Quantized Kalman Filter-Based Pattern Matching for Detection and Tracking of Moving Objects

Matheswari Rajamanickam

***Abstract** – Detection And Tracking Of Multiple Moving Objects From A Sequence Of Video Frame And Obtaining Visual Records Of Objects Play An Important Role In The Video Surveillance Systems. Transform And Filtering Technique Designed For Video Pattern Matching And Moving Object Detection, Failed To Handle Large Number Of Objects In Video Frame And Further Needs To Be Optimized. Several Existing Methods Perform Detection And Tracking Of Moving Objects. However, The Performance Efficiency Of The Existing Methods Needs To Be Optimized To Achieve More Robust And Reliable Detection And Tracking Of Moving Objects. In Order To Improve The Pattern Matching Accuracy, A Quantized Kalman Filter-Based Pattern Matching (Qkf-Pm) Technique Is Proposed For Detecting And Tracking Of Moving Objects. The Present Phase Includes Three Functionalities: Top-Down Approach, Kernel Pattern Segment Function And Kalman Filtering. First, The Top-Down Approach Based On Kalman Filtering (Kf) Technique Is Performed To Detect The Chromatic Shadows Of Objects. Next, Kernel Pattern Segment Function Creates The Seed Points For Detecting Moving Object Pattern. Finally, Object Tracking Is Performed Using The Proposed Quantized Kalman Filter Based On The Center Of Seed Point Affinity Feature Values Are Used To Track The Moving Objects In A Particular Region Using The Minimum Bounding Box Approach. Experimental Results Reveals That The Proposed Qkf-Pm Technique Achieves Better Performance In Terms Of True Detection Rate, Pattern Matching Accuracy, Pattern Matching Time, And Object Tracking Accuracy With Respect To The Number Of Video Frames Per Second.*

***Keywords:** Moving object detection, tracking, Quantized Kalman Filter, Pattern Matching, Top-down approach, kernel pattern, seed point, bounding box.*

I. INTRODUCTION

Moving object detection and tracking is a popular research area in computer vision due to its wide applications in the intelligent video surveillance, human motion analysis, human–computer interaction and augmented reality. There are a few factors making this problem extremely challenging.

In [1], Scale Invariant Feature Transform technique (SIFT) method is introduced for point extraction and matching. This method effectively locates regions of the image where a residual motion occurs. However, color information is not involved for a robust point matching strategy. More local and global features, such as object contour and geometrical relationship, can be applied to trade of noise and image distortion. In [2], an Enhanced Rao-Blackwellized Particle Filter (E-RBPF) is introduced for multiple target detection and tracking. However, this method failed to track large number of targets in crowded areas.

In [3], an efficient ATI-GoDec approach is introduced for detecting the moving targets. But it takes more time to detect the object in video frames. In [4], an on- line sequential framework called as Contiguous Outliers Representation via Online Low-Rank Approximation (COROLA) is introduced for detecting the moving objects and determining the background model simultaneously. However, this approach failed in case of severe illumination changes.

In [5], an improved moving object detection algorithm, which combines frame difference with background subtraction is introduced. However, this method is applicable only in the case of fewer moving objects and longer background. In [6], a robust object tracking based on Simplified Codebook Masked Camshift algorithm (SCMC) is introduced for improving the object detection rate. But, the method loses its efficiency in case of rapid background changes and it may track a false object if two objects have quite similar colors.

In [7], A robust moving object detection technique is introduced which adjusts to the motion of the camera in an unstable environment. However, the erroneous object regions were detected outside of the image. These errors are caused by the lens distortion with the increased error of the affine transform towards the outside of the image.

In [8], cognitive and statistical information is combined to interpret and disambiguate the uncertainties occurred due to complicated situations in tracking. However, investigating the object specific actions and event interpretation in dynamic scenes needs to be improved.

In [9], an integrated analysis of object descriptors and appearance model is introduced. However, this method focuses only at the level of the appearance model and is not focused on object detection. In [10], a synthetic algorithm for tracking a moving object in a multiple-dynamic obstacles environment based on kinematically planar manipulators was introduced. This method is feasible only to track a moving object in a multidynamic obstacle environment.

Therefore, to overcome these issues in detecting and tracking of moving objects, a Quantized Kalman Filter based pattern matching (QKF-PM) technique is proposed. The contribution of the paper is described as follows,

Revised Manuscript Received on October 15, 2019.

Matheswari Rajamanickam, Assistant Professor, Department of Computer Science, M.E.S College of Arts, Commerce and Science, Bangalore, Karnataka, India. (Email: matheswarir@gmail.com)

- QKF-PM technique is introduced to improve the pattern matching accuracy. Initially, input video file are extracted in to sequence of frames. Next, the chromatic shadows of objects are identified using top-down approach from the input video frame to detect the moving objects in a particular time.

Next, the associations between the foreground and shadow of objects are identified in order to reduce the false shadow detection.

- Kernel pattern segment function is used to formulate the seed point for detecting the moving objects in the sequence of frames. Then the Euclidean distance (D) between the two seed points are measured to classify the seed point of both the foreground and background. Next, the foreground seed point of the first and the successive frames are measured to perform the pattern matching. Then the detected moving objects are marked in a bounding box.
- Kalman filter based on the center of seed point affinity features are used for identifying the moving objects' search region to track the object within the bounding box more accurately.

The rest of the paper is organized as follows: Section 2 discusses the reviews related to the research works. Section 3 presents the QKF-PM technique. Section 4 presents the experimental setup. Section 5 presents experimental results and discussion. Section 6 presents conclusion and future works.

II. RELATED WORKS

A normalized human height estimation algorithm using an uncalibrated camera was introduced in [11]. The normalized human height is estimated using multiple uncalibrated cameras. The proposed method can be applied to object tracking and recognition in a very-large area video surveillance system.

