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Efficient Moving Vehicle Detection Algorithm for Various Traffic Conditions

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Abstract*: *Many computer vision applications needs to detect moving object from an input video sequences. The main applications of this are traffic monitoring, visual surveillance, people tracking and security etc. Among these, traffic monitoring is one of the most difficult tasks in real time video processing. Many algorithms are introduced to monitor traffic accurately. But most of the cases, the detection accuracy is very less and the detection time is higher which makes the algorithms are not suitable for real time applications. In this paper, a new technique to detect moving vehicle efficiently using Modified Gaussian Mixture Model and Modified Blob Detection techniques is proposed. The modified Gaussian Mixture model generates the background from overall probability of the complete data set and by calculating the required step size from the frame differences. The modified Blob Analysis is then used to classify proper moving objects. The simulation results shows that the method accurately detect the target.

Keywords: Vehicle detection, Gaussian Mixture Model, Morphological filter, Blob Detection techniques etc.

I. INTRODUCTION

Security is a big challenge in today's society. For security purpose there is a need to detect the objects that are moving in any video streams. This will eliminate the need of manually searching of moving contents which needs human supervision and it prone to errors. To overcome from such problems it is needed to perform automatic detection. Efficient detection of vehicle is a vital role in intelligent transportation systems. Availability of video data and the advances of computer vision techniques increases the number of applications such as traffic monitoring, border portal, military applications search and rescue, vehicle counting and tracking, visual surveillance, automatic driving, people counting and tracking, etc. Various techniques are proposed to detect object. The simplest method is, Background Subtraction [1][2] but this approach is not suitable for most of the application due to its sensitivity to changes in environmental condition also its suitability only for static background. As a result different techniques were introduced to generate background from the video frames itself. Some of these existing techniques of moving object detection are discussed below.

II. RELATED WORKS

The authors of the paper [3] proposed a new object detection and tracking where both detection and tracking are integrated to get better performance. This algorithm is suitable for multi-object detection and tracking by reducing the total searching area. This algorithm uses "target crossing" and "object occlusion" to detect track the object with some degree of robustness.

In paper [4] moving object detection using RGB color space and edge ratio is proposed. Here the moving objects and shadows are determined separately. This method can detect and track object at very faster rate which makes it suitable for real time high speed applications. But due to the movement of the shadow of the corresponding object leads extra detections which are not true objects. Bayesian fusion method for surveillance application is proposed in paper [5]. This method uses kernel density estimation function to model the background from video frames and then foreground is generated using Gaussian formulation of the same. The total computation time of this method for detecting object is very less and it works properly with all probable types of background. If the feature of the object is similar to the background then this technique cannot detect the moving object.

The Gaussian mixture model is combined with edge detection to get better object detection [6]. The uses of neighborhood based differences make this method more suitable for real time implementation with good capacity of noise reductions. But this method is sensitive to low level noises. In paper [7] hyper complex Fourier Transform (HFT) is used to generate static salient region of the current frame. Then using three frame reference algorithms, the salient region of the moving object is decided. But the disadvantage in this method is that it can only be applied to the salient moving objects. Authors in paper [8] used improved version of optical flow algorithm with double three image interpolation algorithm in the region and iterative reweighted least squares algorithm for moving object detection. Here the proposed method was able to obtain higher accuracy and efficiency for real-time collision detection. The disadvantage is that increased computational time requirement which leads to degradation of real time object detection. To reduce the detection time and improve accuracy, frame-difference method is proposed [9].

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This method increases the detection speed by 21.06 times and the detection accuracy by 8%. But it needs training dataset for proper detection. To improve the detection efficiency, optical flow method is merged with a novel fusion technique [10]. This is mainly aimed to detect and track object in complex background conditions. The main advantage of this algorithm is that it can detect object correctly at complex scenario than other existing techniques. Frame difference method is used to detect moving object in the paper [11] where to solve the "hole" problem "XOR" and "OR" operators are used which generates almost proper background with very less amount of noises. This technique can detect moving object accurately within very less time. But here the detected object shape is not very clear. To get complete information about the detected object, the frame difference method is combined with canny edge detection in the paper [12]. This method works well in normal environment but it fails to detect object properly at changing background with jitter. To address the above issues in this paper a new adaptive learning algorithm to generate proper background model is proposed.

