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Development of a Real-Time Video Image Tracking Algorithm for Incident Detection

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요 약

현재 비디오 영상처리시스템(VIPS: Video Image Processing System)은 실시간으로 들어오는 영상정보를 분석하여 유용한 정보를 제공하고, 하나의 카메라로 여러 차로를 동시에 감시할 수 있는 알고리즘으로 교통량, 속도뿐만 아니라 밀도 및 점유율 등 다양한 정보를 제공하나, 안전지대에서는 효과적이지 못한다. 그러나, 영상검지시스템에서 개별차량에 대한 추적시스템으로 개발할 경우 사고 및 차로 변경의 위험요소 감지 등 실시간으로 보다 다양한 정보를 제공할 수가 있다.

본 논문은 컴퓨터비전 기술을 이용하여 개별차량의 추적시스템을 개발하였으며, 이 시스템을 실제 도로영상에 적용하여 Tripwire에서 수집할 수 있는 교통정보뿐만 아니라 사고, 상충정보 등 다양한 정보를 제공한다. 본 연구의 검증을 위하여 개별차량 추적시스템으로 1) 돌방상황 감지 2) 급차로 변경과 같은 비정상적인 차량흐름의 경우를 감지하는 실험을 수행하였다.

Abstract

The current VIPS are not effective in safety point of view, because they are originally developed for mimicking loop detectors. Therefore, it is important to identify vehicle trajectories in real time, because recognizing vehicle movements over a detection zone enables to identify which situations are hazardous, and what causes them to be hazardous. In order to improve limited safety functions of the current VIPS, this research has developed a computer vision system of monitoring individual vehicle trajectories based on image processing, and offer the detailed information, for example, incident detection and conflict as well as traffic information via tracking image detectors. This system is capable of recognizing individual vehicle maneuvers and increasing the effectiveness of various traffic situations. Experiments were conducted for measuring the cases of incident detection and abnormal vehicle trajectory with rapid lane change.

Key words: Video image processing system, individual vehicle tracking, incident detection, conflict information

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Ⅰ. Introduction

The current traffic management systems require real time information, and newly developed ITS technologies providing more detailed traffic information are becoming more effective. As a result, the increasing needs for better vehicle detection rely on traffic surveillance such as wide-area detectors. One promising approach among the wide-area detectors is vehicle tracking via video image processing (VIPS), which can yield traditional traffic parameters such as flow and velocity.

Image detector systems are divided into two categories, one is tripwire system to get the spot information at a single point, and the other is tracking system [1]. Spatial traffic information such as the vehicle tracks or trajectories can be more useful than tripwire information at a single point, because it is possible to measure true density instead of simply recording detector occupancy. In fact, by averaging trajectories over space and time, the traditional traffic parameters are more stable than corresponding measurements from point detectors, which can only be averaged over time. Additional information from the vehicle trajectories could lead to improved incident detection, both by detecting stopped vehicles within the camera's field of view and by identifying lane change maneuvers and acceleration/deceleration patterns that are indicative of incidents beyond the camera's field of view [2].

However, the current VIPS are not effective in safety point of view, because they are originally developed for mimicking loop detectors. Also, the commercial VIPS have limit to incident detection due to the fact of measuring only spot information.

According to the Road Accident Statistics of 2007, there were 213,745 police-reported traffic crashes in Korea in 2006. It is therefore imperative that researchers in the field of transportation make enormous efforts to significantly enhanced road traffic safety. In order to make effective strategies for comprehensive traffic safety measurement, it is important to identify vehicle trajectories in real time, because recognizing vehicle movements over a detection zone enables to identify which situations are hazardous and what causes them to be hazardous.

In order to improve limited safety functions of the current VIPS, we have developed a computer vision system of monitoring individual vehicle trajectories based on image processing and offering the detailed information, for example, incident detection and conflict as well as traffic information via tracking image detectors. This system is capable of recognizing individual vehicle maneuvers and increasing the effectiveness of various traffic situations.

Experiments have been conducted for the measuring these cases as follows:

1) Detection of stopped vehicles on the road
2) Detection of backward-moving vehicles
3) Detection of abnormal vehicle trajectory with rapid lane change

Experiments were conducted on image data captured with video camera installed on a downtown street in Wonju city, South Korea.

