실시간 영상처리를 이용한 개별차량 추적시스템 개발

Development of a Real Time Video Image Processing System for Vehicle Tracking

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Abstract

Video image processing systems (VIPS) offer numerous benefits to transportation models and applications, due to their ability to monitor traffic in real time. VIPS based on wide-area detection, i.e., multi-lane surveillance algorithm provide traffic parameters with single camera such as flow and velocity, as well as occupancy and density. However, most current commercial VIPS utilize a tripwire detection algorithm that examines image intensity changes in the detection regions to indicate vehicle presence and passage, i.e., they do not identify individual vehicles as unique targets. If VIPS are developed to track individual vehicles and thus trace vehicle trajectories, many existing transportation models will benefit from more detailed information of individual vehicles. Furthermore, additional information obtained from the vehicle trajectories will improve incident detection by identifying lane change maneuvers and acceleration/deceleration patterns. The objective of this research was to relate traffic safety to VIPS tracking and this paper has developed a computer vision system of monitoring individual vehicle trajectories based on image processing, and offer the detailed information, for example, volumes, speed, and occupancy rate as well as traffic information via tripwire image detectors. Also the developed system has been verified by comparing with commercial VIP detectors

Keywords : VIP, vehicle tracking, ITS, traffic information

요 지

영상처리시스템(VIPS: Video Image Processing System)은 실시간으로 들어오는 영상정보를 분석하여 유용한 정보를 제공하며, 하나의 카메라로 여러 차로를 동시에 감시할 수 있는 알고리즘으로 교통량, 속도뿐만 아니라 밀도 및 점유율 등 다양한 정보를 제공한다. 영상검지시스템으로 상용화 제품은 Tripwire시스템으로 검지영역의 픽셀 변화량으로 차량검지를 하나, 이는 교통량, 속도 등 단편적인 정보에 국한될 수 밖에 없다. 반면, 영상검지시스템이 개별차량에 대한 추적시스템으로 개발할 경우 사고 및 차로 변경의 위험요소 감지 등 보다 다양한 정보를 제공할 수가 있다. 본 논문은 컴퓨터비전 기술을 이용하여 Tripwire에서 수집할 수 있는 교통정보와 동일한 정보를 제공하는 개별차량의 추적시스템을 개발하였으며, 이 시스템을 실제 도로영상에 적용하여 상용화된 시스템과 결과를 비교함으로써 성능검증을 하였다.

핵심용어: 영상검지기, 차량추적, ITS, 교통정보

1. INTRODUCTION

ITS technology includes advanced traffic management systems, advanced traveler information systems, advanced public transportation systems, and advanced sensor systems for on-line surveillance, such as traffic video analysis (Chen et al., 2003).

In video surveillance very popular technology of ITS,

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the detection and tracking of moving objects are the important tasks of the computer vision, and the video surveillance system is not only need to track the moving objects but also interpret their patterns of behaviors. The advantages of video surveillance are minimizes the user interaction, less amount of prohibitive bandwidth, and minimizes the cost and time (Simeon Indupalli)

Recently, closed circuit television (CCTV), video image processing systems (VIPS) and probe cars have been used for traffic monitoring and traffic data collection. Especially, wide area CCTV surveillance systems have been extensively deployed to monitor freeways in urban areas. However, while CCTVs have proven to be very effective in monitoring traffic flows and supporting incident management, they simply provide images that must be interpreted by trained operators (Namkoong et al., 2004). The present system is difficult to maintain heavy amount of raw video data, also require higher bandwidth for transmitting the visual data (Simeon Indupalli)

The quest for better traffic information, and the consequent increasing reliance on traffic surveillance, has increased the need for better vehicle detection such as wide-area detectors. Meanwhile, the high costs and safety risks associated with lane closures have directed the search towards non-invasive detectors mounted beyond the edge of the pavement. One promising approach is vehicle tracking via video image processing, 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 (Young C. Kim, 2007). 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 (Coifman et al., 1998).

However, recent evaluations of commercial image processing systems found some problems with congestion, occlusion, shadow, night time lighting, etc. The reliability for traffic surveillance under all conditions has led to research in more advanced image processing system. In this paper, we focus to develop a computer vision system of monitoring individual vehicle trajectories based on image processing, which provides the leading-edge technology in the image processing system. Firstly, we segment individual vehicles and secondly, offer with tracking system the detailed information, for example, volumes, speed, and occupancy rate as well as traffic information via tripwire image detectors. Experiments were conducted on image data captured with video camera installed on a downtown street in Wonju city in South Korea.

