REAL TIME TRAFFIC SURVEILLANCE VIDEO PROCESSING FOR VEHICLE TRAFFIC CONGESTION

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ABSTRACT
Road Traffic has been one of the major concerns of a country as it affects many people both directly and indirectly. Metropolitan cities and traffic go hand in hand drawing inhabitants to congregate in large urban areas in intolerable levels of traffic congestion in urban areas and highways leading to cites. Effective urban governance requires a compromise between agglomeration and excessive congestion posing challenge for transportation, avoid unexpected congestion, follow the shortest path and less intersections to the destination based on historical data and the updates of real time traffic information. In order to obtain a statistical model of the flow of vehicles detailed monitoring of road traffic in intersections is extracted. In conventional methods, sensors at each of the intersection allow for counting, but are limited. The data is invaluable to understand the dynamic of a city’s mobility working and improvement.

New technique is developed to provide information that approaches to analyse video footage of intersections through computer vision algorithms to identify/track individual vehicles. The research aims to detect and track the vehicle from the video frame sequence, through vehicle motion along the frames using Background Subtraction Technique (BST), so that a statistical model may be extracted. The algorithm employs vehicle tracking with centroid based tracking by compensating for camera movement. Development of this approach proved useful for tracking cars, buses and trucks in highways encouraging for future expansion.

Key words: Vehicle Tracking, Video Image Processing, Background Subtraction Technique (BST).

1. INTRODUCTION
The growth of the number of vehicles in urban areas has led to an increase of the need of classifying traffic conditions in traffic networks. The development of the quantity of vehicles in urban territories has prompted an expansion of the need of classifying traffic conditions in metropolitan cities. The data gathered has a few purposes to control vehicular systems, planning, management of network, decision support, giving either route guidance applications or simulators with constant information, enhancing the infrastructures capacity for accommodating more vehicles [1] consistently in the interim empowering crisis vehicles, improving the capacity of infrastructures to accommodate more vehicles every day and enabling emergency vehicles. The few approaches to gather the information which are right now being used include manual counting, loop detectors, radars and devoted camcorders. The research recommends the utilization of video streams as a wellspring of data for this assignment with video streams seen by human controllers or direct usage by target population as opposed to having some programmed processing and giving the overall public treated and enhanced information.

Many proposed motion tracking techniques are based on template matching, blob tracking and contour tracking. Thus, to analyse the reliability and practicability of it, the idea of implementing background subtraction in traffic surveillance system will evaluate its performance. The motion tracking strategies depend on blob tracking, contour tracking, layout coordinating and template matching. The practicability and reliability thought of executing background subtraction in traffic surveillance [2] framework. In regular strategy sensors at every intersection take into account restrictions feeling that is difficult to track a vehicle from beginning to penalty area. The conceivable methodologies are to break down video footage of said intersections by means of computer vision algorithms to distinguish and track every vehicle.

Having individuals physically counting vehicles going through some area of a road is somewhat insufficient and must be made amid experimentation periods. The capacity of OpenCV, is a renowned open source computer library, in traffic surveillance framework. Discovery and tracking is proposed in view of the background subtraction, contour tracking and morphology to recognize highway traffic flow by a filtering of image, background extraction, vehicle location, morphological change, segmentation strategies and phases.

The objectives are:
- To assess and evaluate practicability and OpenCV ability in traffic surveillance system application.
- To present Background subtraction and Mixture of Gaussian model-based traffic surveillance system to track vehicle movements.

First, the background model was established, using statistical means of the rapid sequence. Using the background of the video images to do background subtraction and then images of the vehicles were accurate detection of mathematical morphology and foreground detection. A highway traffic flow has been detected by a background extraction, image filtering, image binary, morphological transformation, vehicle detection, segmentation methods and steps.
2. RELATED WORK
Tracking moving vehicles in video streams has been an active area of research in computer vision from many years. Tracking entire vehicles, moving object recognition method described. Detection and tracking are simply preliminary steps in vehicle classification.