A new object detection method for image matching and coupling was presented in [12]. However, this method is not fastest enough. An optimized coupling framework called couple control theory needs to be incorporated.

A general purpose method which combines the advantage of spatio-temporal differencing with the basic background subtraction method was introduced in [13]. However, locating multiple moving objects separately in the real time scenarios is still promising.

An algorithm based on the Sum of Squared Difference (SSD) and an adaptive template matching to enhance the quality of the template matching in object tracking was introduced in [14]. However, SSD is not robust against strong illumination changes.

The moving object detection and tracking using reference background subtraction model was presented in [15]. However, the chromatic shadow of objects remains unaddressed.

A novel method was introduced in [16] for the detection of moving objects in surveillance applications which combines adaptive filtering technique with the Bayesian change detection algorithm. However, the algorithm is not able to recognize a motionless foreground unless it starts moving again. Also many foreground pixels are misclassified when a color similarity exists between foreground and background.

An efficient background subtraction algorithm was introduced in [17] to support the object-tracking task under static and dynamic background conditions. However, the method needs to be implemented in better localization of moving or stationary object than other background subtraction schemes used for tracking.

An algorithm which uses the matching trajectory to realize the target tracking based on the Gaussian mixture model was introduced in [18]. However, it failed to track the targets effectively when the targets were large.

A tracking algorithm based on adaptive background subtraction model was presented in [19]. A framework for active contour-based visual tracking using level sets was introduced in [20]. However, these methods require embedding pattern matching techniques for improved accuracy.

A review on moving object tracking in video was presented in [21]. The paper discusses about novel tracking methods which is classified into many categories for recognizing and tracking the objects. The Bayesian filter approximation was applied for multiple targets tracking in [22]. Bayesian filter approximation was employed for associating the simultaneous object detection and tracking with variation approximation. However, the accuracy of tracking was not improved.

A survey on appearance models in visual object tracking was presented in [23]. The paper presents many 2D appearance models which is classified according to the composition modules. A Simple Background subtraction method and Temporal Difference method were designed in [24] for obtaining moving objects in video sequences. However, the method consumed more time for detecting and tracking objects.

III. PROPOSED METHOD

A. QKF-PM Technique for Moving Object Detection and Tracking

Quantization is the process of mapping a range of values to a single quantum value. QKF-PM technique detects and tracks the location of objects in video frames.

First, the proposed technique extracts sequence of frames from the input video file, which serves as the input for further processing.

Next, moving objects are segmented and classified. As a result, patterns are drawn. These patterns are stored for further processing. Next, QKF-PM technique improves moving object detecting and tracking process by matching the presence of an object that enter and leave the scene with the stored patterns. Next, chromatic shadows of objects are detected using top-down approach. In general, shadows of objects can either be static or dynamic. Static shadows resulting from static background objects like trees, buildings and parked cars and the dynamic shadows resulting from moving objects like people, vehicles and so on needs to be tracked efficiently for improved object detection and recognition.

Hence, the QKF-PM technique uses top-down approach to detect the dynamic shadows of objects.

Dynamic shadows with a combination of dark shadows and soft shadows can be of any size and shape. The soft shadow provides chromaticity value of background with low intensity values.

The dark shadow shows multiple chromaticity values and their intensity values are closer to that of its neighboring objects appearing in the frames. In general, the chromatic shadows of objects are those whose chromaticity of soft shadows is different from the chromaticity of the global background illumination. Hence the proposed QKF-PM technique using top-down approach improves the detection of chromatic shadows of objects.

B. Chromatic Shadow Detection Using Top-Down Approach

This step is essential because methods that operate at the pixel-level highly decrease their performance in those cases where shadow camouflage and chromatic shadows occur. The first step in the design of QKF-PM technique is the detection of the chromatic shadow of objects as shown in figure 1.

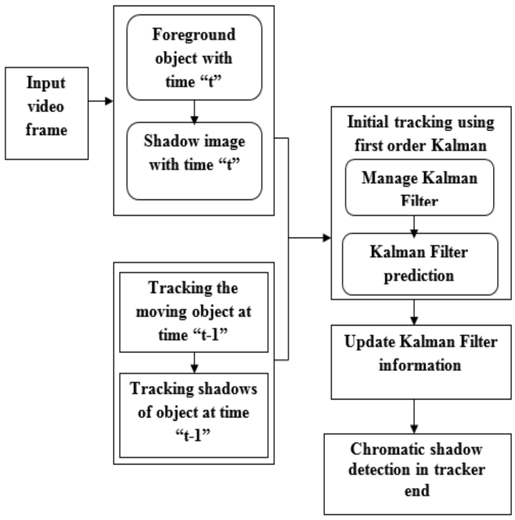


Figure 1. Top-down approach for chromatic shadows detection

Figure 1 shows the detection of chromatic shadow of objects using top-down approach. Video frames are given as input to the tracking system for detecting shadows. From the input video frame, the moving object (i.e. foreground) are detected with respect to time "t". The detected objects are tracked using first order Kalman filter. The images obtained are shown in figure 2.

