
An Improved Video Object Segmentation and Tracking based on Features using Threshold Filtering Technique

P. Vijayakumar¹, A. V. Senthilkumar²

¹Department of Computer Applications, Sri Jayendra Saraswathy Maha Vidyalaya College of Arts and Science, Coimbatore, Tamilnadu, India

²Department of Computer Applications, Hindusthan College of Arts and Science, Coimbatore, Tamilnadu, India

E-mail: P_viji_kumar@yahoo.com, avsenthilkumar@yahoo.com

Abstract

Video object segmentation and tracking is significant research topic in a video surveillance application. Recently, many researches has been developed for video object segmentation and detection, however, the video object segmentation based on features like shape, texture, intensity was not efficiently performed. In this paper, an Improved Threshold Filtered Video Object Detection and Tracking (ITFVODT) framework is designed for efficient video object segmentation based on their features like shape, texture, intensity and tracking of moving objects. ITFVODT framework initially takes video file as input. Then, ITFVODT framework segments the video frames based on shape, texture, intensity of image. After the object segmentation, filtering technique is applied for tracking the video objects. Filtering technique is used in ITFVODT framework for improving the video quality by reducing mean square error. Finally, ITFVODT framework performed the video objects detection task with help of Thresholding technique which in turn improves the video object detection accuracy. The proposed ITFVODT framework using video images obtained from Internet Archive 501(c) (3) for conducting experiment. The performance of ITFVODT framework is tested with the metrics such as object segmentation accuracy, Peak Signal to Noise Ratio, object tracking accuracy, Mean Square Error and object detection accuracy of moving video object frames. Experimental analysis shows that the ITFVODT framework is able to improve the video object segmentation accuracy by 12% and also improve video object detection accuracy by 17% when compared to the state-of-the-art works.

Keywords: Video object segmentation, detection, shape, texture, intensity, filtering technique, thresholding technique

INTRODUCTION

Video Object segmentation is significant for video compression principles by means of identification, event analysis, understanding and video manipulation. Moving object identification techniques can be used to segment a video file into different frames for video surveillance, traffic surveillance and criminal pattern identification and so on. Many research works has been conducted for video object segmentation and detection.

For example, Self Crossing Detection for Parametric Active Contours (SCD-PAC) was developed in to tracking objects in real world video sequence using Sobolev active contours [1]. Though, the object detection accuracy remained unaddressed. The Automatic Estimation of Multiple Motion (AEMM) was designed in using motion correspondence algorithm which significantly detects the multiple motions of objects [2].

Moving object segmentation was performed in video by using mean shift; kalman and particle filter with aiming at improving object tracking accuracy [3]. In, multi target object was efficiently identified based on continuous energy minimization and multiple objects were tracked in a more significant manner [4].

Video object segmentation was presented in where object segmentation was performed with complex scenes without region of interest (ROI) [5].

Automatic foreground object detection was introduced in using probabilistic consensus foreground object template for enhancing the foreground object detection [6]. However, foreground object was cannot perfectly detected. Multimodal analysis for moving objects using Canonical Correlation Analysis (CCA) was performed in to improve the accuracy of moving object detection [7]. However, sounding object segmentation is not effective in some complex scenarios. In, an analysis of moving object detection using diverse image registration techniques was introduced [8].

Object tracking using Support Vector Machines (SVM) was introduced in for multiple objects tracking with aiming at solving the robustness and accuracy of object tracking [9]. A parallel histogram using particle filters was applied to improve the robustness of object tracking [10]. A survey of visual object tracking was performed in both from theoretical and practical viewpoint [11]. Laser-based tracking of multiple objects were performed in using online learning based

method for improving the tracking accuracy under complex situations [12]. Though, tracking accuracy under the presence of occlusions was performed. But, the peak signal noise ratio remained unsolved.

A novel Margin Nearest Neighbor algorithm was designed to support multiple kernels that detect caption in videos using decision tree was introduced in which results in the improvement of detection system [13, 14]. In, Adaptive Appearance Model was introduced for video tracking using application dependent thresholds [15]. However, object tracking accuracy was not at required level.

A robust algorithm was designed in for automatic, noise detection and removal from moving objects in video sequences [16]. Dynamic threshold method was introduced in for moving object detection and Tracking [17]. Detecting and tracking robust algorithm was developed for moving object of intelligent video surveillance system that optimizes the accuracy while maintaining the computational complexity low [18].

A study of localizing target was conducted in to improve detection accuracy [19]. Though, accuracy was improved, but the

mean square error incurred during object tracking remained unsolved. The object segmentation was performed in by applying the multi-model background and subtraction algorithms which improves the robustness of object detection [20].

