objectives: To develop a novel approach for tracking the object in multiple camera environments. The object tracking in situation of suspect person is the challenging task for a researcher for a long time. The situation get worst if the object hided beside any other object, or if the object moves from the range of camera span **Methods/Statistical Analysis:** The object is tracked using Optical Flow Estimation techniques in which magnitude along the gradient direction is observed. The threshold magnitude comparison of the images detects the desired target. **Findings**: Detection parameters in the our proposed methods such as SIMILARITY, F1, PRECISION, RECALL are better in comparison with the existing methods in existing methods viz RADCT, MSDE, SDE and SSD. The proposed algorithm can easily detect object even if it is either hided or it moves to the frame of camera 2, or any other camera installed within the same camera network. **Application/ Improvements:** The proposed methods tracked and detects the suspected object target for the application of safety and security system more accurately and better ease of implementation than other existing motion detection system such as RADCT, MSDE, SDE and SSD.

Keywords: Algorithm, CCTV Camera, MATLAB R2012B, Object Tracking, , Safety and Security

1. Introduction

We assemble a statistical representation of the scene background that helps sensitive detection of moving objects in the scene

Background modelling generates a platform for the image processing and it develops a stabilized back-ground in order to calculate the motion. In back-ground modelling we assemble a statistical representation of the scene background that helps sensitive detection of moving objects in the scene, but it is difficult to manage the static environment of back-ground in the different environment condition like morning ,evening , rainy condition, snowing season etc. Back-ground modelling is one of the milestones in the processes of motion detection.

1.1 Simple Background Subtraction (SBS)

In this method of back-ground modeling, both the reference image which are called as back-ground image $B_t(x,y)$ and existing video frames $C_t(x,y)$ which are gotten from video sequence and will get subtracted. Binary motion recognition mask D(x,y) is calculated as follows:

$$D_t(x,y) = \begin{cases} 1 & \text{if } |Ct(x,y) - Bt(x,y)| > £ \\ 0 & \text{if } |Ct(x,y) - Bt(x,y)| < £ \end{cases} \quad (1)$$

where, £ is the predefined threshold parameter. On upon the difference of current and background pixels of frame are less then threshold £, then binary mask is zero, which refers no motion, if this difference is greater than £, the binary mask refers motion. This method does not respond accurately when noise and static image comes in current frame $\mathbf{C_t(x,y)}$ in real time video sequences. **Bt(x, y)** is the reference frame which is representing the fixed background mode.[1]

1.2 Running Average (RA)

This method overcomes the problem[2] of SBS up to great extent and it gives the environment to produce the adap-

**Author for correspondence*

tive background model to adapt to momentary variations occurred in the video sequence. RA is differentiated from SBS in the sense that it can update each background image frame **Bt (x, y)** by running following average:

$$Bt(x,y) = Bt-1(x,y) + \beta Ct(x,y) - \beta Bt-1(x,y) \qquad (2)$$

The preceding background frame $\mathbf{B_{t-1}(x, y)}$ and unique arriving video frame $\mathbf{C_t(x, y)}$ are combined with the existing background image results in the adaptive background model which is achieved using the above formula.

In above formula, **β** is an empirically flexible parameter whose massive coefficient β leads to a quicker background updating velocity; it could additionally causes the creation of artificial trails back of the shifting of moving objects in the background model. After the modelling the adoptive background binary movement, detection mask is advanced which is as follows:

$$D_t(x,y) = \begin{cases} 1 & \text{if } |Ct(x,y) - Bt(x,y)| > £ \\ 0 & \text{if } |Ct(x,y) - Bt(x,y)| < £ \end{cases} \qquad (3)$$

Where, **Ct (x, y)** is the existing received video frame, **Bt (x, y)** is the existing background model, and **£** is an experimentally predefined verge to create the binary movement detection[3].

1.3 Sum and Difference Estimation (SDE)

SDE[4] possess better approach of back-ground modelling in which **sgn (signum)** function is used to evaluate the back-ground intensity. The **sgn** function is expressed as follows.

$$sgn(a) = \begin{cases} 1 & \text{if } a > 0 \\ 0 & \text{if } a = 0 \\ -1 & \text{if } a < 0 \end{cases} \qquad (4)$$

Where a is the input real value. Then the background estimation formula is expressed as follows:

$$Bt(x,y) = Bt-1(x,y) + sgn(Ct(x,y) - Bt-1(x,y)) \qquad (5)$$

Where Bt(x,y) is the current background frame, Bt–1(x,y) is the previous background frame, and Ct(x,y) is the current incoming video frame. As the value of sgn function adds 1 or -1 to the pixel value of background frame. There is an absolute difference of image intensity [Δt (x, y)] can be calculated as the estimative difference between Ct (x, y) and Bt (x, y) which is follows:

$$\Delta t(x, y) = |Ct(x, y) - Bt(x, y)| \qquad (6)$$

In a similar fashion, the time-variance Vt (x, y) is calculated by utilizing the sgn function which measures motion activity in order to determine whether each pixel should be designated as "background" or "motion object."

$$Vt(x, y) = Vt-1(x, y) + sgn(N \times \Delta t(x, y) - Vt-1(x, y)) \qquad (7)$$

Where Vt (x, y) is the current time-variance, Vt−1 (x, y) is the previous time-variance, and N is the predefined parameter which ranges from 1 to 4. Based on the generated current time-variance Vt (x, y), the binary motion detection mask D(x, y) is detected as follows.

$$D_t(x,y) = \begin{cases} 1 & \text{if } \Delta t(x,y) > Vt(x,y) \\ 0 & \text{if } \Delta t(x,y) \le Vt(x,y) \end{cases} \qquad (8)$$

SDE is relatively better than RA method, Background updation in constant time period is important feature of SDE method. There are small issues while working with SDE which is handling of some complex scenes, as many moving objects are constituents one scene refers to difficulty in SDE.