(a) (b) (c)

Figure 2. (a) Input frames (b) Shadows of object at time "t" (c) Foreground objects at time "t"

Figure 2 shows the input frame, the shadows of objects at time "t" and the foreground object at the given time "t". Kalman filtering, also known as linear quadratic estimation (LQE) uses a sequence of images captured over time "t". The detected shadows are tracked over time rather than being discarded. The general first order Kalman filter can be expressed as follows,

$$x_k = S_k x_{k\,(t)-1} + b_k c_k + n_k \tag{1}$$

From (1), "x_k" denotes a "k^{th}" frame, "S_k"represents the state transition model which is applied to the prior state "x_{k-1}" (i.e. $(k-1)^{th}$frame) . Here, "b_k"denotes a control input model which is applied to control vector "c_k". Here, "n_k" is the process noise which is assumed to be zero with covariance. At time't', an observation (i.e., measurement) "y_k" of the true state "x_k" is derived as follows,

$$y_k = C_k x_k + u_k \tag{2}$$

From (2), "C_k" denotes observation model which maps the true state space into the observed space and "u_k" is the observation noise which is assumed to be zero with mean Gaussian white noise 'N' with covariance "R_k" and $u_k \sim N(0, R_k)$. The initial state and noise at each step $\{x_0, n_1, \ldots. n_k\ , u_1 \ldots. u_k\}$ are considered to be mutually independent. Each track is correlated with these parameters and Kalman filter (KF) is used to predict the object's location using first order motion model.

In Kalman filter, the state of the filter is obtained using the state estimation "x_k" and the error covariance estimation "p_k". The Kalman filter includes two step process: prediction and update. Using the prior state, the prediction phase performs state estimation for obtaining current state as follows:-,

Prediction state estimation= $x_k = S_k x_{k-1} + b_k c_k$ (3)

Prediction error covariance =$p_k = S_k p_{k-1} + S_k + n_k$ (4)

From (3) and (4), the prediction state estimation, is also called as a prior state estimation because doesn't contain observation information about the current state. In addition, the current a priori prediction is combined with the current observation information for enhancing the state estimation. Hence, the updated a posteriori state estimation is further derived as follows:-,

$$X_k(t) = X_k(t) + L_k(t)\, r_k(t) \tag{5}$$

The Updated (a posteriori) covariance estimate is derived as follows:-,

$$p_k(t) = (1 - L_k(t) D_k(t)) p_k(t) \tag{6}$$

From the above equation (5) and (6), the element "$X_k(t)$" denotes the updated state estimation of the "k[th]" frame at discrete time't' and "$L_k\,(t)$" is the information obtained at discrete time 't'. Here, "$r_k(t)$ " is the measurement of the pre-fit residual and "$p_k(t)$" is the updated covariance estimation at discrete time't'. Also, "$D_k(t)$" represents the different observation matrices. The Kalman filter is expressed in terms of *Riccati* equation and is formulated as follows:-,

$$p_k(t) = x_k(t)\left[p_k(t) - p_k(t)C_k(t)^T\left((C_k(t)p_k(t)C_k(t)^T) + \right.\right.$$
pkt−1 CktpktxktT+xkt (7)

From (7), "$C_k(t)^T$" denotes observation model which maps the true state space at time 't' in to the observed space at time 'T' and "$x_k(t)^T$" denotes the updated state estimation of the "k^{th}" frame from time 't' to the observed spaced at time 'T'. If the pair of {x, C} is fully visible, then the Riccati equation using time invariant system is combined with the steady state covariance.

Moreover, the information about both foreground objects and shadows objects are clearly stored for further upcoming frames. The stored information is analyzed to confirm the feasible data. When testing for temporal reliability in the association between foreground and shadow with their particular KF, three major actions like matching, splitting and merging a foreground and shadow images can take place. In matching, the association between foreground and shadow images is created at a time 't-1' and at a time 't'. During splitting condition, the association between foreground and shadow images are created at a time 't'. Temporal relation of a splitting shadow is applied to overcome the false detected shadows in subsequent video frames. The Temporal association is related to time. In merging condition, the association between foreground and shadow images at time t-1 is lost at time t, since the shadow images are falsely detected.

The information about the new associations between the foreground and shadow blobs, and their respective Kalman filters are updated. Top-down approach improves the detection of chromatic shadows and updates KF values of the foreground and shadow images correctly at the tracker end. The association between foreground and shadow images approach, further improves the accuracy of chromatic shadow detection. The updated shadow images are shown in figure 3.

(a) (b)

Figure 3 (a) Original frame (b) Associations between foreground and shadow blobs

Figure 3 shows the association between foreground and shadow images to detect the moving objects. With the help of Kalman filtering approach, the foreground and shadow images are detected. This helps to improve the true detection rate.

C. Kernel Pattern Segment Function For Moving Object Detection

Once the chromatic shadow images are detected, the QKF-PM technique performs moving object detection. When background, foreground, and all moving objects are mixed, it is very difficult to categorize pixels (or patterns) belonging to a moving object in a video frame. Hence, the moving objects are detected by using kernel pattern function. Kernel pattern segment function analyses the moving objects in a video frame. The kernel pattern function can be defined in terms of input mapping and be can be formulated as follows:-,

$$K_m(x,y) = \emptyset\,(x).\emptyset(y) \tag{8}$$

From (8), "K_m" is the kernel pattern segment function and "$\emptyset\,(x_i).\emptyset(y_i)$" denotes an inner product between two seed points in the frame. The kernel function uses frequent patterns mined from a set of objects in a frame. The kernel with two seed points (x, y) can be represented using feature vectors of a frame and can be formulated as follows:-,

$$K_m(x,y) = \exp\left(\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{9}$$

From (9),$\|x-y\|$ denotes a squared Euclidean distance between the two seed points and "σ"is a free parameter. By using equation (8) and (9), the kernel pattern segment function "$K_m(x,y)$" for each object in the frames of the testing images and the training images are computed. The kernel function provides a better local similarity measure among multiple patterns of the objects and they are insensitive to noise.

