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# A Survey on Vehicle Counting - Double Virtual Line

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***Abstract: Traditionally magnetic loop detectors are usually used to count vehicles passing over them in the intelligent transportation system. Real-time image sequences are captured by video surveillance system. The virtual loop that emulates the practicality of inductive loop detectors is placed on images. It's more convenient however it happens in false detection and discrimination once vehicles are lane departure due to overtaking or crossing. This paper presents an efficient approach for vehicle numeration based on two double virtual lines DVL for counting vehicles and for calculating speed. Double virtual lines are assigned on frames which are across two-way multi-lane. The region between DVL is the detection zone instead of virtual loop zone in every lane thus on the scale back the proportion of false detection and misjudgment from lane departure for vehicles. Then in the detection zone the dual-template convolution is designed to detect and find moving vehicles to eliminate the mapping of one-many and many-one. The effective rules are given in terms of the constraint of the horizontal and vertical distances to improve the accuracy of vehicle numeration.***

***Keywords: Intelligent transportation system, vehicle numeration, DVL dual-template convolution.***

## I. INTRODUCTION

Traffic density on roads gives challenges in TMS. Vehicle detection classifying counting is common application of Intelligent Transportation System project. Loop detectors are used to count and classify vehicles crossing over the other vehicles. Over the magnetic loop detectors researchers over vehicles on the road are more. Video monitoring system gives more advantages of the existing method. Video surveillance system, traffic parameters like vehicle parking, lane changes etc... be achieved. An effective approach DVL is assigned for vehicle counting. Due to vehicle overtaking or crossing DVL are assigned on the video frames. DVL is used detecting the vehicles on the road. In the process of vehicle detection the dual-template convolution method is applied for detecting and locating the passing objects like vehicles. Vehicle-counting steps are given to improve the accuracy of traffic flow estimation. The algorithm is the use of DVL which scale off the proportion of false detection and misjudgment of the vehicle in the lane. Dual-template convolution eliminates false detection for the greater accuracy of the vehicle detection and the vehicle counting.

## II. RELATED WORK

Virtual loop assignment was done to identify the vehicle type and block-based direction-biased for motion estimation [1] the features of the approach was that a number of loops were automatically assigned to each lane. The merit of doing this was that it accommodates the actions without needing further human interaction. Second the size of the virtual loops which was much smaller for estimation accuracy. This enabled the use of standard block-based motion estimation techniques that were well developed for video coding. Third the number of virtual loops per lane is large. The motion content of each block may be weighted and the collective result offers a more reliable and robust approach to motion estimation.

The implementation of VL includes modules as VL assignment detection of the vehicle and traffic parameter estimation. There are many published works concerning moving vehicle detection [5, 6, 7, 8, 9] as for VL assignment literature [3, 4] proposed that virtual lines i.e. reference lines were drawn across the road. Space-time images are generated when a vehicle crosses the virtual lines. Then the generated images are used for vehicle counting. Lien [2] developed a scene adaptive vehicle counting system which worked by first tracking moving targets then applying virtual loop detector to analyze the traffic flow. Generally the counting system with tracking block is higher than that of only virtual loop detector in the average accuracy. Existing virtual loop detectors are mainly suitable for vehicular traffic that conforms to lane discipline. These sensors will not properly function when vehicles are roadway departure due to overtaking or crossing. Accurate knowledge of traffic volume efficient virtual loop or lines is essential. On the other hand the mapping of One-Many and Many-One inherently exists in the visual detection method. Surveying the literature there has been little work on how to eliminate the false mapping which has a very serious impact on the accuracy of traffic parameters estimation.

## III. DOUBLE VIRTUAL LINES ASSIGNMENT

Taking into account the cases of overtaking and crossing vehicles are not restricted to move in one lane. Double virtual lines are assigned to images which are across bidirectional multi-lane. The region between, DVL is the detection zone rather than virtual loop zone in each lane so as to reduce in the proportion of false detection and misjudgment from lane departure for vehicles. To be adapted to roads surveillance at difference height the assignment of DVL is analyzed at first. The size of the vehicle on images varies with the height of surveillance camera perspective. There exists homography between any of space planes and its image [10]. Thus the interval width l between DVL has estimated automatically in terms of the homography theory. Assume that the space plane is on z=0 of the ground plane since vehicles move on the ground plane. The homography is established between the ground plane and the image plane. The projection of B with respect to camera perspective P is the point B1 on the ground plane, according to triangle similarity relation; the spatial coordinates of the point B1 are,

$$\left( \frac{z_p}{z_p - z_B} x_B,\ \frac{z_p}{z_p - z_B}(y_B - y_p) + y_p,\ 0 \right) \qquad \textbf{(1)}$$

## IV. DVL-BASED VEHICLE COUNTING

Real-time image sequences are captured by visual surveillance system. DVL are assigned across bidirectional multi-lane on images. In the detection zone dual-template convolution operation is designed to detect and locate moving targets as well as to eliminate the mapping of one to many, many to one. The effective rules of vehicle counting are given in terms of the constraint of the horizontal and vertical distances to statistic vehicles. The principle of the whole scheme is shown in Fig. 1, mainly including the following steps.

