A Scheme for Measuring Traffic Queue Length based on the Biorthogonal Wavelet Transform

Joon Young Min*, Jong Uk Choi**, In Jung Lee***, Hyoung Lee****, Hyun Sook Cho****

Regular Members

요 약

본 논문은 도심 교차로에 설치된 영상검지기로부터 들어온 교통정보 중 공간교통정보에 해당하는 차량 대기길이를 측정을 하는 방법으로 각 차선(lane)별 검지영역에 대하여 웨이블렛 변환(Wavelet Transform)을 하고 이중 고주파 계수를 대상으로 임계값 처리를 하여 차량을 검지하고, 검지영역 내에서 차량의 대기길이를 측정하는 알고리즘을 제안한다. 본 논문에서 이용한 필터로는 Cohen-Daubechies-Feauveau(3,3)로 각 영상별 차량 점유에 따른 복원영상을 F검증을 한 결과 CDF(3,3)필터와 다른 필터들 사이의 F분산률이 유의수준 이상 값이 나와 유효한 것으로 나왔다.

본 알고리즘은 기존의 윤곽선 추출(edge detection) 방법이나 배경영상의 차이에 의한 차량검지 방법 등 공간상에서의 차 영상에 의한 방법에 비하여 영상 노이즈에 크게 영향을 받지 않을 뿐만 아니라 시간대 변화에 따른 도로의 명암값(intensity or gray level)을 추정할 필요가 없다는 특징이 있다. 특히, 야간 영상인 경우 차량 헤드라이트로 인한 검지오류도 감소할 수가 있다.

본 논문에서 실험은 주간, 야간 각각 1개 차선의 80개 표본크기로 실험을 하였으며, 대기길이는 정지 대기길이(standing queue length)와 이동 대기길이(moving queue length)로 나누어 측정을 하였다. 그 결과 주간, 야간의 경우 정지 대기길이는 2.14%, 2.24%, 이동 대기길이는 2.59%, 2.74%의 오차율로 측정이 되었다.

ABSTRACT

In this paper, an algorithm is suggested in which vehicle detection in each lane is conducted using wavelet transform and then traffic queue length in detection area is measured. For vehicle detection, the image reconstructed by only detail coefficient is used, and to detect existence of the vehicle in detection area is interpreted by predetermined threshold. We use the Cohen-Daubechies-Feauveau(3,3) filter because the almost F value of the variance ratio of reconstruction image data between CDF(3,3) and the other filters is greater than significant level at occupancy case, and it is not at non-occupancy case.

Different from previous approaches such as edge detection method, background difference method, and spatial difference method, the algorithm is robust to noise and rapid changes in environment. For the reason, estimation of intensity of background image is not needed. In addition, the error rate caused by the headlight beam in nighttime can be drastically reduced.

In the experiments with 80 samples in standing queue in a single lane for daytime and nighttime, the error rate was 2.14% and 2.24%, respectively. For the moving queue the error rate for daytime and nighttime was 2.59% and 2.73%, respectively.

I. Introduction

Even though many a huge national projects have been initiated for building intelligent transportation system (ITS), little improvement has be

* 상지영서대학 전자계산과　　** 상명대학교 정보과학과
*** 호서대학교 컴퓨터공학과　　**** 대전대학교
논문번호 : 00253-0704, 접수일자 : 2000년 7월 4일

achieved in traffic data collection. Every country has common problems in building ITS. Still, many traffic control centers are suffering from lack of accurate traffic data, because of error-prone data collected by inductive loop detectors. One of substitutes for traditional detectors is image detector. The most important advantage of the image sensor is its comprehensiveness in collecting traffic data: simultaneously handling more than a single lane. The sensor can measure traffic volume, speed, and occupancy rate of multiple lanes. Additionally, the sensor can be employed for incident detection and monitoring lanes[1][2].

Measuring queue length at intersection is important for controlling traffic flow and signals. The realization of advanced traffic signal control will become possible by using image sensors which can measure upper traffic streams without time delay[1]. Queue length measuring mainly relies on the data whether a vehicle exists in a predefined cell in camera-captured images. In other words, the information on existence of vehicle in a specific cell is fed into the system to determine queue length with location data of the cell.