Organizations: *The rest of the paper is organized as follows related work is given in section II proposed algorithm is given in section III, in section IV Performance Analysis is given and finally conclusion is given in section V.*

III. PROPOSED ALGORITHM

The flow diagram of the proposed algorithm for moving object detection is given in Fig.1. Here a finite number of the frames are created from the input video sequences which h are directly proportional to video timing. From the video frames, the background models are generated through Modified Gaussian Mixture Model. But the generated background consists of many high frequency components which are superimposed due to various environmental conditions such as light intensity, presence of fog etc. Morphological filters are then used to remove the effect of the unwanted noises and to get a noise free, clean background model. The generated background is then used to detect moving object present in the input video frames through Modified Blob Detection Technique. Next step is to insert box into the detected object in the frame and merge the frames to generate video sequences. This process will continue until the last frame of the input video is processed.

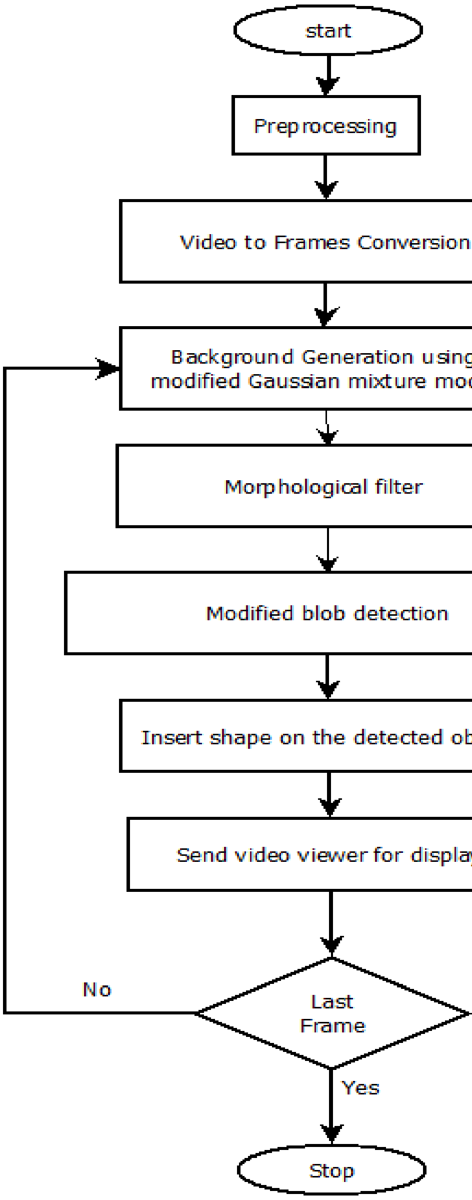

Fig. 1.Flow diagram of the Vehicle Detection Algorithm

A. Pre-processing

In the preprocessing phase, the input image is converted into a standard size of 512x512 and Gaussian filter [13] is applied to smoothen the input frame and is given in Fig.2.

(a) Input Frame (b) Pre-procesed Frame

Fig. 2.Pre-processing of a Traffic Video

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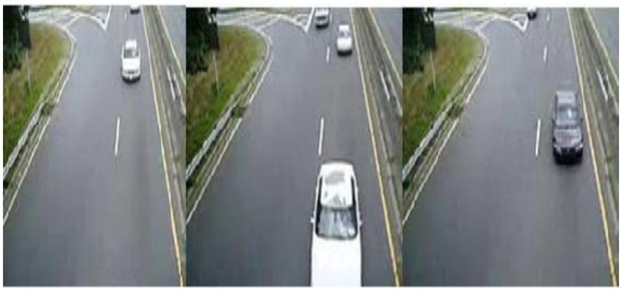
B. Video to Frame Conversion

