Automatic Vehicle Detection and Counting Algorithm

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Summary
This study proposes an algorithm to detect and count vehicles passing a certain point for video-based monitoring of traffic flow. The unique feature of this algorithm is to calculate an approximate value of speed while counting vehicles using GMM background modeling, object histogram and pyramidal Lucas Kanade method. In addition, another feature of this algorithm is to use the preprocessing video that is converted into distance coordinate system in consideration of radar sensor and data coordination.

Key words:
Traffic monitoring, Vehicle counting, GMM background modeling, Optical flow

1. Introduction

Recently, the intelligent transportation system is monitoring traffic flow with a high definition camera and improving its performance by integrating Doppler method based radar sensor and detection data. A radar has more advantages in terms of night, bad weather and speed accuracy. However, its performance is much reduced when it runs at a crowding low speed, which occurs frequently. As a result, it is required to develop a video-based algorithm that can detect and count vehicles even at a crowding low speed driving and measure approximate speed.

As for the most prominent methods, there are the following two methods: one is to calculate edge histogram after dividing those objects obtained through background modeling into block unit and analyze the shapes after classifying them as SVM and the other one is to use HOG descriptor[1],[2]. An adaptive bounding box size is used to detect and track vehicles according to their estimated distance from the camera given the scene-camera geometry[3]. There is also the technique to group based on probabilistic characteristics after dividing vehicle contour horizontally and vertically for prompt detection speed[4]. Although there is the real-time high performing algorithm such as TLD framework, this study proposed a relatively light algorithm that can detect vehicles passing at an assigned location and measuring the speed toward progress direction as excluding the object learning part.

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2. Related works

2.1 Gaussian Mixture Background Model

To extract objects, the method to separate the foreground and background is often used. The most prominent techniques are background subtraction technique and Gaussian Mixture Background Model technique. This thesis uses Gaussian Mixture Model proposed by Stauffer for detecting unexpected situations in consideration of external environmental changes. In theory, it is possible to model a background only with one Gaussian distribution when a single background has a certain degree of brightness. However, the brightness of a background varies gradually over time. Thus, the adaptive Gaussian distribution is used for modeling this. If there exists a pixel value that does not correspond to a Gaussian distribution for background, then this will be called foreground. When there are K Gaussian distributions, the collection of pixel samples for background will be { $X_1, \ldots, X_t$ }. At this point, the probability function is expressed as shown in Eq. (1).

$$P(X_t) = \sum_{i=1}^{k} w_{i,t} \eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \qquad (1)$$

$w_{i,t}$, $\mu_{i,t}$ and $\Sigma_{i,t}$ represent the weighted value, mean value and covariance matrix of i th Gaussian Model when the time is t hours and t hours, respectively.
η means probability density function and it can be expressed as shown in Eq. (2).

$$\eta(X_t, \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}} \left|\Sigma\right|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t-\mu_t)^T \Sigma^{-1} (X_t-\mu_t)} \qquad (2)$$

2.2 Pyramidal Lucas Kanade Method

It is the method to measure the movement of an object at two continuous frames of video; thus, the algorithm to calculate optical flow as shown in Fig. 1 is mainly utilized.

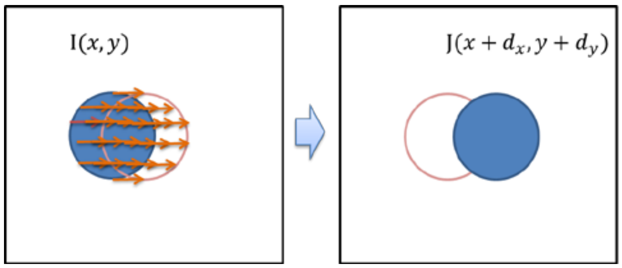


Fig.1 Illustration of optical flow.

