International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Vehicle Counting Method Based On Gaussian Mixture Models And Blob Analysis

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DOI: https://doi.org/10.55248/gengpi.2022.3.6.36

ABSTRACT:

Combination of a Gaussian Mixture Models and Entropy to detect vehicles in motion from any sort of video sequences. The proposed method is composed of four major steps: background subtraction, improved GMM, Blob Analysis, Voting Scheme processing. An implementation of proposed technique has been performed using MATLAB R2017a. Vehicle detection process provides relevant information about traffic patterns, crash occurrences and traffic peak times in roadways. Detection of number of vehicles and traffic monitoring will be helpful by implementing motion and object detection using background subtraction, Monitoring traffic from video footages will provide a greater reality in terms of vehicle count. Gaussian Mixture Model is most advanced model in motion detection due to the reliability that it has shown in the background extraction and foreground segmentation process. Here we are going to find motion of object in video sequences under both static camera arrangement and dynamic background sequences by using background subtraction method and blob analysis approach and analyzing them

Keywords: Improved GMM, Background subtraction, Foreground Extraction, Blob Analysis, Voting Scheme.

INTRODUCTION

Counting the number of vehicles based on video sequences in each frame has then been a challenging task dueto low efficiency and minimum accuracy. As a result, the results obtained were harder to believe and had no proper accuracy. Therefore, to get the accurate results in counting the number of vehicles in a particular video frame in video sequences one must come up with better results. Especially for dynamic backgrounds which possess maximum distortions. Background subtraction algorithms are used to generate a background model of the incoming video sequence and so it can be compared to the video frame obtained from the background model from the video sequence to detect the objects from the video frame. This proposed model can be utilized in various dynamic environmental conditions in which the background keeps on changing. We hereby use improved GMM and with the inclusion of concept of Blob analysis,it is easier in dynamic moving backgrounds to detect the moving objects in the particular frame.

In certain cases, for object detection, background keeps on changing, so as a result it is very difficult to locate the foreground object due to the presence of video noise, target occlusion, illumination changes, brightness distortion and several other factors. The existing models/algorithms cannot handle sudden illumination changes sometimes.

So therefore, in this proposed model detect the moving objects for both static and dynamic background and count the number of desired objects we use the following criteria in thisproposed model.

Using Advanced background subtraction and improvedGMM and Voting Scheme for consequent sequences.

PROPOSED MODEL

Gaussian Mixture Model (GMM) is a prominent method in vehicles detection and counting due to its reliability that it has proved in the background extraction and foreground segmentation for the video sequences from the surveillance.

Constantly varying background will produce noise up to a certain extent which can be rectified with improvised techniques. It remains a challenging problem to develop algorithm for dynamic background, lighting changes and cluttered scenes.

The main objective of this process is to distinguish the region property of each pixel. According to the principle of regional block, pixels which do not belong to the motion region are mentioned as the background noise or pixels. After implementation of Gaussian mixture model, we include the voting scheme which provides optimum selection of accurate pixels for vehicle detection.

BACKGROUND SUBTRACTION

Background subtraction technique is a widely used technique in video sequences for foreground objects (vehicles) detection. These background subtraction techniques are the main processes used apparently to diagnose the moving object from the sequence of video frames that varies considerably with respect to the background.

Since a video is generally defined as a sequence of frames which consist of images, where each sequence of images is displayed with high speed as frame rate of the video, this is where background saturation is made into action to detect changes between the adjacent moving frames. By using image threshold, the unwanted part of the image will be removed. The frame operation can be explained for background subtraction as:

| Frame (i)–Frames (i-1) | > Th……… (1)

Where, 'Th' denotes the threshold value for background subtraction, 'i' represent the adjacent frames

Background subtraction is the first and foremost operation to be performed in video processing and its main objective is to reduce the effective image size in subsequent processing steps by segmenting the mostly static background from the moving or changing foreground pixels and to extract the background. A binary difference image D (x, y) is calculated by

$$D(x, y) = \begin{cases} 1\ ;\ \mathrm{I}(x, y) - \mathrm{B}(x, y) > \tau \\ 0;\ Otherwise \end{cases} \ldots\ldots\ldots..(2)$$

where, is empirically defined noise threshold to distinguish foreground and background pixels.

