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칼로게로 모제 시스템을 활용한 4차선 도로의 사고검지 폐쇄회로 카메라 시스템

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CCTV-Aided Accident Detection System on Four Lane Highway with Calogero-Moser System

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요 약

도로변에 설치된 폐쇄회로 카메라를 통해 사고를 감지하여 교통사고 대책반에 전송하는 시스템이 연구되어 많은 성과를 거두고 있다. 더하여 고속도로에서는 고장으로 인한 정지차량이 차량의 흐름을 방해하는 것도 사고로 간주해야 하는 상황이 발생한다. 본 논문에서는 차량의 흐름을 각 차선 별로 모니터링하고 있다가 정지차량이나 사고로 인한 차량흐름의 변화를 감지하여 이를 사고 대책반에 알리는 시스템을 소개한다. 각 차선 별 차량흐름은 레벨 스페이싱 곡선들로서 위치벡터에 대한 Wigner 분포를 이룬다. 여기에 해밀토니안 및 칼로게로 모제 시스템을 적용하면 각 레벨스페이싱 커브간의 간격에 대한 확률식을 얻게된다. 이 식으로부터 변동이 큰 이상 신호를 찾으면 사고상황과 잘 맞는다. 이것은 한 차선에 대한 이상 신호를 찾는 것과는 다르다. 전체적인 차량 흐름 속에서 찾아야만 사고를 감지하는 효과를 보기 때문이다. 각 차선 별 차량흐름을 모니터링 하는 과정에서 카메라의 특성상 차량의 그림자를 차량으로 오인하게 되면 사고감지에도 영향을 미친다. 이를 방지하기 위해 그림자를 제거하는 방법도 소개한다. 본 시스템의 평가를 위해 베이지안 네트워크 방법을 사용한 시스템과 비교하였다. 특별히 고장으로 인한 정지차량으로 생겨난 차량흐름의 변화를 사고로 인식하는 데는 본 시스템이 우수한 것으로 나타났다.

Key Words : Wigner distribution, detection abrupt signal, Calogero-Moser System

ABSTRACT

Today, a number of CCTV on the highway is to observe the flow of traffics. There have been a number of studies where traffic data (e.g., the speed of vehicles and the amount of traffic on the road) are transferred back to the centralized server so that an appropriate action can be taken. This paper introduces a system that detects the changes of traffic flows caused by an accident or unexpected stopping (i.e., vehicle remains idle) by monitoring each lane separately. The traffic flows of each lane are level spacing curve that shows Wigner distribution for location vector. Applying calogero-moser system and Hamiltonian system, probability equation for each level-spacing curve is derived. The high level of modification of the signal means that the lane is in accident situation. This is different from previous studies in that it does more than looking for the signal from only one lane, now it is able to detect an accident in entire flow of traffic. In process of monitoring traffic flow of each lane, when camera recognizes a shadow of vehicle as a vehicle, it will affect the accident detecting capability. To prevent this from happening, the study introduces how to get rid of such shadow. The system

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using Basian network method is being compared for capability evaluation of the system of the study. As a result, the system of the study appeared to be better in performance in detecting the modification of traffic flow caused by idle vehicle.

Ⅰ. Introduction

There are two different methods that detects vehicle accidents. The one is to detect by sensor and the other is analyzing the camera images. In the method of analyzing the camera images, there are two methods. While the one is to detect the accident by observed images, when the camera is viewed from individual accident vehicles, the other is to find abnormalities in the flow of traffic when the accident is occurred, at the very moment, the flow of traffic should be controlled.

In study of accident detecting by using sensor[1], an accelerometer has been used in a car alarm application so that dangerous driving can be detected. It is used as a crash or rollover detector of the vehicle during and after a car crash. With signals from an accelerometer, a severe accident can be recognized. Vibration sensor detects the signal if a car rolls over, and Micro electro mechanical system sensor detects the signal and sends it to controller. The weakness of the system using sensors, however, is that it can be very sensitive to noise.

It is proposed that an intelligent RFID traffic cone applied for vehicle accident detection and identification is based on image compressing analysis and RFID detection tracking in an accident clamming system and traffic reporting system[2]. This RFID technique deals with multi-vehicles, multi lane and multi road even or traffic junction area. It provides an efficiency in time management scheme with correct data reporting, in which a dynamic time schedule is worked out in real time for the driver or passengers of each accident situations. In this case, the probability of misrecognition problem increases according to location of RF sensor.