In, ELT Method was introduced for multiple moving object segmentation in video surveillance [21]. In, proposed a novel Framework for Specific Object Tracking in the Multiple Moving Objects Environment [22]. In, MELT method was introduced for moving object segmentation in video sequences [23]. In, IELT technique initiates the process of video object segmentation, object tracking and finally object detection [24]. In, TFVODT is designed for effective detection and tracking of moving objects [25].

In this paper, a novel framework is designed called Improved Threshold Filtered Video Object Detection and Tracking (ITFVODT) framework for efficient video object segmentation based on shape, texture, intensity and detection of moving video objects. Proposed ITFVODT framework used filtering technique for video object segmentation and tracking. ITFVODT framework performs the video objects detection by using thresholding technique which

significantly improves the objects detection accuracy.

DESIGN OF IMPROVED THRESHOLD FILTERED VIDEO OBJECT DETECTION AND TRACKING (ITFVODT) FRAMEWORK

The design of Improved Threshold Filtered Video Object Detection and Tracking (ITFVODT) framework is detailed described in this section. All moving objects in a video sequence have to be segmented accurately for facilitating efficient surveillance and monitoring. As a result, video segmentation is considered to be one of the most significant processes as it has higher influential rate during the working of the other modules.

The main objective of applying video segmentation to the moving objects in a video sequence is that it signifies and detects the region of interest (ROI) from video stream with the support of their visual and motion properties. Simultaneously, it is also important as video segmentation in moving objects plays a essential role by minimizing the information (i.e., size) to be processed at the later stages, like object tracking, classification of the ROI, segmentation of

ROI and locating the target position (target ROI).

The main objective of ITFVODT framework is to efficiently segment the vide objects based on their features like shape, texture, intensity and to perform the video object detection using Thresholding and filtering techniques. Initially, The ITFVODT framework used filtering technique for improving the video quality and reducing the noise frame.

With the help of filtering techniques, ITFVODT framework performs the video object segmentation and tracking task. Then, Threshold technique is applied in TFFVODT framework to perform efficient moving object detection. In ITFVODT framework, the thresholding technique is done with the help of Gaussian-based Neighbourhood Intensity Proportion (GNIP). The architecture diagram of Improved Threshold Filtered Video Object Detection and Tracking framework is shown in Figure 1.

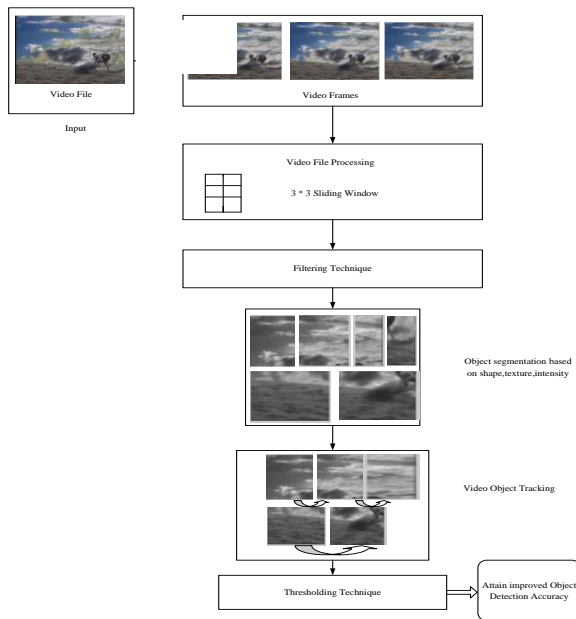


Fig. 1: Architecture Diagram of ITFVODT Framework.

As shown in Figure 1, ITFVODT framework initially takes the video file as input. The video file is divided into number of video frames. All the video frames obtained in ITFVODT framework do not have same characteristics such as quality, brightness or contrast. With the aim of obtaining high quality video images without compromising the quality, brightness or contrast, preprocessing has to be performed for each input video file. Next, filtering techniques are applied on the video frames for video object segmentation and tracking. With the help of filtering technique, ITFVODT framework removes the noise video frame and improves the video quality. ITFVODT framework performs the object

segmentation task based on their features like shape, texture, intensity which results in improved object segmentation accuracy. With the assists of segmented object, ITFVODT framework performs effective object tracking which in turn improves the object tracking accuracy. Finally, ITFVODT framework performs effective moving object detection with the help of moving tracked objects by using thresholding techniques.

Video File Preprocessing

The first step involved in the design of ITFVODT framework is video file preprocessing. Figure 2 given below shows the preprocessing of video file using filtering technique.

