

# An Effective Multiple Moving Objects Tracking using Bayesian Particle Filter-Based Median Enhanced Laplacian Thresholding

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**Abstract** - Automated video surveillance systems are highly required to facilitate wide range of applications in computer vision. The applications include form human activity understanding, object tracking, traffic monitoring to conservation of endangered species and so on. Though efficient object tracking was performed using Support Vector Machine and Graph models, with the growing size involving in multiple moving object the error and object tracking accuracy gets compromised. Bayes Particle is one solution to solve these limitations which aims to minimize the error by filtering out noisy data from a given training dataset. In this paper, Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding (BPF-MELT) is introduced. The Bayes Sequential Estimation is constructed based on the posterior and prior function. To represent a comprehensive representation, Bayes Estimation algorithm discriminately trains the high quality video files with aiming at reducing the mean square tracking error. The Color Histogram-based Particle Filter measures the color histogram value using the likelihood function. The Histogram-based Particle Filter algorithm in BPF-MELT framework improves the object detection accuracy. Experiments have been carried out on video images obtained from Internet Archive 501(c) (3). An intensive and comparative study shows the efficiency of these enhancements and shows better performance in terms of mean square error, peak signal to noise ratio, object tracing accuracy and object tracking execution time on high quality video files, true positive rate, and false positive rate. Experimental analysis shows that BPF-MELT framework is able to reduce the Peak Signal to Noise Ratio by 7.79% and minimize the Mean Square Error by 29.89% when compared to the state-of-the-art works.

**Keywords** - Support Vector Machine, Graph models, Bayes Particle, Median Enhanced Laplacian Thresholding, Bayes Sequential Estimation Color Histogram.

## I. INTRODUCTION

Video tracking is the process of locating a moving object or multiple objects over time using a camera. The objective of video tracking is to associate target objects in consecutive video frames. The association can be especially difficult when the objects are moving fast relative to the frame rate. Many research works have been conducted on multiple moving object tracking. Object tracking using Support Vector Machines (SVM) [1] was carried out for multiple objects being tracked with aiming at solving the robustness and accuracy of object tracking.

Automatic Estimation of Multiple Motion (AEMM) [2] fields were performed using motion correspondence algorithm that aiming at improving the automatic identification of trajectories. A parallel histogram using particle filters [3] was applied to improve the robustness of object tracking.

Detection and localization of object tracking using SVM was designed in [4] to improve the accuracy of localization. In [5], sequential Monte Carlo-based target tracking was performed with the objective of minimizing the localization error. A study of localizing target was conducted in [6] to improve detection accuracy. Though accuracy was improved, the mean square error incurred during object tracking remained unsolved. This mean square error is reduced by applying the Bayes Sequential Estimation in BPF-MELT framework.

With the objective of reducing the distortion rate in [7], mean absolute difference was identified that also resulted in the accuracy rate. Multiple Kernel Nearest Neighbor was applied in [8] with aiming at improving the relative importance for object localization. Posterior Mapping and Retrieval (PMR) [9] was applied in order to reduce the effect of insufficient postures using K-Posture Selection and Indexing. With the aim of removing the noise present in color video, fuzzy rules were applied [10] that resulted in the minimization of Mean Absolute Error (MAE) and Peak Signal-to Noise Ratio (PSNR). Object tracking in Disruption Tolerant Network was applied in [11] to improve the tracking efficiency.

In [12], Dynamic Graph-based Tracker was applied for occluded object tracking with aiming at improving the targets being tracked. Another method for dynamic probabilistic was presented in [13] which using Time Warping (TW) with aiming at minimizing the noise introduced during dynamic entrance. Though error was reduced but at the cost of time. In BPF-MELT framework, Histogram-based Particle Filter algorithm is applied to reduce the object tracking time.

Layered sensing is modus operandi for several applications where different number of sensors is provided with. The layered sensing of image refers to the imageries obtained from several aspects by different sensors. In [14], object tracking for layered images was performed using joint segmentation and registration technique. In [15], detection of objects using boosting algorithm and

constrained optimization problem was introduced to achieve object detection accuracy. In [16], a survey of object tracking in the presence of occlusions was performed using task driven approach.

A survey of visual object tracking was conducted in [17] both from theoretical and practical viewpoint. In [18], laser-based tracking of multiple objects was performed using online learning based method that resulted in the improvement of tracking under complex situations. Though tracking accuracy under the presence of occlusions was performed, the peak signal noise ratio remained unsolved. Using BPF-MELT framework, this is solved using Bayes posterior and prior functions.