GAUSSIAN MIXTURE MODEL

Generally, Gaussian mixture model consists of a mixture of 'K' Gaussian distributions which can be illustrated by these parameters: mean (μ), weight (w), and variance (σ2). Pixels whose weight factor is slightly low and whose standard deviation is high are considered as foreground pixels, whereas pixels whose weight factor is higher and has the same value of standard deviation shall be therefore considered as background pixels.

Gaussian Mixture Models (GMM) is a type of density model consisting of Gaussian function components. This algorithm shall be used to perform the background extraction process because it is much more reliable towards light variances and repetitive object detection scenarios.

The Gaussian mixture model to calculate the mean and variance can be represented as,

$$P(x_i) = \sum_{i=1}^{K} w_{i,t} \times \frac{1}{(2\pi)^{\frac{n}{2}}|\varphi_{i,t}|} e^{-\frac{1}{2}(x_t-\mu_{i,t})^{\mathrm{T}} \Sigma_{i,t}^{-1} (x_t-\mu_{i,t})}.(3)$$

where,

$\mu_{(i,t)}$= mean value of the Gaussian distribution at time t,

$\varphi_{(i,t)}$= covariance matrix,

K =Number of distributions.

5.3 BLOB DETECTION

Blob detection is a versatile technique in which system can trace and track the movements of objects in the frame from the video sequence. A Blob generally is a group of pixels that identifies a particular object. The blob area to place the bounding boxes must be well defined before processing the blobs in which the pixels with similar light illumination values or color values are grouped together to find the blob. In this proposed algorithm, blob detection uses contrast values in the binary image to compute and process a detected region, its centroid and along with the area of the blob. The GMM supplies the pixels detected as foreground as well as background.

In general Blob analysis, the algorithm identifies potential objects to be detected and puts a box around the detected objects. It finds the area of the blob and finds a rectangular fit around each blob, the centroid of the object can be extracted and obtained for tracking the object. Counting the total number of vehicles passing by plays an important role in an intelligent transport system. Vehicle detected by bounding box through blob analysis can be used to count the number of vehicles passing the particular video sequence.

5.4 VOTING SCHEME

The voting scheme is performed to get the pixels into consideration while detection of objects. We perform the voting scheme, whether to take the pixel as background pixel or as foreground pixel based on the results obtained from the voting scheme.

By implementing the voting scheme for the pixel categorization into foreground and background based on the threshold value set by the user for avoiding the complexities into making them as foreground or background objects. The threshold value determines the image pixel as object or background. This voting scheme compares two simultaneous output frames for the same frame and therefore the frame with more accurate result shall be voted as the required result.

Based on the proposed adaptive background model, the binary motion detection mask D (x, y) is defined as

$$D(x,y) = \begin{cases} 1, & \text{if } |I_t(x,y) - B_t(x,y)| > \tau \\ 0, & \text{if } |I_t(x,y) - B_t(x,y)| \leq \tau \end{cases} \ldots.(4)$$

Where,$'\tau'$is the threshold empirical value,I_t (x, y) represents the incoming video frame, B_t (x, y) represents the background model, t represents the frame number

PROPOSED METHOD RESULTS

Results after performing Background Subtraction

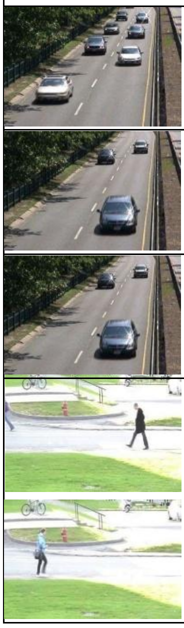
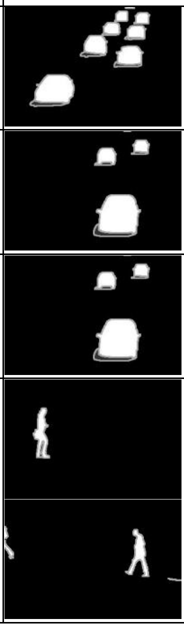
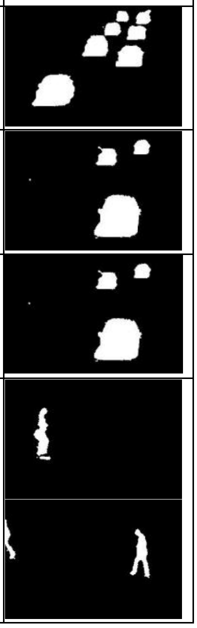
Sampled Frames	Ground Truths	Proposed method result
		

Table (1) explaining the various sequences taken and on which background subtraction is performed and obtained results are represented in above table.