Any video consists of a number of frames. To process any video, it is needed to convert it into a finite number of frames. Fig.3.shows The randomly chosen frames are given in Fig.3. This is done by capturing video frames at different time intervals where the intervals are very small and equal which is represented mathematically [14] as

$$Video = \cup_t frame_{\Delta t} \tag{1}$$

Where, t – Total video time
Δt – Frames at particular time slots



(a) Frame 14 (b) Frame 24 (c) Frame 48

Fig. 3.Different Frames of a Traffic Video

C. Modified Gaussian Mixture Model

To get the segmented foreground of any video, it is needed to consider a set of observation samples from the video frames at each sample time “t” which are then used to generate background and foreground of the video.
Let us consider the observation samples as “X”, and it is modeled through mixture of k-Gaussian densities [15], where each state is represented as

$$f_{X|k}(X|k,\theta_k) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma_k|^{\frac{1}{2}}} e^{-\frac{1}{2}(X-\mu_k)^T \Sigma_k^{-1}(X-\mu_k)} \tag{2}$$

Where, θ_k=Total number of parameter sets
μ_k=Mean value
Σ_k=Covariance matrix of the k^{th} density.

In most of the cases Σ_k is diagonal and is represented by the n^{th} dimensional variance σ_k^2. To get accurate σ_k value, non-linear color space is considered. In such cases the density of the parameter set is defined as

$$\theta_k = \{\mu_k, \sigma_k\} \tag{3}$$

The equation (2) is for a particular “k” and the total set of parameters becomes

$$\phi = \{\omega_1, \dots, \omega_k, \theta_1, \dots, \theta_k\} \tag{4}$$

Where, ω_k=Priori probability of the surface ‘k’.

Since, the events ‘k’ isdisjoint; the distribution of “X” is modeled as

$$f_X(X|\phi) = \sum_{k=1}^{k} p(k) f_{X|k}(X|k,\theta_k) \tag{5}$$

Where, p(k) = ω_k

To select the proper distribution, it is necessary to estimate which of the k-distribution is suitable for current sample (i.e., X=x). Then from Baye’s theorem [16] posterior probability is calculated as

$$P(k|X,\theta) = \frac{P(k) f_{X|k}(X|k,\theta_k)}{f_X(X|\phi)} \tag{6}$$

From equation (5) the maximum posteriori (MAP) estimation [17] is determined as

$$\hat{k} = argmax_k\{P(k|X,\phi)\} \tag{7}$$

Substituting equation (7) into equation (6), the relation is written as

$$\hat{k} = argmax_k\{\omega_k f_{X|k}(X|k,\theta_k)\} \tag{8}$$

To generate background depending upon the overall probability “T” as

$$B = argmin_b\left(\sum_{k=1}^{b} \omega_k > T\right) \tag{9}$$

Where, B=Ranked State

Then the complete data set is written as

$$P(X_1, X_2, \dots, X_N, k|\phi) = \prod_{t=1}^{N} \omega_k f_{X|k}(X_t|k,\theta_k) \tag{10}$$

Where, X_t= Pixel value at time “t”
X_N= Last sample

By solving eq (9) for various “k” values, the relation is given as

$$\widehat{\omega_k} = \frac{1}{N}\sum_{t=1}^{N} P(k|X_t,\phi) \tag{11}$$

$$\widehat{\mu_k} = \frac{\sum_{t=1}^{N} X_t P(k|X_t,\phi)}{\sum_{t=1}^{N} P(k|X_t,\phi)} \tag{12}$$

$$\widehat{\sigma_k^2} = \frac{\sum_{t=1}^{N}((X_t-\widehat{\mu_k}).(X_t-\widehat{\mu_k})P(k|X_t,\phi)}{\sum_{t=1}^{N} P(k|X_t,\phi)} \tag{13}$$