2.1. Motion Segmentation
The objects are distinguished from the background by segmenting the images of the objects from the separate vehicles. There are different methods like shifting degree [3] of value. The segmentation precisely separates vehicles from the background, and operates fast in real time, weather and lighting climate conditions require a less volume of supplementary data.

2.2. Feature Based Tracking
Dealing the sequence of images, generally one includes have been distinguished, needs to track over multiple frames to detect/describe movement of vehicles or by drone, as exemplified in Figure 1.

![Figure 1 Feature Detection](image)

The technique to achieve this is to apply the Lucas-Kanade algorithm to estimate the perceived motion of a vehicle which relies on pixel’s intensity remaining constant between two consecutive frames and neighbouring pixels moving in a similar fashion.

Lucas-Kanade algorithm [4] takes the 3x3 matrix of pixels centred on the feature being considered and uses that patch for tracking which is only applicable in case the motion is small enough. As the motion is too fast, it’s common to apply it iteratively, starting with low-resolution versions of the image and moving onto higher-resolution improving the model obtained with the coarser images. Further improvements have been achieved by carefully choosing the features to track by applying the Shi-Tomasi feature detector which forms the basis for the Kanade-Lucas-Tomasi feature tracker (KLT). Both Lucas-Kanade and Farneback’s algorithms are provided by OpenCV.

2.3. Blob Detection
Blob detection focus on the identification of ROI of image. A ROI is defined by set of connected points which share some common property such as brightness or color which can be constant or vary within a range of values, but will always be different from other points surrounding the blob. Intensity-based detection [5] is based around the concept of defining the property, Figure 2 being analysed as a function of position and then differentiating this function, locating local maxima and minima, looking for sudden changes in intensity in the picture.
2.4. Detecting Edge and Filtering

To detect edge points of the uninterrupted images the edge curves are twisted [6] by alliance edge points using morphological operations.

2.5. Absolute Differential Motion Detection

Absolute Differential Motion Detection also known as frame differencing, the most basic and effective technique. In any image the difference of initial position and final position from the motion of the points is called as motion of an object in two images. In an image when Pt₁ and Pt₂ are initial and final position, if Pt₁ is not equal to Pt₂ along these links the distinction indicates that object has been moved starting with one position then onto the next position. The difference time (t & t-1) from the given two images, differential motion analysis methods will discover the distinction between two pictures, it's called the motion of objects. This method is compelling and effective in specific conditions., In various conditions, this method will create distinctive intriguing outcome.

For instance, A is taking two images from a images sequence, image sequence is holding properties of low frame per-second (FPS). The clear initial and final position of the object can provide Absolute frame differencing. However, don’t give the trace of the moving object.
2.6. Background Subtraction Techniques

Background subtraction, in simplest explanation, subtract out the background always static, thus leaving active object for further analysis. Expelling foundation data from a picture, expecting every intriguing objects are situated in the forefront. It is generally connected to video information and is based around building a model subtracting from the frame being prepared. It is valuable to avoid futile information and lessen the multifaceted nature of further preparing advances.

Background subtraction is a widely used approach for detecting moving objects from static cameras. The most significant step in background subtraction [7] is the modelling of the background, as the quality of the results directly correlates to this. It is desirable that the model adapts to changes in illumination, to new objects entering the scene and remaining there and to the background varying in geometry. Due to the limited computational resources of the past, it was not always possible to guarantee all of these properties. The initial proposed techniques essentially displayed a pixel's qualities after some time by fitting a Gaussian probability density function by methods for keeping a running normal of the pixel's values. Later on, it was suggested that it may be all the more intriguing to rather utilize the median value of the pixel's last n values.

A different approach is the one proposed by which is based around inferring which pixels belong to the foreground based on a histogram of previous pixel values. In current PC vision field, segmentation of vehicle exceptionally related with motion tracking and analysis. Before performing motion tracking, object ought to be unmistakably recognized and after that apply the tracking.

2.6.1. Advanced Background Subtraction

Absolute frame differencing's drawback is the background must retain static over time contrasting the current and the previous frame. In real, many background contains like, complicated moving things, trees waving is likewise result in pixel changing, it significantly affects the effectiveness and accuracy of absolute frame differencing. Giving the background model is exceptionally useful for creating better background subtraction result by comparing each pixel on current frame with the given background model.