1.4 Multiple Sum and Difference Estimation (MSDE)[5]

MSDE method is similar up to some extend with the RUNNING AVERAGE method. The method of background modelling is somehow similar, the only difference is, it uses sgn function and model the back-ground by taking the some series of frames.

$$b^i_t(x,y) = b^i_{t-1}(x,y) + sgn(b_t^{i-1}(x,y) - b^i_{t-1}(x,y)) \qquad (9)$$

Where $b^i_t(x, y)$ is existing i^{th} reference back-ground, $b^i_{t-1}(x,y)$ is preceding reference i^{th} background , $b_t^{i-1}(x,y)$ is the current $(i-1)^{th}$ reference background. Addition to this reference difference $\Delta^i_t(x,y)$ and reference time variance $v_t^i(x,y)$ are calculated as follows:

$$v_t^i(x,y) = v_{t-1}^i(x,y) + sgn(N * \Delta^i_t(x,y) - v_{t-1}^i(x,y)) \qquad (10)$$

Where $\Delta^i_t(x,y) = |C_t(x,y) - B^i_t(x,y)|$ Now with the use of $v_t^i(x,y)$ $b^i t(x, y)$ we can calculate $B_t(x,y)$.

$$B_t(x, y) = \Sigma[i = 1, R] \frac{\frac{\alpha_i \; b_t^i(x,y)}{v_t^i(x,y)}}{\frac{\alpha_i}{v_t^i(x,y)}} \qquad (11)$$

Where the α_i is predefined variable, i is the reference frame number, and $B_t(x,y)$ is the adoptive background frame. R is the total number of i, according to [4] experimentally it is [3].

$$\Delta t(x, y) = |Ct(x, y) - Bt(x, y)| \quad (12)$$

The time-variance $Vt(x, y)$ is calculated by utilizing the sgn function which measures the motion activity in order to determine whether each pixel should be designated as "background" or "moving object" or not.

$$Vt(x, y) = Vt-1(x, y) + sgn(N \times \Delta t(x, y) - Vt-1(x, y)) \quad (13)$$

where $Vt(x, y)$ is the current time-variance, $Vt-1(x, y)$ is the previous time-variance, and N is the pre-defined parameter i.e. ranges from 1 to 4. Based on the produced existing time-variance $Vt(x, y)$, motion detection mask $D(x, y)$ is detected as follows:

$$D_t(x, y) = \begin{cases} 1 & \text{if } \Delta_t(x, y) > V_t(x, y) \\ 0 & \text{if } \Delta_t(x, y) \leq V_t(x, y) \end{cases} \quad (14)$$

1.5 Simple Statistical Difference (SSD)[6]

SSD scheme refers to average significance & benchmark deviation and develops an environment for background modelling, through computing the average value for the distinct pixels of the preceding video frames. The background image has been produced by each pixel value $\Gamma_{x,y}$ of preceding frames in the time interval of (t_0, t_{k-1}). For each pixel, a threshold is also defined by the standard deviation σ_{xy} for the same interval.

$$\Gamma_{x,y} = \frac{1}{j}\sum_{j=0}^{j-1} j_t(x, y) \quad (15)$$

$$\sigma_{xy} = \sqrt[2]{\frac{1}{j}\sum_{j=0}^{j-1} (j_l(x, y) - \Gamma(x, y))^2} \quad (16)$$

To accomplish motion detection, the entire difference between the inward video frame and the background model is calculated. Predefined parameter defined by λ, i.e. multiplied by average value of pixels and decides the movement. If the absolute difference is less or equal to $\lambda^*\sigma_{xy}$, it denotes no motion:

$$D_t(x, y) = \begin{cases} 1 & if\ |Ct(x, y) - \Gamma x, y| > \lambda\ \sigma xy \\ 0 & if\ |Ct(x, y) - \Gamma x, y| \leq \lambda\ \sigma xy \end{cases} \quad (17)$$

1.6 RA with DCT Domain (RADCT)

The RADCT algorithm[7] is similar to the RA[2] method which we have discussed earlier; it differs with the method RA in the sense that it calculates the DCT of the each pixel block instead of pixel average[8]. In this manner model the adaptive background in the DCT domain. The adaptive background model is prepared by:

$$d_t^{B,K} = (1 - \beta)\, d_{t-1}^{B,K} + \beta d_t^{K} \quad (18)$$

Where β is an empirically adjustable parameter much like that used inside the conventional RA algorithm[9], d_t^K denotes the DCT coefficient vector of the k^{th} pixel block for the contemporary incoming video body, $d_t^{B,K}$ denotes the history estimation of the k_{th} pixel block in the DCT domain, and $d_{t-1}^{B,K}$ denotes the previous heritage estimation in the DCT area. While big coefficient β leads to a quicker background updating velocity, it also causes the creation of artificial trails in the back of shifting objects within the heritage model. Now after the modelling the adoptive back-ground, binary motion detection masks is develops as follows.

$$D_t(x, y) = \begin{cases} 1 & if\ \ d_t^k - d_t^{B,K} > \hat{o} \\ 0 & if\ \ d_t^k - d_t^{B,K} < \hat{o} \end{cases} \quad (19)$$

$D_t(x,y)$ =1, represent motion is detected, $D_t(x,y)$=0 means no motion.