2. STATE OF THE PRACTICE

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 as (1)

$$D_t(X) = \begin{cases} 1 \; if \mid I_t(X) - I_B(X) \mid > threshold(\theta) \\ 0 \qquad\qquad otherwise \end{cases} \quad (1)$$

X is M*N pixel matrix.

where $I_t(X)$ denotes current image at time t
$I_B(X)$ is background Image

However, this approach has a problem very sensitive to the background changes, according as time changes of day, weather, and seasons. To solve this problem, effective background maintenance algorithm have been proposed the background prediction and weight learning method such as wallflower (Kentaro Toyama, 1999), Gaussian Mixture Learning (Dar-Shyang Lee, 2005), and Kalman Filter technique (B. Coifman, 1998).

In temporal differencing, moving objects changes intensity faster than static one, it uses consecutive frames to identify the difference, as (2), and is adaptive dynamic scene changes.

$$D_t(X) = \begin{cases} 1 \; if \mid I_t(X) - I_{t-1}(X) \mid > threshold(\theta) \\ 0 \qquad\qquad otherwise \end{cases} \quad (2)$$

where $I_{t-1}(X)$ denotes previous image at time t−1
$I_t(X)$ is current image at time t

Improved version uses three frames difference instead of two.

The Optical flow is to identify characteristics of flow vectors of moving objects over time, it 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 (Chen et al., 2003). 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 (Coifman et al., 1998).

Model-based tracking (Koller et al., 1993) is highly accurate for a small number of vehicles. And this approach consists of the following main steps.
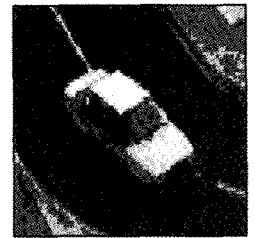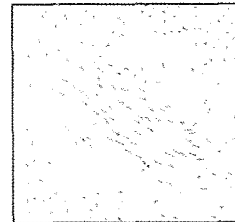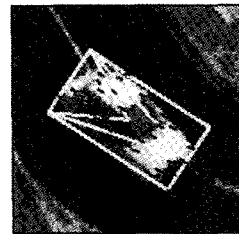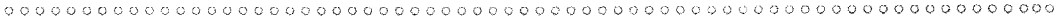
2.1 Motion segmentation:

Image section ↓

displacement vectors ↓

vector cluster

Figure 1. One step of Model-based tracking, 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.

2.2 Generic polyhedral vehicle model:

Koller et. al. use a 3D generic vehicle model parameterized by 12 length parameters. This enables the instantiation of different vehicles, for example 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 (see Figure 2).
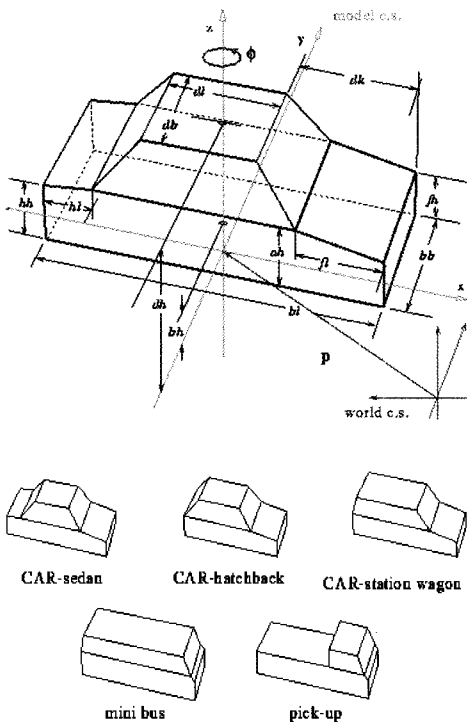

CAR-sedan   CAR-hatchback   CAR-station wagon

mini bus   pick-up

Figure 2. The next step, 3D generic vehicle model parameterized by 12 length parameters