Ⅱ. Prior Researches and State of the Practices

The vehicle detection technologies can be classified to three methods; background subtraction, temporal differencing, and optical flow. The background subtraction is calculated the difference between the current image and the reference background image in pixel by pixel fashion. However, this approach has a problem which is very sensitive to the background changes, according to time changes of day, weather, and seasons. To solve this problem, the effective algorithm have been proposed using background prediction and weight learning method such as wallflower [3], Gaussian Mixture Learning [4], and Kalman Filter technique [2]. In temporal differencing, moving objects changes intensity faster than static one, it uses consecutive frames to identify the difference, and it is adaptive dynamic scene changes. The optical flow is to identify characteristics of flow vectors of moving objects over time, and it is used to detect independently moving objects in presence of camera. Also, it has to require a specialized hardware to implement.

The previous image processing and object tracking techniques have been mostly applied to traffic video analysis to address queue detection, vehicle classification, and volume counting [5]. From the computer vision literature, the different tracking approaches for video data can be classified as 1) Model-based tracking, 2) Region-based tracking, 3) Active contour-based tracking, and 4) Feature-based tracking [2].

Model-based tracking [6] is highly accurate for a small number of vehicles. Also, this approach consists of the following main steps.

1. Motion segmentation: The first step is a motion segmentation, which segments moving objects from the stationary background. Koller et. al. apply a discrete feature-based approach to compute displacement vectors between consecutive frames. A cluster of coherently moving image features provides then the rough estimates for moving regions in the image.
2. Generic polyhedral vehicle model: This enables the instantiation of different vehicles such as cedan, hatchback, station wagon, bus, or van from the same generic vehicle model. The estimation of model shape parameters is possible by including them into the state estimation process as shown in Fig. 2.
3. Object recognition and alignment: Straight line edge segments extracted from the image are matched to 2D model edge segments - a view sketch - obtained by projecting a 3D polyhedral model of the vehicle into the image plane, using a hidden-line algorithm to determine their visibility.
4. Motion model: It is the dynamic vehicle motion in the absence of knowledge about the intention of the driver. In the stationary case, in which the steering angle remains constant, the result is a simple circular motion with constant magnitude of velocity and constant angular velocity around the normal of a plane on which the motion is assumed to take place. The unknown intention of the driver in maneuvering the car is captured by the introduction of process noise.

The most serious weakness of this approach, however, is the reliance on detailed geometric object models. It is unrealistic to expect to be able to have detailed models for all vehicles on the roadway.

In region-based tracking, the process is typically initialized by the background subtraction technique. In this approach, the VIPS identify a connected region in the image, a 'blob', associated with each vehicle and then tracks it over time using a cross-correlation measurement. A Kalman-filter based on adaptive background model allows the background estimation to evolve such as the weather and time of day affect lighting conditions. Foreground objects (vehicles) are detected by subtracting the incoming image from the current background estimation, looking for pixels where this difference image is above some threshold and then finding connected components [2]. However, this approach works fairly well in free-flowing traffic under congested traffic conditions, vehicle partially occlude one another instead of being spatially isolated, which makes the task of segmenting individual vehicles difficult. Such vehicles will become grouped together as one large blob in the foreground image.

Complementary to the region-based approach, active contour-based tracking is based on active contour models or snakes. The basic idea is to have a representation of the bounding contour of the object and keep updating it dynamically. The advantage of having a contour-based representation instead of a region-based one is reduced computational complexity. However, the inability to segment vehicles that are partially occluded remains. If a separate contour could be initialized for each vehicle, then each one could be tracked even in the presence of partial occlusion. [2, 7].