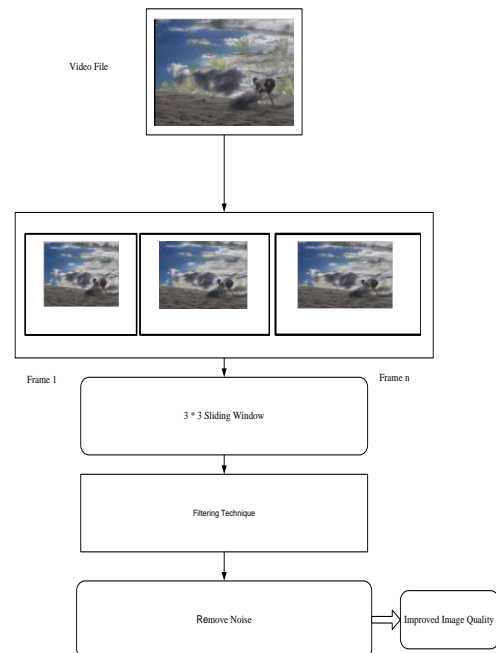


Fig. 2: Video File Preprocessing Using Filtering Technique.

From the Figure 2, when an input video file is given to the file preprocessing, the video file ' VF_i ' is divided into video frames ' f_i '. All the video frames obtained do not possess same features such as quality, brightness or contrast. Normally, several frames in video will not be of good quality, perfect size or with good brightness and contrast. In order to acquire high quality video images without compromising the quality, brightness or contrast, preprocessing has to be performed for each input video file.

The proposed ITFVODT framework uses filtering technique to reduce the noise and so that the preprocessed video frames is used for further process. Let us consider the video frames ' f_i ' with the proposed ITFVODT framework de-noised using a 3×3 sliding window and is mathematically formulated as given below,

$$VF_i \rightarrow f_1, f_2, \dots, f_n \quad (1)$$

From (1), the input video file ' VF_i ' is split into ' n ' frames as the input video file cannot undergo pre-processing without obtaining frames. With the obtained frames 3×3 sliding window for denoising is mathematically formulated as given below:

$$VF_i = \sum_{i=1}^n f_i (3 \times 3) \quad (2)$$

From (2) the frame ' VF_i ' perform denoising using ' 3×3 ' sliding window. After that, the video frames are subjected to the noise detection during the video preprocessing stage.

Video Object Segmentation and Tracking using Filtering Technique

The second step involved in design of ITFVODT framework is video object segmentation and tracking. Proposed ITFVODT framework performs the video object segmentation and tracking tasks with the help of filtering technique. After obtaining the high quality image, video objects are efficiently segmented in ITFVODT framework based on their characteristics like quality, brightness or contrast which improves the object segmentation accuracy. With the assists of segmented video objects, ITFVODT framework effectively tracks the moving objects by using filtering technique which in turn improves the object tracking accuracy. In ITFVODT framework, Filtering technique initially estimates the Bayes Sequential Estimation that measures posterior and prior function for tracking of multiple objects in a video sequence (i.e., videos) with the objective of reducing the peak signal to noise ratio (i.e., PSNR). Each particle ' V_i^j ' evolves consistent with

the state space model and yields an approximation of the prior function as given below:

$$Prob(V_i) = \frac{1}{n} \sum_{j=1}^n (V_i - V_i^j) \quad (3)$$

After, the prior function using Color Histogram-based Particle Filter is acquired, the posterior function for each particle is computed for each particle at time 'T' as given below:

$$Prob(V_i | a_{1 \rightarrow n}) = \sum_{i=1}^n W_T^i (V_i - V_T^i) \quad (4)$$

From (3) and (4), the prior function and posterior function for each particle based on the weight of each particle ' W_T^i ' is obtained. The likelihood model (i.e., prior and posterior function) assists in enhancing the object tracking accuracy by using filtering technique. The algorithm description of video object tracking using filtering technique is shown in below Figure 3.

Input: video sequence ' $V_i = V_1, V_2, \dots, V_n$ '
Output: Improved video object tracking accuracy
Step 1: Begin Step 2: For each video sequence ' V_i ' Step 3: Evaluate likelihood function of the color histogram Step 4: Measure particle prior function using (3) Step 5: Measure particle posterior function using (4) Step 6: End for Step 7: End

Fig. 3: Video Object Tracking Algorithm using Filtering Technique.

From the Figure 3, video object tracking algorithm using filtering technique includes three steps. For each video sequence, the first step evaluates the likelihood function of color histogram. Next, second and third step computes the particle prior and posterior function respectively, which in turn increases the object tracking accuracy.