Where, “.”=Hadamard multiplication

The parameters present in eq. (11)-(13) is converted to an on-line cumulative average [18] as

$$\widehat{\omega_{k,t}} = (1-\alpha_t)\omega_{k,t} + \alpha_i P(k|X_t,\phi) \tag{14}$$

$$\widehat{\mu_{k,t}} = (1-\rho_{k,t})\mu_{k,t} + \rho_{k,t}\, x_t \tag{15}$$

$$\widehat{\sigma_{k,t}^2} = (1-\rho_{k,t})\sigma_{k,t}^2 + \rho_{k,t}\left((X_t-\widehat{\mu_{k,t}}).(X_t-\widehat{\mu_{k,t}})\right) \tag{16}$$

Where, $\rho_{k,t} = \frac{\alpha_t P(k|X_t,\phi)}{\widehat{\omega_{k,t}}}$

$$\alpha_t = \frac{1}{t}$$

Now if any new frame comes at (t + 1) time, a test is conducted to find the match between each pixels. In such cases a pixel matches a Gaussian distribution if,

$$\sqrt{(X_{t+1}-\mu)T\sum_{i,t}^{-1}(X_{t+1}-\mu_{i,t})} < k.\sigma_{i,t} \tag{17}$$

Where, ‘k’ is the constant threshold.

The minimum time required to generate the background model is

$$t_{\min} \geq \left(\frac{1}{\ln(1-\alpha)}\right).\frac{\ln((k+\lambda-3))}{(k-2)(\alpha-1)} \tag{18}$$

Now the new adaptive learning rate ‘ y_k ’and parameter updating μ_k with relative probability is

$$q_{k=}N(X;\ \mu_k,\sigma_k) \tag{19}$$

The pixel of k^{th} Gaussian model is then written as

$$y_k(t) = Y_k\,(t-1) + \frac{k+1}{k}q_k - \frac{1}{k}\sum_{i-1}^{k} q_i \tag{20}$$

This is used as a replacement of ‘β’ values and is used to avoid saturation phenomenon occurs at the time of variable updates. Now by using the modifications, the variance equation is updated as,

$$\sigma_k^2\ = (1-\eta)\sigma_k^2(t-1) +\ \eta.t_{a,b}\big(X,\mu_x(t-1)\big) \tag{21}$$

Where, η=constant learning rate

$t_{a,b}(X,\mu)$ Bounds the variance of the domain D ϵ ((a+b)/2b).

D. Morphological Filter

The Morphological filters [18] are used to eliminate noises present in the generated background model through Modified MOG algorithm. In the proposed algorithm, morphological opening operation is used to filter the noisy background images. This is mainly due to the ability of smoothening the contour of the images by removing narrow gaps. This is implemented by “erosion” and “dilation” operations to eliminate all pixels presents in a user-defined regions that is too small to contain any possible structuring elements [19].
The “erosion” of a binary image “f”of structuring elements”s” produces a new binary image “g” as

$$g = f \ominus s \tag{22}$$

The image “g” with ones in all locations (x,y) of a structuring elements origin at which that structuring element “s” fits the input image “f” as

$$g(x,y) = \begin{cases} 1;\ if\ "s"\ fits\ "f" \\ 0;\ Otherwise \end{cases} \tag{23}$$

The process is repeated as described by eq (12) for all pixel coordinates (x,y)

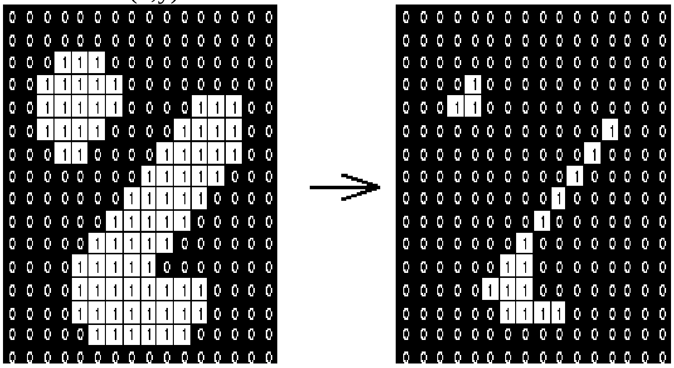


Fig. 4.Erosion Operation

Erosion decreases the size of region of interest with small square structuring elements or kernels (i.e., 2x2 to 5x5), and removes the small details which is given in Fig.4. Boundary of each region can be found by subtracting eroded image from the original.
On the other hand the “Dilation” of an image “f” by structuring element “s” produces a new binary image “g” as

