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Object Detection using Particle Swarm Optimisation and Kalman Filter to Track Partially-occluded Targets

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ABSTRACT

Motion estimation, object detection, and tracking have been actively pursued by researchers in the field of real time video processing. In the present work, a new algorithm is proposed to automatically detect objects using revised local binary pattern (m-LBP) for object detection. The detected object was tracked and its location estimated using the Kalman filter, whose state covariance matrix was tuned using particle swarm optimisation (PSO). PSO, being a nature inspired algorithm, is a well proven optimization technique. This algorithm was applied to important real-world problems of partially-occluded objects in infrared videos. Algorithm validation was performed by realizing a thermal imager, and this novel algorithm was implemented in it to demonstrate that the proposed algorithm is more efficient and produces better results in motion estimation for partially-occluded objects. It is also shown that track convergence is 56% faster in the PSO-Kalman algorithm than tracking with Kalman-only filter.

Keywords: Motion estimation; Kalman filter; Motion compensation; Particle swarm optimisation; Infrared; Tracking

1. INTRODUCTION

Thermal imaging is translation of spatial domain thermal signatures of targets and backgrounds into user comprehensible visual images. This imaging technique works perfectly well in low light levels or even in the absence of visible light[1-2]. In surveillance applications, these thermal imagers are utilised as surveillance cameras for target detection and tracking. Categorisation of the target tracking methods can be done as: region-based tracking, filtering-based tracking, model-based tracking, feature-based tracking and active contour-based tracking. Filtering-based tracking involves estimation of the target state, which could be position, speed, angular rotation, scale variance, etc. Kalman filter[3] can deal with linear and Gaussian problems, whereas extended Kalman filter (EKF) can be applied in certain nonlinear and non-Gaussian problems; however, EKF will fail in case the conditional probability density is multimodal. Region-based tracking algorithms work on determining the similarity between target templates and real time image sequences. Template matching[4] is one of the most important classification methods. Sequential similarity detection[5], product correlation[6] and differential correlation[7] are some of the commonly used algorithms in this category. However, they are computationally intensive and have a lower tracking efficiency. In Model-based tracking algorithm classification, a 3-D target model and its motion model are first prepared using the apriori knowledge and the target is estimated by its present image sequence. This classification is time and resource consuming and not applicable in real time surveillance applications. Active contour-based tracking algorithms[8] depend on the contour line of target. Feature-based tracking algorithms extract some common features from images such as point, edge, corner, and texture. Some of the proposed algorithms in this category include SIFT[9], SURF[10], ORB[11] and Hessian Laplace. Infrared image tracking is challenging owing to a small amount of information available in IR images. Color information is absent, real time IR target tracking causes scale variation, occlusion, false alarm, rotational dissimilarity, deformation, perspective change, among other issues. Furthermore, several types of noise also degrade the IR image quality. All these result in feature loss, which further causes tracking failure. In recent years, several excellent trackers have been built, but this field still needs continuous efforts to improve the tracking accuracy, reduce false alarm, tracking in occlusion and develop robust, fast and field deployable tracker algorithm. Existing object tracking algorithms perform exceptionally well, but in some situations severe performance degradation is observed while handling occlusion and multiple objects. Thus, in the field of computer vision, an urgent need is felt for a less computationally complex and robust algorithm. In this study, an attempt is made to develop a new and more efficient template matching technique by modifying local binary pattern (LBP) for detection, and it is further integrated with Kalman filter for tracking on one platform to improve the robustness of real time target tracking. Kalman filter provides a robust solution among all these algorithms and is considered to be one of the best candidates for IR image tracking

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applications. Considering its limitation in its applicability in nonlinear, non-Gaussian systems, an attempt is made to include an evolutionary algorithm like particle swarm optimisation (PSO)[12] for optimisation. The novelty of the present work lies in application of revised LBP for detection with Kalman filter and PSO for real time Infrared video tracking, and better results were obtained when only Kalman filter was applied.