Traditionally, image sensors determine intensity, brightness or gray-level, of the background image as a presetting, mostly road image, and then recognizes existence of vehicles when the changes in the intensity value of the region is larger than pre-determined threshold value. Even though the method is simple to implement, it is very so sensitive to noise that accuracy level becomes low when unexpected changes occurs in weather or external environment. To remedy this problem, Gil, Malanese and Pun[3] suggested a Kalman filtering method in which the intensity of background image is estimated, when detection time shifts from daytime to nighttime. Even though this method showed better results than presetting method, it cannot maintain the accuracy level when environment is changing very rapidly, for example, cloudy sky approaches in daytime. Especially error rate is very high when headlight beam is very strong in night time..

In this research, vehicle detection is conducted for each lane using wavelet transform, and an algorithm is suggested for measuring traffic queue length. The family of wavelets has various types of filter, we use the biorthogonal Cohen-Daubechies-Feauveau(3.3) filter among from those filters.

This algorithm is robustness to rapid changes in environment and external noise, and thus needs not estimate intensity of the background image. Especially, as the algorithm is robust enough to accurately handle headlight beam in nighttime, error rate is drastically reduced in measuring queue length. Data was collected from CCD cameras installed on 11 meter-high pole, at inter-section in urban area. Images were captured at IV-450Pro grabber board, 320×240 pixels with 256 gray-level. Measuring standing queue length and moving queue length was conducted in daytime and nighttime.

Ⅱ. Previous Research on Vehicle Detection

1. Wide Area Detection System(WADS)

WADS project[4][5] was initiated for vehicle detection, vehicle velocity measurement and vehicle tracking. For vehicle detection in WADS project, a single horizontal line (perpendicular to the road) is used with 50 pixels per lane, for total of 3 lines. The data from five lanes, each 10 frames apart, are kept in buffer at any instant. 50 frames separate lines 1 and 6, i.e., almost 2 s which, under normal speeds of more than 20*km/h* and for vehicle lengths of 15m or less, means that lines 1 and 6 will not belong to the same vehicle, in case of vehicle detection. WADS was used by Eq. 1 for vehicle detection.

$$V_D = \sum_{i=1}^{50} \left| R_i^{'} - L_i \right| \tag{1}$$

where, $R_i^{'} = \omega R_i + (1-\omega) B_i$, $i=1,2,\cdots,50$

ω : weighting factor

In Eq. 1, R_i' is the estimated intensity of pixel i of line $1+j$, and L_i is the brightness of pixel i for incoming line $6+j$ where $j=0,1,2,3,4$. In other words, line 1 and 6, 2 and 7, 3 and 8, 4 and 9, 5 and 10 are compared, pixel by pixel, and the absolute values of the difference between corresponding pixel intensities are added. After this operation is completed, lines 6-10 replace lines 1-5 in the buffer and process is repeated using lines 6-10 and 11-15, etc. To compute R_i', R_i is the previous estimated intensity of same pixel, and B_i is the intensity of pixel i for line in the second set of the current two 5-line set comparison with minimum variation. The influence of the old estimate on the new one depends on the weighting factor ω, and the influence of the current line with V_{min} depends on $(1-\omega)$. ω should be adjusted dynamically to account for factors such as moving clouds.

If the average intensity of the detection line with no vehicle in it is known, the variation of incoming lines with respect to this "road line" can be computed and if it exceeds some preset threshold, a vehicle is detected.

$T=3V$ where, V is the variation corresponding to the B_i line($i=1,2,\cdots,50$), if $V_D > T$ during 5 lines with a maximum dropout of one line in between, a vehicle detected.

As result to test the reliability of this algorithm[3], vehicle detection produced an error of 4% during sunny weather and light traffic, and of 10% during moving clouds weather and light traffic. In summary, the WADS algorithms produce good results under good weather conditions, but were not evaluated under adverse weather conditions such as rain, fog or snow.

2. Takaba's Method

The system proposed by Takaba, university of Tokyo[4], shares with the WADS system the characteristic of only specific regions of the image for vehicle detection[4]. First a pattern of brightness for the sample points without traffic is obtained. The road surface can have, in general, an upper and lower intensity bound L_u and L_l, respectively. The intensity of the pixels comprising the nth sampling point is averaged and symbolized by $\mathbf{I}(n,t)$ where n is the nth sampling point and t is the tth frame. Takaba normalized the intensity to 8 levels and used only one average road intensity (L_i=L_l=3), the brightness vehicle being 7 and darkest object 0.