### *A. Background Subtraction*

The algorithm as simple as possible, background subtraction is used to detect vehicle. Regarding background subtraction, there were methods that model the variation of the intensity values of background pixel with Gaussians model, mean filter, etc. Mean background models have relatively high memory requirements. Gaussians model is a classical method to copy with background changes.

The surveillance camera is fixed and the background is more likely to appear on the scene. The background image $f_{bg}$ is estimated from previous frames $f_{0:i-1} = \{f_0, \ldots, f_{i-1}\}$ using Gaussians model.

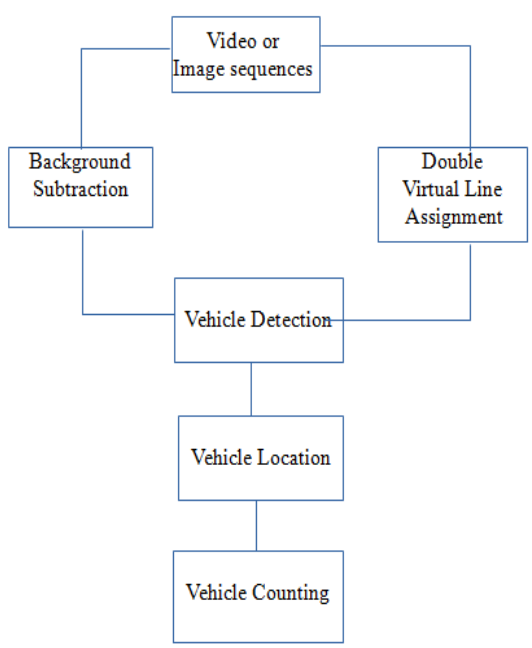


Fig: 1 Block Diagram

### *B. Vehicle Detection*

Vehicle detection in the current frame fi is conducted using background subtraction,

$D_i(x,y)=f_i(x,y)–f_{bg}(x,y)$ (2)

Where (x,y) is the pixel position, Di(x,y) is already the mask of foreground targets. Morphological filtering is used to remove the holes and enhance the targets. Dilation operation with a disk-shaped structuring element is used.

$D_{i(obj)}(x,y)=dilate\{D_i(x,y)\}$ (3)

### *C. Vehicle Location*

Dual template convolution is used to solve the problem mentioned as 'mapping of one-many or many-one.

1) *Mapping of One-Many:* The first template, which is a matrix filled with 1's, is designed to deal with the mapping of one-many. Let tmp1 donate the first template. The convolution operation is performed only in the detection zone, i.e. between the DVL. After the convolution operation, the peaks of the curve indicate the candidate targets. This distinguishes the two nearby vehicles, thus deals with the mapping of one-many.
2) *Mapping of Many-One:* The second template is designed to detect holes within the target area. I found that this operation is unnecessary because of the following two reasons The holes can be eliminated as long as the background subtraction method is robust enough, and morphological filtering is appropriately used. Even if there do exist some tiny holes within the target area, their influence can be fully eliminated by properly designed counting rules.

### *D. Vehicle Counting*

Located vehicles are identified by the peak. Vehicle counting rules are to be followed to overcome the inaccurate counting rules. The peak is a vehicle only if it satisfies all the following rules.

1) *Rule – I:* Large peak value: the peak value should be larger than the threshold value.
2) *Rule – II:* Horizontal safety space: the distance between two neighboring peaks should be larger than the threshold.
3) *Rule – III:* Vertical safety space: the distance between any of the two peaks in two consecutive frames should be larger than the threshold; clearly, this rule is designed to eliminate repeat counting.

## IV. CONCLUSION

DVL which is vehicle counting approach works for bidirectional multi-lane. The DVL and dual template convolution are to detect, locate and count vehicles. DVL assignment, the use of DVL detector increases the detection rate. The use of dual-template convolution eliminates the false detection of detecting and locating the vehicles. Vehicle counting rules are discussed to avoid the miscount of vehicles. I hope this discussion will help for further process.

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