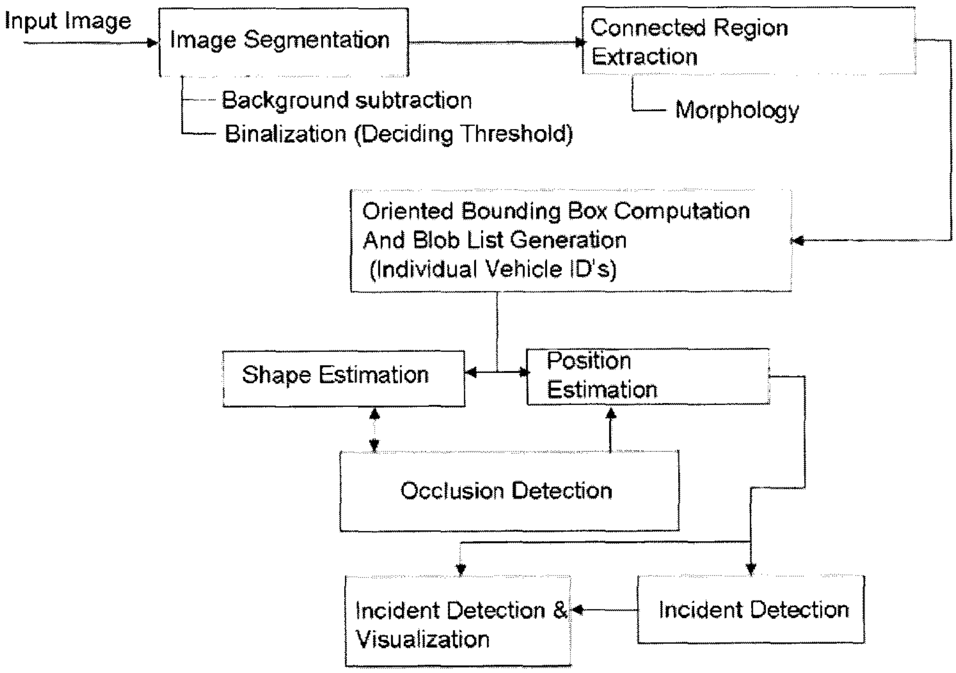
An alternative approach to tracking abandons the idea of tracking objects as a whole and instead tracks sub-features such as distinguishable points or lines on the object. The advantage of the feature-based tracking approach is that even in the presence of partial occlusion, some of the features of the moving object remain visible. Furthermore, the same algorithm can be used for tracking in daylight, twilight or night-time conditions. It is self-regulating because it selects the most salient features under the given conditions, such as window corners, bumper edges during the day and tail lights at night [2].

Ⅲ. Methodology of Vehicle Tracking Algorithm

This chapter explains the basic idea of the tracking algorithm developed from this research.

For vehicle tracking, we used the region based tracking approach, which is utilized by most commercial VIPS. We have not just only performed individual vehicle tracking but measured safety information such as incident or conflict detection via tracking.

The tracking algorithm for moving object extraction and incident detection processing is implemented as shown in Fig. 1[8]. First, image segmentation is performed using background subtraction, and binalization through deciding threshold and then connecting in-



<Fig. 1> Tracking and incident detection approach, [8]

dividual vehicle region, i.e., moving object region (MOR) has been extracted using morphology after which the tracking algorithm is applied. Second, blob tracking is performed by finding association between the blobs in the current frame, *ith* frame and the previous frame, *(i-1)th* frame, based on the proximity of the blob, and gives the same vehicle ID's in the ith frame. The results from the tracking module are then passed onto the visualization module, where tracker results can be viewed graphically.

1. The procedures of tracking and incident detection

1) Acquisition of Image

In moving object extraction, the video background subtraction algorithm uses the vehicles that pass through the detection area. The background template in the detection area, $f(x, y, t_0)$ is saved beforehand and the current frames, $f(x, y, t_i)$ are taken, and the differences between the two images are calculated pixel by pixel. Fig. 2 shows a sample difference image between two images taken at times t_o and t_i.

2) Deciding the threshold

In an ideal case, a histogram with a colored or gray distribution has a deep and sharp valley between the two peaks that represent the objects and the background. For most real images, however, it is often difficult to precisely detect the bottom of the valley [9]. Therefore, the optimal threshold can be obtained by running the experiment several times.

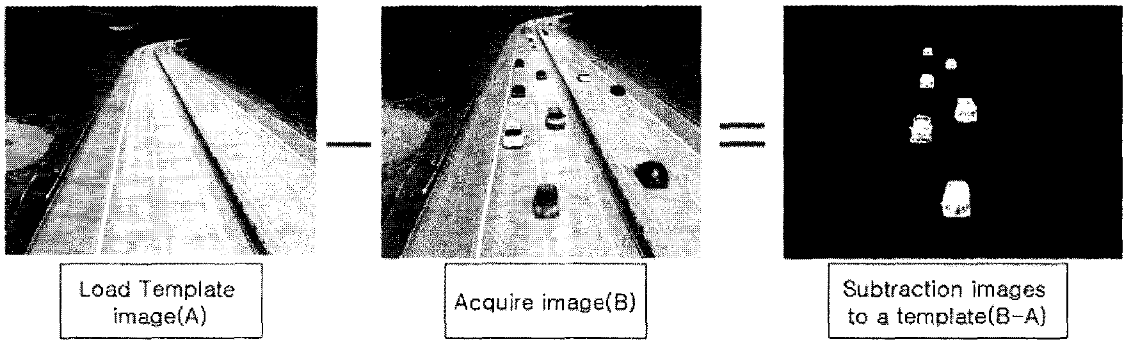
Another way of finding the optimal threshold using a theoretical approach is with the Otsu algorithm. This popular approach is based on the principle that the optimal threshold has been found as the point that maximizes the between-class variance (σ_B^2) and minimizes the within-class variance (σ_W^2) in the pixel distribution (See Eq. 1).