If

$$p(n,t)=\begin{cases}1, & \mathbf{I}(n,t)>L_u \quad or \quad \mathbf{I}(n,t)<L_l \\ 0, & L_\mu > \mathbf{I}(n,t) > L_l\end{cases}$$

then

$$\mathbf{P}(n,t)=\begin{cases}1, & P(n,t-1)=0 \ \ and \ \ p=1 \ \ for \ \ t-\Delta+1<\tau<t \\ 0, & P(n,t-1)=1 \ \ and \ \ p=0 \ \ for \ \ t-\Delta+1<\tau<t\end{cases}$$

For the second case **P** is kept at zero for values of time τ, $t<\tau<t+\Delta'-1$ and frame counts for p=1 are then stopped. In all other cases, **P** is unchanged. The purpose of requiring a number of consecutive counts of p=1 before setting **P**=1 is to filter noise. In tests Δ was set the values between 3 and 5. Its value in the tests was set to 20. $P(n,t)$ is the status index on the presence of vehicles, **P**=1 means detection; **P**=0 means no detection.

The test of this system was performed in downtown Tokyo and vehicles detected during traffic light cycles[4]. For total 317 detected vehicles by an operator, the system's detection error was less than 5% during 11 traffic light cycles with stable illumination conditions. In case of noticeable changes in illumination due to presence of clouds, the background intensity has to be estimated automatically. As result to experiment of this estimation algorithm, good results were obtained. But this method also cannot be applied to all case of foul weathers.

3. Silhouette Vision

This system is proposed by A. Saito et. al.[6], is a video vehicle detection system with side-silhouette imaging technology that utilizes two lenses and vehicle model-matching based on 3-D information. The flow of this algorithm is as followings.

(a) Stereo Image Input: It obtains two images from a pair of lens' (stereo-camera) at the same time.

(b) Feature Extraction: It extracts feature points from the one obtained image.

(c) Correspondence: It obtains each correspondent point by correlation in those two images.

(d) 3-D Calculation: It calculates those correspondent points' positions in 3-D coordinates from the camera parameters along with the installation parameters.

(e) Silhouette Extraction: It projects those correspondent points along the side direction, obtaining a side-silhouette.

(f) Model Matching: It detects a vehicle by using simple model matching between extracted side-silhouette and vehicle models.

(g) Vehicle Tracking: It tracks each vehicle every processing cycle.

As field test, this system is evaluated 97% or more vehicle detection accuracy under sunny and rainy day, but this system has too much cost because of using two cameras.

Ⅲ. An Algorithm for Vehicle Detection using Biorthogonal Wavelet Transforms

Wavelets can be classified into various type of families such as orthogonal wavelet, semiorthogonal wavelet and biorthogonal wavelet. In case of orthogonal wavelet, scaling function $\phi(t)$ and wavelet function $\varphi(t)$ are used, but on the other hand, in biorthogonal wavelet, dual function $\tilde{\phi}(t),\tilde{\varphi}(t)$ are used as well as scaling and wavelet function $\phi(t),\varphi(t)$. This construction usually has the advantage of computational speed compared to the orthogonal setting[10][11] and more flexible and generally easy to design.

In this research, the family of biorthogonal CDF(Cohen-Daubechies-Feauveau) Wavelet Filters are used, especially, for deciding whether the detection area is occupied by vehicle or not, CDF(3,3) filter is used[9].

This family of biorthogonal wavelets has some properties:

- The scaling function $\phi(t)$ is always symmetric.
- The wavelet function $\varphi(t)$ is always symmetric or antisymmetric.
- The wavelet filters are finite.
- The coefficients of the wavelet filters are of the form $\frac{z}{2^n}$, with z is integer and n is a natural number.

In this research, first, the captured image in each detection area is decomposed using biorthogonal CDF(3,3) filter and reconstructed by only detail coefficient(d_{HH}) is used to detect existence of the vehicle in detection area.