Video Object Detection using Thresholding Technique

The final step involved in design of ITFVODT framework is video object detection using thresholding technique. The thresholding technique is applied in our ITFVODT framework with the aim of improving the object detection accuracy. In ITFVODT framework, Thresholding techniques preformed with the assist of Gaussian-based Neighbourhood Intensity Proportion (GNIP). ITFVODT framework significantly identifies the target position in each frame by applying the Neighbourhood Intensity Proportion. The feature vectors are mined with the help of correlation in object detection phase. The TFVODT framework deals with a neighbourhood intensity proportion through incorporating the sophisticated object detection algorithm. The algorithmic process of Video object Detection is shown in Figure 4.

Input: Video ' $V_i = V_1, V_2, \dots, V_n$ ', Video Frame ' $VF_i = VF_1, VF_2, \dots, VF_n$ ', weight of contour video object ' $Weight_c$ ', weight of foreground video object ' $Weight_f$ ', number of foreground pixels in contour video object ' $N_c(i, j)$ ', number of contour pixels in foreground video objects ' $N_f(i, j)$ '

Output: Enhanced video object detection accuracy

Step 1: Begin
Step 2: For each video frame ' V '
Step 3: Evaluate neighbourhood intensity proportion
Step 4: Compute the actual value of pixels
Step 5: Evaluate Neighbourhood Intensity Proportion Distribution
Step 6: Evaluate Enhanced Moving Video Object Contour
Step 7: Measure correlation coefficient
Step 8: End for
Step 9: End

Fig. 4: Video Object Detection Algorithm using Thresholding Techniques.

As shown in above Figure, the video object detection algorithm process is described in five steps. For each video frame, the first step calculates the neighbourhood intensity proportion for obtaining the foreground video object. After that, the second step determines the actual value of pixels for removing the noise present in the video object. After removing the noise, the third step calculates the Neighbourhood Intensity








Proportion Distribution for identifying the foreground video object. The fourth step evaluates the Enhanced Moving Video Object Contour. Finally, the correlation coefficient is determined with the intension of improving the moving object detection accuracy.

EXPERIENTIAL SETUP

The proposed Improved Threshold Filtered Video Object Detection and Tracking (ITFVODT) framework is implemented using MATLAB. The video files used for conducting experimental work is obtained from Internet Archive 501(c) (3), a non-profit organization. The Internet Archive includes texts, audio, moving images and software as well as archived web pages.

The video file information illustrated in Table 1 contains the name of the video file, resolution of the video files and their size respectively, for estimating the performance of ITFVODT framework. Experimental evaluation using ITFVODT framework is conducted on various factors such as object segmentation accuracy, Peak Signal to Noise Ratio, object tracking accuracy, Mean Square Error and object detection accuracy with respect to different videos and video frames. The video used for object segmentation and tracking using ITFVODT framework is shown below Table 1 with detailed information.

Table 1: Video File Information.

Name	Video file information		
	Video Frames	Resolution	Size (KB)
Blossom.avi		216 * 192	349.5
Sample.avi		256 * 240	113.6
Vehicle.avi		510 * 420	323.7
Atheltic.avi		854 * 480	905.3
Person.avi		320 * 240	936.2
Flower.avi		350 * 240	454.5
Rose.avi		458 * 213	635.2

DISCUSSION

The result analysis of ITFVODT framework is discussed in this section. The performance of ITFVODT framework is compared against with exiting three methods namely, Self Crossing Detection for Parametric Active Contours (SCD-PAC), Automatic Estimation of Multiple Motion (AEMM) and Threshold Filtered Video Object Detection and Tracking (TFVODT) framework [1, 2]. The performance of ITFVODT framework is estimated with the following metrics.

Impact of Object Segmentation Accuracy

The object segmentation accuracy using ITFVODT framework is defined as the ratio of objects being segmented to the total number of frames/second. The object segmentation accuracy is measured in terms of percentage (%) and mathematically formulated as below:

$$\text{object segmentation accuracy} = \frac{OS}{\text{Number of frames/second}} * 100 \quad (5)$$

From (5), '*OS*' represent objects being correctly segmented based on shape, texture, intensity. When the object segmentation accuracy is higher, the method is said to be more efficient.

Table 2: Tabulation for Object Segmentation Accuracy.

Number of Frames/Second	Object Segmentation Accuracy (%)			
	ITFVO DT	TFVO DT	SCD-PAC	AEMM
10	76.48	72.78	63.71	59.17
20	80.87	76.14	68.27	63.24
30	85.89	81.07	72.41	67.87
40	88.97	84.34	78.26	71.39
50	90.78	86.47	81.64	75.07
60	94.68	90.77	84.19	79.78
70	96.81	92.17	91.81	83.87

Table 2 given above demonstrate the object segmentation accuracy of ITFVODT, TFVODT, SCD-PAC, AEMM methods [1, 2]. From the Table, it is

illustrative that the object segmentation accuracy using ITFVODT framework is higher as compared to TFVODT, SCD-PAC, AEMM methods [1, 2].