An online system for multiple interacting objects was performed in [19] using fusion based approach resulting in the improvement of object tracking accuracy and time cost factor. In [20], Adaptive Appearance Model was introduced for video tracking using application dependent thresholds. An efficient algorithm [21] was developed for detecting a moving object using background elimination technique. However, it not efficient for combination of higher dimensional features with some additional constraints in addition, a novel probabilistic approach [22] was designed for detecting and analyzing stationary objects driven visual events in video surveillance system. But, it is difficult to track all the objects accurately in crowded situations. Another method [23] is proposed for motion detection which detects moving objects precisely. However, the real object movement still cannot be separated from the background. In [24], ELT Method was introduced for multiple moving object segmentation in video surveillance. In [25], proposed a novel Framework for Specific Object Tracking in the Multiple Moving Objects Environment. In [26], MELT method was introduced for moving object segmentation in video sequences. In [27], a novel framework of object detection for video surveillance called Improvised Enhanced Laplacian Threshold (IELT) technique.

In order to overcome the above limitations, we propose a novel Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding (BPF-MELT) framework for multiple moving object tracking tasks. In BPF-MELT framework, we also employ Histogram-based Particle Filter algorithm with the aim of improve the object tracking accuracy. We present an elegant extension of Median Enhanced Laplacian Thresholding and Particle Filter model to a probabilistic Bayes Estimation model. We accomplish this by treating the problem in a generative probabilistic setting, both using the posterior and prior function.

The remainder of this paper is organized as follows. In Section II, analyze the Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding framework. Next, to develop Bayes Estimation model and Color Histogram-based Particle Filter. Section III presents simplified empirical models with the aid of parametric definitions and metrics evaluation. Performance evaluations and discussions are presented in Section IV using table form and graph. Finally, Section V concludes the achievement of the paper.

## II. BAYESIAN PARTICLE FILTER-BASED MEDIAN ENHANCED LAPLACIAN THRESHOLDING

In this section, we introduce Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding framework in details. The BPF-MELT framework is implemented under the Bayesian Particle filter framework and employs Color Histogram to train corresponding high quality video files respectively. We present how to implement the Bayes Sequential Estimation to estimate the multiple tracking of objects by evaluating posterior and prior function, and then introduce the Bayes Estimation algorithm, to determine the tracking results. Besides, we describe the Color Histogram-based Particle Filter with aiming at improving the object tracking accuracy.

### A. Design of Bayes Sequential Estimation

The objective of the proposed framework is to perform simultaneous object detection and multiple tracking of objects in a video sequence. The Bayes Sequential Estimation in BPF-MELT framework measures posterior and prior function to estimate the multiple tracking of objects in a video sequence (i.e. videos) with the objective of reducing the peak signal to noise ratio (i.e. PSNR). Fig.1 shows the block diagram of Bayes Sequential Estimation.

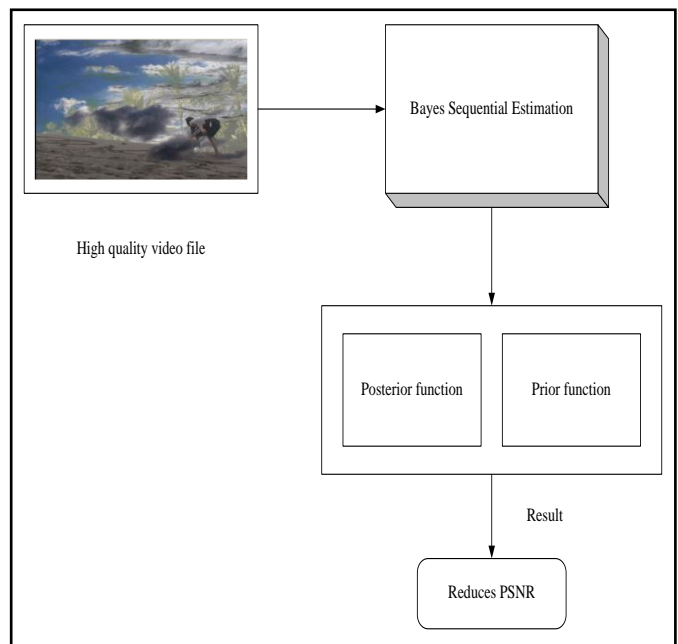


Fig 1. Block Diagram of Bayes Sequential Estimation

As shown in the figure, the Bayes Sequential Estimation accepts high quality video file from Median Enhanced Laplacian Thresholding. Then evaluates two functions such as posterior function and prior function is evaluated for the video frames in an iterative manner with the objective of reducing the PSNR rates multiple object tracking. Let us consider the video sequence ' $V_i = V_1, V_2, \dots, V_n$ ' where ' $V_i$ ' denotes the pixel values of image at discrete time instant ' $i$ '. The state space representation model in the proposed framework requires a vector model and is formulated as given below.

$$Vec(V_i) = prob\left(\frac{a_i}{a_{i-1}}\right) \quad (1)$$

From (1), the vector model 'Vec' for the video sequence 'V<sub>i</sub>' is extracted through the evolution of state i.e. 'a<sub>i</sub>'. With the state space representation model, the link between the state space and current measurement is formulated as given below.