2.6.2. Background Modelling

The drawback of total casing differencing is basic and must remain static over time differentiating the present edge and the past edge. Generally, various foundations scenes contain mystified moving things, for instance, trees waving is in like manner result in pixel changing, which will essentially impact the precision of supreme edge differencing. Foundation display is exceptionally useful for making better foundation subtraction result. Moving vehicle still can be recognized by subtracting each pixel on current casing with the foundation demonstrations exhibit gave.

2.7. Road Traffic Monitoring

Historically, there have been two exceptionally particular methods for road traffic. Physical sensors put on/close to the street identify the nearness of a vehicles through loop sensors, microwave detectors and pressure tubes. Computer vision solutions apply algorithms to images caught by a camera went for the street and identify to count the vehicles. Physical sensors give helpful information but are expensive and clumsy to install and maintain, it is based on the computer vision based tracking methods.
2.8. **Unmanned Aerial Vehicle (UAV)**

An unmanned aerial vehicle (UAV), widely known by drone, is an aircraft without a human pilot aboard. UAVs are a part of an [8] unmanned aircraft system (UAS), which incorporate a UAV, a ground-based controller, and a communication system between the two. The trip of UAVs may work with different degrees of independence: either under remote control by a human administrator or independently by on-board computers. UAVs are substantially more powerless to climate changes since they fly low. Automaton advocates imagine a future in which swarms of UAV will be in travel or performing assignment, so information about their traffic management will be a key to movement administration. That navigation route will require something other than a fundamental street map. Notwithstanding areas of physical buildings, navigation systems additionally need to get dynamic information data that changes progressively and empowers UAVs to avoid hazardous or limited zones that can incorporate changing environment factors.

3. **PROPOSED WORK**

The proposed work encompasses vehicle detection, tracking and counting using video processing by the method of background subtraction and foreground detection for the detection of vehicle and centroid based tracking for vehicle tracking on road by UAV. OpenCV library like matplotlib and pandas are used to plot traffic density curve.

The following steps were taken to achieve the intended results.

1. **Data Acquisition:** A video of a street segment is captured on the ground level. This is to capture the side view of each passing vehicle.
2. **Vehicle Detection:** Moving vehicles were detected via performing background subtraction, morphological closing, rectangle fitting, and filtering. Trained vehicle detector is then used to verify whether each of them is a vehicle or not.
3. **Vehicle Tracking:** The tracking of vehicles was accomplished by using Kalman filtering giving a label and its properties and recorded. Efforts were made to ensure that vehicles that become occluded (i.e. vehicles traveling in opposite directions) would not be re-assigned to a new label in later stage.
4. **Vehicle Counting:** Based on vehicle tracking results the algorithm keeps track of the number of vehicles that have currently entered the frame assigning an incremented label to a new vehicle in the frame.

![Figure 4. Block diagram](image-url)
The main algorithm behind this video processing is Mixture of Gaussian (MOG) model based background subtraction method. This method involves processing of sequence of images in the video frame by frame and then applying foreground detection to detect vehicles and centroid based tracking, Fig 4.

The implementation of the video processing of the traffic videos consists of data acquisition and processing acquired from the camera by segmenting the video into sequence of images. Background subtraction is performed and foreground detection is used to detect vehicles in the video, Fig 5. Centroid based tracking algorithm is utilised for tracking the vehicles and ROI is utilised for counting vehicles number on road to plot density graph for analysis.

![Figure 5. Overview](image)

### 3.1. Data Acquisition

A video clip on a street segment is captured in 25-30 frames per second (FPS). A UAV was installed on a tripod to stay static while capturing in a two-way street and there are pedestrians and motorcycles Fig 6. Also, it’s flurry and drizzling weather conditions which brings slight camera shake and environment noises.

### 3.2. Workflow of Proposed System

There are four main parts in the proposed system:

- Image pre-processing
- Foreground or Background image segmentation
- Pixel clusterisation
- Multiple Tracking.