2.3 Object recognition and alignment:

Straight line edge segments extracted from the image are matched to the 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. The matching of image edge segments and model segments is based on the Mahalanobis distance of line segment attributes. The midpoint representation of line segments is suitable for using different uncertainties parallel and perpendicular to the line segments, which emerge in the edge detection process.
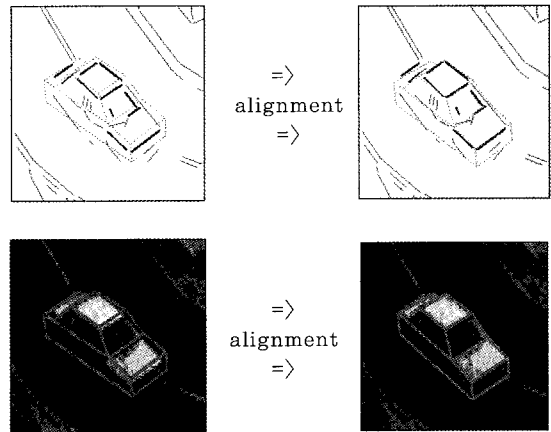

Figure 3. The third step, Object recognition and alignment

These figures shows the alignment results: the left column the initial model instantiation and the right column the optimal pose estimate. The Figure 3exhibits the image edge segments (red), the model instantiation (green dashed lines) and the matched image edge segments (thick pink lines).

2.4 Motion model:

Koller et. al. establish a motion model which describes 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 measure. A Kalman-filter based adaptive background model allows the background estimate to evolve as the weather and timeof day affect lighting conditions. Foreground objects (vehicles) are detected by subtracting the incoming image from the current background estimate, looking for pixels where this difference image is above some threshold and then finding connected components.

This approach works fairly well in free-flowing traffic, however, 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. Figure 4, illustrates this phenomena on a hypothetical one dimensional roadway (i.e., no width) viewed from camera's perspective (B. Coifman, 1998).

Complementary to the region-based approach, active contour-based tracking is based on active contour models or snakes.
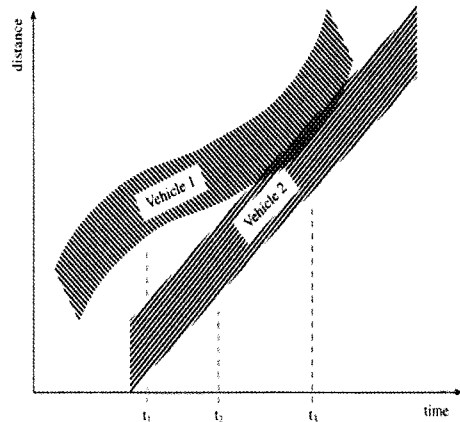

Figure 4. An example of region based tracking. By time t_3, vehicle 2 has partially occluded vehicle 1, resulting in potential segmentation problems (B. Coifman, 1998).

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 (Koller et al., 1994a B. Coifman, 1998).

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 (B. Coifman, 1998).
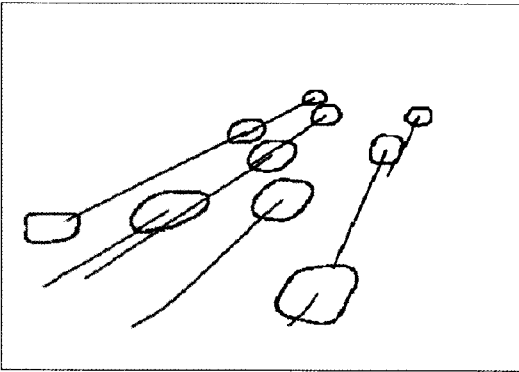
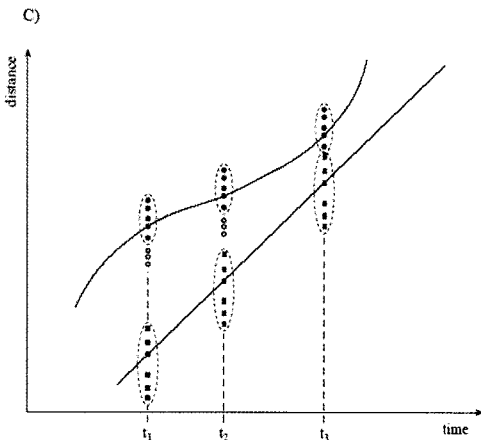Figure 5. An example of Contour based Tracking (S. Indupalli)

c)

Figure 6. Features are grouped together based on common motion, avoiding segmentation problems due to occlusion. Because the features move together, one feature track is selected as being representative of the vehicle trajectory (B. Coifman, 1998).