It is much faster than traditional RA method, here each pixel block is designated by a DCT coefficient vector instead of pixel value so the computational complexity is reduced, and computation is directly of DCT's of frames.

1.7 Temporal Median Filter

Temporal median[9] represents the average of preceding frames in a given sequence of video to generate a stable background model for simple background subtraction. The first application of temporal median background update technique[10] became for congestion recognition of underground stage. This method is also very much applicable in generating a stable background for sudden changes of intensity in the certain scenes[8]. Temporal median filter method have less memory requirement although it is working at high data rate, that's why it is use full in many computer vision systems[11-15]. Consequently, it is the most popular background subtraction approaches. Became for congestion detection of underground platform.

1.8 Background Modelling Using Mixture of Gaussians[16]

In situation of a movement surveillance scheme, Friedman and Russel proposed[17] to model each background pixel using a mixture of three Gaussians similar to road, vehicle and shadows. Then, the Gaussians are manually labelled in a heuristic manner as follows: the darkest component is labelled as shadow; in the remaining two components, the one with the biggest variance is labelled as vehicle and the other one as road. This stays fixed for all the procedure. For the foreground detection, each pixel is compared with each Gaussian and is classified according to it corresponding Gaussian.[18]

2. Proposed Algorithm

The proposed algorithm is used in the CCTV surveillance system where the challenging task is to track the object in multiple camera frames. In case if object partially occlude beside any object, then its apparent in the frame will automatically track. When person moves from one camera frame to another, it will automatically get track into that frame.

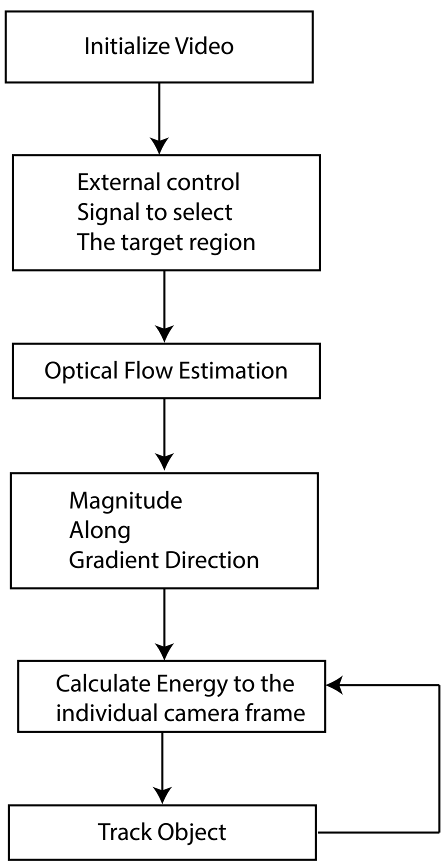

Figure 1. Flow Chart of the Object Selection in the Frame.

Figure 1 Shows Flow chart of Object selection in frame by using external control of the signal to select the target region for finding the possible route we approaches to Optical Flow Estimation and take Magnitude and Gradient Direction of frame based on that we Calculate Energy level for the individual camera frame to Track the Object.

Figure 2 Shows the Flow chart for Object tracking, in the target area we calculate the threshold and will do the segmentation and leveling of the object then calculating the centroid of the target picture frame and video separately.

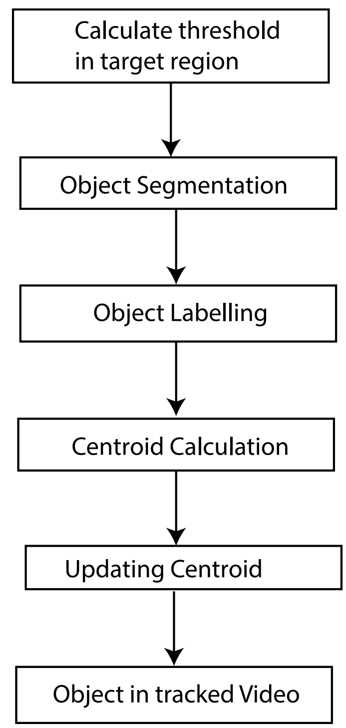

Figure 2. Flow Chart for Object Tracking.

So many methods have been presented to localize the moving body in scene. In this work, the background detection is adopted due to its better ease of implementation than other motion detection system. Background subtraction approach is beneficial in fixed camera arrangement system due to the easily available static background information. In addition to that, it produces sufficient amount of information of the moving blobs for its fast processing that produces more easy information than corner and edges. Such an approach requires less time and memory complexities than the other existing method for moving object segmentation.