2. PARTICLE SWARM OPTIMISATION

PSO[13-17] is a nature inspired search technique. The algorithm was devised by Kennedy and Eberhart. This is inspired by the manner in which flocks of birds and schools of fish search for their food. It mimics the intelligent, collective, and synchronised behaviour of swarms without any leader. In PSO, the best performance of each particle and the overall best performing particle is tracked and noted. Each particles' best performance is known as its personal best, and the particle with the best performance is known as the global best. The two equations that define the PSO are:

Velocity vector:

$$u_{jk} = du_{jk} + a_1 r_1 (q_{jk} - y_{jk}) + a_2 r_2 (q_{gk} - y_{jk}) \quad (1)$$

Position vector: $y_{jk} = y_{jk} + u_{jk}$ (2)

where the various constituents of equation for j^{th} particle of dimension k are:

u_{jk} velocity vector,
q_{jk} best previous position,
q_{gk} best global position amongst all neighbours,
y_{jk} current position,
d inertia weight,
a_x acceleration constant,
r_x uniformly generated random numbers between 0 to 1,
$a_1 r_1 (q_{jk} - y_{jk})$ cognitive component i.e. personal thinking of particle,
$a_2 r_2 (q_{gk} - y_{jk})$ social component i.e. cooperation among particles.

Velocity of the particles is governed by inertia weight. It plays a key role in balancing exploration and exploitation. Table 1 shows the variation of inertia weight and acceleration constant and their influence over PSO vectors.

The particle's trajectory is controlled by coefficient a_1 and is responsible for maintaining the diversity, whereas impact of social component and group's convergence is controlled by coefficient a_2. Figure 1 explains the PSO algorithm and its implementation as a flowchart. PSO was chosen as optimisation technique because of the advantages like convergence is rapid, implementation becomes faster, efficiency in computation and controlling parameters is robust. There are other evolutionary algorithms like Genetic algorithm, ant & bee colony optimisation, cuckoo search, firefly algorithm, simulated annealing etc. But PSO was selected in this paper based on its advantages above other algorithms.

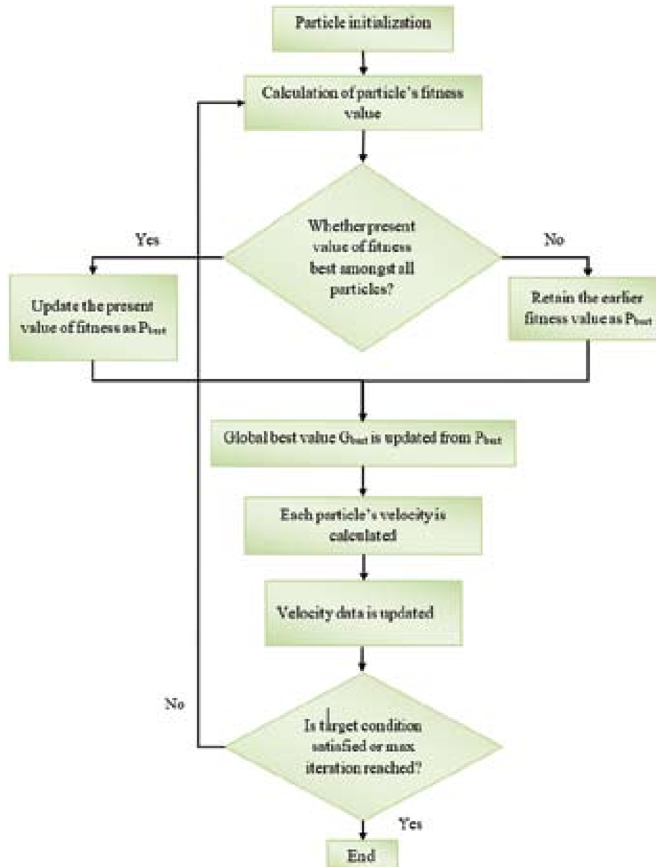


Figure 1. Flowchart depicting PSO algorithm.