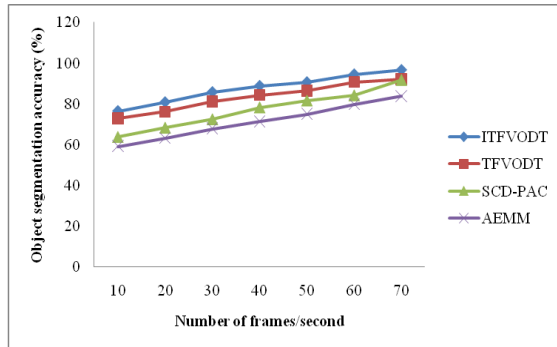


Fig. 5: Measurement of Object Segmentation Accuracy.

Figure 5 demonstrates the impact of object segmentation accuracy with respect to varying frames being sent per second in the range of 10 to 70. The results reported above confirm that with the increase in the number of frames being sent, the object detection accuracy also increases. As illustrated in Figure 5, the proposed ITFVODT framework performs relatively well when compared to two other methods TFVODT, SCD-PAC, AEMM [1, 2]. This is because of the application of filtering technique in ITFVODT framework that replaces the noisy pixels and efficiently segments the video objects based on their characteristics like shape, texture, intensity. Therefore, the object segmentation accuracy using ITFVODT framework is improved by 5% as

compared to TFVODT method and 12% as compared to SCD-PAC method and 19% as compared to AEMM method respectively [1, 2].

Impact of Peak Signal to Noise Ratio

In ITFVODT framework, Peak Signal-to-Noise Ratio measures the ratio between the reference video frame and the distorted video frame being detected in a video file. When higher the PSNR, the closer the distorted video frame is to the original. As a result, higher PSNR value associate with higher quality image (i.e., detected image) and is mathematically formulated as given below:

$$MSE = \sum_{i=1}^n (V_i - V'_i)^2 \quad (6)$$

$$PSNR = 10 \log_{10} \frac{R^2}{MSE} \quad (7)$$

From (6), the mean square error ' MSE ' is defined as the difference between the actual frame size ' V_i ' and the estimated frame size ' V'_i ' being detected. From (7), the peak signal-to-noise ratio ' $PSNR$ ' is calculated using the unsigned integer data type (with size 255) with respect to mean square error rate ' MSE ' respectively.

Table 3: Tabulation for PSNR.

Size of Video File (KB)	Peak Signal to Noise Ratio (%)			
	ITFVODT	TFVODT	SCD-PAC	AEMM
113.6	29.34	25.78	19.65	15.11
323.7	34.17	30.84	24.87	19.59
349.5	40.19	36.24	29.33	23.78
454.5	43.11	38.47	31.82	27.17
635.2	45.37	41.73	34.43	31.10
905.3	49.87	43.15	37.51	35.97
936.2	51.24	46.88	40.28	39.98

In the experimental setup, the size of video file ranges from 100 KB to 1000 KB. The results of seven simulation runs conducted to measure the Peak Signal-to-Noise Ratio are listed in Table 3. The Peak Signal-to-Noise Ratio obtained using our ITFVODT framework offer comparable values than the state-of-the-art methods.

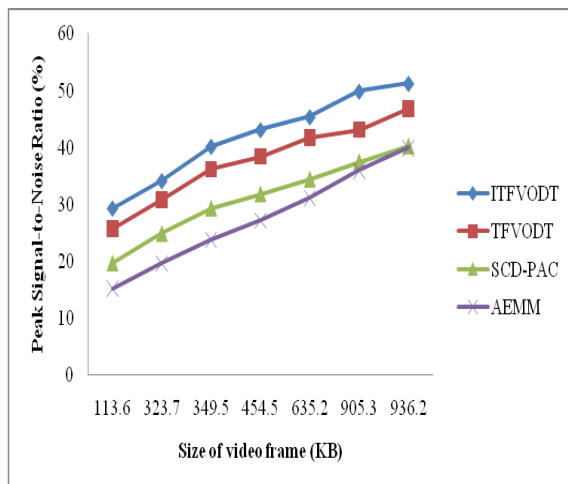


Fig. 6: Measurement of Peak Signal to Noise Ratio.