$$g = f \oplus s \tag{24}$$

The image “g” with ones in all locations (x,y) of a structuring element origin at which the structuring elements “s” hits the input image “f” as

$$g(x,y) = \begin{cases} 1;\ if\ "s"\ hits\ "f" \\ 0;\ Otherwise \end{cases} \tag{25}$$

The process described by eq (12) is repeated for all pixel coordinates (x,y)

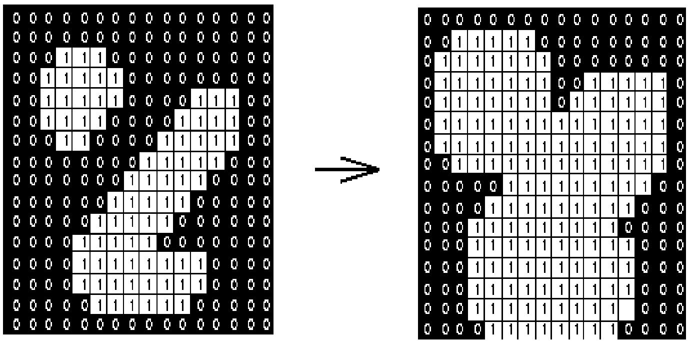


Fig. 5.Dilation Operation

Fig.5. shows the dilation operation. “Dilation” and “Erosion” are dual operations which have opposite effects. The combined operation of dilation and erosion is given in Fig.6. Let “f_c” represent the complement of an image “f” then this duality is written as

$$f \oplus s = f^c \oplus s_{root} \tag{26}$$

Where, s_{root} = Structuring element of “s” rotated by 180°

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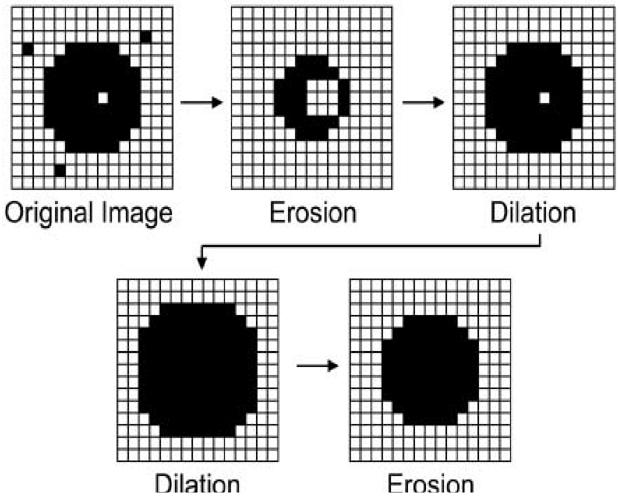

Fig. 6.Combined Dilation and Erosion Operation

E. Modified Blob Analysis

In image processing, Blob analysis is defined as the connectivity of pixels present in an image. To implement Blob analysis, the statistical blob method is used [20]. In this process, markers are generated from the statics of each blobs present in the image which gives various characteristics of the geometric parameters present in the input images such as borderline, area, center and perimeter etc. Since the blob is extracted from the output of the morphological operation, so the normal statistical blob [21] is not suitable. For this reason it is needed to modify the existing statistical blob [22] method.
First analyze the image processed by morphological operation which is then used to find and tag every blob present in the image. If $y^i(x,y)$ is a blob between two point then all the elements present in $y^i(x,y)$ is written as

$$X_k^i = \left(x_{k-1}^i(x,y) \oplus B\right) \cap A \tag{27}$$

Where, k=1,2,3……
$x_0^k(x,y)=Ø$
B= Element of the structure
A,P=Two concourse points belonged to $y^i(x,y)$