3. OBJECT DETECTION AND TRACKING USING PARTICLE SWARM OPTIMISATION INTEGRATED KALMAN FILTER

Automatic target detection and tracking can be achieved by applying revised Local Binary Pattern (m-LBP) for detection and then Kalman filter with PSO for tracking. Papers related to this topic are referred[16-21] but none of them illustrate the proposed method. To detect and track the object, we must perform some sequential methods. The first step capturing an input image frame from the video. The second step is the background estimation. The algorithm considers a fixed number of frames as training frames from which it estimates the background and foreground separately. The third step is the

Table 1. Inertia weight (d) and acceleration constant (a_1, a_2) values and their influence over PSO

$d \geq 1$	Velocity increases over time
$0 < d < 1$	Deceleration of particles, their convergence relies on the values of a_1 and a_2.
$d < 0$	Velocity decreases over time, eventually reaching 0.
$a_1 << a_2$	Swarm will converge prematurely as the group's bias is more towards achieving global best position
$a_1 >> a_2$	Swarm will demonstrate delayed convergence or nil convergence due to group's bias is more towards achieving personal best position
$a_1, a_2 >> 1$	Swarm will diverge due to very high acceleration
$a_1, a_2 << 1$	Swarm will converge very slowly due to very low acceleration

object detection. The foreground is detected using the stored knowledge of background. It compares each pixel value of the current frame with the known background knowledge to determine the current foreground. A morphological filter like opening and closing operation is then applied to reduce the noise in the differentiated image. Blob Analysis is performed followed by centroid estimation to obtain the coordinates of the detected object. The fourth step in the algorithm is object tracking using Kalman filter. The detected position is passed to the Kalman filter to determine the next predicted state of the object. The Kalman filter uses this detected position and the previously calculated predicted state to provide the corrected estimate of the object. When the object is not detected, Kalman uses its predicted state only to find the new position. The fifth step of the proposed algorithm is updating noise vector of Kalman filter using the PSO. The process noise covariance of Kalman filter is updated with each frame using the global search ability of the PSO. N different particle swarms consisting of N different Kalman filters deduce the most optimum noise covariance. This G_{best} or the optimum noise covariance is then used in the main Kalman filter discussed in step four. Updating of the noise covariance matrix using PSO facilitates in obtaining an accurate state vector to track the object by Kalman filter. The last step of the algorithm is to plot the detected and predicted trajectories of the object. When the object is occluded, only then the predicted trajectory is updated. When the detection is complete, the overall trajectories are plotted in a single image frame to compare the results. Figure 2 shows the algorithmic flow of the PSO integrated Kalman Filter.

3.1 Revised Local Binary Pattern Detection Algorithm

Revised Local Binary Pattern based detection algorithm in template matching considers image gradient magnitude (G_{mag}) matrix of both source image and template image and compares each element to its eight neighbouring elements. It labels each element of that matrix by thresholding, obtains an 8-bit binary number, and applies a logical operator between both the binary results to calculate maximum non-zero elements. This technique is repeated for the entire image. The point leading to the maximum value of non-zero numbers is defined to be the point where the image will be marked as a matched template. It is popular in template matching because of its computational simplicity, which helps in easy implementation on real-time template matching. Templates identify characters, numbers, and other simple objects. There are many types of template matching techniques, but not all of them are robust in real-time

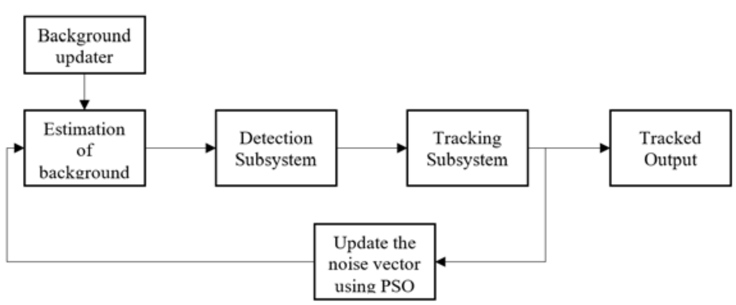


Figure 2. Algorithmic flow of PSO integrated Kalman filter.

object tracking. A general derivation for an LBP operator of any size with central pixel as basis is presented here. Equation 3 gives the grey scale values of p neighbouring pixels as:

$$L = mat(X_c, X_0 ...., X_{P-1}) \tag{3}$$

where X represents the central and neighbouring pixels. All the $(P-1)$neighbouring pixels are at a radial distance of r from the central pixel. The coordinates of the neighbours are given by equation 4:

$$\left[x_p, y_p\right] = \left[x_c + r\cos\left(\frac{2\pi p}{P}\right), y_c + r\sin\left(\frac{2\pi p}{P}\right)\right] \tag{4}$$