$$Vec(V_i \rightarrow V_{i+1}) = prob\left(\frac{V_i}{a_i}\right) \quad (2)$$

From (2), 'V<sub>i</sub>' represents the state space measurement whereas 'a<sub>i</sub>' represents the current measurement. With the improved video quality image given as input, the goal of Bayes Sequential Estimation Model is to formulate the probability function for multiple moving object tracking. It is formulated as given below

$$PF = prob\left(\frac{V_i}{a_{i-n}}\right) \quad (3)$$

From (3), the probability function 'PF' is measured according to the state 'V<sub>i</sub>' at time 'i' for different video frames from 'a<sub>i</sub>' to 'a<sub>n</sub>' respectively. The assumption made in Bayes Sequential Estimation in the proposed framework BPF-MELT is that the initial posterior function of state space 'a<sub>i</sub>' is known. Then the posterior function '(\frac{V\_i}{a\_{i-n}})' is obtained in an iterative manner.

Let us assume that the posterior function 'Pos(V<sub>i-1</sub> | a<sub>1-i-1</sub>)' for multiple object tracking is given then the forecasting value for multiple object tracking is formulated as given below.

$$Pos(V_i | a_{1-i-1}) = \int Prob(V_i | V_{i-1}) * Prob(V_{i-1} | a_{1-i-1}) dx_{i-1} \quad (4)$$

From (4), 'V<sub>i</sub>' is the video frame at time 'i' and 'a<sub>1-i-1</sub>' is the observation sequence of video frame from time interval '1' to 'i-1'. Followed by this, the prior function using Bayes Sequential Estimation 'Prio(V<sub>i</sub> | a<sub>1-i</sub>)' for multiple object tracing is given as below.

$$Prio(V_i | a_{1-i}) = \frac{Prob(a_i | V_i) * Prob(V_i | a_{1-i-1})}{\int Prob(a_i | V_i) * Prob(V_i | a_{1-i-1}) dx_i} \quad (5)$$

From (5), 'V<sub>i</sub>' is the video frame at time 'i' and 'a<sub>1-i</sub>' is the observation sequence of video frame from time interval '1' to 'i'. Figure 2 shows the algorithmic description of Bayes Estimation model.

As shown in the Fig. 2, with the objective of minimizing the mean square error tracking using the forecasting value,

Bayes posterior and prior functions are applied for each video sequence. To start with, high quality video file from Median Enhanced Laplacian Thresholding is extracted. With the extracted video file, Bayes estimation of posterior and prior function is applied for multiple object tracking. With the application of Bayes estimation algorithm, mean square tracking error is reduced in a significant manner.

Input: video sequence 'V <sub>i</sub> = V <sub>1</sub> , V <sub>2</sub> , ..., V <sub>n</sub> '
Output: Reduced minimum square error for multiple object tracking
Step 1: Begin
Step 2: For each video sequence 'V <sub>i</sub> '
Step 3: Extract vector model of each video sequence using (1)
Step 4: Evaluate state space representation using (2)
Step 5: Measure the probability function using (3)
Step 6: Evaluate posterior function using (4)
Step 7: Evaluate prior function using (5)
Step 8: End for
Step 9: End

Fig 2. Bayes Estimation algorithm

#### B. Design of Color Histogram-based Particle Filter

After applying the Bayes Sequential Estimation model, we employ it into Color Histogram-based Particle Filter with aiming at improving the object tracking accuracy. Fig.3 shows the block diagram of Color Histogram-based Particle Filter.

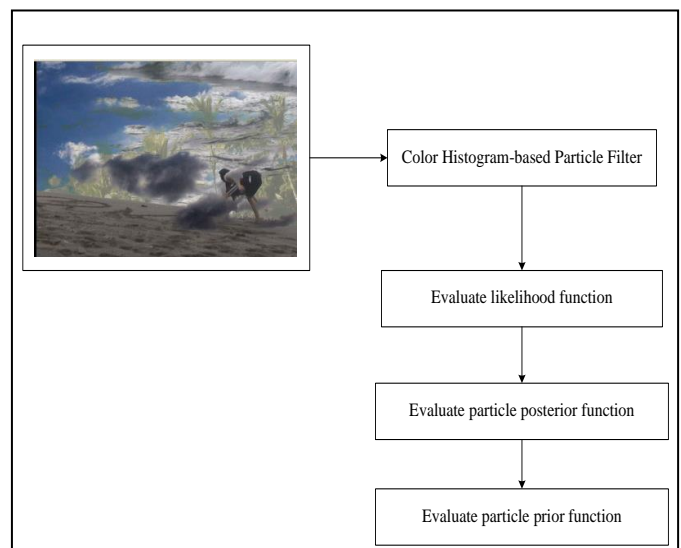


Fig 3. Block diagram of Color Histogram-based Particle Filter

From the above figure, the Color Histogram-based Particle Filter involves three steps. The first step evaluates the likelihood function of the color histogram of the objects to be tracked. The second and third step evaluates the particles posterior and prior function with aiming at improving the object detection accuracy. The BPF-MELT technique extracts from the video file the color histogram 'CH<sub>i</sub>', evaluated inside the image region specified by the state space vector model 'a<sub>i</sub>'. The likelihood function of the color histogram is evaluated as given below.