Also, in the study of accident detecting by image processing, in Osaka and Kobe[3], acknowledgement has been done by emergency calls, cameras and patrol cars, and it takes about 8 minutes to acknowledge the accidents and about 22 minutes before an urgent car comes to at the spot where the accident occurs. This paper underwent experiments that installed 7 cameras on two different spot to detect accidents. It was acceptable to install multiple cameras on black spot, however, when it comes to large area, the cost will surmount the benefit. It is proposed that a new framework for real-time automated traffic accidents recognition using histogram of flow gradient (HFG)[4]. This framework performs two major steps. First, HFG-based features are extracted from video shots. Second, logistic regression is employed to develop a model for the probability of occurrence of an accident by fitting data to a logistic curve. In case of occurrence of an accident, the trajectory of vehicle by which the accident was occasioned is determined. However, the system is insufficient to explain the complexities of phenomena related to multiple lanes.

Other researchers develop a real-time traffic accident detection system(RTDS)[5]. This system helps us to cope with accidents and discover the causes of traffic accident by detecting the accident. It is gathered video data recorded at several intersections and used them to detect accidents at different intersections which have different traffic flow and intersection design. This system is a type of algorithm to detect accident by using Baysian Network. It, however, fails to recognize an occasion of a vehicle in idle on the road as an accident. It is reasonable to recognize a vehicle that remains in idle as an accident situation.

The study is to introduce the system that detects an accident by recognizing vehicles in idle by monitoring the relation of 4 different lanes. (Fig. 1.)

The one of the major problem of CCTV, however, is shadows of vehicle. It affects the image of different lanes when image of CCTV is being processed for tracing vehicle for each lane. The

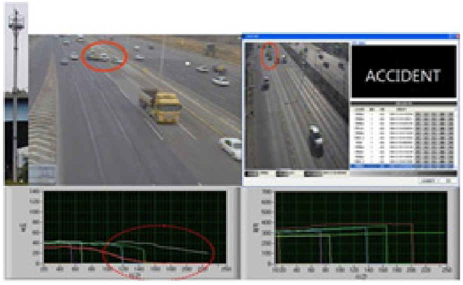


Fig. 1. System main monitor

system is to introduce an algorithm recognizing an accident by monitoring traffic flow after eliminating tracing vehicles.

The flow of vehicle trace is as level spacing distribution and Wigner distribution in the level statistics when we represent this trace avoidable. From this distribution we can derive a probability induced by different of position for each lane. Using this equation we can find abrupt state of vehicle flow comparing with normal flow. For this system evaluation, we shall show statistical results from some experiments. In section 2, we introduce an advanced shadow elimination technologies. In section 3, we explain the fact that traffic flow is showing Wigner distribution for position vector as level-spacing curves, and applying calogero-moser and Hamiltonian system will derive probability equation for space between each level-spacing curve.

Ⅱ. Shadow Elimination

The goal of a traffic monitoring system is to extract traffic information, such as the vehicle volume count, traffic events, and traffic flow, which plays an important role for traffic analysis and traffic management. In these extracting information, the occlusions have taken place when two or more vehicles and shadows are regarded as one vehicle because of overlapping from the viewpoint of camera. Many cases are explicit occlusion because of identifying individual vehicles before occlusion. The shadows can cause various unwanted behavior such as object shape distortion and merging, affecting surveillance capability like target counting and identification [9].

Generally, image processing and object tracking techniques have been mostly applied to traffic video analysis to address queue detection, vehicle classification, and volume counting[10,11]. In this case, Model-Based tracking is highly accurate for a small number of vehicles[12].

If the number of vehicle is increasing, we need new background model like as the Kalman-filter-based adaptive background model, because the background changes rapidly. In this situation, if a separate contour could be initialized for each vehicle, then each one could be tracked even in the presence of partial occlusion[6,7,13]. They introduce there are three types occlusions, that is track occlusions, background object occlusions and apparent occlusions[15].

In track occlusions, in order to resolve more complex structures in the track lattice, the bounding box tracking used by appearance based modeling[14]. The appearance model is an RGB color model with probability mask similar to that used by Ismail Haritaoglu et. Al[16]. In methods to solve the implicit occlusion problem in moving objects, the fusions of multiple camera inputs are used to overcome occlusion in multiple object tracking[17]. The Predictive Trajectory Merge-and-Split (PTMS) proposed to uses a multi stage approach to determining the vehicle motion trajectories and eventually the lane geometry[18,19]. Some shadow elimination techniques have been classified in the literature into two groups, model-based and property-based technique[19]. The shadow removal approaches are based on an assumption that the shadow pixels have the same chrominance as the background but lowerluminance[8,20]. The earliest investigations in shadow removal proposed by Scanlan et. Al[21]., the image was split into square blocks and produced an image based on the mean intensity of each block. We know the vision-based with nighttime images was RACCOON system[22] which has been integrated into a car experiment on the CMU Navlab II, tracks car taillights. Also, another pattern classifier algorithm is Support Vector Tracking (SVT) which integrates the SVM classifier into optic-flow based on tracker[23]. The bright regions in the nighttime generated by headlights, tail lights, break lights, and reflected lights around light sources are recognized as the vehicle feature.