This kernel segment function formulates a seed point to detect the moving objects in the sequence of frames based on user criterion like pixels in a definite grayscale range, pixels consistently located on a grid and so on. The matching relations of the seed points in two successive video frames can be formulated as follows:-,

$$P_1 = AP_2 \tag{10}$$

In equation (10), P_1 and P_2 are the known seed points of the two frames. Here, "A" represents the fundamental 3X3 matrix and "P_1" and "P_2" represents the seed point projected in image planes as (x_1, y_1) and (x_2, y_2) respectively. Therefore, equation (10) can further be described as follows:-,

$$\begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} a_0 & a_1 & a_2 \\ a_3 & a_4 & a_5 \\ a_6 & a_7 & a_8 \end{bmatrix}\begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} \tag{11}$$

The normalization of the above function can be obtained as follows:-,

$$W\begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \begin{bmatrix} a_0 & a_1 & a_2 \\ a_3 & a_4 & a_5 \\ a_6 & a_7 & a_8 \end{bmatrix}\begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} \tag{12}$$

In equation (11), "W", is the normalization factor and can be defined as follows:-,

$$\left.\begin{aligned} Wx_1 &= a_0x_2 + a_1y_2 + a_2 \\ Wy_1 &= a_3x_2 + a_4y_2 + a_5 \\ W &= a_6x_2 + a_7y_2 + a_8 \end{aligned}\right\} \tag{13}$$

Here, the values of the variables ranging from $a_0 \sim a_8$ represents the various image features of objects. From the extracted image features, the variable values are computed. Also, for detecting moving objects, at least four pairs of equivalent seed points are required. Hence the Euclidean distance (D) between the two seed points are measured as follows:-,

$$D = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (14)$$

Once the distance is measured, the threshold value is assigned to classify the foreground and background region.

$$P(x,y) = \begin{cases} FG\ , if\ D > T_H \\ BG\ \ , otherwise \end{cases} \qquad (15)$$

The above equation (14), clearly shows that, if the Euclidean distance measure is greater than the threshold value "(T_H)" then it is set as a foreground (FG) seed point, otherwise, it is set as a background (BG) seed point. After classification, the foreground seed points obtained for the $(k-1)^{th}$ frame is used to obtain additional foreground seed points of the k^{th} frame with minimum time. Finally, these additional foreground seed points are combined with the foreground seed points of thek^{th} frame to obtain the updated foreground feature points.

The foreground seed point of the "K^{th}" frame can be formulated as follows:-,

$$P_k = \{P_{(x,y,k)} | \forall\ p_{(x,y,k)} \in FG\} \qquad (16)$$

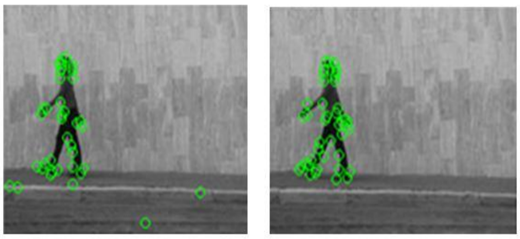
Similarly, the foreground seed point in the $(k-1)^{th}$ frame is defined as follows

$$P_{k-1} = \{P_{(x,y,k-1)} | \forall\ p_{(x,y,k-1)} \in FG\} \qquad (17)$$

The foreground seed point of the "K^{th}" and "$(K\text{-}1)^{th}$" is shown in figure 4.

Figure 4 (a) 'k' input frame (b) $(\mathbf{k-1})^{\mathbf{th}}$ frame

Figure 4(a) and (b) shows the two input frames for which pattern matching is performed for identifying the moving objects in video frames. The foreground seed point of the two frames are extracted using functions defined in equations (10) and (11).



(a) (b)

Figure 5(a) Foreground seed point of $\mathbf{k^{th}}$ frame (b) Foreground seed point of $(\mathbf{k-1})^{\mathbf{th}}$ frame

As shown in figure 5 (a) and (b), the foreground seed points of the two video frames are obtained for pattern matching. Pattern matching uses the foreground seed points of the "$(k-1)^{th}$" frame to find the equivalent foreground seed points of the k^{th} frame. Pattern matching approach examines part of an image that matches with an image (template) in each frame with the seed point. The matching process contains the image template for all feasible positions of the source image. Finally, pattern matching can be formulated as follows: -,

Finally, pattern matching can be formulated as follows: -,

$$f\left(P_{(x,\ y,\ k-1)}\right) = P_{(x+\Delta x,\ y+\Delta y,\ k)} \qquad (18)$$

$$F(P_{k-1}) = \{f\left(P_{(x,\ y,\ k-1)}\right) | \forall P_{(x,\ y,\ k-1)} \in P_{k-1}\} \qquad (19)$$

From (18) and (19), the matching function "f" and "$P_{(x,y,K\text{-}1)}$" represents the foreground seed point of the $(k-1)^{th}$ video frame. Here, $P_{(x+\Delta x, y+\Delta y, k)}$ denotes an updated foreground seed point of the k^{th} video frame. Finally, the FG regions of the moving objects can be formulated as follows: -,

$$P_k'' = F(P_{k-1}) \cup P_k \qquad (20)$$

In (20), "P_k''" represents the FG video frame and "F" represents the updated matching function. The obtained foreground regions and the updated foreground seed points are combined to obtain the regions of moving objects. Each updated foreground seed points are examined to determine it's presence in the foreground region and once when they are present, then that foreground component is designated as the region of moving objects.

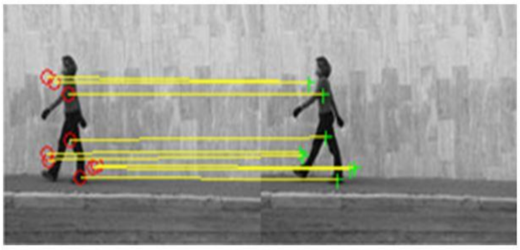


Figure 6. Pattern matching with updated FG feature points

Figure 6 shows the updated foreground feature points from the k^{th} frame and $(k-1)^{th}$ frame. Next, the bounding box approach is applied to detect the moving objects. Bounding box is a rectangular margin around an object in video frame that drags to move, transform, and rotate. The minimum bounding boxes of the moving objects are obtained using two vertical segmentations and one horizontal segmentation. The object with the bounding boxes is shown in figure 7.

