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Improvising Enhanced Laplacian Thresholding Technique For Efficient Moving Object Detection In Video Surveillance

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Abstract: - Video Object Detection is more demanding in various video surveillance application i.e., public and private domains. The video object detection, identify similarity of objects and object parts between consecutive frames of video. The moving object detection, analyze the video frames with its foreground and back ground image objects. The foreground image objects are usually considered to be moving ones and the background objects are considered to be static. Recently several contributions in the video object detection had been made, but lacks detection accuracy and unaddressed background object detection in the video frames. In this paper, a novel framework of object detection for video surveillance called Improvised Enhanced Laplacian Threshold (IELT) technique. The improvisation of ELT is done with Gaussian-based Neighbourhood Intensity Proportion (GNIP). The IELT technique initiates the process of video object segmentation, object tracking and finally object detection. In video object segmentation, the input video frames are segmented with the help of Median Filter-based Enhanced Laplacian Thresholding to improve the video quality. In object tracking, Color Histogram-based Particle Filter is applied to the segmented objects by computing the likelihood function, particle posterior and particle prior function based on the Bayes Sequential Estimation model. Finally, the object detection is performed with improvisation of enhanced Laplacian threshold by analyzing neighbourhood Intensity proportion of moving object contour. IELT with Gaussian distribution of neighbourhood proportion improves video object detection accuracy and identify background moving object detection. Experimental evaluation is done on IELT with performance metrics such as time taken for object segmentation, object tracking and detection accuracy, and peak signal-to-noise ratio of moving video object frames. The data set sample of different videos extracted from Internet Archive 501(c) (3), a non-profit organization on effective video object detection for video surveillance. Experimental analysis shows that the GNIP framework is able to reduce the object segmentation time by 52% and improve the video object detection accuracy by 12% compared to the state-of-the-art works.

***Keywords**: Object Detection, Gaussian-based Neighbourhood, Intensity Proportion, Enhanced Laplacian Thresholding, Particle Filter, Bayes Sequential*

I. INTRODUCTION

Recently, several contributions have been proposed and successfully demonstrated for video object detection. However, these algorithms need to resolve the difficulties such as denser environments and target noises encountered during detection process.

Estimation of Multiple Motion Fields using Region Matching (EMMF-RM) [1] designed a motion correspondence algorithm to estimate the multiple motion fields. Self Crossing Detection for Parametric Active Contours (SCD-PAC) [2] performed successful tracking in real world video sequences using Sobolev active contours. However, the segmentation time remained unaddressed. The GNIP framework addressed this issue by applying Median Filter-based Enhanced Laplacian Thresholding technique.

Real time objection detection involving face detection has several computer vision applications, including, video surveillance, teleconference systems and human motion analysis. Several detectors have been proposed in the literature. Sparse Eigen vectors [3] were applied to achieve high detection results, Coarse Grain Quality Scalability (CGQS) [4] used the Mean Absolute Difference (MAD) to improve the accuracy of the object being detected.

A novel algorithm to support multiple kernels called, Margin Nearest Neighbour [5], detect caption in videos using decision tree was introduced in [6] that resulted in the improvement of detection system. However, the rate of object tracking accuracy remained unsolved, which is addressed in GNIP framework using Color Histogram-based Particle Filter technique.

With the increasing use of digital cameras, mobile phones and PDAs, content-based video object image analysis techniques are receiving greater amount of interest in recent years. Conditional Random Field (CRF)

[7] achieved higher precision and recall performance in detecting video objects. Video Quality Assessment (VQA) [8] with the aid of Mean Opinion Score (MOS) was designed to improve the video quality.

Contour tracking using deformable trellis [9] was performed to demonstrate the effectiveness in terms of image quality. Online object tracking using Bayesian inference [10] framework was designed to improve the robustness in object tracking. An integrated framework using segmentation and registration [11] was performed to improve the object tracking efficiency by applying divide and conquer method.

Moving object detection from video sequences is the most important steps to be performed in several video surveillance applications. In [12] object segmentation with the objective of object detection was performed using multi-model background and subtraction algorithms to improve the robustness of object detection. In [13], polynomial post-nonlinear mixing model was applied in hyper spectral images to improve the object detection strategy.

Contour-based object detection was performed in [14] based on shape similarity to detect multiple objects. In [15], object detection using curvilinear structures was applied to detect both foreground and background images. A video surveillance framework based on threat assignment algorithm was designed in [16] with the objective of reducing the false alarms being generated.