In this method, the work is aimed to use background frames for the object detection by accompanying the background updating scheme. It is noted that, the person is switched from one background environment to other background environment. To detect the object, successfully in different background environment, the two separate background frames are handled.

For the experimental purpose, we have considered two separate recorded footage of CCTV. These two video may be simultaneously accessed in the sequences. However, in that case, an extra shot detection process would be needed under such circumstances. The background subtraction task begins by calculating, a reference background frame using. Some initial frames of video sequence in which no moving object has been seen.

Two separate background frames are handled to detect the object under different background conditions. In this work, $B_A^{ref}(x,y)$ is initial reference background frame under first background condition, while $B_B^{ref}(x,y)$ is second reference background body.

The $B_A^{ref}(x,y)$ and $B_B^{ref}(x,y)$ are generated for the distinct camera sequences using taking some initial frames. First an average of k frames are taken through first camera to generate a temporary frame $T_A(x,y)$.

$$T_A(x,y) = \frac{1}{K}\sum_{n=1}^{k} I_n(x,y) \tag{20}$$

Where $I_n(x,y)$ is existing frame.

A temporary frame $T_B(x,y)$ is generated for the second cameras using the modified moving appropriate as follows:

$$I_n(x,y) = I_n(x,y) + \frac{1}{K-1}\sum_{n=1}^{k-1} I_n(x,y) \tag{21}$$

The final initial reference frames have been generated by averaging the equation (20) and (21).

$$B_A^{ref} = \frac{T_A(x,y)+T_B(x,y)}{2} \tag{22}$$

In the background subtraction scheme, an object is detected by subtracting the background reference frame $B_A^{ref}(x,y)$ using a suitable threshold.

The approximate moving pixels are detected using the equation as follows:

$$C_t(x,y) = |I_t(x,y) - B_t^{ref}(x,y)| \tag{23}$$

The object and background pixels are threshold out using a suitable threshold:

$$C_t(x,y) = \begin{cases} 1 \; if \; |I_t(x,y) - B_t^{ref}(x,y)| > \hat{o}_1 \\ 0 \; if \; |I_t(x,y) - B_t^{ref}(x,y)| < \hat{o}_1 \end{cases} \tag{24}$$

The threshold value is calculated as follows:

$$\hat{o} = mean\left(C_t(x,y) + K.Std(C_t(x,y)\right) \tag{25}$$

The 'K' is estimated as:

$$K = \frac{abs\,|I_t(x,y) - B_t^{ref}(x,y)|}{B_t^{ref}(x,y)} \tag{26}$$

A background updating procedure is necessary to produce a suitable motion mask on the foreground. Moreover, an updating scheme is also necessary to adapt the changing environmental condition for a suitable foreground and background classification. The update is done using recursive temporal filter. The current background is estimated as:

$$B_t^{ref}(x,y) = \begin{cases} \hat{a}B_A^{ref}(x,y) + (1-\hat{a})\left(I_t(x,y) - B_A^{ref}(x,y)\right) if \; R_t(x,y) > \hat{o}_2 \\ B_A^{ref} \quad else \end{cases} \tag{27}$$

$$R_t(x,y) = |I_t(x,y) - B_A^{ref}(x,y)| \tag{28}$$

Where $B_A^{ref}(x,y) = B_t(x,y)$

The threshold $\hat{o}_2$ is defined using the mean of $R_t(x,y)$.

The similar procedure is followed when the object falls under second camera environmental condition. Switching from first background condition to second background condition is done on the base of entropy.

The global entropy of the difference image is evaluated at each stage of the generated approximate moving pixels. It is known that the dark region has low entropy than the bright region, whenever the no object is subjected to present in the scene, the entropy of the system will be very low. At this stage, the second background frame will be selected to start the object extraction procedure.

Entropy of the system is defined as:

$$E_t(x,y) = -\sum P(x,y)\log P(x,y) \tag{29}$$

The probability *P(x,y)* is calculated using the histogram of the difference image generated through equation (23).

An optical flow constraint is also imposed into the switching mode mechanism to incorporate the object detection task. Optical flow reflects the approximation of the local motion into a video frame using the local derivatives. We have utilized Lucas kanade approach to calculate the velocity components of moving object[19]. At time 't' and 't+δt', the motion between the pixels in the frame is calculated. The intensity change between two time instant can be given using following equation

$$I(x,y,t) = I(x+\delta t, y+\delta y, t+\delta t) \quad (30)$$

Using Taylor series, higher order terms are eliminated of above equation. Equation can be written as follows

$$\frac{dI}{dx}V_x + \frac{dI}{dy}V_y + \frac{dI}{dt} = 0 \quad (31)$$

$$(I_x \quad I_y)\begin{pmatrix} V_x \\ V_y \end{pmatrix} = -I_t \quad (32)$$

Where, V_x and V_y are velocity gradient along x and y direction.

above equation is solved using least square method as follows –

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = \begin{bmatrix} \sum I_{x_i}^2 & \sum I_{x_i} I_{y_i} \\ \sum I_{x_i} I_{y_i} & \sum I_i^2 \end{bmatrix} \begin{bmatrix} -\sum I_{x_i} \sum I_{t_i} \\ -\sum I_{y_i} \sum I_{t_i} \end{bmatrix} \quad (33)$$

The magnitude of the optical flow value is calculated as-

$$M_n(i,j) = \sqrt{V_x^2(i,j) + V_y^2(i,j)} \quad (34)$$

The magnitude $M_n(i,j)$ is also used to sense the presence of object in the scene and cooperated to switch from one background condition to another background condition. The object tracking module is incorporated by calculating and updating the centroid of the object.