The reason of using CDF(3,3) filter is that the result of using CDF(3,3) is more efficient than the others such that CDF(1,3), CDF(2,4), CDF(4,4) and CDF(5,5). For showing this efficient, we analysis the variance ratio of detail coefficients of four filters, CDF(1,3), CDF(2,4), CDF(4,4) and CDF(5,5) by CDF(3,3) as using F test. Table 1 is illustrated the result of F value of 20 samples between CDF(3,3) and the other filters when the detection area is occupied by vehicle and is not occupied by vehicle.

As shown in Table 1, the almost F value of the variance ratio of reconstruction image data between CDF(3,3) and the other filters is greater than significant level at occupancy case, and it is not at non-occupancy case. This means that CDF(3,3) is more efficient at occupancy case.

Ⅳ. An Algorithm for Vehicle Detection in Intersection

In this research, detection area is installed in each lane and divided into N cells as shown in Fig. 1, wavelet transform is conducted in each cell.

Each cell is normalized by 18×12 pixels and in deciding whether the each detection area(called by cell) is occupied by vehicle or not, wavelet

Table 1. *F* Value for Variance Ratio of Reconstruction Image using CDF(· , ·) by using CDF(3,3)

Samples	Non-occ. Cdf13/33	Non-occ. Cdf24/33	Non-occ. Cdf44/33	Non-occ. Cdf55/33	Occ. Cdf13/33	Occ. Cdf24/33	Occ. Cdf44/33	Occ. Cdf55/33
1	*0.098	1.55	24.216	5.362	68.496	35.834	34.454	9.009
2	*20.462	*0.122	36.868	70.645	36.41	25.927	51.329	19.764
3	29.632	10.241	*0.181	50.608	49.251	45.35	10.933	2.291
4	231.988	4.71	8.092	43.591	156.938	1.985	4.203	*0.005
5	*0.26	*0.322	*0.38	89.822	127.786	19.288	0.719	4.302
6	33.218	10.011	4.546	30.078	105.298	14.753	3.946	*0.049
7	*0.341	37.55	7.394	42.009	125.142	6.597	19.203	13.285
8	3.184	*0.017	14.437	15.332	153.148	1.367	*0.0191	1.496
9	3.764	3.071	33.385	3.042	100.102	5.126	1.873	*0.005
10	4.425	*1.455	27.311	38.09	122.925	21.05	31.36	*0.075
11	1.65	4.332	14.294	5.419	130.602	36.103	2.909	40194
12	3.038	3.563	0.703	*0.43	103.355	23.224	33.778	1.928
13	*0.019	3.182	*0.0	4.922	56.241	30.653	5.432	9.332
14	38.455	*0.331	37.744	6.596	159.627	3.671	*0.0	58.218
15	10.111	32.18	2.139	6.506	135.307	*0.048	15.6	0.852
16	*0.339	*0.256	28.131	42.036	140.665	*0.185	31.3	1.588
17	4.72	219.78	3.459	17.56	104.059	50.602	*0.383	0.798
18	11.141	28.631	19.848	*0.234	144.158	31.417	21.147	70.542
19	*0.113	*0.451	50.658	107.587	134.109	5.802	2.716	6.043
20	1.51	*0.079	25.397	0.931	182.245	31.116	5.163	0.019*

In this table, * marked value is less than significant level, Non-occ is non-occupancy case and Occ is Occupancy case.

transform is used. For vehicle detection, the image reconstructed by only detail coefficient is used to detect existence of the vehicle in detection area. Fig. 2 shows the shape of when the cell is occupied by vehicle, and when the cell is not occupied by vehicle. As shown in Fig. 2 (a) and (c), if the cell is occupied by vehicle, the number pixels with high gray value are appeared more than non-occupancy of vehicle as shown in Fig. 2 (b) and (d). Thus, occupancy and non-occupancy of vehicle can be interpreted by number of high gray value pixels which are made by only detail coefficients of reconstructed image using wavelet transforms. In our experiment, when the number of pixels whose gray value exceeds 200 are larger than predetermined threshold(θ), it means occupancy of vehicle. Otherwise, it means non-occupancy of vehicle. As an experiment result, same results are shown on daytime and nighttime. In our experiment, threshold value is determined on 12.