Visual recognition system using local invariant detectors was applied in [17] to improve the rate of features being detected and tracking performance using template-based descriptor. Automatic foreground object detection was performed in [18] using probabilistic consensus foreground object template to improve the foreground object detection results. Multimodal analysis [19] for moving objects using Canonical Correlation Analysis (CCA) was performed to improve the precision of moving objects being detected. An analysis of moving object detection using different image registration techniques was presented in [20]. In [21], ELT Method was introduced for multiple moving object segmentation in video surveillance. In [22], proposed a novel Framework for Specific Object Tracking in the Multiple Moving Objects Environment. In [23], MELT method was introduced for moving object segmentation in video sequences.

Based on the aforementioned techniques and methods presented, in this work we present a novel framework of object detection for video surveillance is presented. We focus on segmenting, tracking and detecting video objects for video surveillance.

Based on the Median Filter-based Enhanced Laplacian Thresholding technique, we calculate the median value to remove the noise. Followed by this, the segmented video objects are used for efficient tracking of objects using the Color Histogram-based Particle Filter. Finally, to perform object detection, we propose an Improvising Enhance Laplacian Thresholding (IELT) technique using Gaussian distribution for Neighbourhood Intensity Proportion for moving object detection. From our experimental results, it can be verified that the use of our IELT technique produces excellent foreground object detection results for video surveillance.

The paper is organized as follows. In Section II, we describe in detail our IELT using Gaussian distribution of neighbourhood intensity proportion of moving object detection, including a detailed derivation of our IELT video detection algorithm. Section III, introduces the different experimental settings studied in this work. We evaluate our algorithm for object detection and compare with the state of the work, discuss in detail in Section IV. Finally, conclusions are presented in Section V.

II. DESIGN OF IMPROVISING ENHANCED LAPLACIAN THRESHOLD (IELT) BY USING GAUSSIAN-BASED NEIGHBOURHOOD INTENSITY PROPORTION

IELT technique works with the distribution of moving object using Gaussian probability and the neighbourhood intensity proportion of moving objects in both background and foreground of the video frames are analyzed. Figure 1 shows the block diagram of IELT using Gaussian distribution and neighbourhood intensity proportion of objects in the video frames.