3. METHODOLOGY OF VEHICLE TRACKING ALGORITHM

This chapter explains the basic idea of the tracking algorithm developed from this research. For vehicle tracking, we have been based on the region based tracking approach, which is utilized by most commercial VIP systems, for the reason that we have not just only performed individual vehicle tracking but measured traffic information such as volume, speed, occupancy time, as well as incident or conflict detection via tracking. Image processing time is critical in the VIP systems, while feature based tracking, mainly extracting color distribution, have taken longer processing time than region based.

The tracking for moving object extraction is implemented as following shown in Figure 7. The moving objects have to be extracted exactly using image processing, background subtraction, threshold and morphology, after which the tracking algorithm is applied. The moving objects have to be extracted exactly using image processing, background subtraction, threshold and morphology, after which the tracking algorithm is applied.

Firstly, in moving object extraction the vehicles passing through the detection area are used by video background subtraction algorithm, the background template, $f(x,y,t_0)$ in the detection area is saved beforehand and the current frames $f(x,y,t_i)$ are taken, and the differences of the two images are calculated pixel by pixel. A difference image between two images taken at time t_0 and t_i, an example is presented in Figure 8.

Secondly, the threshold for binarization is defined (prior referred to Eq. (1)). In an ideal case, the histogram with a color or gray distribution has a deep and sharp valley between two peaks representing the objects and background. However, for most real images it is often difficult to detect the valley bottom precisely (Otsu, 1979).
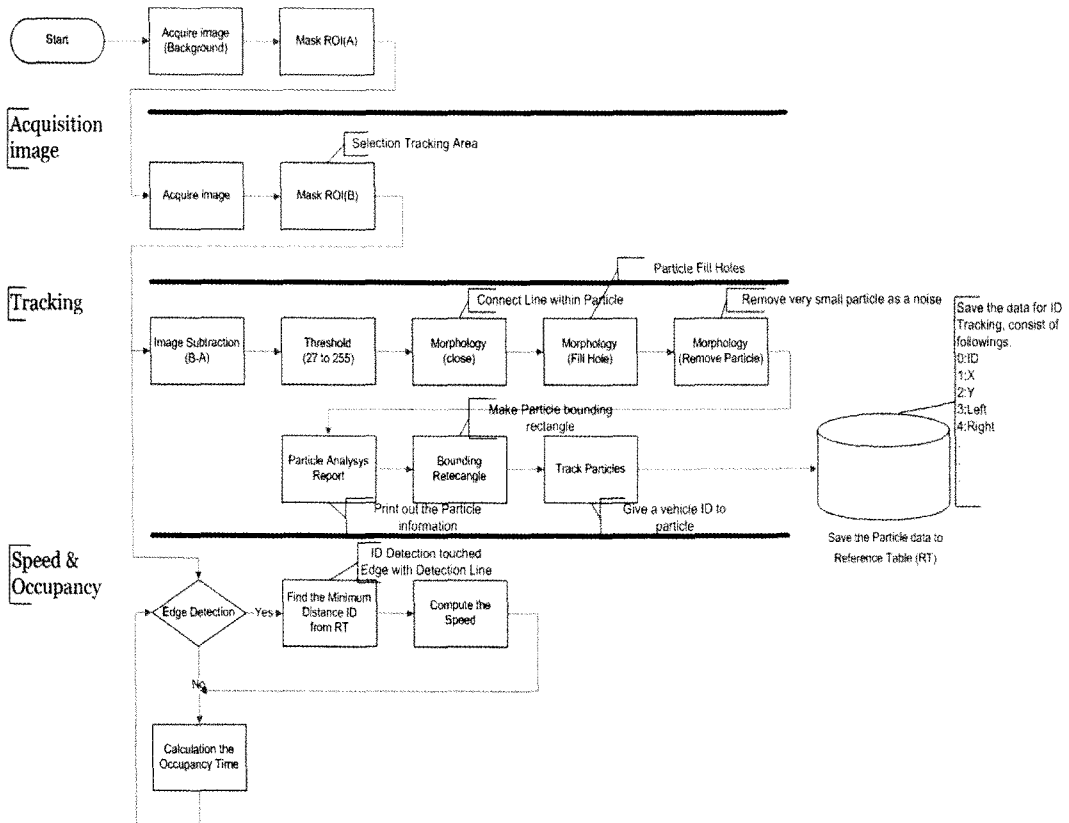
Acquisition image