$$Prob\left(\frac{CH_i}{V_i}\right) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{Dist_i}{2\sigma^2}\right) \quad (6)$$

From (6), the likelihood function is evaluated using the probability function, where 'Dist<sub>i</sub>' measures the distance between the reference color histogram of objects to be tracked and the color histogram 'CH<sub>i</sub>' evaluated from the current video frame 'a<sub>i</sub>' specified by the state vector 'V<sub>i</sub>'. Color Histogram-based Particle Filter is a hypothesis tracker that approximates the filtered posterior distribution with the aid of set of weighted particles aiming at improving the object tracking accuracy. Here the sample video file taken as input is referred to as the because of their discrete representation.

The Color Histogram-based Particle Filter starts with a weighted set of samples 'V<sub>i</sub>, W<sub>j</sub> = W<sub>1</sub>, W<sub>2</sub>, ..., W<sub>n</sub>' distributed according to 'prob( $\frac{V_i}{a_{i \rightarrow n}}$ )', new objects are tracked. This probability distribution depends on the prior state and the new measurements, i.e., 'V<sub>i</sub> | a<sub>1→i</sub>' and 'V<sub>i</sub> | a<sub>1→i-1</sub>' respectively.

Each particle 'V<sub>i</sub><sup>j</sup>' evolves according to the state space model and yields an approximation of the prior function is formulated given below.

$$Prob(V_i) = \frac{1}{n} \sum_{i,j=1}^n (V_i - V_i^j) \quad (7)$$

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

$$Prob(V_i | a_{1 \rightarrow n}) = \sum_{i=1}^n W_T^i (V_i - V_T^i) \quad (8)$$

$$W_T^i = a_T | V_T^i \quad (9)$$

From (8) and (9), the posterior function for each particle based on the color histogram and the weight of each particle. The likelihood model helps in improving the object tracking performance with the aid of color histogram-based particle filter. This in turn improves the object detection accuracy. Fig.4 shows the algorithmic description of Histogram-based Particle Filter model.

The Fig.4 shows the Histogram-based Particle Filter algorithm that includes three steps. For each video sequence, the first step evaluates the likelihood function of color histogram. Followed by this, the second and third step measures the particle prior and posterior function respectively. This in turn increases the object tracking accuracy.

Input: video sequence 'V <sub>i</sub> = V <sub>1</sub> , V <sub>2</sub> , ..., V <sub>n</sub> ', color histogram 'CH <sub>i</sub> ', particle 'V <sub>i</sub> <sup>j</sup>
Output: Improved multiple object tracking accuracy
Step 1: Begin Step 2: For each video sequence 'V <sub>i</sub> ' Step 3: Evaluate likelihood function of the color histogram using (6) Step 4: Measure particle prior function using (7) Step 5: Measure particle posterior function using (8) Step 6: End for Step 7: End






Fig 4.Histogram-based Particle Filter algorithm

### III.EXPERIMENTAL SETTING

The Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding (BPF-MELT) framework for object tracking performs experimental work on MATLAB. The BPF-MELT framework using the video files and their sizes are listed in Table I 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 listed in table 1 includes the name of the video file, resolution of the video files and their size respectively for evaluating the BPF-MELT framework. The Internet Archive includes texts, audio, moving images, and software as well as archived web pages. The video used for moving object segmentation using MF-ELT method is shown below with detailed information. The BPF-MELT framework is evaluated in different aspects, Peak Signal-to-Noise Ratio, Mean Square Error, Object detection accuracy and time for object detection, true positive rate, false positive rate, with respect to different videos and video frames.

Table I. 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
Athletic.avi		854 * 480	905.3
Person.avi		320 * 240	936.2





Flower.avi		350 * 240	454.5
Rose.avi		458 * 213	635.2

Table I describes the video file information used in BPF-MELT that comprises of video file name, resolution of video file and video file size used as sample video files in BPF-MELT framework. The proposed BPF-MELT method is compared with three existing methods namely, Median Filter-based Enhanced Laplacian Thresholding (MF-ELT), Object Tracking with Support Vector Machines (OT-SVM) [1], and Automatic Estimation of Multiple Motion (AEMM) [2].