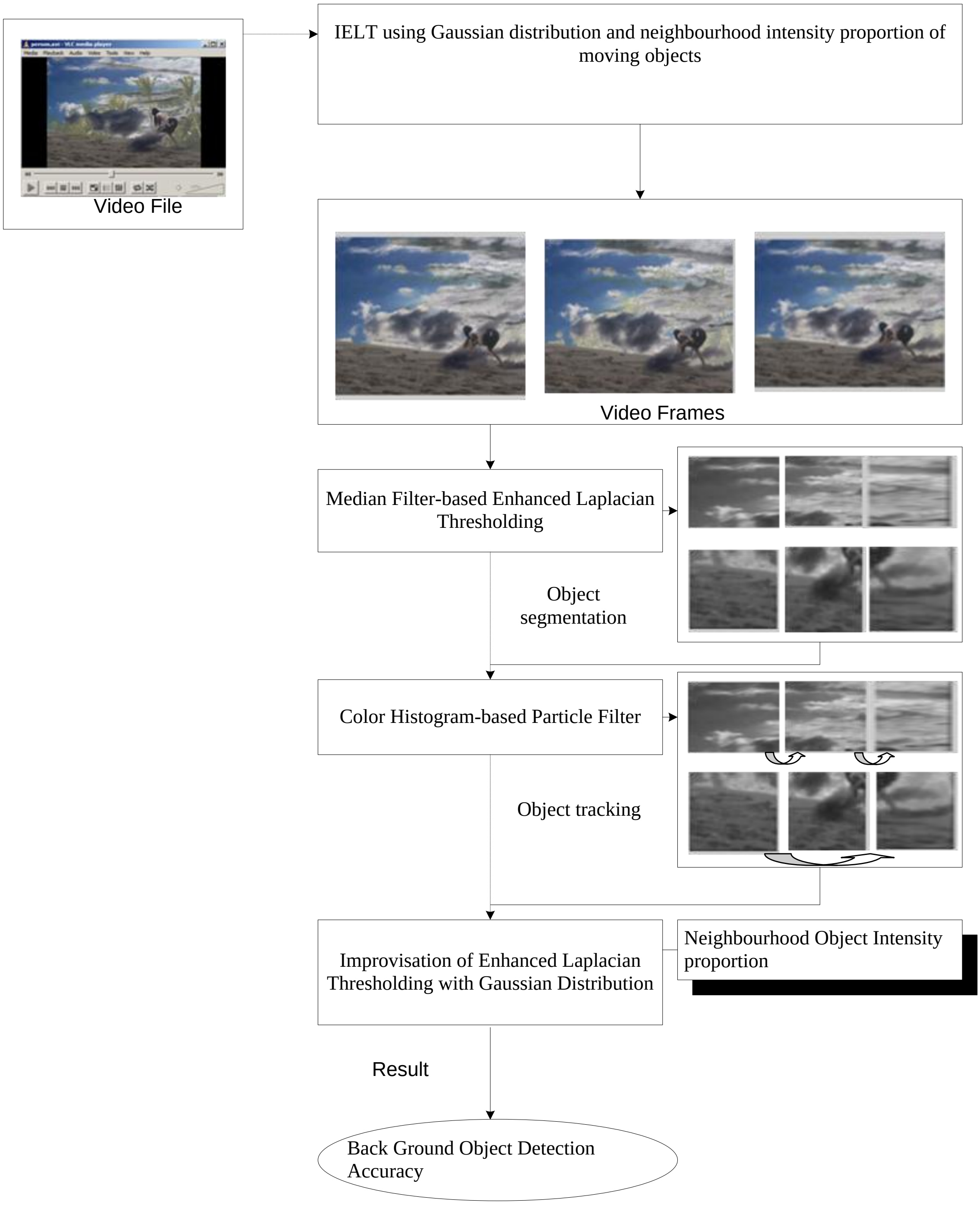

Figure 1 Block diagram of Gaussian-based Neighbourhood Intensity Proportion

As shown in the figure, we first segment the video objects by applying Median Filter-based Enhanced Laplacian Thresholding, find the median value replaces the noisy pixels according to the number of row and columns that posses the noisy pixels with respect to the overall size of video frames. Next, with the segmented object, efficient object tracking is performed based on particle filter and then compute the particle posterior and particle prior function to improve the object detection accuracy. After computing the particle of moving tracked objects, we then perform a Gaussian-based Neighbourhood Intensity Proportion for efficient object detection.

2.1 Median Filter-based Enhanced Laplacian Thresholding

The first step in the design of Gaussian-based Neighbourhood Intensity Proportion is Median Filter-based Enhanced Laplacian Thresholding for efficient object segmentation. An Un-symmetric Trimmed Median Filter is applied on the video frames with the objective of reducing the Peak Signal Noise-to Ratio (PSNR). Un-symmetric Trimmed Median Filter outs noisy frames applying a three dimension sliding window model and is formulated as given below.

$$VF_i = \sum_{i=1}^{n} f_i \ (3 * 3) \tag{1}$$

From (1), 'VF_i' symbolizes the video frame that performs perform denoising using '$3 * 3$' sliding window. Followed by this the median value is calculated to replace the noisy pixels and is formulated as follows for a given '$M_{columns} * N_{rows}$' of frame 'f_i',

$$M3D[M * N] = median \ \{\frac{M_{columns} N_{rows}}{Total \ video \ frames}\} \tag{2}$$

Next, Hierarchy-based Laplacian Thresholding is applied to the pre-processed video frames to process complex video image frame by frame. This Frame selection decision model reduces the mean square error substantially.

2.2 Color Histogram-based Particle Filter

The second step in the design of Gaussian-based Neighbourhood Intensity Proportion is Color Histogram-based Particle Filter is to perform object tracking in an efficient manner. The Color Histogram-based Particle Filter initially estimates the Bayes Sequential based on the posterior and prior function and therefore improving the object detection accuracy. Each particle 'V_i^j' evolves according to the state space model and yields an approximation of the prior function as given below.

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

Once, the prior function using Color Histogram-based Particle Filter is obtained, the posterior function for each particle is measured for each particle at time 'T' as given below.

$$Prob \ (V_i \mid a_{1 \to n}) = \sum_{i=1}^{n} W_T^i \ (V_i - V_T^i) \tag{4}$$

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) helps in improving the object tracking performance with the aid of color histogram-based particle filter.