Interpolation estimates the grayscale values of coordinates positioned between pixels. Generally, texture is defined as the first derivative of pixel intensities. The neighbouring pixel grayscale values are subtracted from the central value and further divided by the radial distance to present the discrete derivative shown in equation 5:

$$L = mat\left(\frac{X_0 - X_c}{r}, ...\frac{X_{p-1} - X_c}{r}\right) \tag{5}$$

The texture now describes the relation of the neighbourhood such that a value larger than zero describes an increase in relations, whereas that less than zero shows a corresponding decrease. This presents information of what type the central pixel is, such an edge in a direction or corner. All other information can be regarded as scaling of this information. To make the data invariant to this information, a step function is included as given in equation 6:

$$s(X) = \begin{cases} 1 & , t \geq 1 \\ 0 & else \end{cases} \tag{6}$$

This function is applied to each value, and as the radius R also is a scaling value, it does not have any effect on the result after the step function. This can also be ignored, resulting in equation 7:

$$L = mat\left(s\left(X_0 - X_c\right), ..., s\left(X_{p-1} - X_c\right)\right) \tag{7}$$

A binary weight is given to each neighbour so that a unique number is given to each relation. The result in equation 8 defines the LBP code:

$$LBP_{P,r}\left(x_c, y_c\right) = \sum_{p=0}^{P-1} s\left(X_p - X_c\right)2^p \tag{8}$$

3.2 Methodology of m-LBP

The template matching technique of dominant orientation[18] is more effective in real-time scenarios than the others because intensity values of image does not provide reliable information than gradient information. Here, the orientation of gradients is classified as binary numbers, which makes it easy to apply logic operators and reduces the overall computation cost. But solely depending on orientation can be tricky because it requires templates to have strong gradients. Therefore, if the template is hazy and unclear, the algorithm performance is poor. LBP can assist in overcoming this problem, because in LBP, each neighbouring pixel is compared with the central pixel grayscale value and thresholded to provide a binary pattern. In the orientation method, the image frame is segmented in miniscule blocks and the maximum

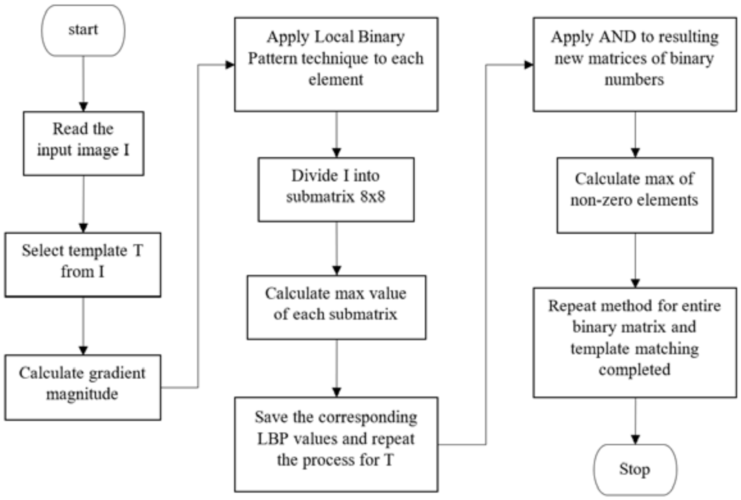


Figure 3. Flowchart of m-LBP algorithm.

gradient of each block is considered. A revision is proposed in the LBP by thresholding in place of maximum gradient, the pitfalls of earlier method can be covered for dynamic scenarios, and it could result in a new and improved template matching technique. The method of creating this new template matching technique has been elaborated in the flowchart shown in Fig. 3.

This method adopts a standard sliding window method to test the similarity of LBP template T and image I by bitwise AND operations. The final decision is made by thresholding the lookup table of the binary quantised representations of LBP. Figure 4 explains the thresholding technique elucidatively. However, template matching alone is not sufficient for object tracking as it does not consider real-world scenarios in which occlusion is a common phenomenon. Therefore, Kalman filter is used, as it runs simultaneously with new template matching. In case of occlusion, when this new template matching technique fails, Kalman's estimated location is treated as a measurement until target matching is achieved again. Thus, even if the object is impeded for a while, the overall performance of the algorithm will not be hindered.