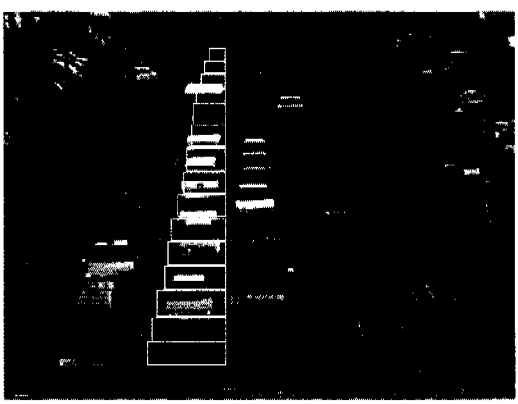
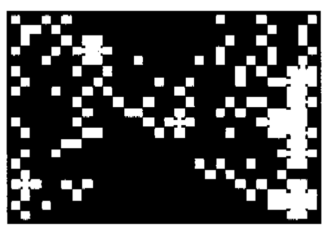
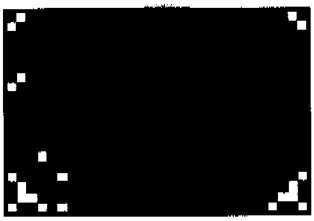


Fig. 1 Installation of detection area

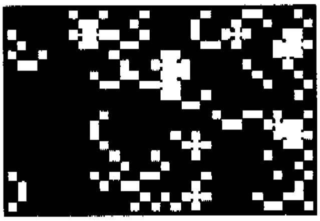
These steps are executed repeatedly in all detection area, if i^{th} cell is occupied by vehicle, D_i should be 1, otherwise should be 0 as shown Eq. 2.



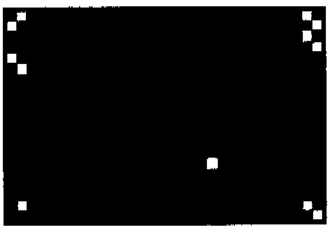
(a) occupancy case(daytime)



(b) non-occupancy case(daytime)



(c) occupancy case(nighttime)



(d) non-occupancy case(nighttime)

Fig. 2 Patterns of occupancy and non-occupancy case

$$D_i = \begin{cases} 1, & if \quad N_i \geq \theta, \ VehicleDetect \\ 0, & \quad otherwise \end{cases} \tag{2}$$

where, D_i : Detect the vehicle in i^{th} cell.
N_i : the number of pixels whose gray value exceeds 200 in i^{th} cell.
θ : threshold

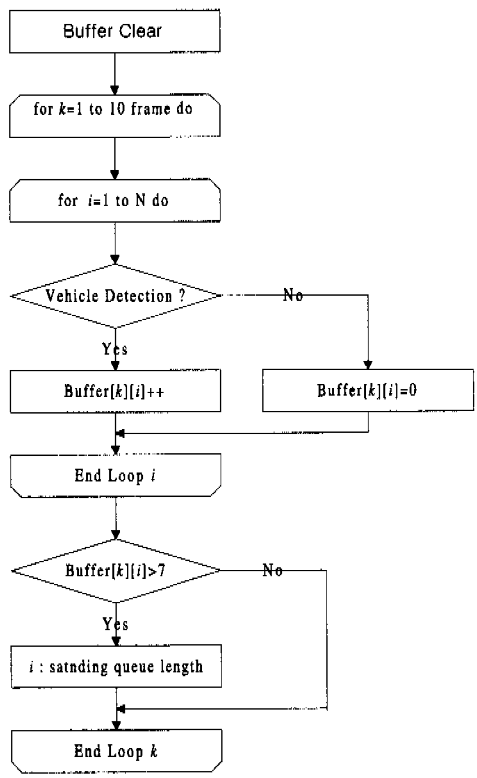
In this research, standing queue length as well as moving queue length is measured. Standing queue is defined as the maximum queue length in waiting line from red lights in traffic signals and moving queue is defined as the length of vehicles running in the intersection from green light is on.