Start → Acquire image (Background) → Mask ROI(A)

Selection Tracking Area

Acquire image → Mask ROI(B)

Tracking

Particle Fill Holes

Connect Line within Particle

Remove very small particle as a noise

Image Subtraction (B-A) → Threshold (27 to 255) → Morphology (close) → Morphology (Fill Hole) → Morphology (Remove Particle)

Save the data for ID Tracking, consist of followings:
0:ID
1:X
2:Y
3:Left
4:Right

Make Particle bounding rectangle

Particle Analysys Report → Bounding Retecangle → Track Particles

Print out the Particle information

Give a vehicle ID to particle

Save the Particle data to Reference Table (RT)

Speed & Occupancy

ID Detection touched Edge with Detection Line

Edge Detection → Yes → Find the Minimum Distance ID from RT → Compute the Speed

No → Calculation the Occupancy Time

Figure 7. The processing of tracking for moving object extraction

Load Template image(A) Acquire image(B) Subtraction images to a template(B-A)
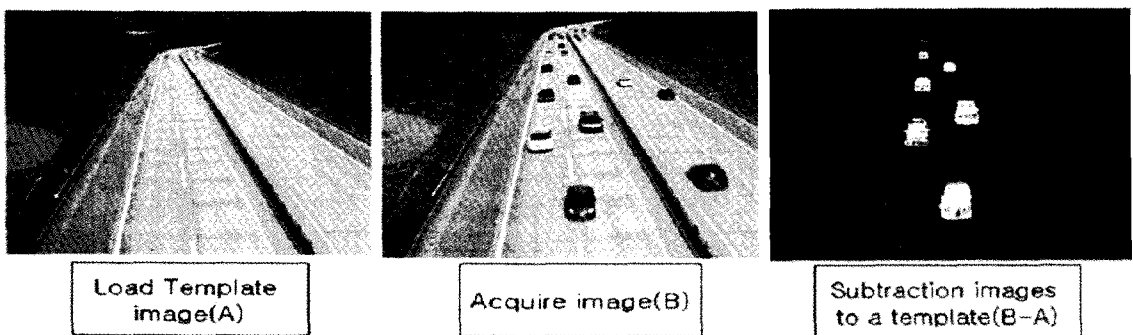
Figure 8. Background subtraction for extracting individual vehicle from road

We have chosen the threshold heuristically based on the experimental position, because the threshold exhibits wide variance depending on each position and time. Therefore, the optimal threshold can be obtained by running the experiments several times. In this experiment, the threshold was chosen at a gray level of 27.

Thirdly, mathematical morphology is a tool for extracting image components that are useful in the
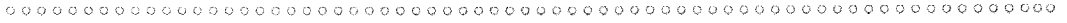
representation and description of a region's shape, such as boundaries, skeletons, and the convex hull (Gonzalez et al., 1992).

We use dilation which is one of the two basic operators in the area of mathematical morphology.

In basic Minkowisky set operations using morphology, given two sets A and B, the dilation operation is presented by Eq. 3.

$$D(A,B) = A \oplus B = \bigcup_{\beta \in B} (A + \beta)$$ (3)

where, β : structuring element that determines the precise effect of the dilation on the input image (R. Fisher, 2000).