2.3 Improvising Enhanced Laplacian Threshold with Gaussian Distribution and Neighbourhood Intensity Proportion

Finally, the third step is the design of Gaussian-based Neighbourhood Intensity Proportion. It is used for efficient object detection to detect the target position in each frame with Neighbourhood Intensity Proportion. In object detection phase, the feature vectors are extracted using correlation. Correlation is used in deriving neighbourhood intensity proportion that provides direct measure of similarity between two video frames. The proposed model deals with a neighbourhood intensity proportion by incorporating the sophisticated object detection algorithm such as Gaussian Contour Foreground Video Detection.

In this work, a Gaussian mixture model with neighbourhood intensity proportion is used to extract the foreground. The neighbourhood intensity proportion for a video frame 'V' is given as below.

$$NIP \ (i,j) = \frac{I(i,j) * V(i,j)}{I \ (a,b)} \tag{5}$$

From (5), 'NIP' symbolizes the Neighbourhood Intensity Proportion for the pixel 'i,j', '$I(i,j)$' represents the intensity of the pixel 'i,j', whereas '$V(i,j)$' represents the number of pixels in video 'V'. Therefore the distribution of Neighbourhood Intensity Proportion is formulated using Gaussian model to detect the foreground. It is presumed that the images are corrupted by Gaussian noise and is formulated as given below.

$$P_a \ (i,j) = P_r \ (i,j) + \varphi \ (i,j) \tag{6}$$

From (6), '$P_a \ (i,j)$' symbolizes the actual value of pixels '(i,j)', '$P_r \ (i,j)$' symbolizes the real value of pixels '(i,j)' and '$\varphi \ (i,j)$' represents the noise present in the video object. Then, the Neighbourhood Intensity Proportion Distribution is as given below.

$$NIPD = \frac{P_r\,(i,j)}{P_r\,(a,b)} \tag{7}$$

With the Neighbourhood Intensity Proportion Distribution, the recent history of each pixel is maintained using 'm' Gaussian distributions with the value of 'm' chosen as a threshold constant that depends upon the frame size. In this way the foreground video object is detected using the Gaussian model.

Some parts of the foreground video object 'V_f' may be darker than the background and hence are easily false detected as background. In order to avoid this, enhanced foreground video objects are used to erase the noises and to get moving video objects contours video object 'V_c' without shadow. Let us consider a pixel '$P\ (i,j)$' being not foreground pixel in contours video object, the weighted foreground pixel intensity of a neighbourhood proportion in the contour video object and foreground video object is as given below.

$$EMVOC\ (i,j) = \frac{Weight_c * N_c\,(i,j) + Weight_f * N_f(i,j)}{V\,(i,j)} \tag{8}$$

Where $N_c(i,j) \in V\,(i,j)$ & $N_f(i,j) \in V\,(i,j)$

From (8), '$Weight_c$' and '$Weight_f$' symbolizes the weight of contour video object and foreground video object. '$N_c(i,j)$' and '$N_f(i,j)$' represents the number of foreground pixels in contour video object and number of contour pixels in foreground video objects respectively. Finally the enhanced moving video objects contour '$EMVOC\ (i,j)$' is obtained.

In proposed Gaussian-based Neighbourhood Intensity Proportion framework, the correlation block evaluates the cross correlation between the training video frame (i.e. frames applying a three dimension sliding window) and test video frame (i.e. enhanced moving video objects contour). At each frame, the cross correlation coefficient has inflated values for matching video objects and deflated values for non-matching video objects. The cross correlation coefficient values for each video object are formulated as given below.

$$CC(i,j) = V(i,j) * EMVOC\ (i+a, j+b) \tag{9}$$

From (9), the inflated values symbolizes the presence of video objects (i.e. video objects being detected) in consecutive frames whereas the deflated values symbolizes the absence of video objects (i.e. video objects not being detected). Figure shows the algorithmic description of Gaussian Contour Foreground Video Detection.