The undertaking of image pre-preparing is to improve picture imported from a video stream utilizing a blur filter. After pre-handling, the image is gone through Fg/Bg picture division to isolate frontal area from background sections in the picture. This strategy depends
on making a background show from an extensive number of pre-processed pictures and contrasting it and the new pre-processed picture. The result of Fb/Bg segmentation is then gone through pixel clusterisation, processes area of every vehicle in a scene and tracks its direction through sequential images. The last part for tracking multiple vehicles of the proposed framework performs additionally including utilizing markers characterized the scene.

With a specific end goal to precisely track, count and detect vehicles acquired video traffic needs to fulfil resulting prerequisites:
(i) camera viewpoint in the video footage must be steady after some time
(ii) every single moving objects in the scene are vehicles
(iii) video traffic must not be beforehand pre-prepared using image enhancing algorithms.

![Flowchart](image)

**Figure 6** Data Acquisition

### 3.2.1. Image Pre-processing

Each image of road traffic video footage comprises a specific level of clamour. The presence of noise muddles the vehicle discovery process and essentially diminishes described system accuracy therefore it should be limited with a 4X4 matrix Gaussian blur filters generally used for reduction of noise to decrease the quantity of points of interest in the picture comprising noise.

Once effectively completion of pre-processing of image, background or foreground image segmentation is carried out, Fig. 10. The procedure comprises of making scene background model and compare the contrasting background model with the most recent imported image through the video.

\[
BG_t = BG_{t-1} + \sum_{i=1}^{n} \frac{sign_i(i)-BG_{t-1}}{n}
\]  

(1)
Here $BG_i$ and $BG_{i-1}$ symbolizes specific pixel value for the background model in progress frame and preceding frame respectively, $I(i)$ symbolizes value of a specific pixel in $i^{th}$ image and ‘n’ represents quantity of images stored.

3.2.2. Pixel Clusterization

Once classification of image, every pixel as section of background model or some portion of foreground object, then carries out pixel clusterization. Utilized approach depends on denoting all neighbouring pixel having a similar pixel value as a piece of a particular cluster. A short time later, all pixels inside a similar cluster are calculated, establishing ‘x’ and ‘y’ coordinates for minimum and maximum values. The clusters symbolized as rectangles with data, cluster centre is considered as rectangle centre and square shape focus is utilized as bunch focus.

![Vehicle detection and tracking flowchart](image)

Figure 7. Vehicle detection and tracking flowchart

In the proposed framework, pixel clusterization is performed just on closer view pixels. All the clusters which will not contain enough pixels with respect to clusters are disposed of avoiding additional processing.
3.3. Vehicle Tracking
The various types of vehicle tracking approaches consist of:

3.3.1. Feature Tracking
In the proposed framework, for filtering the spatio temporal vehicles tracking in a scene is utilized. Each formerly tracked vehicle in the scene is contrasted to each cluster recognized in the present image. The cluster which is not matched with any of already distinguished vehicles is fixed as new vehicle.

![Feature Tracking Diagram]

**Figure 8. BST**

The cluster matching is carried out via searching biggest weight factor identified with the cluster and particular vehicle. The cluster is assigned for the vehicle which is having highest weight factor.

\[
W_{\text{dist}} = 1 - \frac{d - d_{\text{min}}}{d_{\text{max}} - d_{\text{min}}}
\]

\[
W_{\text{area}} = 1 - \frac{a - a_{\text{min}}}{a_{\text{max}} - a_{\text{min}}}
\]

\[
W_{\text{cover}} = \frac{a_{\text{is}}}{\max(a_{\text{vch}}, a_{\text{cl}})}
\]

\[
W = \frac{W_{\text{dist}} + W_{\text{area}} + W_{\text{cover}}}{3}
\]

Here, ‘d’ is the distance between location of the specific cluster and estimated vehicle location, \(d_{\text{min}}\) and \(d_{\text{max}}\) are minimum and maximum distance among entire clusters and processed vehicle, ‘a’ is difference among the cluster size of area and estimated vehicle area, \(a_{\text{min}}\) and \(a_{\text{max}}\) are minimum and maximum difference among all the clusters area and expected vehicle area correspondingly, \(a_{\text{is}}\) is intersection area among cluster and vehicle, \(a_{\text{vch}}\) is area of the vehicle and \(a_{\text{cl}}\) is processed cluster area. In order to calculate distance between location of the specific cluster and assessed vehicle location their geometric centres are utilised.