As shown in Figure 9, the dilation morphology process in this research consists of three methods: closing by using dilation of a 3x3 structuring element, filling in the hole with vehicles, and removing very small objects from this frame when considered to be noise. After the moving objects in this frame are extracted, the center coordinates of each object can be obtained.
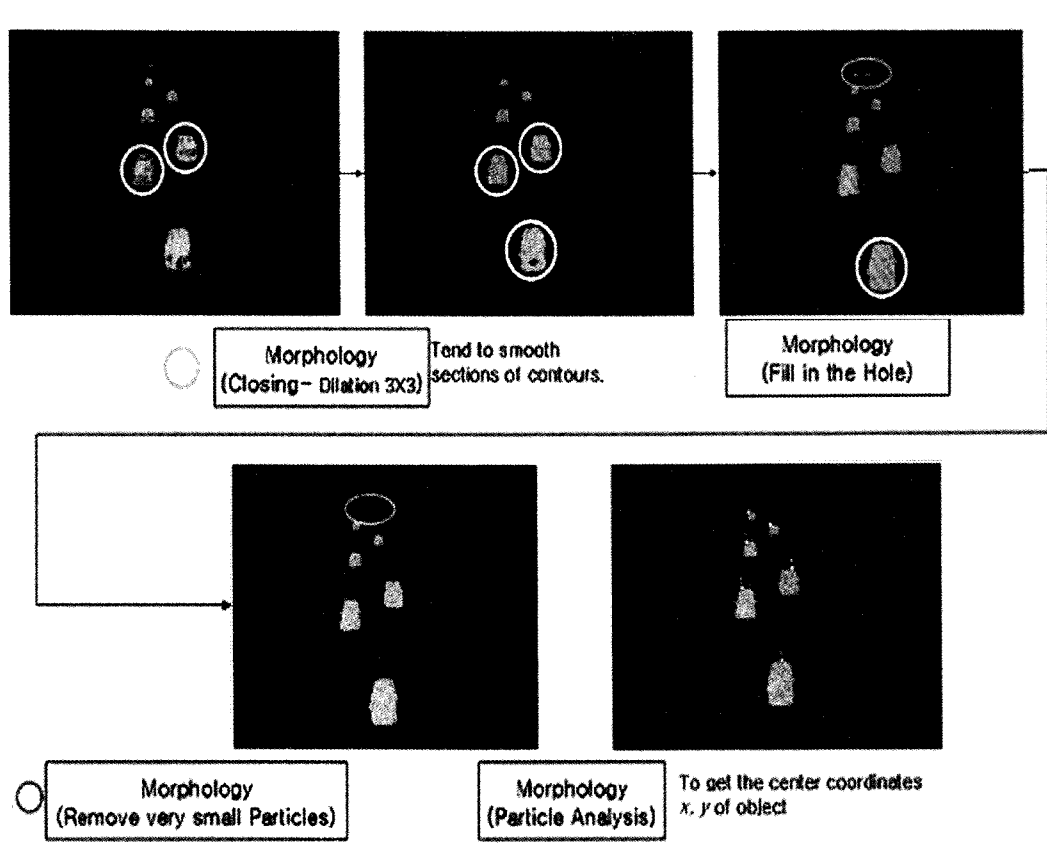

Figure 9. The dilation morphology processing for extracting moving objects, and removing very small particles as a noise.
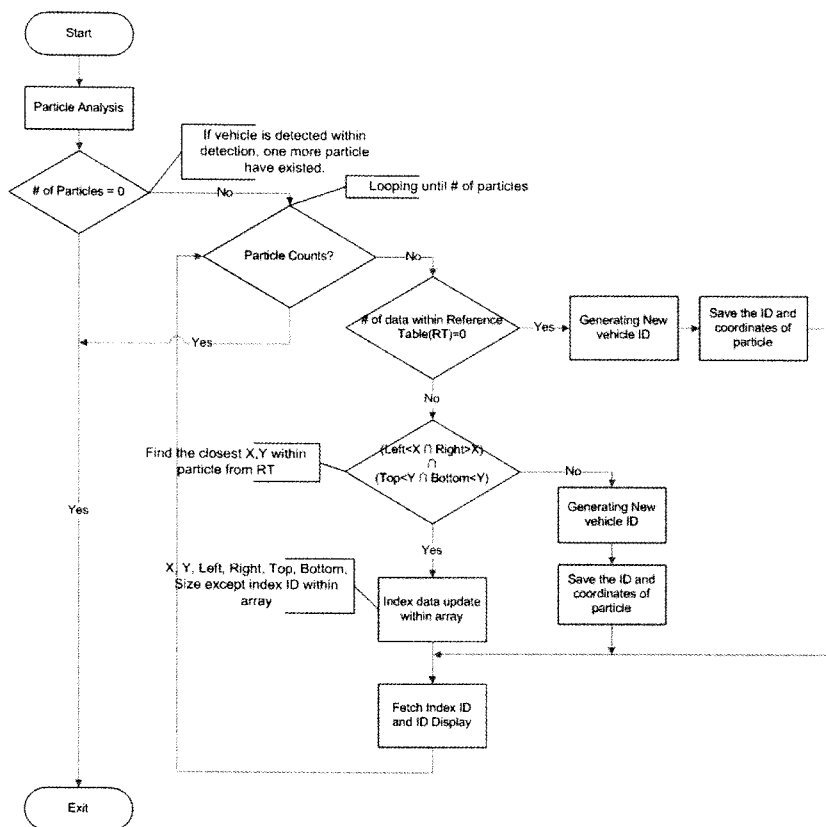
Track Particles