To find the optimal threshold K*, the discriminant criteria maximize λ which is given by

$$\lambda = \sigma_B^2 / \sigma_W^2$$
$$\sigma_B^2(k^*) = \max_{1 \le k \le L} \sigma_B^2(k) \tag{1}$$

where the pixel of given picture is represented in L gray levels [1, 2, ..., L].

The threshold in this research was chosen heuristically based on the experimental position, because the threshold exhibited a wide variance based on each position and time. Therefore, the optimal threshold can be obtained by running the experiment several times. In this experiment, the threshold was set at a gray level of 27.



<Fig. 2> Background subtraction for extracting individual vehicle from road

3) Morphology

The mathematical morphology is a tool for extracting image components that are useful in the representation and description of a region's shape such as boundaries, skeletons, and the convex hull [10]. As shown in Fig. 3, the morphology process in this research consists of three methods: closing using the dilation of a 3 X 3 block, filling of the hole with vehicles, and removal from this frame of very small objects that were considered noise. After the moving objects in this frame were extracted, the center coordinates of each object were obtained.

4) Generating Vehicle IDs

The vehicles in the frame, I_t were drawn within a bounded rectangle, and each of them was given a new ID, with their (x, y) and (top, bottom) coordinates saved in the reference table. In the next frame, I_{t+1}, the number of particles within the detection zone were counted. When the closest coordinate rectangle was compared with the rectangle coordinates in the prior frame I_t from the stored reference table, it was found to have the same vehicle ID as the rectangle in the prior frame. In other cases, a new vehicle ID was generated, either when a new vehicle entered the detection zone or when it is needed to separate the two vehicles bounded with one rectangle in the prior frame.

5) Incident Detection

Depending on the traffic accident recording and reporting system (ARRS) which is an image actuated moving picture recording and reporting system on the road, it extracts features for accident detection such as the acceleration, position, area(size), direction of the moving vehicles as followings [1].

(1) Acceleration and retardation

In general, a traffic accident causes rapid change to vehicle speeds. Hence, we used the variation rate of vehicle speed (acceleration and retardation) for accident detection.

(2) Variation rate of the position

When an accident has taken place somewhere on the road, an image that represents an object consists of positive valued pixels for long time against background of 0-value.

(3) Variation rate of the area

When the vehicle moves away from the camera, the size of the moving vehicle is decreased, and as it moves towards the camera, the size of the moving vehicle is increased, however its variation rate is small. On the other hand, the accidents cause rapid change to the size of moving vehicle.

(4) Variation rate of the direction

The mean optical flow obtained by averaging the normal optical flow of each pixel in the extracted part is represented by V_n, and the motion vector obtained by cross correlation is represented by V_i. The angle, θ formed between the two motion vectors can be expressed as

$$\cos\theta = \frac{V_n \cdot V_i}{|V_n||V_i|} \tag{2}$$

If $cos\theta$ is over the predetermined range, we can consider that an accident has been occurred.

6) Printing detection Results

The system has displayed the rectangle with each individual vehicle every frame in normal time, but an accident has taken place on the road, the system has drawn the bound at accident position, and displayed the warning message. Also the vehicle ID, accident time, coordinates are saved within database.