As shown in the Figure 6, the Peak Signal to Noise Ratio of four different schemes ITFVODT, TFVODT, SCD-PAC, AEMM are analyzed [1, 2]. From the Figure, the proposed ITFVODT framework provides better performances as compared to the other methods TFVODT, SCD-PAC, AEMM. This is because of the application of Filtering technique in ITFVODT framework. Filtering technique used Bayes Sequential Estimation that measures posterior and prior function for tracking of multiple objects in a video sequence and significantly reduces the Peak Signal to Noise Ratio. Therefore, Peak Signal to Noise Ratio using ITFVODT framework is reduced by 10% as compared to TFVODT method and 26% as compared to SCD-PAC method and 36% as compared to AEMM method respectively [1, 2].

Impact of Object Tracking Accuracy

The object tracking accuracy using ITFVODT framework is defined as the ratio of objects being tracked to the total number of frame/second. The object tracking accuracy is measured in terms of percentage (%) and formulated as below:

$$\text{object tracking accuracy} = \frac{OT}{\text{Number of frames/second}} * 100 \quad (8)$$

From (8), '*OT*' refers the objects being correctly tracked. When the object

tracking accuracy is higher, the method is said to be more efficient.

Table 4: Tabulation for Object Tracking Accuracy.

Number of Frames/Second	Object Tracking Accuracy (%)			
	ITFV ODT	TFV ODT	SCD-PAC	AEMM
10	78	75	72	69
20	82	79	76	73
30	87	84	81	78
40	81	77	74	71
50	86	82	79	77
60	89	85	82	79
70	91	88	84	83

In Table 4, we compare the object tracking accuracy with respect to different number of frames being sent per second in the range of 10 to 70. From the table, it is illustrative that the object tracking accuracy using ITFVODT framework is higher as compared to TFVODT, SCD-PAC, AEMM methods [1, 2].

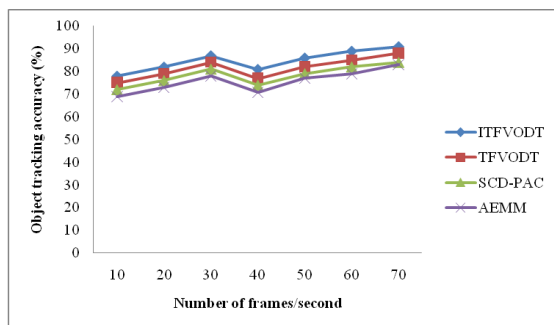


Fig. 7: Measurement of Object Tracking Accuracy.

Figure 7 depicts the Object tracking accuracy with respect to different number of frames being sent per second in the range of 10 to 70. From the results shown in the Figure, it is observed that the Object tracking accuracy using ITFVODT framework is comparatively higher when compared to other TFVODT, SCD-PAC, AEMM methods [1, 2]. This is because of the application of filtering technique in ITFVODT framework which efficiently tracks the moving objects in video sequences. Therefore, object tracking accuracy using ITFVODT framework is improved by 4% as compared to TFVODT method and 8% as compared to SCD-PAC method and 11% as compared to AEMM method respectively [1, 2].

Impact of Mean Square Error

In ITFVODT framework, The Mean Square Error (MSE) is used to measure the video quality being obtained during multiple object tracking. The MSE represents the error between the tracked frames and the original video frame. When lower the value of MSE, the method is said to be more efficient and it is measured in terms of db.

$$MSE = \sum_{i=1}^n (V_i - v_i) \quad (9)$$

From (9), the mean square error '*MSE*' is the difference between the actual frame

size ' V_i ' and the estimated frame size ' V_i' ' being tracked.

Table 5: Tabulation for Mean Square Error.

Size of Video Frame (KB)	Mean Square Error (db)			
	ITFVODT	TFVODT	SCD-PAC	AEMM
113.6	15.48	18.15	22.04	26.11
323.7	17.35	20.54	24.54	27.54
349.5	18.57	22.97	27.88	32.87
454.5	24.59	27.67	30.97	34.71
635.2	31.34	34.79	36.17	41.25
905.3	37.67	40.81	43.95	46.84
936.2	45.78	48.07	52.64	54.98

Table 5 shows the Mean Square Error rate with respect to varying size of video frames. To better perceive the efficiency of the proposed ITFVODT framework, substantial experimental results are illustrated in Figure 8 and compared against with the TFVODT, SCD-PAC, AEMM methods respectively [1, 2].

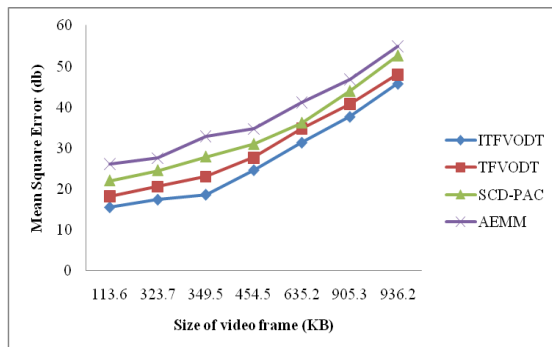


Fig. 8: Measurement of Mean Square Error Rate.