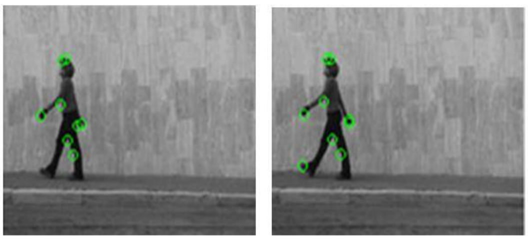


Figure 7. Moving object with minimum bounding box

Figure 7 shows the moving object with minimum bounding box to mark the object. As shown in figure, the green color box indicates the bounding box. The moving object detection algorithm is described as follows: -

Input: *Number of Video frames* $VF_i = VF_1, VF_2, VF_3 \ldots, VF_n$
Output: *Pattern matching and Object detection*
Step 1: *Begin*
Step 2: *For each video frames 'VF'*
Step 3: *Apply kernel pattern function to formulate the seed point using (2) (3)*
Step 4: *Measure the relation between the seed point in the two successive video frames using (4)*
Step 5: *Calculate the distance between the two seed points using (8)*
Step 6: *If (D> T_H) then*
Step 7: *Mark as foreground seed point*
Step 8: *else*
Step 9: *Mark as background seed point*
Step 10: *End if*
Step 11: *Calculate foreground seed point in the k^{th} and $(k-1)^{th}$ frame using (10) and (11) for moving object detection*
Step 12: *Perform pattern matching with the foreground seed point in the k^{th} and $(k-1)^{th}$ frame using (12)and (13)*
Step 13: *Update the foreground in video frame using (14)*
Step 14: *If the Updated foreground seed point is located in foreground region then*
Step 15: *Foreground region is assigned as the region of moving object*
Step 16: *else*
Step 17: *Not assigned as the region of moving objects*
Step 18: *End if*
Step 19: *Apply minimum bounding box to mark the moving objects for moving object detection process.*
Step 20: *End for*
Step 21: *End*

Algorithm 1. Moving object detection algorithm

As shown above, moving object detection algorithm is described with kernel pattern segment function. This function creates a seed point to detect the moving object in a particular frame. Next, the relations between two successive frames are measured to detect the foreground and background seed point. Next, the Euclidean distance between two seed points are measured and verified with threshold value. If the distance is greater than the threshold values, then the seed points are classified as foreground (FG), otherwise the seed points are classified as background (BG). After classification of seed points, the matching of k^{th} and $(k-1)^{th}$ frame is performed. The foreground images in video frames are updated. Next, the integration of foreground frame and updated foreground are matched for detecting the moving object's region. QKF-PM technique verifies the presence of the updated seed points in a FG region. Finally, the bounding box is applied to mark objects in a rectangular bounding box. This helps to improve the pattern matching accuracy. As a result, the moving objects in a video frame are detected.

D. Quantized Kalman Filter-Based Moving Object Tracking

After the detection of moving objects in a video frame, object tracking is carried out using QKF-PM technique. Quantization is a process of mapping large set of sequence of video frames in to a smaller set (i.e., finite set). Quantization is employed to reduce the information loss and improve the moving object tracking accuracy in proposed QKF-PM. Quantization is used to further optimize the Kalman filter with respect to the quantization levels for providing efficient QKF-PM. The quantized Kalman filter based on the center of seed point affinity feature values of the moving object region are performed using minimum bounding box method. The center of seed point affinity feature values of the moving object region can be formulated as follows: -,

$$C = \frac{1}{N} \sum_{i=1}^{n} P(x_i\ , y_i) \qquad (21)$$

In (20), "C" represents the center of the seed point affinity, and "N" denotes the total number of seed point in the region of moving object. Here, "$P(x_i, y_i)$" is the seed points of the moving objects' region. Next, the moving object search region (SR) is measured to perform tracking of objects more accurately within the bounding box. The search region is measured as follows: -

$$SR = \rho W_{Box} + \tau H_{Box} \qquad (22)$$

From (21), "W_{Box}" denotes a width of the bounding box and "H_{Box}" is the height of the bounding box. Where, "ρ" and "τ" are the constant parameters. Object tracking obtained is shown in figure 8.

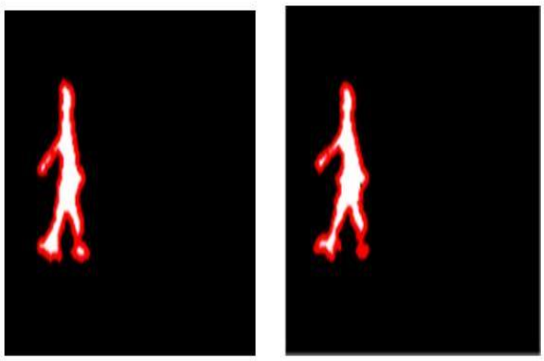


Figure 8. (a)Tracking the moving object of 'k' input frame (b) $(\mathbf{k-1})^{\mathbf{th}}$ frame

Figure 8 clearly shows the original frame and tracking the moving object with bounding box. The moving object tracking algorithm is described as follows: -,

Input: *Video frames* $VF_i = VF_1, VF_2, VF_3 .., VF_n$
Output: *Improve moving object tracking*
Step 1: *Begin*
Step 2: *For each detected moving object*
Step 3: *Calculate center of seed point affinity with Kalman Filter using (15)*
Step 4: *Tracked object is searched within the search region SR using (16)*
Step 5: *Obtain tracked objects to find the location of every moving object in a video frame*
Step 6: *End for*
Step 7: *End*

Algorithm 2. Kalman Filter-based moving object tracking algorithm

The algorithm 2 designed for moving object tracking involves identifying images from video frames and tracking its movement and position. For each detected object, the center of the seed point affinity value is calculated. Next, the search region is measured to locate the prediction of all moving objects using Kalman filter technique along with minimum bounding box.