The quality of video files received at the receiving end measures the efficiency of the method. Therefore, during object tracking, the quality of the video files at the receiving end should not be deteriorated with the presence of noise. The Mean Square Error (MSE) in BPF-MELT framework 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.

$$MSE = \sum_{i=1}^n (V_i - V'_i) \quad (10)$$

From (10), the mean square error 'MSE' is the difference between the actual frame size 'V<sub>i</sub>' and the estimated frame size 'V'<sub>i</sub>' being tracked. Peak Signal-to-Noise Ratio measures the ratio between the reference video frame and the distortion video frame being tracked 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 and is mathematically formulated as given below.

$$PSNR = 10 \log_{10} \frac{R^2}{MSE} \quad (11)$$

From (11), the peak signal-to-noise ratio 'PSNR' is evaluated using the unsigned integer data type 'R' (with size 255) with respect to mean square error rate 'MSE' respectively. The object tracking accuracy is the ratio of objects being tracked using the different methods to the total number of frames /second. The object tracking accuracy is formulated as below

$$OTA = \frac{OT}{\text{Number of frames/second}} * 100 \quad (12)$$

From (12), '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 (%). The object tracking time is the time taken to track each frames with respect to the number

of frames taken for experimental purpose. The object tracking time is mathematically formulated as given below.

$$OTT = \text{No. of frames per sec} * \text{Time (frame)} \quad (13)$$

From (13), the object tracking time 'OTT' is measured in terms of milliseconds (ms). The true positive rate is defined as the ratio of number of correctly detected frames from the video sequence to the total number of the frames in the video sequence. The true positive rate is formularized as given below,

$$\text{True Positive Rate} = \frac{\text{No. of correctly detected frames from video sequence}}{\text{total number of frames in video sequence}} * 100 \quad (14)$$

When higher the true positive rate, the method is said to be more efficient and it is measured in terms of percentage (%). Then the false positive rate is defined as the ratio of number of incorrectly detected frames from the video sequence to the total number of the frames in the video sequence. The false positive rate is formularized as given below,

$$\text{False Positive Rate} = \frac{\text{No. of incorrectly detected frames from video sequence}}{\text{total number of frames in video sequence}} * 100 \quad (15)$$

When lower the false positive rate, the method is said to be more efficient and it is measured in terms of percentage (%).

#### IV.DISCUSSION

The Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding (BPF-MELT) framework is compared against the existing Median Filter-based Enhanced Laplacian Thresholding (MF-ELT), Object Tracking with Support Vector Machines (OT-SVM) [1], and Automatic Estimation of Multiple Motion (AEMM) [2]. The experimental results are compared and analyzed through the table and graph given below.

##### A. Impact of MSE

To support transient performance, in Table II we apply a Bayes Estimation algorithm and comparison made with three other existing methods namely MF-ELT, OT-SVM [1] and AEMM [2].

Table II. Tabulation for mean square error

Size of video frame (KB)	Mean Square Error (db)			
	BPF-MELT	MF-ELT	OT-SVM	AEMM
113.6	19.3	24.4	26.5	32.4
323.7	21.4	26.5	28.7	34.6
349.5	24.2	29.1	30.1	37.4
454.5	28.7	33.8	35.9	42.3
635.2	35.3	40.4	42.6	48.5
905.3	41.2	46.3	48.5	54.6
936.2	49.3	54.4	56.5	62.6

Table II show that the Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding (BPF-MELT) framework provides lower mean square error rate when compared to ME-ELT, OT-SVM [1] and AEMM [2]. The mean square error is reduced with the application of Bayes estimation algorithm.

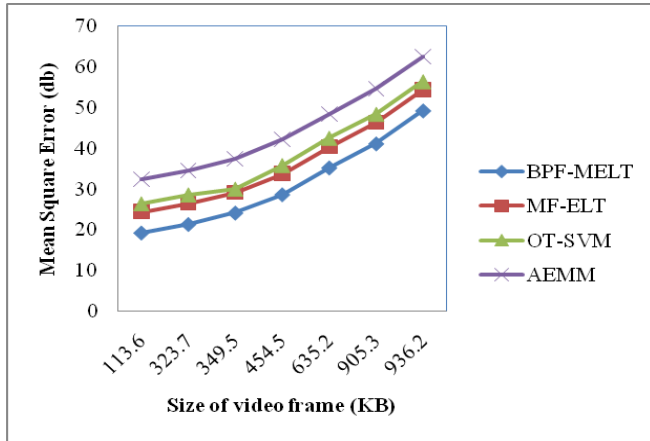


Fig 5. Measure of mean square error

Fig.5 shows the mean square error rate efficiency with size of the video frame taken as the input for multiple moving object tracking. With the application of Bayes Estimation algorithm, Bayes estimation of posterior and prior function is evaluated in an efficient manner. This in turn is applied for multiple moving object tracking and transformational data perturbation, the data perturbation is performed in an efficient manner with high quality video file extracted from Median Enhanced Laplacian Thresholding. This in turn helps in reducing the mean square error for multiple moving object tracking using BPF-MELT by 17.92% compared to MF-ELT and 24.84% compared to OT-SVM [1] respectively. Moreover, the BPF-MELT framework by applying Bayes Sequential Estimation that takes state space as input that helps in decreasing the mean square error by 46.91% when compared to AEMM [2].