Ⅳ. Application of the Incident Detection Algorithm

The applications of incident detection algorithm conducted the detection of the three cases:

1) Detection of stopped vehicles on the road
2) Detection of backward-moving vehicles
3) Detection of abnormal vehicle trajectory with rapid lane change

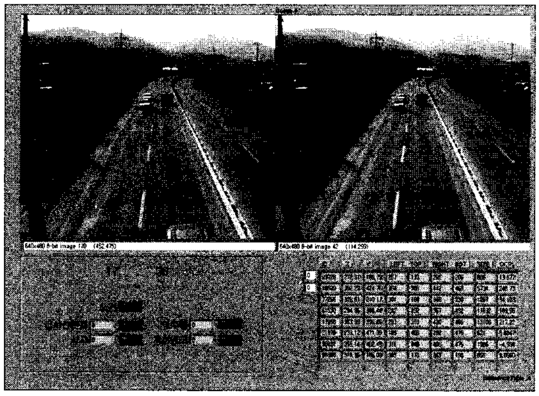
The experimental tests were conducted on a downtown street in Wonju city, the detection length is 80m for 37 minutes recording time. Since it is difficult to obtain incident images in real world, we made a few accident cases intentionally using four vehicles. The experiments were mainly conducted in order to examine whether our system could detect these cases or not.

Two methods were used for incident detection, "Variation rate of the position" and"Variation rate of the area". However, we did not use the "Acceleration and retardation", because the experiment site was not installed any other detectors for comparing with our test results.

The test scenario was made by occurring the three cases randomly and we measured incident detections. <Fig 3> shows image examples, which contains collisions with the median and stopping vehicles due to a disabled vehicle.

In order to detect backward moving data, the conflict scenarios were divided into two cases, which are shown in <Fig 4>, stopping vehicle detection on the shoulder, and backward moving vehicles detection. The stopping vehicle on the shoulder was detected by tracking the vehicle, stopping time is over the predetermined time, such as one or two minutes, and then gives the message "SHOULDER". If this vehicle was moving back, followings tracking with vehicle,

(a) Collision with the median



(b) Stopping vehicle due to a disabled vehicle

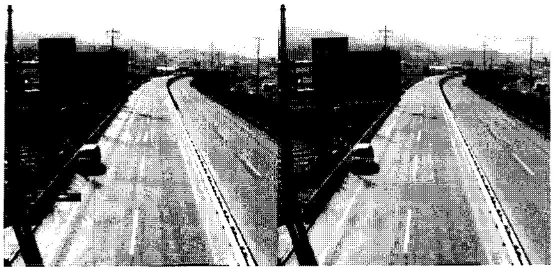
<Fig. 3> Two examples of collisions with the median and stopping vehicles due to a disabled vehicle.

the moving was in the opposite direction, also the message was given by "BACK MOVING"

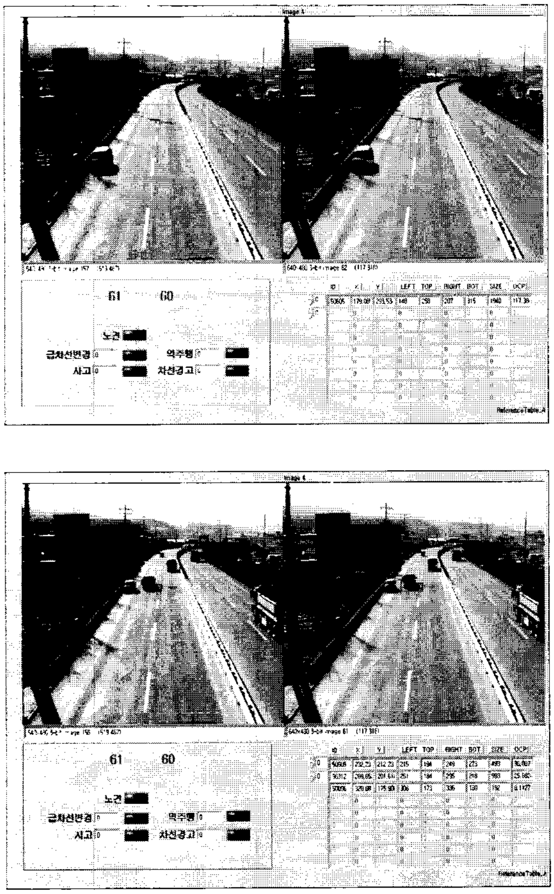
Finally, for detecting abnormal vehicle trajectories including rapid lane change, it has to be measured continuously, all frames of individual vehicle be checked and measured how many times the frame is omitted with the same vehicle ID. In average, the 90~150 frames are processed for vehicle passing through the 80m detection zone. <Fig 5> shows the test images for detecting abnormal vehicle trajectories.