Input: Video '$V_i = V_1, V_2, \ldots, V_n$', Video Frame '$VF_i = VF_1, VF_2, \ldots, VF_n$', 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: Improved video object detection accuracy
Step 1: Begin Step 2: For each video frame 'V' Step 3: Measure neighbourhood intensity proportion using (5) Step 4: Measure the actual value of pixels using (6) Step 5: Measure Neighbourhood Intensity Proportion Distribution using (7) Step 6: Measure Enhanced Moving Video Object Contour using (8) Step 7: Measure correlation coefficient using (9) Step 8: End for Step 9: End

Figure 2 IELT with Gaussian Contour Video Object Detection algorithm

As shown in the figure, the algorithmic description of Gaussian Contour Foreground Video Detection includes five steps. For each video frame, the first step measures the neighbourhood intensity proportion to extract the foreground video object. Followed by this, the second step measures the actual value of pixels removing the noise present in the video object. Next, the third step measures the Neighbourhood Intensity Proportion Distribution detect the foreground video object after removing the noise. The fourth step measures the Enhanced Moving Video Object Contour and finally, the correlation coefficient is evolved improving the video object detection accuracy.

III. EXPERIMENTAL SETUP

The Gaussian-based Neighbourhood Intensity Proportion (GNIP) framework for object detection performs experimental work on MATLAB. The GNIP framework uses the video files and their sizes and the video files used to conduct experiment are listed in Table 1. The video files are 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.

Experiments conducted using the video files and their information listed in table 1 includes the name of the video file, the video frames obtained, their corresponding resolution and their size respectively for evaluating the GNIP framework. The video used for object detection using GNIP framework is shown below with detailed information. Experimental evaluation using GNIP framework is conducted on various factors such as object segmentation time, peak signal-to-noise ratio, object detection accuracy and object tracking performance with respect to different videos and video frames.

Table 1 Experimental settings

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

IV. DISCUSSION

The performance of IELT with Gaussian-based Neighbourhood Intensity Proportion (GNIP) framework is compared with the existing Estimation of Multiple Motion Fields using Region Matching (EMMF-RM) [1] and Self Crossing Detection for Parametric Active Contours (SCD-PAC) [2].The performance is evaluated according to the following metrics.

4.1 Impact of Object segmentation time

Object segmentation time refers to the time taken to segment the object video with respect to the size of the video file. The mathematical formulation for object segmentation time is as given below.

$$OST = Size\ of\ video\ file * Time\ (video\ segmentation) \qquad (10)$$

From (10), the object segmentation time ‘’ is measured according to the size of video file given as input. Lower the object segmentation time, more efficient the method is said to be and is measured in terms of milliseconds (ms).

Table 2 Tabulation for object segmentation time

Size of video file (KB)	Object segmentation time (ms)		
	IELT	EMMF-RM	SCD-PAC
113.6	5.75	10.02	10.55
323.7	8.32	13.37	15.42
349.5	11.46	16.51	18.56
454.5	14.39	19.44	21.49
635.2	13.16	18.21	20.26
905.3	15.92	20.97	22.98
936.2	17.23	22.28	24.28

The table 2 represents the object segmentation time obtained using MATLAB simulator and comparison is made with two other methods, namely EMMF-RM [1] and SCD-PAC [2].