The goal is to find the movement d_x and d_y that minimizes residual function ε at the two contiguous images I(x, y) and J(x, y) as shown in Eq. (3). However, it is influenced by accuracy and robustness depending on w_x and w_y, size of window for feature tracking.

$$\varepsilon(d_x, d_y) = \sum_{x=u_x-w_x}^{u_x+w_x} \sum_{y=u_y-w_y}^{u_y+w_y} (I(x,y) - J(x+d_x, y+d_y))^2 \quad (3)$$

There is therefore a natural tradeoff between local accuracy and robustness when choosing the integration window size. An iterative implementation of the Lucas-Kanade optical flow computation provides sufficient local tracking accuracy[5].

3. Proposed Algorithm

As shown in Fig. 2, the proposed algorithm can be divided into Preprocessing, Gaussian Mixture Background Modeling, Foreground Histogram Analysis, Pyramidal Lucas Kanade Method and Decision Making Process. Vehicle detection and counting at the selected ROI can be formed by a relatively simple algorithm. Since it is linked with a separate tracking algorithm or radar vehicle detection data at decision making process, it is possible to realize a better performance.

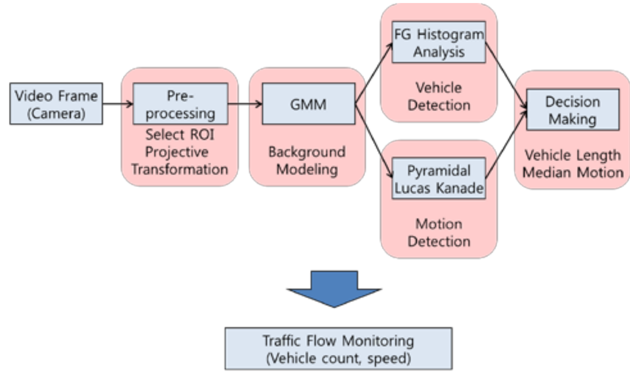


Fig. 2 Automatic vehicle detection and counting algorithm.

3.1 Preprocessing

In general, the road lane gets a certain angle with x and y coordinate axes depending on the angle of camera installation. Also, the distance ratio per pixel varies depending on the location. Thus, it will be convenient to measure velocity if converting y-axis into the distance coordination system to display distance up to a vehicle by using ROI 4 coordinates that were selected by a user. Moreover, it will be possible to coordinate with the radar detection data.

$$w\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (4)$$

Eq. (4) represents homography matrix coordinates conversion.

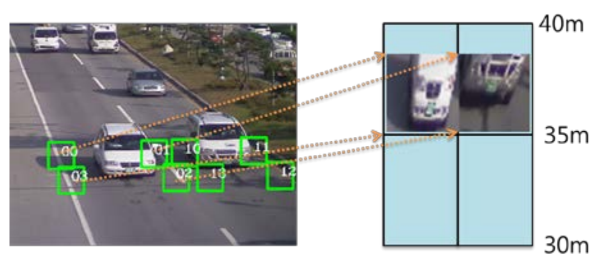


Fig. 3 Perspective projective transformation of ROI.

The performance of video-based vehicle detection system is measured by comparing with the loop detector using magnetic field under the road or the detector to investigate laser vertically. Fig. 3 is an example of converting distance coordinates as to 4 meter ROI section of double and four-lane road.

3.2 Foreground Histogram Analysis

When a foreground and background are separated, PDF taken by a foreground in y-axis direction will be a histogram. It is required to remove noise by using median filter or an operator of opening and closing for morphology.

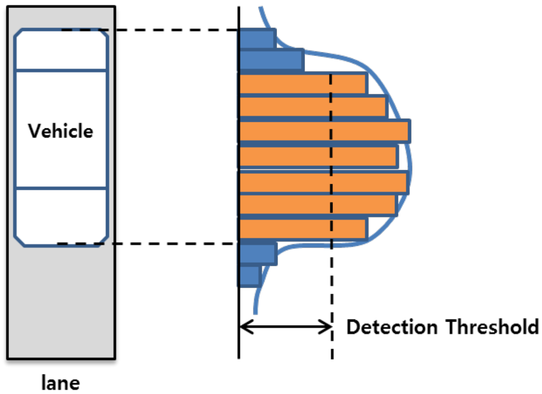


Fig. 4 Illustration of foreground histogram analysis.