Figure 10. The procedure of generating vehicle ID of developed tracking system.

Finally, the particle as vehicles at the frame I_t has been drawn a bounded rectangle and giving a new ID for each vehicles, save the coordinates of (x,y), (top, bottom) to the reference table(RT). In the next frame I_{t+1}, count the number of particles within detection zone, if the closest coordinate rectangle was found comparing with rectangle coordinates in prior frame I_t from stored reference table, it has a same vehicle ID as rectangle in prior frame. Otherwise cases, generating a new vehicle ID, because new vehicle enter into detection zone or separating the two vehicles bound with one rectangle in prior frame. The procedure of generating vehicle IDs is illustrated in Figure 10.

4. DEVELOPMENT OF THE TRAC KING SYSTEM AND FIELD TEST

The tracking system was tested with three traffic criteria: volume, speed, and occupancy time. Because the objective of this research was to relate traffic safety to VIPS tracking, these data were used to other application of traffic basically such as conflict detection in real traffic world. The experiment was conducted on the two sites, one is at the Jungang highway near south Wonju and the other is at the downtown street in Wonju city, the tracking length of both is around 80m.

Table 1. Experimental results of comparing our system between commercial VIPS, with 281 passing vehicles

Time	Our System		commercial VIPS		Error
	Vol. Count	Speed (km/h)(A)	Vol. Count	Speed (km/h)(B)	|A-B|
9:31:25	1	94	1	96	2
9:31:35	2	107	2	111	4
9:31:42	3	105	3	103	2
9:31:43	4	96	4	107	11
9:31:45	5	107	5	107	0
9:31:49	6	121	6	123	2
9:31:52	7	112	7	114	2
9:31:52	8	121	8	115	6
9:32:09	9	110	9	112	2
9:32:22	10	118	10	120	2
−	−	−	−	−	−
9:42:00	−	−	133	20**	−
−	−	−	−	−	−
9:55:13	277	128	272	128	0
9:55:23	278	105	273	110	5
9:55:24	279	102	274	105	3
9:55:26	280	87	275	92	5
9:55:29	281	100	276	101	1
9:55:46	282	102	277	117	15
9:56:10	283	89	278	93	4
9:56:14	284	121	279	116	5
9:56:18	285	110	280	112	2
9:56:20	−	−	281	119	
Total	284*		281		
Average		111		113	

* 209th vehicle data has an error, thus total volume counts are 284.
** The commercial VIPS also has errors itself.

In test at the Jungang highway, as illustrated in Figure 11, the data have measured two items, volume count, speed, and comparing with commercial VIPS, total passing vehicles are 281 for 25 minutes. The results of the first tests are shown in Table 1 (J−T. Oh, 2007).

We have conducted the experiment only comparing with commercial VIPS, because the test site is not installed any other detectors such as loop detector.

The total volume count and average speed as shown in Table 1 are 284 vehicles, 111km/h of our system and 281 vehicles, 113km/h of commercial VIPS respectively. The real data of observed passing vehicles of detection area are 285, the errors are 1 and 4 vehicles, and there is no difference of speed with each other.

In the second experiment on the downtown street for 28 minutes, the detection zone has been drawn manually using the mouse and detection lines are segmented at each length, such as 10m, illustrated in Fig.11. In this test, three test items, the traffic volume, speed, and occupancy time are generated via vehicle passing on line segments. The experimental

results are shown in Table 2.