3.3 Tuning of Particle Swarm Optimisation Integrated Kalman Filter (PSO-KF)

The PSO-KF considers the noise factor to estimate the correct location of object. It considers two noise factors:

- Measurement noise covariance
- Process noise covariance

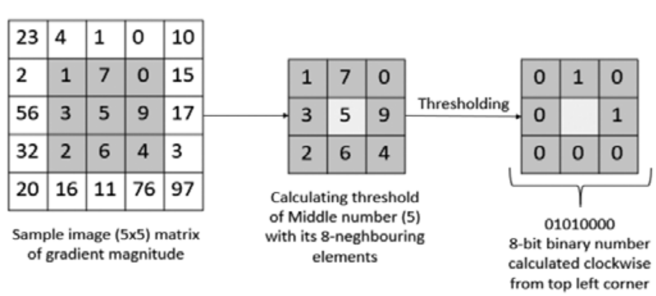


Figure 4. Thresholding of a value by comparing it to its neighbouring elements.

In the proposed algorithm, the value of process noise covariance is optimised using the global search ability of the PSO technique. According to the empirical result, we have assigned the constant values for d=0.6951 and the $a_1 = a_2 = 1.51$ for the convergence behaviour of PSO. After initializing the particles of the swarm each time when object is detected, we update the value of process noise covariance with the global best value of PSO. To determine the global best value, the Euclidean distance is difference of estimated and detected position for a particular particle. The Euclidean distance formula is given by:

$$X = \left[(p_2 - p_1)^2 + (q_2 - q_1)^2 \right]^{1/2} \tag{9}$$

where X = Euclidean distance

(p_1, p_2) = x-coordinates and (q_1, q_2) are y-coordinates of estimated and detected position of object.

4. EXPERIMENTAL SETUP

The PSO-integrated Kalman filter algorithm is applied over Infrared image sequences. These image sequences are recorded using a thermal imager whose parameters are mentioned in Table 2. Midwave infrared imager is particularly suited for Indian tropical environmental conditions, which are predominantly hot and humid. Numerous video processing algorithms are implemented in Xilinx XC4VLX60 series FPGA based customised video card.

Figure 5(a) shows the realised thermal imager and Fig. 5(b) shows one of the infrared images of a house captured in field conditions at a distance of 500 m.

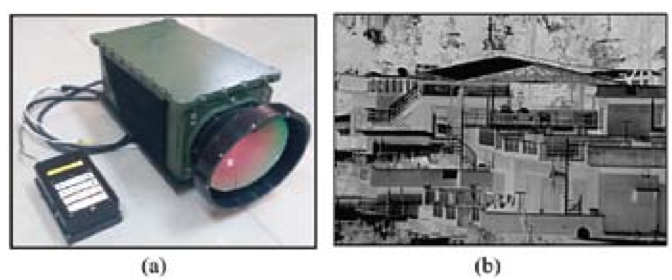


Figure 5. (a) Photograph of thermal imager used and (b) reference thermal image of house.

5. RESULTS

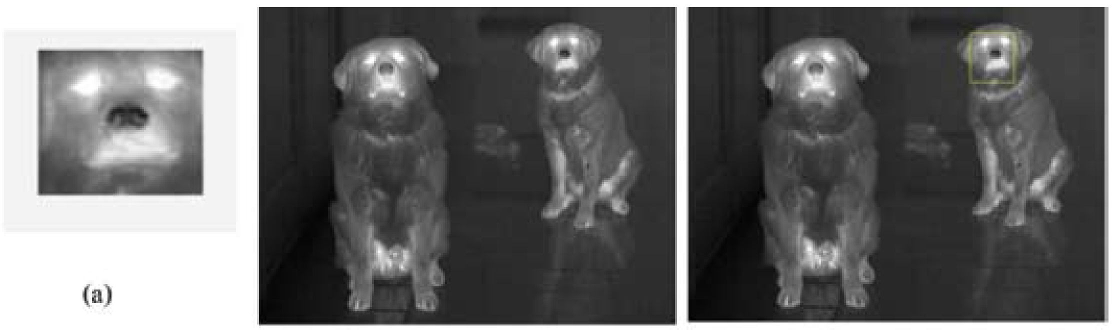
The thermal imager used to record an infrared video sequence consists of numerous frames. The results of m-LBP algorithm for real-time object detection are presented first. Two examples to test the efficiency of m-LBP under different scenarios are presented below.