IV. EXPERIMENTAL SETUP

Experimental evaluation of Quantized Kalman filter-based pattern matching (QKF-PM) technique is implemented using MATLAB to improve the accuracy of moving object detection and tracking. The video file is taken from 168VJ Clips video dataset to perform the experimental evaluation of moving object detection and tracking. This dataset consists of number of video clips with different file size. Experiment evaluation is conducted on .avi file format. The performance evaluation of QKF-PM technique is compared against the state-of-the-art methods, SIFT in [1] and E-RBPF in [2]. The experiment is conducted on the factors such as True detection rate, Pattern matching accuracy, pattern matching time and moving object tracking accuracy.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed quantized Kalman filter-based pattern matching (QKF-PM) method is analyzed with the existing Scale Invariant Feature Transform technique (SIFT) in [1] and Enhanced Rao-Blackwellized Particle Filter (E-RBPF) in [2]. The performance is carried out on the factors such as true detection rate, Pattern matching accuracy, pattern matching time and moving object tracking accuracy.

A. Impact of True Detection Rate

True detection rate is defined as the ratio of the number of shadow image of the objects being correctly detected to total number of objects in video frames.

$$\boldsymbol{TDR} = \frac{\boldsymbol{No.of\ shadow\ objetcts\ correctly\ detected}}{\boldsymbol{No.of\ objects\ in\ video\ frame}}\ \boldsymbol{100} \tag{23}$$

In (23), "TDR" represents the true detection rate, which is measured in terms of percentage (%).

Table 1 Tabulation for true detection rate

No. of Video frames/sec	True detection rate (%)		
	QKF-PM	SIFT	E-RBPF
10	73.65	61.36	50.36
20	76.25	63.47	55.24
30	80.12	65.11	58.46
40	83.65	70.12	60.13
50	85.10	75.38	65.34
60	88.64	78.65	68.35
70	89.12	80.24	70.34
80	91.34	83.65	73.12
90	93.47	85.12	75.24
100	94.36	88.69	78.65

Table 1 clearly depicts the true detection rate, measured using pattern matching to detect the moving objects. The true detection rate is considerably increased in proposed QKF-PM technique compared to existing methods [1] [2]. In QKF-PM technique, Top-down approach is applied using a Kalman filter-based tracking to improve the chromatic shadow detection rate of images. The information about the association between the foreground and shadow blobs, and their Kalman filters are updated to detect the shadow of objects in frames as shown in fig 4. Also to improve the efficiency of the proposed QKF-PM technique, top-down approach is employed to detect the shadows of objects, as shown in fig 3. Finally, the proposed method detects shadows of multiple objects in frames more accurately and quickly with respect to time. Therefore, the true detection rate is increased by 14% and 32% using QKF-PM method compared to existing SIFT [1] and E-RBPF [2] methods respectively.

B. Impact Of Pattern Matching Accuracy

Pattern matching accuracy is defined as the ratio of the number of objects being correctly matched to the total number of objects in video frames. The matching accuracy is defined as follows,

$$\boldsymbol{MA} = \frac{\boldsymbol{Correctly\ matched\ objects\ patterns}}{\boldsymbol{No.of\ objects\ \ in\ video\ frames}}\ \boldsymbol{*100} \tag{24}$$

From (24),"MA" represents matching accuracy and it is measured in terms of percentage (%). Let us consider input video frames ranging from 10 to 100. The numbers of correctly matched patterns are measured for detecting the moving objects.

Table 2 Tabulation for pattern matching accuracy

No. of Video frames/sec	Pattern matching accuracy (%)		
	QKF-PM	SIFT	E-RBPF
10	80.12	71.36	62.86
20	83.47	76.98	65.14
30	85.64	78.12	68.36
40	87.12	82.43	70.12
50	88.54	84.67	75.10
60	90.10	85.45	78.98
70	91.36	87.12	82.15
80	92.65	88.68	84.36
90	93.64	89.12	85.42
100	94.78	90.13	86.48

Table 2 shows pattern matching accuracy with respect to number of video frames.

The objects in video frames are correctly matched to improve the matching accuracy. The QKF-PM method uses Kernel pattern segment function to formulate the seed point to classify both FG and BG regions. The foreground seed points obtained in the $(k-1)^{th}$ frame are matched with the seed points in the k^{th} frame to obtain other FG seed points. This helps to improve the pattern matching accuracy. The matched objects are marked using bounding box to detect the moving objects. The accuracy of pattern matching is increased by 7% and 18% using QKF-PM method compared to existing SIFT [1] and E-RBPF [2] methods respectively.

C. Impact Of Pattern Matching Time

Pattern matching time can be defined as the time taken by the proposed method to match patterns with the training patterns with respect to number of objects in video frames. Pattern matching can be formulated as follows: -,

$$\boldsymbol{PMT = No. of\ objects\ in\ video\ frame * time\ (matching\ )} \tag{25}$$

From (25), "PMT" denotes pattern matching time, measured in terms of milliseconds (ms). A method is considered to be more efficient, if the time taken for pattern matching is minimum (ms).