**B. Impact of PSNR**

The comparison of PSNR for multiple object tracking is presented in Table III with respect to the varied size of video frame in the range of 100KB to 1000 KB collected at different time stamps from the Internet Archive 501(c) (3). With increase in the size of video frames, the PSNR for object tracking is also increased.

Table III. Tabulation for PSNR

Size of video frame (KB)	PSNR (db)			
	BPF-MELT	MF-ELT	OT-SVM	AEMM
113.6	46.13	44.14	43.95	42.89
323.7	54.25	48.22	46.17	43.11
349.5	61.82	55.79	50.74	47.68
454.5	65.32	59.29	54.24	51.18
635.2	70.14	62.11	57.06	54.01
905.3	73.45	64.42	60.37	57.31
936.2	79.47	69.44	66.39	63.33

To ascertain the performance of the PSNR for multiple moving object tracking, comparison is made with three other existing methods MF-ELT, OT-SVM [1] and AEMM [2]. In Fig.6, the size of video frames is varied between 100 KB and 1000 KB. From the figure it is illustrative that the PSNR using the proposed BPF-MELT framework is reduced when compared to existing methods.

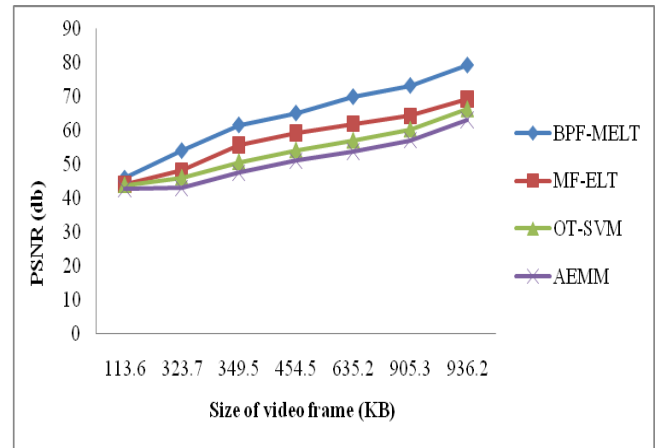


Fig 6. Measure of PSNR

The PSNR rate for multiple moving object tracking is reduced by applying Bayes Sequential Estimation in BPF-MELT framework. With the application of Bayes Sequential Estimation, posterior function and prior function is evaluated for each video frames in an iterative manner that provides the results with respect to varying frame size reducing the PSNR by 10.11% compared to MF-ELT and 15.35% compared to OT-SVM [1] respectively. Besides, by applying the state space representation model between the state space and current measurement, by making an initial posterior function, minimizes the PSNR for multiple moving objects tracking by 19.62% compared to AEMM [2].

**C. Impact of object tracking accuracy**

The rate of object tracking accuracy for multiple moving object tracking using BPF-MELT, MF-ELT, OT-SVM and AEMM is elaborated in table IV. We consider the framework with different number of frames/second in the range of 10 frames to 70 frames for experimental purpose using MATLAB.

Table IV. Tabulation for object tracking accuracy

No. of frames/sec	Object tracking accuracy (%)			
	BPF-MELT	MF-ELT	OT-SVM	AEMM
10	71.35	62.45	52.13	41.43
20	74.85	65.83	57.78	51.73
30	77.38	68.68	60.63	54.58
40	72.16	63.14	55.09	49.04
50	74.39	65.37	57.32	51.27
60	78.25	69.23	59.18	53.13
70	83.45	74.43	66.38	60.35

In Table IV, we depict the rate of object tracking accuracy with different frames per second taken as input ranging from 10 frames to 70 frames for the purpose of experiment. From the figure, the object tracking accuracy using the

proposed BPF-MELT framework is higher when compared to three other existing methods MF-ELT, OT-SVM [1] and AEMM [2]. Besides it can also be observed that by increasing the number of frames per second, the rate of object tracking accuracy is also increased using all the methods. But comparatively, it is higher using BPF-MELT framework.

Fig.7 as shown above measures the rate of object tracking accuracy and is observed to be higher using BPF-MELT framework. The rate of object tracking accuracy is verified for different number of frames. By applying Color Histogram-based Particle Filter, the object tracking accuracy is improved using BPF-MELT framework by 11.81% compared to MF-ELT. In addition, by evaluating the likelihood function of the color histogram in MF-ELT framework, the object tracking accuracy is improved by 23.25% compared to OT-SVM [1]. Furthermore, the BPF-MELT framework approximates the filtered posterior distribution which in turn improves the object tracking accuracy by 32.17% compared to AEMM [2].