The connective proportion $y^i(x,y)$ is given as

$$y^i(x,y) = \cup_{k=1,2,3,\ldots} x_i^k(x,y) \tag{28}$$

If s(.) is the connective region parameters, then it is written as

$$s\left(y^i(x,y)\right) = \sum_{\substack{x_k^i(x,y) \in y^i(x,y) \\ k=1,2,3,\ldots}} x_k^i(x,y) \tag{29}$$

Through eq. (18) the blob is detected of an input image. To get accurate blob, thresholding [18] operation is considered. The pseudo-code for the modified blob is given as

Algorithm:

i. Consider the image after morphological operation as input image.

ii. Find the symmetric difference using the mathematical equations [23]

$$G_1(x,y) = \begin{cases} 0; & |f_{k-1}(x,y) - f_k(x,y)| < \omega \\ 1; & Otherwise \end{cases} \tag{30}$$

$$G_2(x,y) = \begin{cases} 0; & |f_{k+1}(x,y) - f_k(x,y)| < \omega \\ 1; & Otherwise \end{cases} \tag{31}$$

$$DM_k(x,y) = \begin{cases} 1; & |G_1(x,y) \otimes G_2(x,y)| < \omega \\ 0; & Otherwise \end{cases} \tag{32}$$

Where, $f_{k-1}(x,y)$, $f_k(x,y)$ and $f_{k+1}(x,y)$ – three consecutive images
ʘ – AND operation two binary image.
$G_1(x,y)$ – moving target from k-1 to k frame
$G_2(x,y)$ – moving target from k+1 to k frame

iii. Set three thresholds depending upon various categories as TC_1, TC_2 and TC_3.

iv. Analyze the binary image $DM_k(x,y)$ and set the thresholds using eq. (9) to (11) as
***TC*₁:** This is the highest threshold which is used to classify the noises present in the image.
***TC*₂:** It is used to define tree branches swaying.
***TC*₃:** Moving objects.

The modified Blob detection technique is applied to 14th frame of a traffic video frame which is given in Fig.7.

(a) Input Imag (b) Corresponding Blobs

Fig. 7.Proposed Modified Blob Analysis

IV. Performance Analysis

The performance of the proposed Gaussian mixture model is evaluated by calculating the detection accuracy and is compared with some of the exiting methods.

A. Performance Parameters

The detection accuracy of any object detection algorithm is defined by the percentage of the detected object with respect to the total objects present in the video frame at a particular time which is written mathematically [18] as

$$Detection\ Accuracy = \frac{Number\ of\ Detected\ Objects}{Number\ of\ Actual\ Objects}\ x\ 100 \tag{31}$$

For good detection accuracy, the eq. (28) will give high percentages for most of the frames.

B. Simulation Results

The proposed algorithm is coded using standard MATLAB programming language and simulated using MATLAB 2013a software. To check the accuracy of the proposed algorithm, two different scenarios are considered i.e low traffic density and high traffic density and is discussed below.

B.1. Low Density Traffic Conditions

In this case, standard CCTV footages have taken to test the proposed algorithm. The traffic video where the cars are moving at slow speed is considered as a test subject which is given in Fig.8.