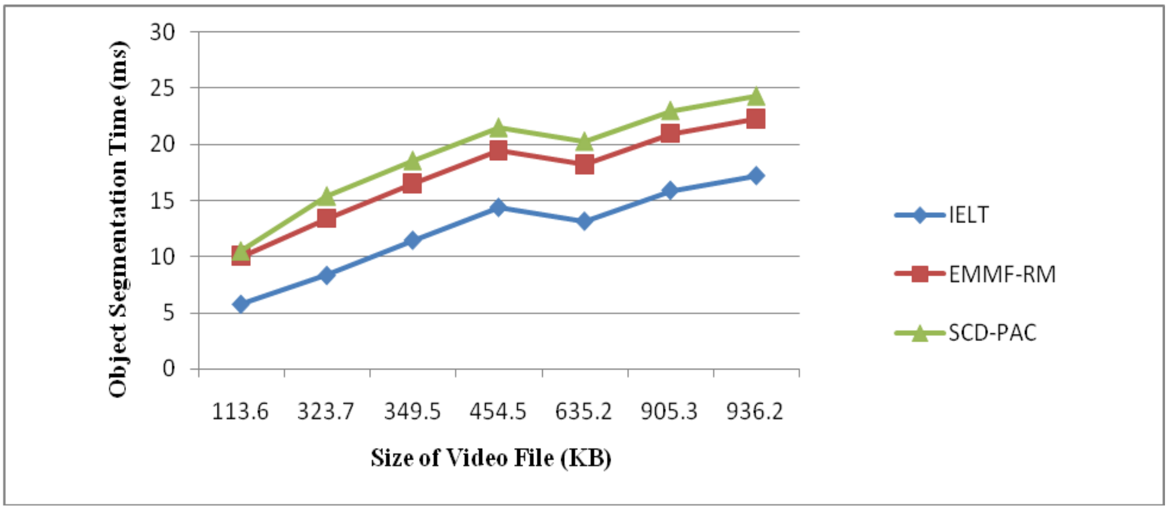

Figure 3 Measure of object segmentation time

Figure 3 shows the measure of object segmentation time using IELT with GNIP, EMMF-RM [1] and SCD-PAC [2] respectively. As shown in the figure, the proposed GNIP framework provides lower object segmentation time when compared to EMMF-RM [1] method and SCD-PAC [2] method. This is because of the application of Median Filter-based Enhanced Laplacian Thresholding technique. The Median Filter-based Enhanced Laplacian Thresholding technique applies an Un-symmetric Trimmed Median Filter based on the neighbourhood intensity on the video frames in order to reduce the noise ratio. By applying a three dimension sliding window model to the video frame, unwanted noise is removed reducing the object segmentation time by 44.78% compared to EMMF-RM and 59.90% compared to SCD-PAC respectively.

4.2 Impact of Object tracking accuracy

The object tracking accuracy is the ratio of objects being tracked using the different methods to the total number of frame / second. The object tracking accuracy is formulated as below

$$OTA = \frac{OT}{Number\ of\ frames\ /second} * 100 \quad (11)$$

From (11), 'OTA' represents the object tracking accuracy whereas 'OT' refers to the objects being correctly tracked. Higher the object tracking accuracy more efficient the method is said to be and it is measured in terms of percentage (%).

Table 3 Tabulation for object tracking accuracy

Number of frames/second	Object tracking accuracy (%)		
	IELT	EMMF-RM	SCD-PAC
10	75.83	67.31	58.21
20	79.21	71.16	62.06
30	84.31	76.26	67.16
40	77.29	69.23	60.13
50	82.16	74.10	65.05
60	85.89	77.83	68.73
70	88.32	80.26	80.16

The object tracking accuracy is presented in table 3 with respect to 70 different frames/second using different video files. With respect to the increasing number of videos and frames/second, the object tracking accuracy is increased though not observed to be linear (i.e. due to the presence of noise), but shows gradual improvement by applying Gaussian distribution for neighbourhood intensity proportion of moving object for IELT when compared to EMMF-RM and SCD-PAC.