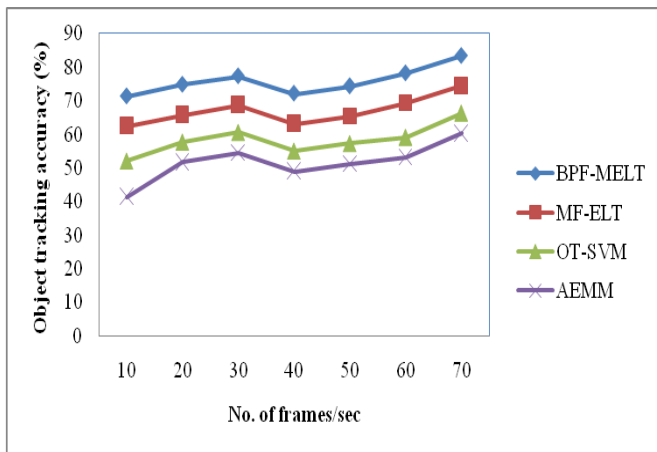


Fig 7. Measure of object tracking accuracy

D. Impact of object tracking time

$$OTT = \text{No. of frames per sec} * \text{Time (frame)}$$

For example: (table calculation)

- i) Proposed BPF-MELT:  
 Object tracking time (ms) = 10 \* 3.9  
 = 39
- ii) Existing MF-ELT:  
 Object tracking time (ms) = 10 \* 4.5  
 = 45
- iii) Existing OT-SVM:  
 Object tracking time (ms) = 10 \* 5.8  
 = 58
- iv) Existing AEMM:  
 Object tracking time (ms) = 10 \* 7.0  
 = 70

Table V Tabulation for object tracking time

No. of frames/sec	Object tracking time (ms)			
	BPF-MELT	MF-ELT	OT-SVM	AEMM
10	39	45	58	70
20	45	51	62	69
30	51	57	68	75
40	57	64	75	77
50	61	68	79	84
60	65	72	83	90
70	73	80	91	98

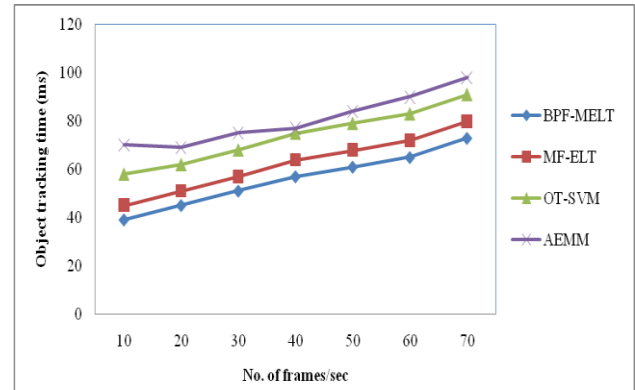


Fig 8. Measure of object tracking time

Table V and Fig.8 shows the measure of object tracking time with respect to different frames per second. As shown in the figure, the object tracking time is reduced using BPF-MELT framework when compared to the three other existing methods MF-ELT, OT-SVM [1] and AEMM [2]. This is because of the application of Histogram-based Particle Filter algorithm. By applying Histogram-based Particle Filter algorithm, with the aid of the probability function, the reference color histogram of objects to be tracked and the color histogram for the current video frame are evaluated in an efficient manner. This in turn reduces the object tracking time by 12% compared to MF-ELT and 33.32% compared to OT-SVM [1] respectively. Furthermore, with the aid of set of weighted particles, and according to the state space model, multiple moving objects are tracked resulting in reducing the object tracking time of BPF-METL framework by 46.48% compared to AEMM [2].

E. Impact of true positive rate

The true positive rate for BPF-MELT framework, MF-ELT, OT-SVM [1] and AEMM [2] versus increasing number of frames per second is shown in table VI. When the number of frames per second is increased, the true positive rate also increases gradually using BPF-MELT framework.

Table VI. Tabulation for true positive rate

No. of frames/sec	True positive rate (%)			
	BPF-MELT	MF-ELT	OT-SVM	AEMM
10	60.14	51.24	45.54	30.14
20	63.25	54.87	48.21	34.75
30	66.57	57.32	51.75	37.18
40	69.78	60.54	54.65	40.87
50	72.54	63.47	57.32	43.58
60	75.89	66.97	60.12	47.65
70	79.19	69.87	64.34	50.35