Scenario I- Figure 6 shows a thermal image of a man pushing a door in which the template is selected by cropping the image, and the m-LBP is applied to match the template with the original image. Here only one object is present in the complete frame. However, in the above scenario, there is only one subject that is highlighted by white, and this makes it easier for the template to detect and match.

Scenario II- Figure 7 shows a thermal image of two dogs that look alike and are almost indistinguishable in the infrared image. This example tests the accuracy of the m-LBP detection algorithm when there are multiple subjects that look alike. The

(a) (b) (c)

Figure 6. (a) Template of man pushing the door captured through a thermal security camera, (b) original image, and (c) detected object in image.



(a) (b) (c)

Figure 7. (a) Template of a dog's face captured through a thermal camera. (b) Thermal image of two dogs, and (c) detected object showing algorithm's accuracy.

Table 2. Various parameters of thermal imaging camera utilised for algorithm validation

Parameter	Value	
Waveband	Midwave Infrared (3-5 μm)	
Detector	640 x 512 format	
Continuous zoom optics	f/No.	4
	Effective focal length	600 mm
	Aperture diameter	150 mm
Video processing features	Image enhancement, dynamic range compression, bad pixel detection and correction non uniformity correction	
Motorised controller	Focus and field of view control	
Power supply	24 V, <100 W	
Operating temperature	-20 °C to +55 °C	
EMI/EMC	MIL STD 461 E compliant	

template matching was repeated several times on the same image to test its accuracy and the results were promising every time. However, there was a mismatch only when the darkest part with respect to temperature variation was selected as template.

The second part of the results presents infrared tracking based on Kalman filtering with PSO. In the recorded video, a man is walking, and for short period of time, he is partially occluded behind a pole between the 21st frame and 41st frame. Various frames of the input infrared image sequence are shown in Figs. 8(a-l).

The PSO integrated Kalman filter algorithm as reported in section 4 was coded and implemented in MATLAB^{R} software[22]. Figures 9(a-f) shows the algorithm results of the tracked man in various frames. The tracked pixel (below waist) is considered. The algorithm worked perfectly well in the whole video, particularly during obscured image frames.

The effect of PSO integrated Kalman Filter algorithm is reported in Fig. 10. In Figs. 10(a-b), the ground truth is shown (purple dotted line), which represents the x- and y- coordinates of the tracked pixel (without obscuration). In the same figure, target detection with m-LBP algorithm is represented (green