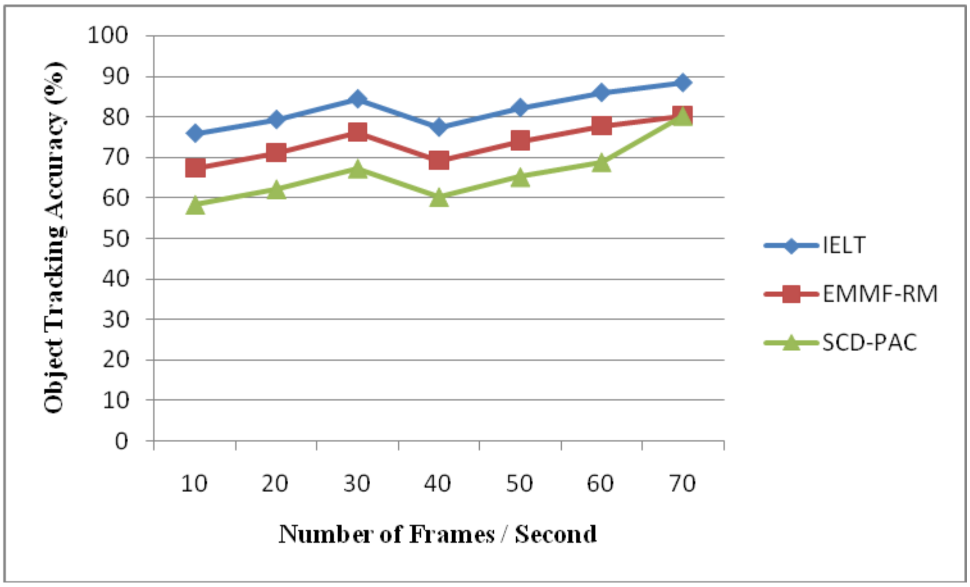

Figure 4 Measure of object tracking accuracy

To ascertain the performance of the object tracking accuracy, comparison is made with two other existing works Estimation of Multiple Motion Fields using Region Matching (EMMF-RM) [1] and Self Crossing Detection for Parametric Active Contours (SCD-PAC) [2]. In figure 4, the number of video frames is varied between 10 and 70. From the figure it is illustrative that the object tracking accuracy for videos is higher or increased using the proposed GNIP framework when compared to the two other existing methods. This is because with the application of Color Histogram-based Particle Filter technique, the GNIP framework exactly and efficiently tracks the object of the detected video by applying the Bayes Sequential based on the posterior and prior function. This in turn improves the object tracking accuracy for videos by 9.95% compared to EMF-RM. Furthermore, based on the posterior and prior function helps in improving the object tracking performance. This symbolizes the improved object tracking accuracy by 19.63% than when compared to SCD-PAC [2] method.

4.3 Impact of Peak signal-to-noise ratio

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

$$MSE = \sum_{i=1}^{n} \left(V_i - V_i'\right) \quad (12)$$

$$PSNR = 10 \log 10 \frac{R^2}{MSE} \quad (13)$$

From (12), the mean square error 'MSE' is the difference between the actual frame size 'V_i' and the estimated frame size 'V_i'' being detected. From (13), the peak signal-to-noise ratio '$PSNR$' is evaluated using the unsigned integer data type (with size 255) with respect to mean square error rate 'MSE' respectively.

Table 4 Tabulation for PSNR

Size of video file (KB)	PSNR (dB)		
	IELT	EMMF-RM	SCD-PAC
113.6	24.35	20.30	18.18
323.7	29.13	25.19	23.53
349.5	35.03	31.52	29.15
454.5	37.19	32.43	30.37
635.2	39.43	34.19	31.19
905.3	42.15	37.89	32.14
936.2	45.82	40.23	37.23

The comparison of Peak Signal-to-Noise Ratio is presented in table 4 with respect to the size of video files in the range of 113.6 – 936.2 KB from seven different video files. With increase in the size of video files, the PSNR also gets increased.

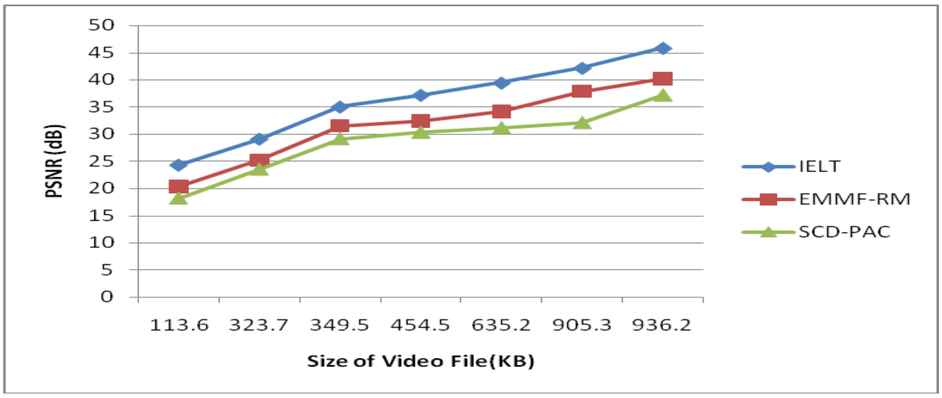

Figure 5 Measure of PSNR

In figure 5, we depict the peak signal-to-noise ratio attained using seven different videos with file size in the range of 113.6 KB to 936.2 KB for experimental purposes using MATLAB. From the figure, the value of PSRN using the proposed GNIP framework is higher when compared to two other existing methods EMMF-RM and SCD-PAC. Besides we can also observe that by increasing the size of the video files, the PSRN rate is also increased using all the methods. But comparatively, it is higher using GNIP framework because with the application of Gaussian-based Neighbourhood Intensity Proportion, the feature vectors are extracted using correlation in an efficient manner that helps in accurately detecting the video object and therefore reducing the PSNR rate in a significant manner. Furthermore, the correlation obtained through neighbourhood intensity proportion that obtains the direct measure of similarity between two video frames further reduces the rate of PSRN using GNIP framework by 12.65% compared to EMMF-RM and 20.44% compared to SCD-PAC respectively.