Table 3 Tabulation for Pattern matching time

No. of Video frames/sec	Pattern Matching time (ms)		
	QKF-PM	SIFT	E-RBPF
10	8.3	12.4	15.3
20	12.5	15.2	18.6
30	15.6	20.1	22.7
40	18.2	22.7	26.4
50	22.1	26.8	31.2
60	26.7	32.1	36.7
70	28.6	35.6	41.9
80	30.4	38.4	46.3
90	34.8	40.2	48.6
100	36.7	43.6	51.2

Table 3 illustrates pattern matching time with respect to number of video frames. The aim of the proposed system is to reduce the time taken for pattern matching. This is accomplished in the proposed system using kernel pattern segment function. The function uses FG seed points of the $(k-1)^{th}$ frame for matching with the FG seed points of the k^{th} frame. Pattern matching technique processes video frames to find seed points of the objects that matches with objects (template) for all possible positions of the objects. This significantly increases the performance of pattern matching with minimum time. The pattern matching time is considerably reduced by 20% and 32% compared to existing SIFT [1] and E-RBPF [2] respectively.

D. Impact of Moving Object Tracking Accuracy

Moving object tracking accuracy is defined as the ratio of number of objects being tracked to the total number of video frames per second. Moving object tracking accuracy is measured in terms of percentage (%) and is formulated as follows:-,

$$\boldsymbol{MOTA = \frac{No.of\ Objects\ being\ Tracked}{Number\ of\ objects\ in\ video\ frames} * 100} \tag{26}$$

Here, "$MOTA$" represents moving object tracking accuracy.

Table 4 Tabulation for Moving object tracking accuracy

No. of Video frames/sec	Moving object tracking accuracy (%)		
	QKF-PM	SIFT	E-RBPF
10	83.68	75.32	63.10
20	85.42	78.12	66.47
30	86.12	80.36	68.89
40	88.65	81.12	71.12
50	90.37	83.69	73.65
60	91.32	85.76	75.20
70	93.45	88.10	78.12
80	94.56	90.12	82.31
90	95.47	92.36	85.65
100	98.21	93.65	87.23

Table 4 illustrates moving object tracking accuracy with respect to number of video frames ranging from 10 to 100.

To better meet the objective of the proposed system, Kalman filter-based pattern matching method tracks the moving objects in video sequences by calculating the center of seed point affinity feature values of the moving objects in a specific region. Finally, moving object search region (SR) is measured to track the objects within the minimum bounding box more accurately. This helps to improve the moving object tracking accuracy by 7% and 21% using QKF-PM method compared to existing SIFT [1] and E-RBPF [2] methods respectively.

Therefore, analysis of quantized Kalman filter-based pattern matching (QKF-PM) technique shows better improvement in moving object detection and tracking.

VI. CONCLUSION

An efficient Quantized Kalman Filter based Pattern Matching (QKF-PM) technique is introduced for detection and tracking of moving objects. The main objective of the proposed QKF-PM technique is to improve the pattern matching accuracy. In the first step, the chromatic shadows of objects are detected using a top-down approach. Kalman filter of the objects and shadow objects are correctly updated. The information about the new associations between the foreground and shadow blobs, and their respective Kalman filters are updated. This facilitates the detection of chromatic shadows improves the true detection rate. Next, kernel pattern segment function is applied to formulate the seed point. Pattern matching between the successive frames are identified. Next, bounding box is applied to detect the moving object. Finally, the moving object tracking is achieved by using Kalman filter-based on the center of seed point affinity features in a particular region with minimum bounding box.

The proposed system improved the overall accuracy of detecting and tracking multiple moving objects. Also the research work reduced the computational time taken for pattern matching of objects. Experimental evaluation of the proposed system is carried out on the parameters like true detection rate, pattern matching accuracy, pattern matching time and object tracking accuracy. The experimental result reveals that the QKF-PM technique significantly improves the pattern matching accuracy with minimum time and improves the true detection rate. The QKF-PM technique also improves the moving object tracking accuracy compared to the existing state-of-the-art methods. Thus, it can be concluded that the developed system met all the objectives and can be considered as a suitable candidate for visual surveillance system.

The proposed methods has a flexibility of extending its functionality to go beyond tracking. The present research work can be extended for developing an intelligent framework for human motion analysis. The features extracted for detecting and tracking moving objects can be stored in the memory for further object recognition system.