For measuring standing queue length, all of 10 frames are scanned and detect the vehicle in N cells of each grabbed frame, if each cell is occupied by vehicles, buffer[i] should be 1, where, i is number of detection areas. To the contrary, when the detection area is not occupied by vehicles, the buffer[i] should be 0. This process is executed repeatedly next 10 frames. If vehicle detected images are over 7 frames, the detection area is occupied by vehicle and after verifying the all of cells, standing queue can be measured from first cell to last detected cell.

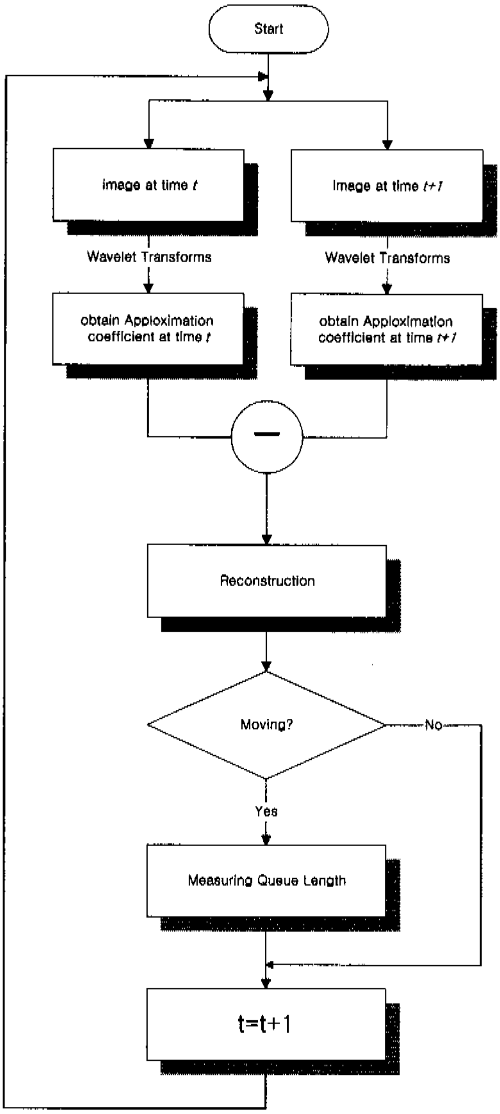
For measuring moving queue length, the difference image is calculated between time t image and $t+1$ image for detection areas using approximation coefficient of wavelet transform. After binarization to 0 and 255 gray level, if the number of detection areas whose gray level 255 is larger than predetermined threshold, it means moving of vehicles.

For the reason, difference images using wavelet transform are more robust to noise such as shadow than difference images which are obtained by spatial domain.

Fig. 3 shows the procedure of measuring standing and moving queue length.



(a) Standing Queue



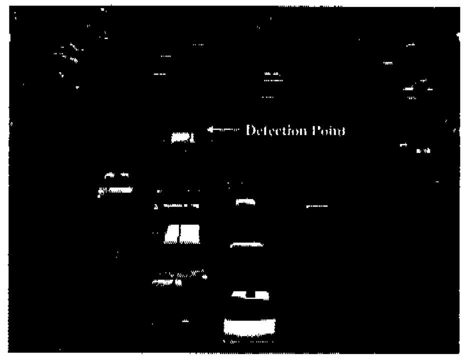
(b) Moving Queue

Fig. 3 Procedure of Measuring Standing and Moving Queue Length

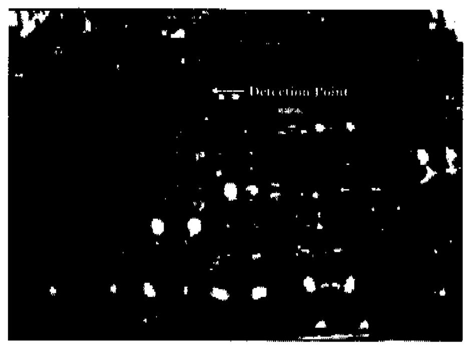
V. Experimental Results

For the research a CCD camera was installed on at the height of 11*m*. Then, images of 320×240 pixels, and 256 gray-levels were collected through grabber board. The target area was limited to a single lane and the number of detection areas was 15, and total is about 120*m* long. The experiments were conducted in daytime and nighttime. The process time of this algorithm is 5 frames per second.