Comparison between Ground Truths and Results

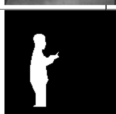
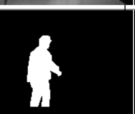
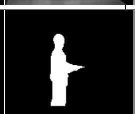
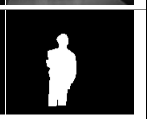
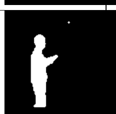
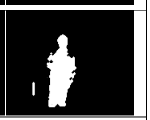
	Frame-22774	Frame-22847	Frame-23857	Frame-23893
Sampled frames				
Ground truths				
Proposed method				
Similarity F1	0.9206 0.9355	0.8785 0.9142	0.8811 0.9051	0.8932 0.9112

Table (2) explaining the similarity between the obtained results and ground truths in MSA sequence

Results after performing Blob Analysis

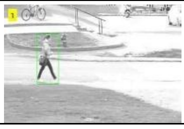
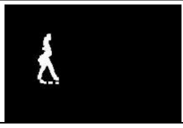
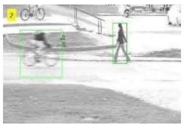
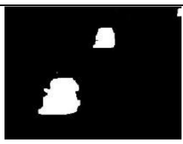
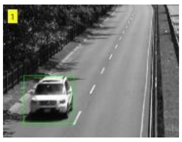
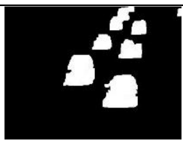
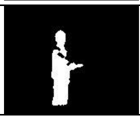
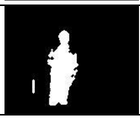
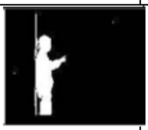
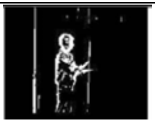
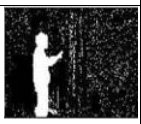
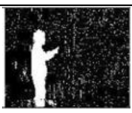
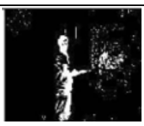
S. No	Blob Count	Foreground Detection
1		
2		
3		
4		
5		
6		

Table (3)-Blob Detection

Table (3) explaining the results obtained after performing Blob Analysis and detecting the number of vehicles in the frames and foreground detection for every frame is represented.

Hence for various frames taken into considerations and performed the algorithm-based operations on the sequences, we obtain the accurate results by blob analysis so as to count the number of vehicles or objects in the particular frame.

Of the various proposed models, we shall compare the proposed models with the previous proposed models to compare the accuracy, precision and other factors. We compared various models for various video sequences as below.

	Frame-22774	Frame-23857	Frame-23893
Sampled frames			
Ground truths			
Proposed method			
SIMILARITY F' Measure	0.9308 0.9550	0.8711 0.9301	0.8332 0.9112
RADCT [12]			
SIMILARITY F' Measure	0.8442 0.9155	0.2898 0.4494	0.3231 0.4884
MSDE [14]			
SIMILARITY F' Measure	0.5136 0.6786	0.2604 0.4132	0.3050 0.4674
SDE[13]			
SIMILARITY F' Measure	0.5261 0.6894	0.1966 0.3286	0.2311 0.3755
SSD [14]			
SIMILARITY F' Measure	0.7770 0.8745	0.3806 0.5513	0.4093 0.5808

Comparison between various proposed models for MR sequence

Table (4) showing the original frames along with the ground truths and resulting frames from proposed models and showing the similarity between the actual ground truth and resulted frames. For the particular MR sequence, the proposed model has the higher rate of similarity when compared to other proposed models for the same video sequences.

CONCLUSION:

In this work, an efficient background model is contributed and tested to handle some complex situations in the video sequences and object tracking task.

Algorithm for various illumination changes in a scene is proposed in this model. The proposed algorithm classifies the obtained illumination changes in a video sequence into three levels by estimating the changes in entropy illuminations between the current frame and the previous frame. Depending on the level of illumination changes are observed in the background model.

The proposed method thus localizes and detects the object without over segmentation errors and aperture distortion and attains much more accuracy rate than other previous proposed background subtraction models. Therefore, accurate vehicle counting can be made using GMM in addition with Blob analysis in a video sequence.

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