3.4. Morphological Closing
The result after background subtraction still requires improvements due to the voids inside detected regions. Also, there are lots of environment noises, e.g. moving leaves on the tree blown by strong wind. A morphological closing transformation was applied to fill in the voids to improve accuracy using OpenCV built-in function.
3.4.1. Fitting Rectangles

Bounding rectangles were drawn around the contours of the detected regions. Due to the presence of noise, some of the drawn rectangles needed to be filtered. Rectangles with sizes that deviated too much from that of a regular vehicle were first excluded, Figure 9.

![Figure 9 Vehicle tracking and counting on lane](image)

4. RESULTS

The images, are used for creating background frame and then background subtraction training occurs for detecting vehicles in the foreground, track the total number of vehicles for counting and plot density curve in python.

4.1. Segmentation Technique

To aggregate the similar vehicles utilised segmentation technique by carrying background subtraction though frame difference and for dynamic vehicles segmentation most appropriate. The result shows input image and previous frame after applying frame difference and subtracting vehicles from background, Fig 10(a).

![Figure 10 (a) Original Video Sequence (b) BST](image)

Conversion of video to a grey scale sequence with the video segmented output in performing background subtraction frame difference and indications of original video sequence, Figure 10(b).

4.2. Vehicle Detection and Tracking

The tracking of vehicles in video performed via centroid tracking method setting moving vehicle motion vector, each vehicle threshold is calculated for tracking and detecting vehicles, Figure 11.

To quantify vehicle paths in sequences of video, tracking is utilised and it is carried out in two phases: (i) in each video frame, generated features for vehicle or foreground sections. (ii) a data association step, for providing communications among the areas of consecutive frames in light of a dynamic model and features.
The video sequence and optical flow method for setting motion vector and shows the vehicle, detection and tracking of vehicles exceeds the threshold value by means of moving vehicles with the foreground of the moving vehicle detected.

The vehicle density for a particular length is checked constantly in a predefined distance. Python console window which consists of all details about the number of frames processed in the video, number of vehicles found on the road. Spyder IDE is used to process the python code for video processing and different libraries of OpenCV are used for computer vision. The data of number of vehicles and corresponding distance are stored in a file of format .csv extension. Using pyplot the density curve is plotted using vehicle count with distance, Figure 12.

**Figure 11.** (a) Original Video Sequence  (b)ROI

**Figure 12** Vehicle Density Plot
5. CONCLUSIONS

For the reason that of increment in highways, superhighways and congestion of traffic, there is an immense measuring potential utilizations of vehicle recognition and tracking them in highways, superhighways. The proposed methods can be utilized as a part of video traffic. It centres in these zones, to be specific vehicle counting, detecting and tracking discovery, with appearance of shadow and partial constriction.

Despite the fact that the input data utilized has some camera quiver, the algorithm is fit for compensating. The algorithm tested against a few clips with various attributes and at various resolutions. It has demonstrated fit for vehicles tracking, buses, trucks and cars. The accuracy of algorithms to the extent the supreme vehicle counting profits by high resolution input data increasing running. The exactness of the conveyance estimation at times stays adequate or even enhances with bring down resolutions.

UAV traffic video monitoring with surveillance is developed by video processing focusing on vehicle detection, tracking and counting. A real-time system is implemented and tested based on the proposed algorithm with detailed information of traffic congestion using image processing methods and analysis tools for estimating vehicles to establish congestion. Results demonstrate the ability of the proposed system to correctly track and count vehicles in traffic even in cases of multiple vehicles simultaneously entering detection zone.

REFERENCES


[8] Sandeep Sagar K S and Dr Narendra Kumar, Kong Wobbler Base Station for Disaster Management, JETIR, Volume 5, Issue 6, June 2018.