Fig. 4 illustrated the experimental results of measuring standing queue length.



(a) daytime



(b) nighttime

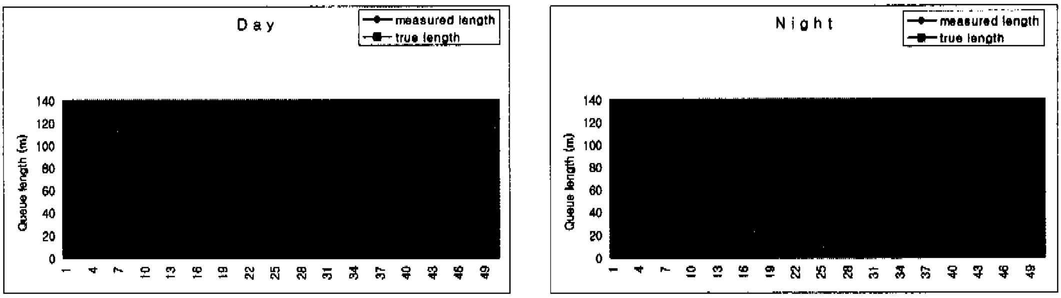
Fig. 4 Experimental Results of measuring queue length

Performance evaluation is conducted by comparing observed queue length with the queue length estimated by the proposed algorithm. Error rate is calculated as in the following Eq. 3:

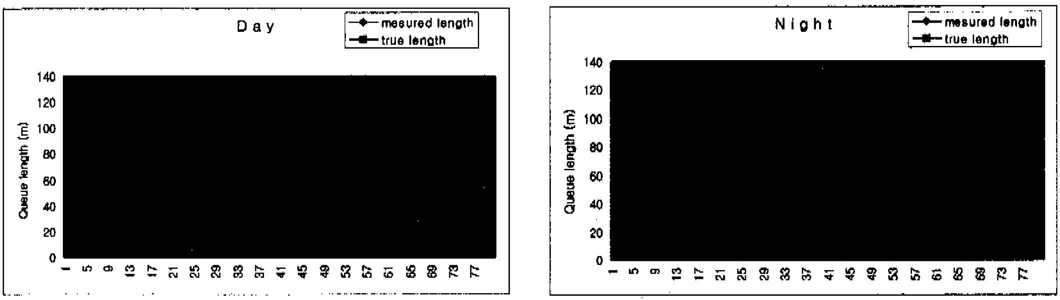
$$\text{error rate}(\%) = \frac{1}{n}\sum_{i=1}^{n}\frac{|v_t - v_m|}{v_t}\times 100 \qquad (3)$$

where, v_t : observed queue length.
v_m : measured queue length.
n : number of sample points.

As shown in Fig. 5, in the performance test with sample size of 80, the error rates in standing queue are 2.14% and 2.24% in daytime and nighttime, respectively. The error rates in moving queue are 2.59% and 2.73 % for daytime and nighttime, respectively.



(a) Standing Queue Length Measurement



(b) Moving Queue Length Measurement

Fig. 5 Results of Queue Length Measurement (80 samples)

The results show that the algorithm is robust enough and very promising. The most important contribution is that the algorithm needs not parameter adjustment for modifying intensity level with changes of time zone and changes in environment. The results can be compared with the measurement method of Higashikubo *et. al.*[13]. Higashikubo *et. al.* tried to measure only standing queue length for 3 days on the intersection of Tokyo, the average of accuracy rates are 98.4% and 96.4% for daytime and nighttime respectively. But accuracy rates of proposed algorithm are 97.9% and 97.7%. As this comparison result, the accuracy of our algorithm is a little inferior in daytime but superior to other algorithm especially nighttime.

Ⅵ. Conclusions

Recently, the most popular traffic detector is ILD (Inductive Loop Detector). However, ILD is an expensive detector in installing and maintaining. Especially, when mechanical problems are found in ILD, road blocking is necessary for repairing parts. Authorities would like to avoid road blocking, as possible as, because of the unavoidable traffic jam and complaints.