Ⅴ. Test Results of the Incident Detection Algorithm

In the experiments, the dangerous cases of traffic flow, stopping vehicle on the shoulder, backward mov-



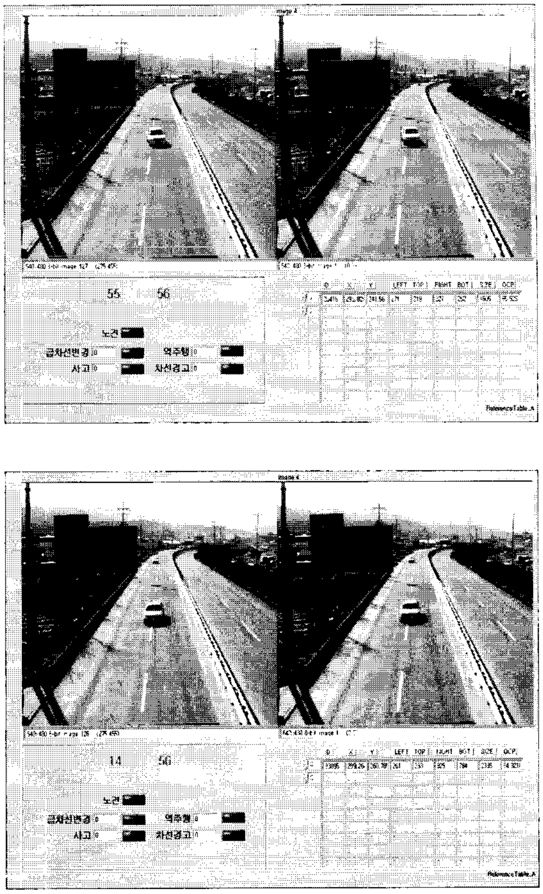
(a) Stopping vehicle on the shoulder



(b) Backward moving vehicles on the lane

<Fig. 4> Two examples of conflict, stopping vehicle on the shoulder, backward moving vehicles

ing vehicles, and collisions with the median, have been made by eleven cases randomly for 37 minutes. As a result, all cases are detected in our system as



<Fig. 5> Abnormal vehicle trajectory with rapid lane change cases

shown in <Table 1>. However, these are ideal cases unlike real world so that we had to conduct the field tests very safely to prevent any other possible accidents due to this test.

1. Detection results of stopped vehicles on the road

The test scenario was made by two cases: stopping vehicle on the shoulder and collision with the median, and we measured whether incident detection works properly. The test results showed that our system detected all cases of the incidents properly as shown in <Table 1>.

<Table 1> Incident detection results in case of stopping vehicle on the shoulder.

Event Cases	Event Time	Detection or NOT
stopping vehicle on the shoulder	From 01:09 To 01:22	Success
stopping vehicle on the shoulder	From 04:56 To 05:02	Success
collision with the median and stopping vehicles due to a disabled vehicle	From 12:10 To 14:40	Success
stopping vehicle on the shoulder	From 14:37 To 14:44	Success
stopping vehicle on the shoulder	From 15:49 To 15:54	Success
collision with the median and stopping vehicles due to a disabled vehicle	From 16:44 To 17:52	Success
stopping vehicle on the shoulder	From 21:34 To 21:41	Success
stopping vehicle on the shoulder	From 30:04 To 32:03	Success

<Table 2> Detection results for back-moving vehicles

Event Case	Event Time	Detection or NOT
backward moving vehicles	From 05:03 To 05:10	Success
backward moving vehicles	From 15:09 To 15:15	Success
backward moving vehicles	From 21:42 To 21:51	Success

2. Detection results of backward moving vehicles

The backward moving incidents occurred randomly and intentionally three times and we measured these cases. The test results show that our system performs well.

3. Detection results of abnormal vehicle trajectory with rapid lane change

Abnormal lane changes will be a high probability of accidents, and will be very difficult detection because they happen in a second. Especially, they cannot be detected via tripwire detectors. The most important thing of detection for abnormal lane change vehicles is detection of individual vehicle trajectory exactly, i.e. the individual reckless vehicle identity, referred to as ID, is equal to every frame within detection zone. However, there are lots of cases which has been taken place for missing tracking ID from some frames because of variable vehicles' passing. We have made five reckless driving cases and measured the tracking ID for each frame.