Initially, the centroid of the object is calculated that belongs to a reference or previous centroid and a bounding box is plotted to reflect the target[20-21]. At each subsequent stage, the centroid of the object is calculated at current position of centroid is subtracted from previous centroid position and a distance is calculated using Euclidian distance formula. If the distance is above the threshold, the previous centroid is updated with the current centroid[22-24].

3. Result & Discussion

In this section, some video sequences have been taken to evaluate the performance of the proposed methodology. The video sequences S1 and S2 have been analyzed qualitatively and quantitatively, while for the other two S3 and S4, the quantitative performance has been presented. The sequence S1 is the office sequence of, in which the person is tracked under multi-camera view arrangement. In the sequence S2, the sequences have taken of the multi-camera of college corridor. It is noted that, the sequences S1 and S2 have different background scene. The qualitative performance of sequence S1 is shown in Figure 3 by tracking accurately the object in the scene despite the complexity produced by the multiple background frames. Figures 3, 4 and 5 show-(Video sequence of Office with track results under multi-camera arrangement) the person tracking on some sampled frame of sequence S1. The motion mask of the S2 sequence has also been evaluated accurately without any high frequency noise, holes, and aperture distortion.

Figure 3 Multicamera view Person in Camera 1 Seq: S1

Figure 4 Multicamera view Person in Camera 2 Seq: S1

Figure 5 Multicamera view Person in Camera 3 Seq: S1

Figure 6 shows the results of motion mask evaluated on first camera view. Figure, first row shows the sample frame with tracked results, while second row shows the ground truth (idea segmentation of object), the last row shows the output through proposed method.

Figure 7 Shows Motion mask evaluated on first camera arrangement, this include the four sample picture frames firstly we show the actual picture without introducing the algorithm and later we introduce the Motion mask using proposed algorithm method[25].

Figure 6. Background Frame and Sample Frame of MANIT College Corridor Sequence.

Figure 8 Shows Motion mask evaluated on second camera arrangement, this include the four sample picture frames firstly we show the actual picture without introducing the algorithm and later we introduce the Motion mask using proposed algorithm method.

The performance of the experimental video sequences has been evaluated quantitatively through four parameter, Precision, Recall (Detection rate (DR)), F1 and Similarity[26]. The Precision and Recall metric are given as follows:

$$Precison = tp/(tp + fp) \quad (35)$$

$$Recall = tp/(tp + fn) \quad (36)$$

Where, 'tp' is the true positive pixels, 'fp' is the false positive pixels, 'fn' is the false negative pixels.

The F1 and Similarity metrics are defined as follows:

$$F1 = 2 * Precision * Recall/(Precison + Recall) \quad (37)$$

$$Similarity = tp/(tp + fp + fn) \quad (38)$$

Figure 9. Performance comparison of proposed method with other method in term of F1 metric (a) S1 sequences (b) S2 sequences. The proposed method has good F1 values for both the sequences. The motion mask has evaluated properly for both the sequences with high accuracy than other existing methods.