Figure 8 shows the impact of Mean Square Error Rate with respect to varying size of video frames in the range of 100 to 1000. The results reported above confirm that with the increase in the size of video frame being sent, Mean Square Error Rate also increases. As illustrated in Figure, the proposed ITFVODT framework performs relatively well when compared to other methods TFVODT, SCD-PAC, AEMM. This is because of the application of filtering and thresholding technique in ITFVODT framework which efficiently removes the noise frames and significantly performs the video object detection task. As a result, Mean Square Error Rate using ITFVODT framework is reduced by 14% as compared to TFVODT method and 30% as compared to SCD-PAC method and 46% as compared to AEMM method respectively [1, 2].

Impact of Object Detection Accuracy

The object detection accuracy using ITFVODT framework is defined as the ratio of objects being detected to the total number of frames/second. The object detection accuracy is measured in terms of percentage (%) and mathematically formulated as below:

$$\text{object detection accuracy} = \frac{OD}{\text{Number of frames/second}} * 100 \quad (10)$$

From (10), '**OD**' refers to the objects being correctly detected. When the object detection accuracy is higher, the method is said to be more efficient.

Table 6: Tabulation for Object Detection Accuracy.

Methods	Object Detection Accuracy (%)
ITFVODT	92
TFVODT	87
SCD-PAC	74
AEMM	68

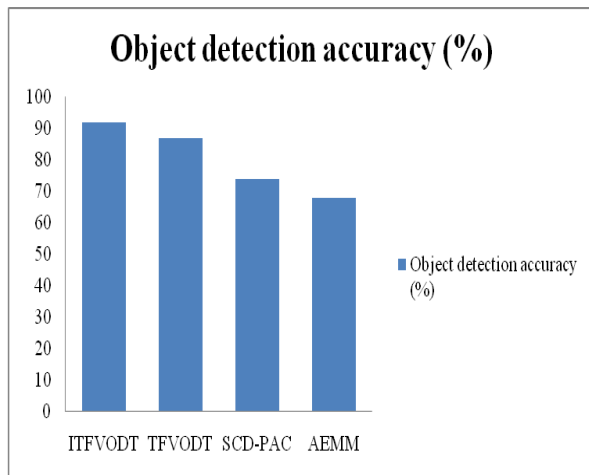


Fig. 9: Measurement of Object Detection Accuracy.

Table 6 and Figure 9 demonstrate the object detection accuracy versus seven different videos obtained from Internet Archive 501(c) (3), a non-profit organization and simulated in MATLAB. From the Figure, the object detection accuracy using ITFVODT framework is

higher framework than when compared to the other methods TFVODT, SCD-PAC, AEMM respectively [1, 2]. This is because of the application of thresholding technique in ITFVODT framework. Thresholding technique significantly identifies the target position in each frame by applying the Neighbourhood Intensity Proportion which results in improvement of object detection accuracy. Therefore, object detection accuracy using ITFVODT framework is improved by 5% as compared to TFVODT method and 20% as compared to SCD-PAC method and 26% as compared to AEMM method respectively [1, 2].

CONCLUSION

In this paper, an enhanced novel framework is designed called as Improved Threshold Filtered Video Object Detection and Tracking (ITFVODT) for efficient video object segmentation based on shape, texture, intensity and detection of moving objects in video frames. The ITFVODT technique improves the object segmentation accuracy by means of reducing the PSNR by filtering technique. The main objective of ITFVODT framework is to improve the object segmentation accuracy based on their features. From the experiments conducted for ITFVODT framework, it is observed

that of video object segmentation accuracy and detection accuracy for different video samples offers more accurate results when compared to state of the art works. The experimental results illustrate that ITFVODT framework provides better performance with an improvement of object segmentation accuracy by 12% and the object detection accuracy by 17% when compared to state of the art works.