<Table 3> Detection rate of vehicle ID with abnormal lane changes and missing ID frames

Vehicle ID with Abnormal lane changes	Detection or NOT	Driving Time	Total frames	Missing ID frames
70161	Success	From 00:48 To 00:52	133 frames	Nothing
44230	Success	From 00:54 To 00:58	154 frames	Nothing
94690	Success	From 04:21 To 04:26	198 frames	Nothing
31121	Success	From 07:02 To 07:07	142 frames	Nothing
57892	Success	From 34:58 To 35:02	98 frames	Nothing

Five cases of abnormal driving patterns with rapid lane changing have been made and total 725 frames are shown in <Table 3>. The detection rate for total events is 100%.

Ⅵ. Conclusions

Most problems of tracking techniques arise due to vehicle occlusions and inaccuracies in separating individual vehicles. Although traffic information such as volume, speed, and occupancy rate can be obtained simply by these approaches, vehicle flow patterns cannot be estimated via tripwire video detectors.

The objective of this research was to relate traffic safety to VIPS tracking. The proposed tracking algorithm will lead to understand individual vehicle maneuvers and increase the effectiveness of incident detection for improved safety monitoring.

We have conducted the experiments of three cases which have been taken place in real traffic world frequently. Traffic volume, speed, occupancy rate, and stopping on shoulder can be measured via tripwire detector, but some of them such as back-moving vehicle or reckless driving trajectory cannot be detected. Therefore, detectors should detect the overall possible traffic cases in real world for safety. Analyzing traffic data from tracking system will improve safety monitoring by providing a warning message of dangerous driving patterns to drivers, automatic traffic monitoring, and incident detection in real time.

Our experiments were made artificially so that we had to conduct the field tests very safely to prevent any other possible accidents during this test. However, in future work, various analysis methods based on these data will be developed and applied to field tests. Furthermore, by gathering more various traffic cases, detection rate can be increased in overall cases. Eventually, it is expected that this system can be applied to the development of video image processing system which delivers both safety and operation oriented traffic information.

References

[1] S. J. You, *The Development of the Traffic Accident Automatic Detection Algorithm based on Image and Traffic Sound*, Ph. D. Dissertation, University of Seoul, July 2007.

[2] B. Coifman, D. Beymer, P. McLauchlan, and J. Malik, "A real-time computer vision system for

vehicle tracking and traffic surveillance," *Transportation Research Part* C, vol. 6, no. 4, pp. 271-288, Aug. 1998.

[3] K. Toyama, J. Krumm, B. Brumitt, and B. Meyer, "Wallflower: principles and practice of background maintenance," *Proc. Int. Conf. Computer Vision*, vol. 1, pp. 255-261, Sept. 1999.

[4] D. S. Lee, "Effective gaussian mixture learning for video background subtraction," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 27, no. 5, pp. 827-832, May 2005.

[5] S. C. Chen, M. L. Shyu, S. Peeta, and C. Zhang, "Learning-based spatio-temporal vehicle tracking and indexing for transportation multimedia database system," *IEEE Trans. Intelligent Transportation Systems*, vol. 4, no. 3, pp.154-167, Sept. 2003.

[6] D. Koller, K. Daniilidis, and H. Nagel, "Model-based object tracking in monocular image sequences of road traffic scenes," *Int. J. Computer Vision*, vol. 10, no. 3, pp. 257-281, Sept. 1993.

[7] D. Koller, J. Weber, T. Huang, J. Malik, G. Ogasawara, B. Rao, and S, Russell, "Towards robust automatic traffic scene analysis in real-time," *Proc. Int. Conf. Pattern Recognition*, vol. 1, pp. 126-131, Oct. 1994.

[8] H. Veeraraghavan, O. Masoud, and P. Nikolaos, "Computer vision algorithms for intersection monitoring," *IEEE Trans. Intelligent Transportation Systems*, vol. 4, no. 2, pp. 78-79, June 2003.

[9] N. Otsu, "A threshold selection method from gray level histogram," *IEEE Trans. Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62-66, Jan. 1979.

[10] R. C. Gonzalez and R. E. Wood, *Digital Image Processing*, Addison Wesley, 1992.

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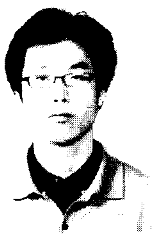

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