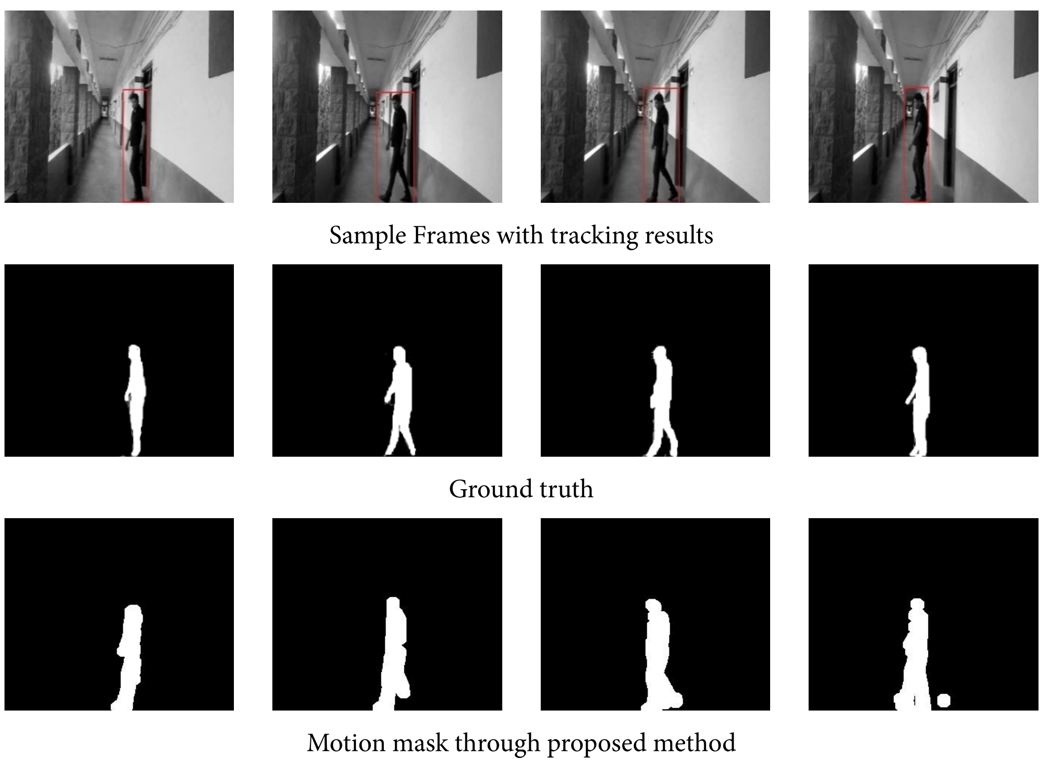

Figure 7. Motion Mask Evaluated on First Camera Arrangement (Kumar S, Yadav J S. Video Object Extraction and its Tracking Using Background Subtraction in Complex Environments. Engineering and Material Sciences. 2016, Vol.8)[26].

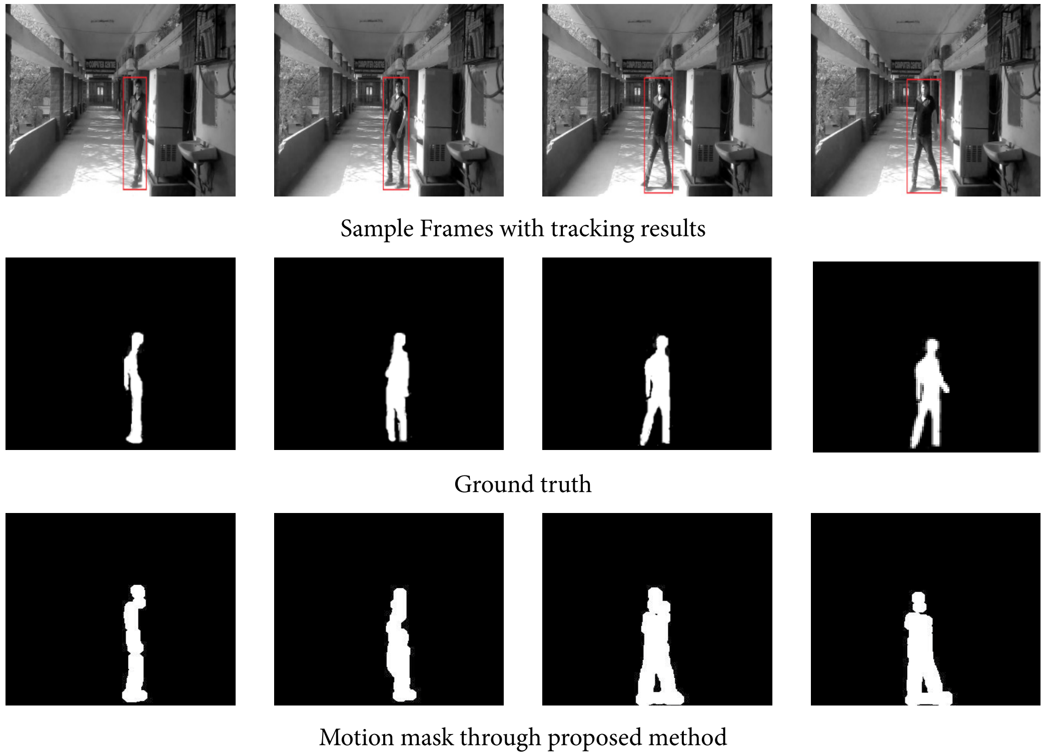

Figure 8. Motion Mask Evaluated on Second Camera Arrangement.

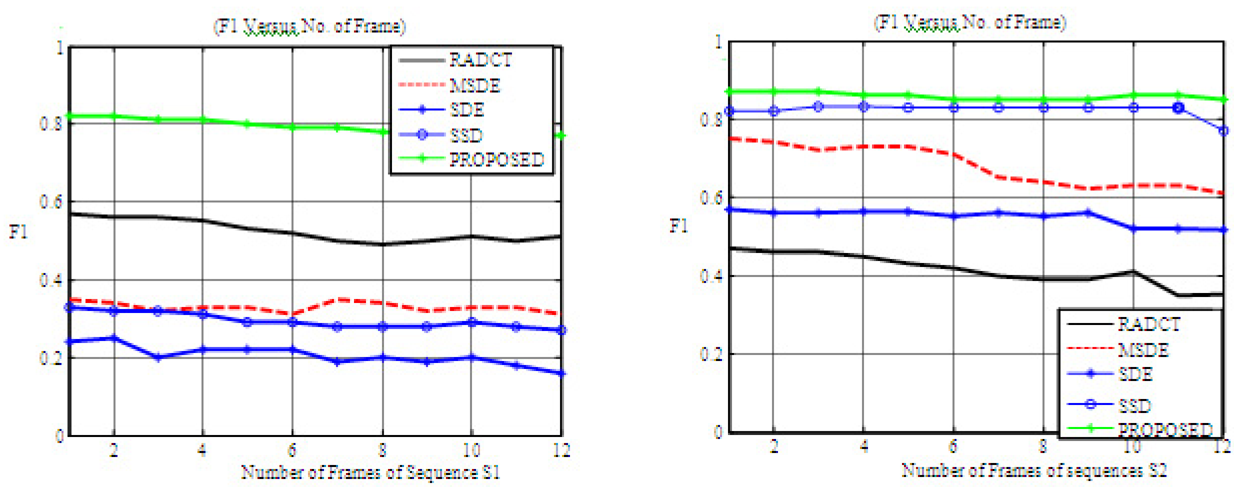

Figure 9. Performance Comparison of Proposed Method with other Method in Term of F1 Metric (a) S1 Sequences (b) S2 Sequences