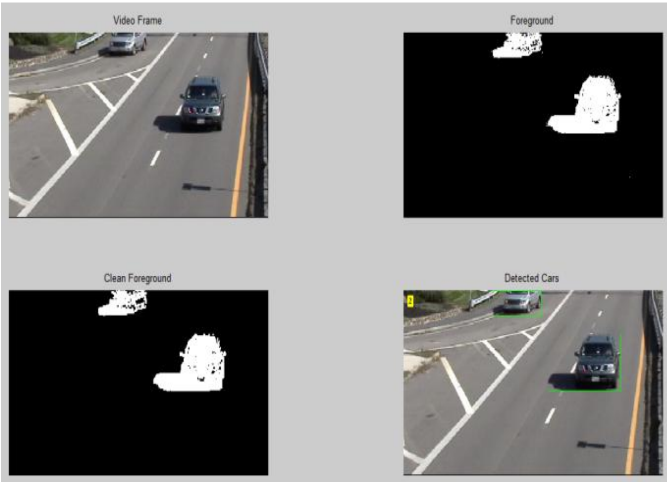

Fig. 8. Simulation Results of Traffic Video with Slow Movement of Vehicles

From Fig.8, it can be seen that all moving cars present in the video is detected correctly.

The detection accuracy of slow movement of vehicles from video is given in Table 1 with respect to different frames. In this case, the actual number of cars are present in randomly chosen frames of the corresponding video are compared with the detected numbers and the average accuracy is found to be 90.90%. For some frames the detected number does not matches with the actual number. The main reason behind this is that the proposed algorithm needs some frames to detect accurately the car which enters into the video newly. But most of the cases, the detected numbers are equal which implies that the algorithm is efficient in detecting slow movement cars from traffic video.

Table- I: Detection Accuracy of different frames presents in traffic video with slow movement of vehicles

Frame Number	Number of Cars		Detection Accuracy
	Actual	Detected	
121	1	1	100%
125	1	1	100%
135	2	1	50%
139	2	2	100%
141	2	2	100%
150	2	2	100%
166	2	2	100%
171	2	1	50%
178	2	1	50%
192	1	1	100%
202	1	1	100%
209	1	1	100%
227	1	1	100%
230	1	1	100%
246	1	1	100%
250	1	1	100%
358	1	1	100%
400	2	1	50%
517	2	2	100%
527	2	2	100%
530	2	2	100%
542	2	2	100%
Average Detection Accuracy			**90.90%**

In similar manner, the traffic video where the cars are moving at high speed is considered as test subject simulation result is given in Fig.9

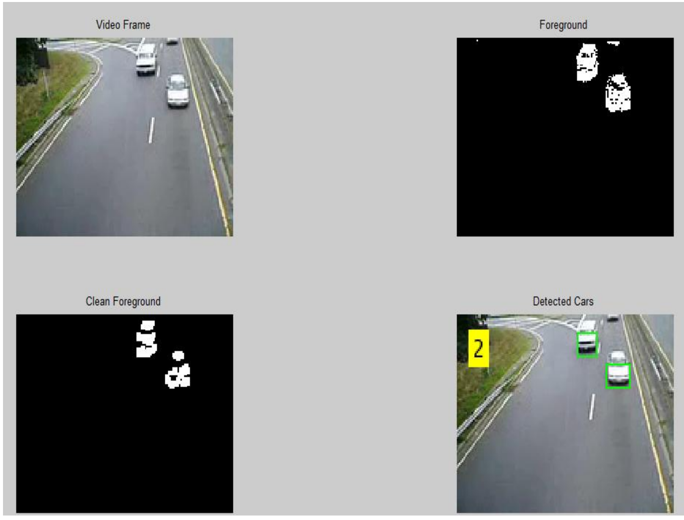

Fig. 9.Simulation Results of Traffic Video with Fast Movement of Vehicles

The detection accuracy of fast movement vehicles from video is given in Table 2 with respect to different frames.

Table- II: Detection Accuracy of different frames presents in traffic video with fast movement vehicles

Frame Number	Number of Cars		Detection Accuracy
	Actual	Detected	
23	1	1	100%
25	1	1	100%
26	3	2	66.67%
28	3	3	100%
30	2	2	100%
32	2	2	100%
34	3	2	66.67%
45	3	3	100%
56	3	3	100%
60	3	3	100%
66	3	3	100%
69	3	3	100%
71	3	3	100%
75	4	3	75%
80	4	3	75%
88	2	1	50%
92	2	2	100%
95	2	2	100%
99	2	2	100%
104	1	1	100%
116	1	1	100%
121	1	1	100%
Average Detection Accuracy			**95.46%**

B.2. High Density Traffic Conditions

In high density traffic condition, the position of moving cars is overlapped which makes it very difficult to detect moving cars correctly. To test the proposed algorithm in such conditions, traffic video with high density traffic is considered. The simulation result is given in Fig.10.