This paper presents a vehicle detection algorithm which is conducted using wavelet transforms and then traffic queue length is measured. In the performance test, it was shown the algorithm based on wavelet transform is more robust than previous approaches: edge detection method, background difference method, and spatial difference method. The advantages of the algorithm are the followings. First, as the image characteristics are not derived from spatial domain, but from frequency domain, the analysis is robust to noise. Second, the previous approaches have to adjust parameter values with the changes of time zone, while the algorithm needs not modify parameter values even in nighttime. Third, in nighttime previous approaches are affected by the headlight beam and thus generally degradation in accuracy result in, while the algorithm is robust enough to be not affected by the headlight beam. Even though performance tests were not conducted in rainy days, we believe that the accuracy level will be much lowered than clear days, because of the inherent robustness of wavelet transform.

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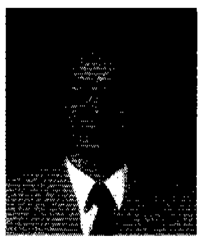
민 준 영(Joon Young Min)



1982년 : 아주대학교 산업공학과 (학사)

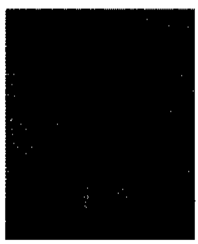
1989년 : 성균관대학교 정보처리 전공 (석사)

1995년 : 성균관대학교 전산통계 전공 (박사)

현재 : 상지영서대학 전자계산과 부교수

<주관심 분야> 영상처리, 패턴인식, 인공신경망, ITS

최 종 욱(Jong Uk Choi)



1982년 2월 : 아주대학교 산업공학과 (학사)

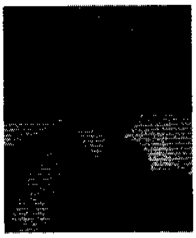
1982년 8월 : 서울대학교 경영학과 석사과정1기 수료

1988년 : Univ. of South Carolina MIS 및 인공지능 전공 (박사)

1982년~1986년 : Institute of Information Manage-

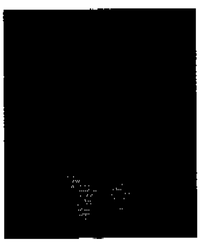
ment Technology & Policy at Univ. of South Carolina, Research Assistant.
1986년~1987년 : Johns C. Smith Univ.(Charlotte NC) Computer System Specialist.
1988년~1991년 : KIST시스템공학연구센터 인공지능부 지식처리연구실장(선임연구원)
현재 : 상명대학교 정보과학과 부교수
㈜마크애니(http://www.markany.com/) 대표이사
<주관심 분야> 인공지능, EC/CALS, 영상처리, ITS, 암호화

이 인 정(In Jung Lee)



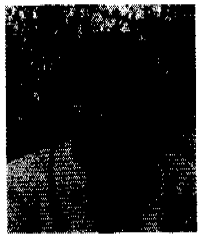
1980년 : 전남대학교 수학과 (학사)
1983년 : 중앙대학교 수학과 (석사)
1990년 : 중앙대학교 수학전공 (박사)
1991년 4월~1992년 3월 : 한국과학기술원 Post Doc.
1992년 3월~현재 : 호서대학교 컴퓨터공학부 조교수
<주관심 분야> 영상처리, 인공지능, 계산이론

이 형(Hyoung Lee)



1964년 : 서울대학교 사범대학 수학과 (학사)
1971년 : 성균관대학교 대학원 전자계산학과 (석사)
1992년 : 조선대학교 대학원 컴퓨터공학과 (박사)
1993년 3월~현재 : 대전대학교 컴퓨터 정보통신공학과 교수
1995년 3월~1997년 2월 : 대전대학교 전자계산소 소장.
1999년 3월~현재 : 대전대학교 공과대학 학장.
2000년 1월~현재 : 한국정보기술응용학회 회장
<주관심 분야> 계산이론, 컴퓨터그래픽스, 영상처리

조 현 숙(Hyun Sook Cho)



1995년 : 대전대학교 수학과 졸업 (학사)
1995년 2월~1997년 2월 : 대전대학교 정보통신공학과 조교
1998년 : FANSHAW College 연수, 영어교사 자격 취득(캐나다, 런던)
2001년 6월 : 대전대학교 정보통신공학과 대학원 졸업 예정.
<주관심 분야> 계산이론, 영상처리