Figure 10. Performance comparison of proposed method with other method in term of Detection Rate metric (a) S1 sequences (b) S2 sequence., It can be seen that the proposed technique is capable of detecting relevant pixels of object only on the foreground frame.

Table 1 Result of the various parameters obtained with proposed algorithm. It can be concluded from the table that when working on the S1 sequence, whose result is shown in Figure 3, 4, and 5, Similarity for the proposed method is found to be 0.6599 which is the best when compared with other available approaches. In the same way, F1, Precision, & Recall are showing in the table justifies that the proposed algorithm is better than the available ones.

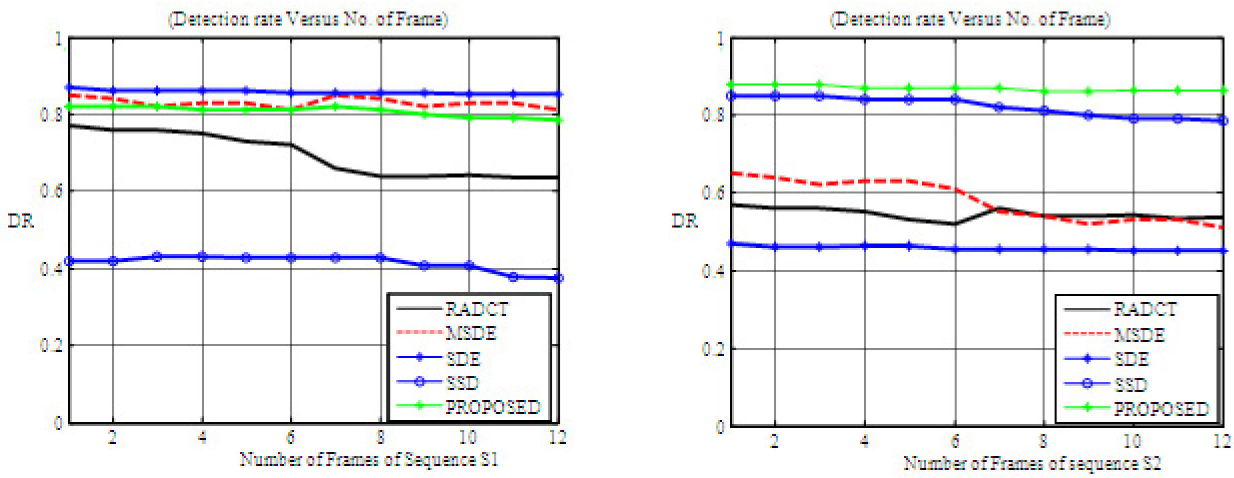

Figure 10. Performance Comparison of Proposed Method with Other Method in Term of Detection Rate Metric(a) S1 Sequences (b) S2 Sequence.

Table 1. Result of Proposed Algorithm for various sequences

Sequence	Parameter	PROPOSED	RADCT	MSDE	SDE	SSD
S1	SIMILARITY	**0.6599**	0.4058	0.2120	0.1528	0.1810
	F1	**0.7917**	0.5744	0.3390	0.2574	0.2936
	PRECISION	**0.7864**	0.4959	0.2257	0.1594	0.2814
	RECALL	0.8025	0.7001	**0.8344**	0.8328	0.3900
S4	SIMILARITY	**0.7660**	0.3874	0.5408	0.3521	0.7213
	F1	**0.8669**	0.5561	0.6977	0.5197	0.8340
	PRECISION	**0.8684**	0.6109	0.8665	0.7406	0.7994
	RECALL	0.8673	0.5311	0.5938	0.4073	**0.8756**
S3	SIMILARITY	**0.5473**	0.5079	0.3845	0.3076	0.3470
	F1	**0.7061**	0.6718	0.5516	0.4661	0.5125
	PRECISION	0.7044	0.6291	**0.7788**	0.7697	0.3648
	RECALL	0.7113	0.7338	0.4281	0.3355	**0.8739**
S2	SIMILARITY	0.8077	0.4463	0.5138	0.3774	0.4559
	F1	0.8929	0.5988	0.6652	0.5328	0.6185
	PRECISION	0.8665	0.6449	0.6651	0.4800	0.7141
	RECALL	0.9246	0.5814	0.7041	0.6224	0.5689

4. Conclusion

This research proposed a novel algorithm for object tracking in multiple camera frames. The result of the proposed algorithm is compared with RADCT, MSDE, SDE, and SSD. The experimental result of the proposed algorithm has shown that the proposed algorithm is tracks the object in better way as compared to the existing approaches. The advantage of the proposed algorithm is that even if an object hidden besides any other object, then its first appears in the frame will automatically be detected. The flow chart of the algorithm shows the detail steps of the proposed work. The direction of movement is the key parameter in the tracking of object, when object moves from one frame to another. The proposed algorithm can be extended for multi object tracking in same environment. It can be used for varying background environment.