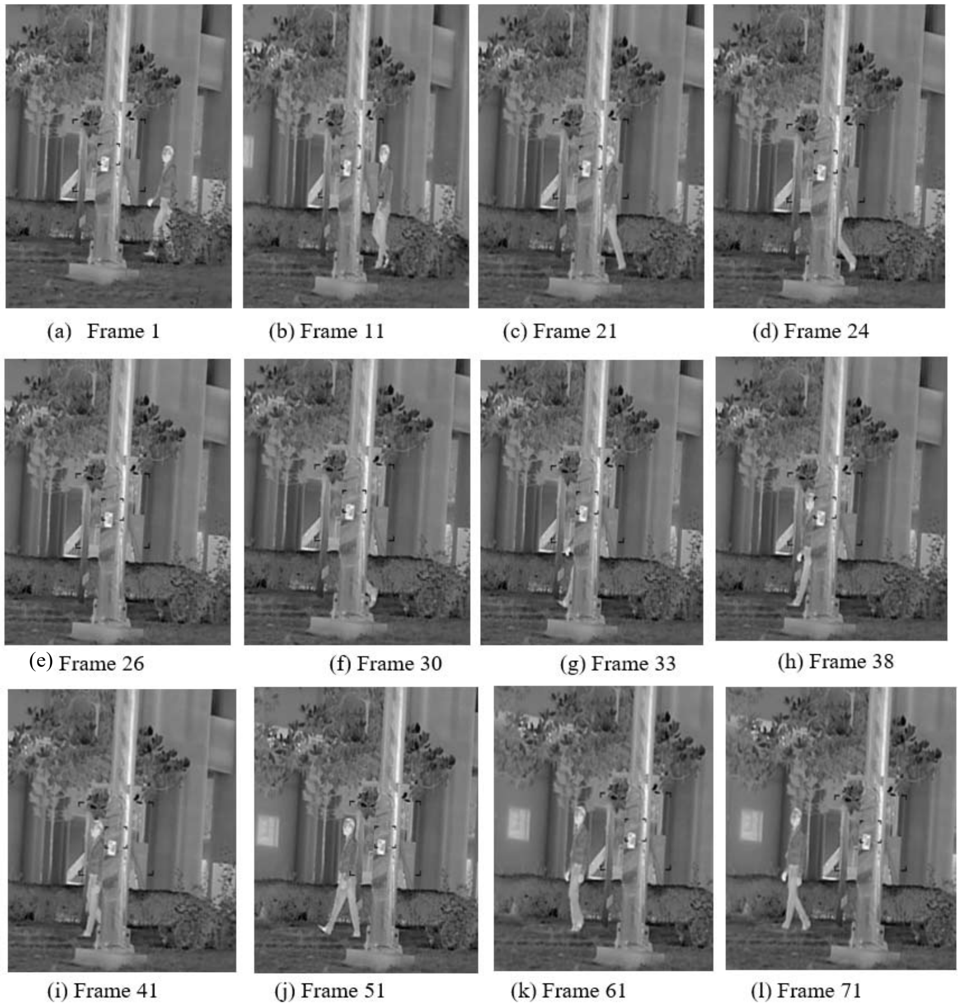


Figure 8. (a-l) Infrared input image sequence of man walking past an occlusion.

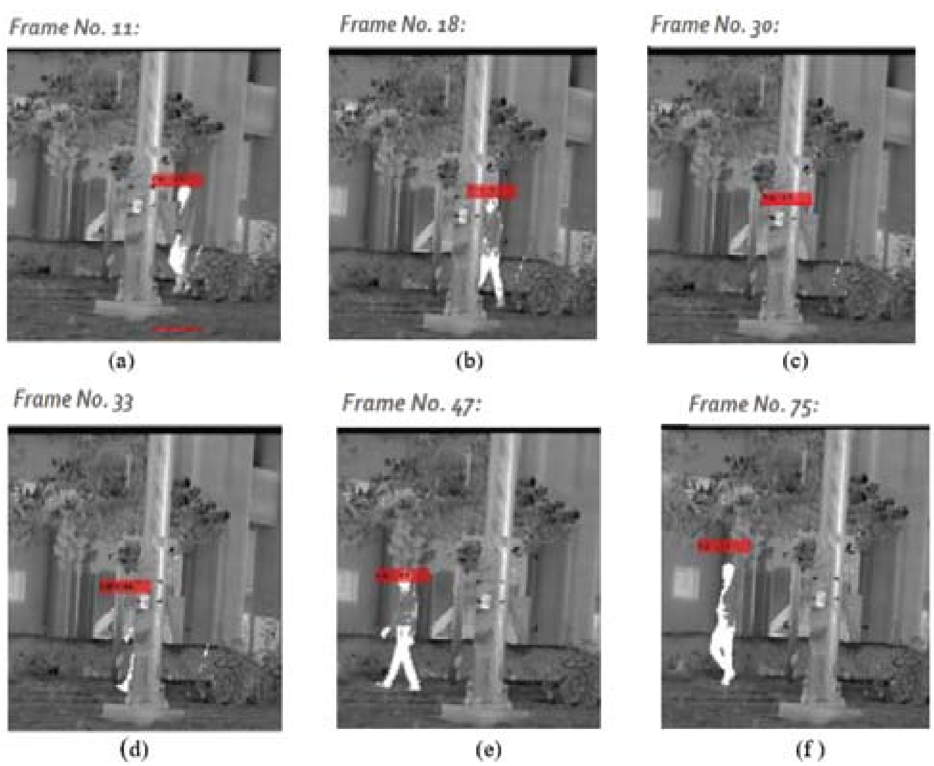
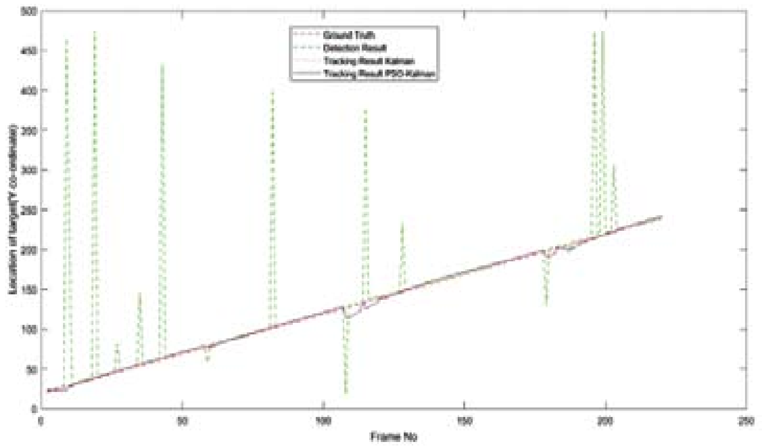
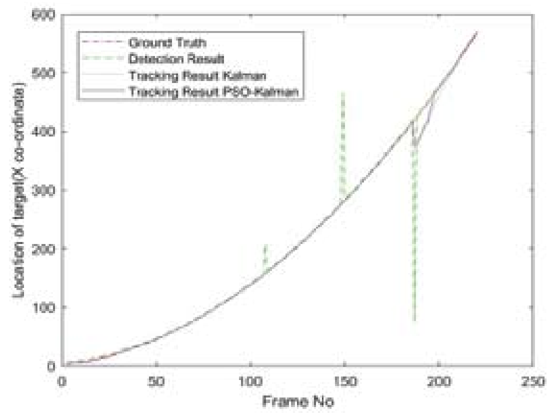