REFERENCES

1. Ahlem Walha , Ali Wali, Adel M. Alimi, "Video stabilization with moving object detecting and tracking for aerial video surveillance", Multimedia Tools and Applications, Springer, Volume 74, Issue 17,September 2015, Pages 6745–6767.
2. Harish Bhaskar, KartikDwivedi, DebiProsadDogra, Mohammed Al-Mualla, Lyudmila Mihaylova, "Autonomous detection and tracking under illumination changes, occlusions and moving camera", Signal Processing, Elsevier, Volume 117, December 2015, Pages 343–354.
3. Jie Li, Yan Huang, Guisheng Liao, Jingwei Xu, "Moving Target Detection via Efficient ATI-GoDec Approach for Multichannel SAR System", IEEE Geosciences and Remote Sensing Letters, Volume 13, Issue 9, SEPTEMBER 2016, Pages 1320 – 1324.
4. Moein Shakeri and Hong Zhang, "COROLA: A sequential solution to moving object detection using low-rank approximation", Computer Vision and Image Understanding, Elsevier, Volume 146, May 2016, Pages 27–39.
5. Kuihe Yang, Zhiming Cai and Lingling Zhao, "Algorithm Research on Moving Object Detection of Surveillance Video Sequence", Optics and Photonics Journal, Volume 3, 2013, Pages 308-312.
6. Yuanyuan Zhang, Xiaomei Zhao, Fengjiao Li, Jiande Sun, Shuming Jiang, and Changying Chen, "Robust Object Tracking Based on Simplified Codebook Masked Camshift Algorithm", Mathematical Problems in Engineering, Hindawi Publishing Corporation, Volume 2015, June 2015, Pages 1-12.
7. Seungwon Lee, Nahyun Kim, Kyungwon Jeong, Kyungju Park, Joonki Paik, "Moving Object Detection Using Unstable Camera for Video Surveillance Systems", Optik - International Journal for Light and Electron Optics, Elsevier, Volume 126, Issue 20, October 2015, Pages 2436–2441.
8. Saira Saleem Pathan, Omer Rashid, Ayoub Al-Hamadi, and Bernd Michaelis, "Multi-Object Tracking in Dynamic Scenes by Integrating Statistical and Cognitive Approaches", International Journal of Computer Science Issues (IJCSI), Volume 9, Issue 4, July 2012, Pages 180-189.
9. Pedro Carvalho, Telmo Oliveira, Lucian Ciobanu, Filipe Gaspar, Luís F. Teixeira, Rafael Bastos, "Analysis of object description methods in a video object tracking environment," Machine Vision and Applications, Springer, Volume 24, Issue 6, 2013, Pages 1149–1165.
10. Hongzhe Jin, Hui Zhang, Zhangxing Liu, Decai Yang, Dongyang Bie, He Zhang, Ge Li, Yanhe Zhu, and Jie Zhao, "A Synthetic Algorithm for Tracking a Moving Object in a Multiple-Dynamic Obstacles Environment Based on Kinematically Planar Redundant Manipulators", Mathematical Problems in Engineering, Hindawi publishing corporation, Volume 2017, April 2017, Pages 1-15.
11. Jaehoon Jung, Inhye Yoon Sangkeun Lee, and Joonki Paik, "Object Detection and Tracking-Based Camera Calibration for Normalized Human Height Estimation, Journal of Sensors," Hindawi Publishing Corporation, Volume 2016, October 2016, Pages 1-9.
12. Yong Chen, Rong hua Zhang and Lei Shang, "A Novel Method of Object Detection from a Moving Camera Based on Image Matching and Frame Coupling", PLOS ONE journal, Volume 9, Issue 10, 2014, Pages 1-6.
13. Tushar S. Waykole and Yogendra Kumar Jain, "Detecting and Tracking of Moving Objects from Video", International Journal of Computer Applications, Volume 81, Issue 18, November 2013, Pages 23-28.
14. Wisarut Chantara, Ji-Hun Mun, Dong-Won Shin, and Yo-Sung Ho, "Object tracking using adaptive template matching," IEIE Transactions on Smart Processing and Computing, Volume 4, Issue 1, 2015, Pages 1–9.
15. Ms Jyoti J. Jadhav, "Moving Object Detection and Tracking for Video Survelliance", International Journal of Engineering Research and General Science, Volume 2, Issue 4, July 2014, Pages 372-378.
16. Elham Kermani and Davud Asemani, "A robust adaptive algorithm of moving object detection for video surveillance", EURASIP Journal on Image and Video Processing, Springer, Volume 27, December 2014, Pages 1-9
17. Satrughan Kumar and Jigyendra Sen Yadav, "Video object extraction and its tracking using background subtraction in complex environments", Perspectives in Science, Elsevier, Volume 8, 2016, Pages 317-322.
18. Min Huang, Gang Chen, Guo-feng Yang, Rui Cao, "An Algorithm of the Target Detection and Tracking of the Video", Procedia engineering, Elsevier, Volume 29, 2012, Pages 2567-2571.
19. [19] Ruolin Zhang and Jian Ding, "Object Tracking and Detecting Based on Adaptive Background Subtraction", Procedia Engineering, Elsevier, Volume 29, 2012, Pages 1351 – 1355.
20. Weiming Hu, Xue Zhou, Wei Li, Wenhan Luo, Xiaoqin Zhang and Stephen Maybank, "Active Contour-Based Visual Tracking by Integrating Colors, Shapes, and Motions, IEEE Transactions On Image Processing, Volume 22, Issue 5, May 2013.
21. Barga Deori and Dalton Meitei Thounaojam, "A Survey on Moving Object Tracking in Video", International Journal on Information Theory (IJIT),

Volume 3, Issue 3, July 2014, Pages 31 – 46.
22. Dmitry Kangin, Denis Kolev and Garik Markarian, "Multiple video object tracking using variational interference", The IEEE conference Sensor Data Fusion: Trends, Solutions, Applications, Oct 2015, Pages 1-6.
23. Xi Li, Weiming Hu, Chunhua Shen, Zhongfei Zhang, Anthony Dick and Anton Van Den Hengel, "A Survey of Appearance Models in Visual Object Tracking", ACM Transactions on Intelligent Systems and Technology (TIST), Volume 4, Issue 4, Pages 1-48, Sep 2013.
24. Jyoti J. Jadhav, Yuvraj R. Patil, "Moving Object Detection for Video Surveillance System", International Journal of Computer Applications (0975 – 8887), National Conference on Emerging Trends in Advanced Communication Technologies (NCETACT-2015), 2015, Pages 7–10.

AUTHORS PROFILE

Matheswari Rajamanickam was born in 1982, Tamilnadu, India. She received the B.Sc. and M.Sc., degrees in Computer Science from Bharathiar University, Tamilnadu, India, during the year 2000 to 2005 and M.Phil. Degrees in Computer Science Bharathiar University, Tamilnadu, India during the year 2008 and currently pursuing Ph.D. degrees in Computer Science from Bharathiar University, Tamilnadu, India. In 2005, she started her career as a lecturer and in 2014, she joined the Department of Computer Science, M.E.S College of Arts, Commerce and Science, Bangalore, and is currently working as Assistant Professor in Computer Science. Her current research interests include Image processing and Object oriented analysis and Design. She has published three research papers in standard referred journals and has presented more than ten research papers in International conferences and conference proceedings.