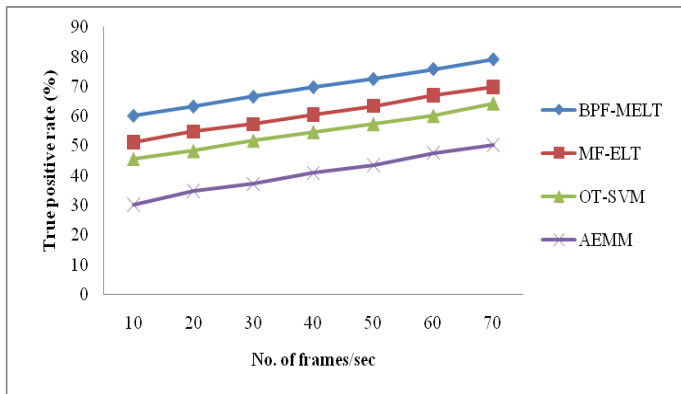


Fig 9. Measure of true positive rate

Fig.9 as shown above measures the true positive rate. From the figure, the true positive rate using the proposed BPF-MELT framework is higher when compared to three other existing methods MF-ELT, OT-SVM [1] and AEMM [2]. This is because of the application of Histogram-based Particle Filter algorithm in the BPF-MELT framework. Histogram-based Particle Filter algorithm measures the particle prior and posterior function effectively thereby it improves the true positive rate by 13.03% and 21.79 % when compared to the MF-ELT, OT-SVM [1] respectively. Furthermore, applying Bayes Sequential Estimation in BPF-MELT framework also improves the true positive rate by 42% when compared to the AEMM [2].

**F. Impact of false positive rate**

Table VII given below shows the false positive rate for BPF-MELT framework, MF-ELT, OT-SVM [1] and AEMM [2] versus increasing number of frames per second. As shown in table VII, the false positive rate is decreases gradually when the number of frames per second gets increased using BPF-MELT framework.

Table VII. Tabulation for false positive rate

No. of frames/sec	False positive rate (%)			
	BPF-MELT	MF-ELT	OT-SVM	AEMM
10	19.35	25.38	30.41	40.57
20	35.45	40.48	45.51	50.64
30	37.55	43.58	48.61	56.47
40	24.35	29.35	35.31	43.98
50	45.35	51.38	56.41	63.14
60	38.33	44.32	48.39	51.57
70	59.35	64.37	68.4	74.58

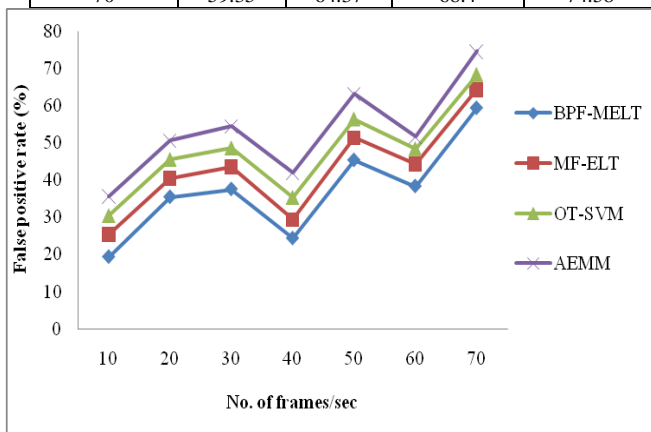


Fig10. Measure of false positive rate

From Fig.10, it is illustrative that the false positive rate using the proposed BPF-MELT framework is lower when compared to three other existing methods MF-ELT, OT-SVM [1] and AEMM [2]. This is because of the application of Histogram-based Particle Filter algorithm in the BPF-MELT framework. Histogram-based Particle Filter algorithm evaluates the particle prior and posterior function effectively thereby it improves the true positive rate which in turn reduces the false positive rate by 17.04 % when compared to the MF-ELT. In addition, BPF-MELT framework reduced the false positive ratio by 32.27% and 46.58 % when compared to the OT-SVM [1] and AEMM [2] respectively.

**V.CONCLUSION**

A Bayesian Particle Filter-based Median Enhanced Laplacian Thresholding (BPF-MELT) framework has been designed with the scope of minimizing the error by filtering the noisy data. The objective of providing such a design is to ensure efficient multiple moving object tracking and to decrease the object tracking time for various video frames. A Bayes Sequential Estimation model is designed as a measure for identifying the posterior and prior function for reducing the error (i.e. MSE and PSNR) while tracking multiple moving object. Bayes Estimation algorithm is also proposed to measure the state space representation model for each video frames. The proposed Color Histogram-based Particle Filter provides object tracking accuracy for different high quality video files obtained for MF-ELT. In addition, the evaluation of likelihood function using probability function helps in improving the object tracking accuracy. Finally, by applying the Bayes estimation algorithm, the object tracking time is significantly reduced. Experimental evaluation is conducted with the video files extracted from Internet Archive 501(c) (3), a non-profit organization to provide high quality object tracking accuracy and measured the performance in terms of MSE, PSNR, object tracking accuracy and object tracking time, true positive rate, and false positive rate. Performances results reveal that the proposed BPF-MELT framework provides higher level of object tracking accuracy and also strengthen the execution time. The proposed BPF-MELT framework provides 22.41% high rate of object tracking accuracy and minimizes the object tracking time by 46.48% when compared to state of the art works.

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