5. References

1. Oral M, Deniz U. Centre of Mass Model–A Novel Approach to Background Modelling for Segmentation of Moving

Objects. Image and Vision Computing. 2007,25(8):1365–76. Crossref

2. Wren CR, Azarbayejani A, Darrell T, Pentl, Pfinder AP. Real-Time Tracking of the Human Body. Pattern Analysis and Machine Intelligence, IEEE Transactions.1997,19(7): 780–5.
3. Stauffer C, Grimson WEL. Adaptive Background Mixture Models for Real-Time Tracking. Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference. 1999, Vol. 2. Manzanera A, Richefeu J. A robust and computationally efficient motion detection algorithm based on sigma-delta background estimation. Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP'04). (2004). Kolkata, India.< hal-01222695>.
4. Hue C, Le Cadre JP, Pérez P. Sequential Monte Carlo Methods for Multiple Target Tracking and Data Fusion. Signal Processing, IEEE Transactions. 2002; 50(2): 309–25.
5. Yilmaz A, Javed O, Shah M. Object tracking A survey. ACM Computing Surveys (CSUR). 2006; 38(4):13.
6. Wang W, Yang J, Gao W. Modeling Background and Segmenting Moving Objects from Compressed Video. Circuits and Systems for Video Technology, IEEE Transactions. 2008; 18(5): 670–81.
7. Zang Q, Klette R. Parameter Analysis for Mixture of Gaussians Model. CITR, The University of Auckland: New Zealand. 2006.
8. Shoushtarian B. A Practical Approach to Real-Time Dynamic Background Generation Based on a Temporal Median Filter. Journal of Sciences, Islamic Republic of Iran. 2003; 14(4): 351–62.
9. Lo BPL, Velastin SA. Automatic Congestion Detection System for Underground Platforms. Proceedings of 2001 International Symposium. 2001. p. 158–61. Crossref
10. Sen-Ching SC, Kamath C. Robust Techniques for Background Subtraction in Urban Traffic Video. Electronic Imaging 2004. International Society for Optics and Photonics. 2004 January. p. 881–92.
11. Cutler R, Davis L. View-Based Detection and Analysis of Periodic Motion. Icpr.1998 August. P.495.
12. Zhou Q, Agrawal JK. Tracking and Classifying Moving Objects from Video. Proceedings of IEEE Workshop on Performance Evaluation of Tracking and Surveillance, Hawaii, USA: 2001 December.p.46–54.
13. McFarlane NJ, Schofield CP. Segmentation and Tracking of Piglets in Images. Machine Vision and Applications. 1995; 8(3):187–93. Crossref
14. Cai J, Shehata M, Badawy W. A Robust Video-Based Algorithm for Detecting Snow Movement in Traffic Scenes. Journal of Signal Processing Systems. 2009; 56(2-3): 307–326. Crossref
15. Bouwmans T, El Baf F, Vachon B. Background Modelling Using Mixture of Gaussians for Foreground Detection-a Survey. Recent Patents on Computer Science. 2008; 1(3): 219–237. Crossref
16. Dempster A P, Laird NM, Rubin DB. Maximum Likelihood from Incomplete Data via the EM Algorithm. Journal of the Royal Statistical Society. Series B (Methodological). 1977; 1–38.
17. Atev S, Masoud O, Papani Kolopoulos N. Practical Mixtures of Gaussians with Brightness Monitoring in Intelligent Transportation Systems. Proceedings. The 7th International IEEE Conference. 2004 October. p. 423–8.
18. Lucas BD, Kanade T. An Iterative Image Registration Technique with an Application to Stereo Vision. IJCAI, Vancouver (British Columbia). 1981; 81: 674–79.
19. Nikolov B, Kostov N. Motion Detection Using Adaptive Temporal Averaging Method. Radio Engineering. 2014; 23(2): 652–658.
20. Fuzx Ha. Centroid Weighted Kalman Filter for Visual Object Tracking. Journal of Measurement. 2012;45:50–5. Crossref
21. Weng SK, Kuo CM, Tu SK. Video Object Tracking Using Adaptive Kalman Filter. Journal of Visual Communication and Image Representation. 2006;17:1190–208 Crossref
22. Yao Li, Ling M. An Improved Mixture-of-Gaussians Background Model with Frame Difference and Blob Tracking in Video Stream. The Scientific World Journal. 2014;1–9.
23. Mandellos NA, Keramitsoglou I, Kiranoudis CT. A Background Subtraction Algorithm for Detecting and Tracking Vehicles. Expert Systems with Applications. 2011; 38: 1619–163. Crossref
24. Kumar S, Yadav JS. Video Object Extraction and its Tracking Using Background Subtraction in Complex Environments. Engineering and Material Sciences. 2016;8: 317–22. Crossref
25. Rahman FYA, Hussain A, Zaki, et al. Enhancement of Background Subtraction Techniques Using a Second Derivative in Gradient Direction Filter. Journal of Electrical and Computer Engineering. 2013;21:1–12. Crossref