Fig. 4 represents foreground histogram analysis as to a vehicle object. Generally, 0.5 is used as detection threshold. It is required to prevent duplicate detection by detecting the following vehicle after confirming a movement of 4 meter or over through motion detection if the front part of a vehicle is detected.

3.3 Decision Making Process

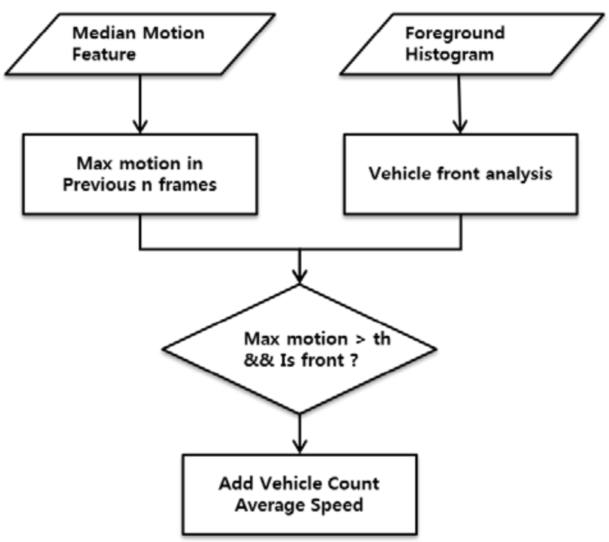
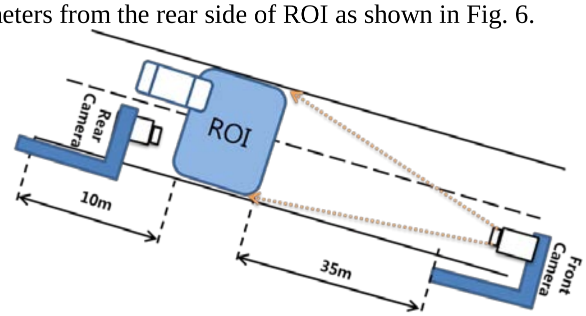


Fig. 5 Flowchart of decision making process.

It is required to obtain the median value of motion feature to be inputted by pyramidal lucas kanade method as shown in Fig. 5 in order to count the number of vehicles passing through. It is determined that there is a vehicle in motion when the largest value for median motion among the n previous frames is larger than the threshold value. It is required to calculate mean velocity of a vehicle by accumulating median motion values after counting the number of vehicles when the value of foreground histogram meets the condition of increasing beyond the detection threshold value.

4. Experimental Results

The dataset used in the experiment was obtained from the camera installed at the location 30 meters from the front side of ROI and the camera installed at the location 10 meters from the rear side of ROI as shown in Fig. 6.



(a)

(b) (c)

Fig. 6 Test Environment.

(a) Illustration of test bed, (b) Front view, (c) Rear view

Table 1: Vehicle Counting Result

Weather	*View point*	*Manual Counting*	*Our Algorithm*	*Accuracy*
Sunlight	Front	200	188	94%
Sunlight	Front	150	143	95.4%
Sunlight	Rear	52	51	98.1%

As a result of the experiment, it was possible to obtain accuracy of 94 percent, 95.4 percent and 98.1 percent even in the afternoon when we were under the influence of the shadow. It was confirmed that the accuracy was reduced at a crowding driving or low-speed driving. As the rear-side camera video with a high degree of incidence angle for a camera had relatively less occlusion, its accuracy was higher.

5. Conclusion

This study proposes an algorithm to detect and count vehicles passing a certain point for video-based monitoring of traffic flow. The unique feature of this algorithm is to use preprocessing video converted by distance coordinate system in consideration of radar sensor and data coordination. As a result of the experiment, it was possible to obtain a high level of accuracy even with a light algorithm that did not have a separate learning process of recognizing an object. The next study objective is to obtain a high level of accuracy even in bad weather through adding radar detection data and coordination algorithm.

Acknowledgments

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