Volume count of our developed system has an error, two vehicles difference between observed real data, whereas data from commercial product are generated exactly. The differences of speed between two systems are 54.8km/h and 54.5km/h respectively, most differences are within 3km/h overall 156 passing vehicles. Also occupancy times are almost similar with each other. In conclusion, the traffic information on the two sites are not to difference via comparing our system with popular commercial VIPS.
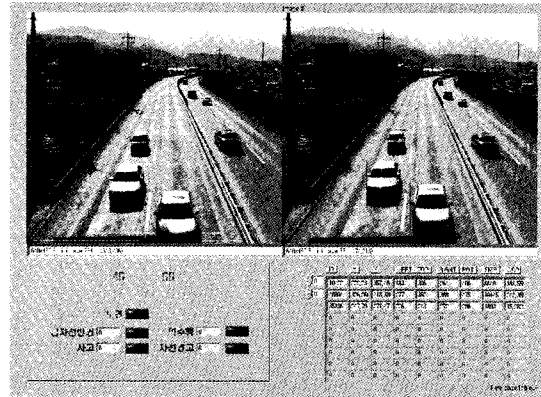

Figure 11. The second experiment on the downtown street in Wonju. detection lines are segmented at each length.

Table 2. Experimental Results of comparing our system between commercial VIPS with 156 passing vehicles

Time	Our System			commercial VIPS			Errors	
	Vol. Count	Speed (km/h)(A)	Occ. Time(B)	Vol. Count	Speed (km/h)(A')	Occ. Time(B')	|A−A'|	|B−B'|
12:44:48	1	54	0.59	1	53	0.50	1	0.09
12:45:00	2	72	0.47	2	67	0.43	5	0.04
12:45:05	3	61	0.64	3	63	0.50	2	0.14
12:45:06	4	76	0.36	4	75	0.47	1	0.11
12:45:18	5	62	0.73	5	61	0.69	1	0.04
12:45:20	6	35	0.62	6	34	0.50	1	0.12
12:45:57	7	57	0.56	7	55	0.57	2	0.01
12:46:03	8	49	0.82	8	47	0.75	2	0.06
12:46:15	9	47	0.70	9	44	0.60	3	0.10
12:46:21	10	59	0.55	10	59	0.43	0	0.12
—				—	—	—		—
—				121	63	0.90		—
—				—	—	—		—
13:11:34	145	67	0.47	147	63	0.50	4	0.03
13:11:47	146	49	0.80	148	49	0.60	0	0.20
13:11:58	147	67	0.59	149	70	0.50	3	0.09
13:12:00	148	67	0.47	150	67	0.40	0	0.07
13:12:00	149	55	0.51	151	56	0.43	1	0.08
13:12:03	150	49	0.64	152	51	0.50	2	0.14
13:12:04	151	56	0.77	153	55	1.04	1	0.27
13:12:06	152	67	0.42	154	65	0.40	2	0.02
13:12:17	153	59	0.67	155	55	0.67	4	0.00
13:12:18	154	61	0.62	156	59	0.54	2	0.08
Total	154*			156				
Average		54.8	0.69		54.5	0.65		

* The observed data of real passing vehicles are 156, two vehicles are omitted.
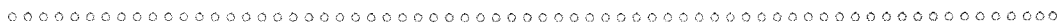
5. CONCLUSIONS

Most commercial VIPS utilize tripwire systems which get the spot information at a single point. However, the quest for better traffic information, and the consequent increasing reliance on traffic surveillance, has increased the need for better vehicle detection such as wide-area tracking. Traffic information from the vehicle 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. Besides, 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 or deceleration patterns.

In this research, we have conducted the experiments on the two sites, track vehicles using region-based tracking. To verify the test results, we also obtained the measuring items of traffic information such as volume, speed and occupancy rate for individual vehicle, and comparing with commercial product for every data, 285 vehicles on the highway and 156 vehicles on the other site.

In two cases in experiments, the newly developed system has a good performance comparing with commercial VIPS, with no differences for every measured category.

The characteristics of this research are deciding parameters basically such as, finding threshold for binirizarion, good criteria of noisy or object and morphology.

In future work, various applications based on these traffic data will be developed and applied to field tests. Furthermore, these applications have extended to conflict, incident detection using vehicle tracking, also gathering more various traffic cases, applied to overall cases as much as possible. Finally, this system will be developed of general purpose safety-oriented video image detectors.

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