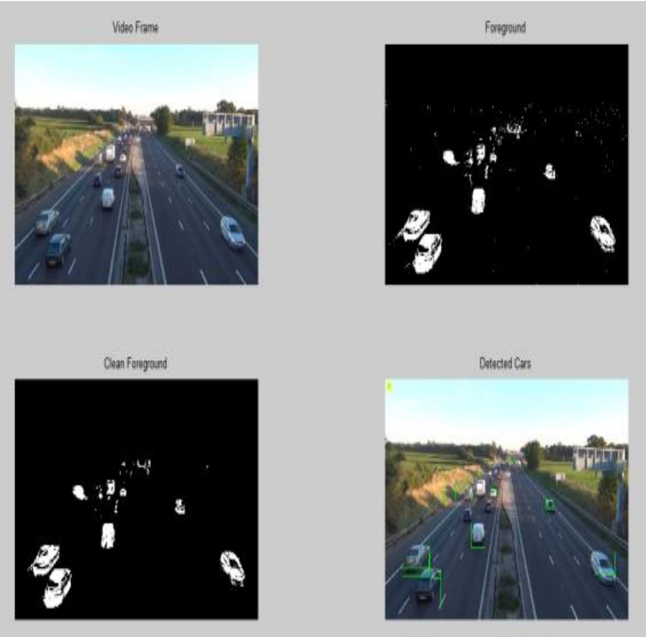

Fig. 10. Simulation Results of High DensityTraffic Conditions

Table- III: Detection Accuracy of different frames presents in traffic video with fast movement vehicles

Frame Number	Number of Cars: Actual	Number of Cars: Detected	Detection Accuracy
368	31	12	38.71%
401	33	18	54.55%
1384	30	25	83.34%
1759	38	26	68.43%
2066	30	22	73.34%
2088	35	23	65.72%
2315	32	22	68.75%
2611	38	25	65.78%
2941	34	21	61.18%
3210	31	19	61.29%
3688	35	22	62.29%

The proposed modified Gaussian mixture algorithm is compared with some of the algorithm available in literature in terms of its accuracy of detection and is presented in table 4.

Table- IV: Detection Accuracy of some of existing method with the proposed method

Authors	Techniques	Maximum Accuracy
Adedeji and Zenghui [23]	Gaussian Mixture Model with morphological filter	92.00%
WonTaek et al. [24]	Two-Stage Foreground Propagation	92.40%
Venkatesan et al. [25]	radial basis perform network	89.68%
Chih-Yang et al. [26]	image bit-planes and hysteresis thresholding	86.30%
Yu and Fenfen [27]	optical flow	89.00%
Proposed	Modified Gaussian Mixture Model with Modified Morphological filter	93.18%

V. CONCLUSION

In this paper, a new algorithm to detect moving object from traffic video sequences is proposed. To reduce external light intensity variations, Gaussian filter is used. The background is then extracted using Modified Gaussian Mixture model which is processed by Morphological filter to remove noise present in it.

In this paper, an efficient algorithm to detect moving object (vehicle) from traffic video is proposed. To reduce the effect of external light intensity variations on the detection efficiency, Gaussian filter is used. Then using Modified Gaussian Mixture model, the corresponding background is extracted which is then processed by Morphological filters to remove small amount of noises present in it. Now the blobs presents in the frames are detected by Modified Blob detection technique and depending upon the blob and it's shape, a box is added to the frame which is then used to generated detected video. The proposed algorithm uses modified Gaussian Mixture Model with Modified morphological filter to increase the detection accuracy. As a result, the detection accuracy of the proposed algorithm reaches 93.18% for slow and fast moving vehicle and 64.0% for high density vehicle.

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