Figure 9. (a-f) Tracked output image sequences using PSO integrated Kalman filter.



(a)



(b)

Figure 10. (a) Tracking results of x-coordinate of tracked pixel in video (b) Tracking results of y-coordinate of tracked pixel in video.

dotted line). As shown in Figs. 10(a) and 10(b) results of proposed algorithms have been compared with Kalman filter-based tracker.

In this analysis, a video sequence with 232 frames was considered. Green peaks in the graph represent a sudden change in the result of detection algorithm. This implies that the object has either been occluded or mis-detected in that duration. From graphical analysis, it can be concluded that the proposed algorithm converges at a higher rate than Kalman filter based tracker in case of occlusion. For the rest of the segment of the graph, as the same algorithm is applied in both cases, results are coinciding. Moreover, comparison of tracking results with Kalman (blue dotted line) and with PSO-Kalman (undotted dark line) is shown. The results clearly show that with PSO-Kalman algorithm, the track converges faster than with Kalman-only algorithm; moreover, the optimisation in the result owing to PSO-Kalman is well established. The quantitative analysis between PSO-Kalman and Kalman-only filter was carried out. Based on the location of target at different frames, the convergence factor is calculated viz.

$$Convergence\ Factor = \frac{\begin{array}{c} Location\ of\ target\ (new\ position) \\ -\,Location\ of\ target\ (previous\ position) \end{array}}{Difference\ of\ frames}$$

At one instant, convergence factor was calculated and in the PSO-Kalman algorithm, track convergence is 56% faster than Kalman-only algorithm.

6. CONCLUSION

A PSO-integrated Kalman filter tracking algorithm with revised local binary pattern for object detection is presented. The proposed scheme is applied to real time thermal images. The result shows that this algorithm works well in partial occlusion, rotational dissimilarity, perspective change, and grey scale inhomogeneity. Furthermore, the results of static background condition are shown. For the dynamic background condition, the background subtraction method cannot be applied as the background knowledge required is dynamic. To overcome this problem, motion compensation method involving transformation of the previous image using required affine transformation can be used. Once the background matches in two frames, frame difference can be employed to detect the motion in frame. This will be taken up as an extension of the present study.

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He has contributed in algorithm performance validation, draft checking, supervision, field results and overall guidance.