4.4 Impact of Object detection accuracy

The object detection accuracy for GNIP framework is elaborated in table 5 and comparison made with two other methods EMMF-RM and SCD-PAC respectively. We consider the method with seven video objects with varying file sizes in the range of 113.6KB to 936.2KB for experimental purpose using MATLAB.

Table 5 Tabulation for object detection accuracy

Methods	Object detection accuracy (%)
IELT	78.35
EMMF-RM	65.12
SCD-PAC	59.31

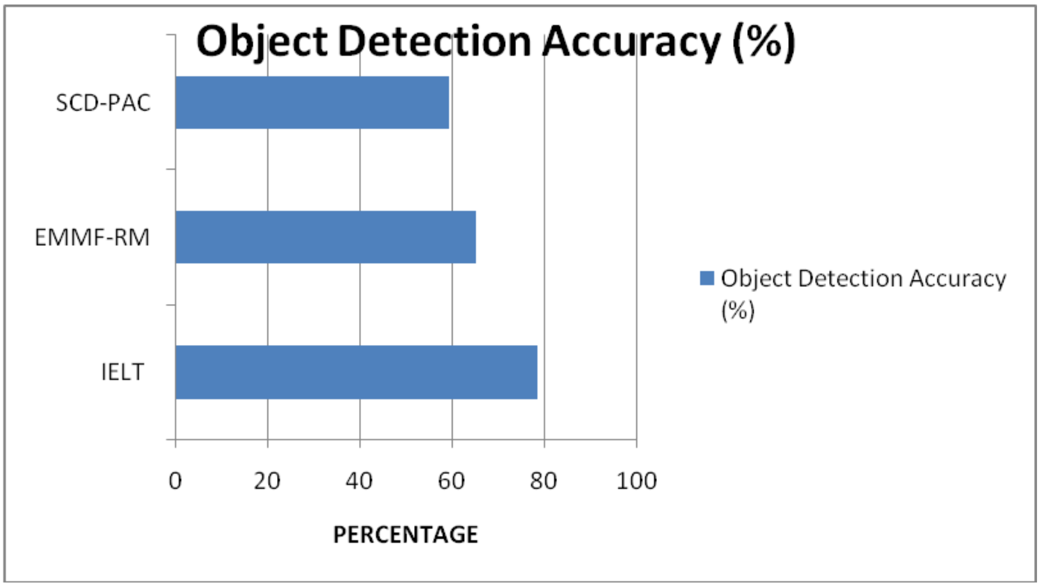

Figure 6 Measure of object detection accuracy

Table 5 and Figure 6 illustrate the object detection accuracy versus seven different videos obtained from number of face images obtained from Internet Archive 501(c) (3), a non-profit organization and simulated in MATLAB. The object detection accuracy is measured in terms of percentage for experimental purpose conducted using MATLAB. From the figure we can note that the object detection accuracy is higher by applying the Gaussian mixture model with neighbourhood intensity proportion in GNIP framework than when compared to the existing methods EMMF-RM and SCD-PAC method respectively. This is because of the application of Gaussian mixture model with neighbourhood intensity proportion that attains 16.88% improvement when compared to EMMF-RM [1] method and 8.92% improvement when compared to SCD-PAC [2] method which shows that there is a significant gain using the proposed GNIP framework. This is because Gaussian Contour Foreground Video Detection algorithm with Neighbourhood Intensity Proportion Distribution and Enhanced Moving Video Object Contour measures the correlation coefficient of the moving video object in an efficient manner. This in turn results in the improvement of object detection accuracy when compared to EMMF-RM and SCD-PAC.

V. CONCLUSION

In this work, an effective Improvising Enhanced Laplacian Threshold technique using Gaussian distribution of neighbourhood intensity proportion of moving object detection in video frames. The IELT technique improves the object tracking accuracy with reduced PSNR and therefore provides improved object detection accuracy for different videos. The goal of our video object detection for video surveillance is to reduce the object segmentation time, improve object tracking and object detection accuracy by demonstrating with training and test video objects obtained from Internet Archive 501(c) (3), a non-profit organization which significantly contributes to the relevance. With the experiments conducted for IELT technique, it is observed that of video object detection for different video samples provided more accurate results compared to existing detection methods. The results show that IELT technique offers better performance with an improvement of object tracking accuracy by 14% and reduces the PSNR rate by 12% compared to EMMF-RM and SCD-PAC respectively.

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