REFERENCES

1. Arie Nakhmani, Allen Tannenbaum. Self-crossing detection and location for parametric active contours. *IEEE Transactions on Image Processing*. 2012; 21(7): 3150–3156p.
2. Many V. Afonso, Jacinto C. Nascimento, Jorge S. Marques. Automatic estimation of multiple motion fields from video sequences using a region matching based approach. *IEEE Transactions on Multimedia*, 2014; 16(1): 1–14p.
3. Barga Deori, Dalton Meitei Thounaojam. A Survey on moving object tracking in video. *International Journal on Information Theory (IJIT)*. 2014; 3(3): 31–46p.
4. Sukanyathara J, Alphonsa Kuriakose. An optimized framework for detection and tracking of video objects in challenging backgrounds. *The International Journal of Multimedia & Its Applications (IJMA)*. 2014; 6(4): 27–38p.
5. Daniela Giordano, Francesca Murabito, Simone Palazzo et al. Superpixel-based video object segmentation using perceptual organization and location prior. *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2015; 4814–4822p.
6. Shih-Wei Sun, Yu-Chiang Frank Wang, Fay Huang et al. Moving foreground object detection via robust SIFT trajectories. *Journal of Visual Communication and Image Representation*. 2013; 24(3): 232–243p.
7. Hamid Izadinia, Imran Saleemi, Mubarak Shah. Multimodal analysis for identification and segmentation of moving-sounding objects. *IEEE Transactions on Multimedia*. 2013; 15(2): 378–390p.
8. Subhabrata Bhattacharya, Haroon Idrees, Imran Saleemi et al. Moving object detection and tracking in forward looking infra-red aerial imagery. *Springer, Machine Vision beyond Visible Spectrum*. 2011; 1–32p.
9. Shunli Zhang, Xin Yu, Yao Sui et al. Object tracking with multi-view

- support vector machines. *IEEE Transactions on Multimedia*. 2015; 17(3).
10. Henry Medeiros, Germán Holguín, Paul J. Shin, et al. A parallel histogram-based particle filter for object tracking on SIMD-based smart cameras. *Elsevier*. 2010; 114(11): 1264–1272p.
11. Xi Li NLPR, Weiming Hu NLPR, Chunhua Shen, et al. A survey of appearance models in visual object tracking. *ACM Transactions on Intelligent Systems and Technology (TIST)*. 2013; 4(4): 1–48p.
12. Xuan Song, Jinshi Cui, Huijing Zhao et al. Laser-based tracking of multiple interacting pedestrians via on-line learning. *Elsevier*. 2013; 115(4): 92–105p.
13. Brian McFee, Carolina Galleguillos, Gert Lanckriet. Contextual object localization with multiple kernel nearest neighbor. *IEEE Transactions on Image Processing*. 2011; 20(2): 570–585p.
14. Xu Zhao, Kai-Hsiang Lin, Yun Fu et al. Text from corners: A novel approach to detect text and caption in videos. *IEEE Transactions on Image Processing*. 2011; 20(3): 790–799p.
15. Samuele Salti, Andrea Cavallaro, Luigi Di Stefano. Adaptive appearance modeling for video tracking: survey and evaluation. *IEEE Transactions on Image Processing*. 2012; 21(10): 4334–4348p.
16. Safvan Vahora, Narendra Chauhan, Nilesh Prajapati. A robust method for moving object detection using modified statistical mean method. *International Journal of Advanced Information Technology (IJAIT)*. 2012; 2(1): 65–73p.
17. Jyoti J. Jadhav. Moving object detection and tracking for video surveillance. *International Journal of Engineering Research and General Science*. 2014; 2(4): 372–378p.
18. Mrinali M. Bhajibhakare, Pradeep K. Deshmukh. To detect and track moving object for surveillance system. *International Journal of Innovative Research in Computer and Communication Engineering*. 2013; 1(4): 945–949p.
19. R. Kwitt¹, N. Vasconcelos², S. Razzaquec et al. Localizing target structures in ultrasound video-A phantom study. *Elsevier*. 2013; 17(7): 712–722p.
20. Pojala Chiranjeevi, Somnath Sengupta. Neighborhood supported model level fuzzy aggregation for moving object segmentation. *IEEE*

- Transactions on Image Processing*. 2014; 23(2): 645–657p.
21. P. Vijayakumar, A. V. Senthil Kumar. Moving object segmentation using enhanced laplacian thresholding method for video surveillance. *IJCA*. 2014; 100(4): 13–17p.
22. P. Vijayakumar, A. V. Senthil Kumar. A novel framework for specific object tracking in the multiple moving objects environment. *IJAER*. 2015; 10(16): 36540–36545p.
23. P. Vijayakumar, A. V. Senthil Kumar. Moving object segmentation using median filter-based enhanced laplacian thresholding. *EJSR*. 133; 415–427p.
24. P. Vijayakumar, A. V. Senthil Kumar. Improvising enhanced laplacian thresholding technique for efficient moving object detection in video surveillance. *IOSRJEN*. 2016; 06(01): 42–52p.
25. P. Vijayakumar, A. V. Senthil Kumar. Threshold based filtering technique for efficient moving object detection and tracking in video surveillance. *IJRET*.