We explain the basic idea behind the tracking algorithm developed in this research. Vehicle tracking has been based on the region-based tracking approach. For individual vehicle tracking the first step, acquisition image sequences and predetermining the detection zones at each lane. The second, we have conducted the background subtraction, deciding threshold for binary images. The background subtraction algorithm requires a relatively small computation time and shows the robust detection in good illumination conditions [19]. The third step, morphology for small particles removal as noise, sets in mathematical morphology represent the shapes of objects in an image, for example, the set of all white pixels in a binary image is a complete description of the image. The next step, it is important to remove cast shadows due to extract the vehicle area exactly, we developed the new algorithm in this paper using by edge detection and vertical projections within the vehicle particles. And the fifth step generates the vehicle ID and labeling to each vehicle, and individual vehicle's bounding rectangle data, i.e., left, top, right, bottom coordinates. These particle data are saved into reference table which can be referred to next sequence frames. In this system, the occlusion detection is easy relatively because of short length of detection zones, less than 15m. And we have considered only limited to explicit occlusion. The explicit occlusion cases have taken place several times during the field test, that is, multiple vehicles enter a scene separately into detection zone, and merge into a moving object region in the scene. In this case, we have maintained each vehicle ID continuously as referred to previous frame.

In the nighttime, diffused reflections on the road due to vehicle headlights pose a serious concern. Thus we need to pre-processing by reflection elimination to adjust the light parameters such as luminosity or brightness, contrast, intensity. For the vehicle extraction exactly, we have to consider about background estimation, occlusion, cast shadow detection and elimination, and light condition processing at night.

Our system has covered the four lanes with single camera. As the more system has to be processed, the less performance of system has been. The reason for that if we have included the implicit occlusion process, the performance evaluation marked low grade especially the calculation of velocity. The occlusion detection of this system is easy relatively because of short length of detection zones, less than 15m.

So many algorithms of cast shadow elimination are proposed, the various cases are occurred in the real traffic flows, for example, dark or light shadows, shadow from trees or clouds.

The proposed algorithms as mentioned before, have been applied to our experiment, the shadows cannot be extracted exactly as a result.

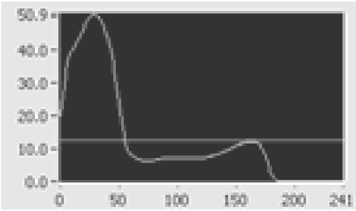
Thus we have developed the appropriate algorithm in our test site. The basic concept is that the shadow area has less edge because of no variance within shadow. On the other side hand, vehicle area has more edges relatively. Let B be a binary image plane and B_x be a set of number of vertical pixels which value is 1 at x. We define a function $Vtical: B/x \to B_x$

$$by\ Vtical(x) = \sum_y B_1(x,y) \tag{1}$$

where $B_1(x,y)$ is a pixel of which value is 1 at (x,y) and B/x is a projection of B into x. In Fig. 2b, the distribution of edges from moving object area can be discriminated between vehicle and cast shadow. And then discard under 25%, that is cast shadow area, Fig. 2b.

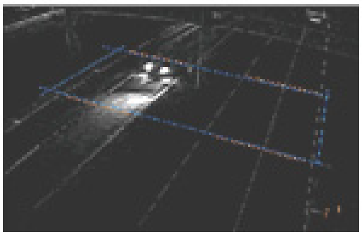
The light condition is a lot different from whether streetlamps are on the road or not. The around road with streetlamps has a bright under night, whereas around the vehicle headlight can be classified distinctly without streetlamp. In the test site has no streetlamp. Diffused reflections on the road due to vehicle headlights pose a serious concern during the night processing even though no streetlamp. Thus we need reflection elimination to adjust the light

(a) Edge of moving object



(b) Shadow area under blue line, 25%

Fig. 2. Cast shadow detection process in our test site



(a) Diffused reflections on the road

(b) Adjust the luminosity in this test due to vehicle headlights

Fig. 3. Diffused reflection elimination during the night

properties such as luminosity or brightness, contrast, intensity. We have adjusted the luminosity in this test in order to eliminate the diffused reflections on the road. Then, vehicle detection can be achieved through the detection of headlight by grey value shown in Fig. 3.

Figure below(Fig. 4.) shows the result of research monitoring two different lane when many shadows presented. Real lane A is number of vehicle counted by manually to compare the number counted by the

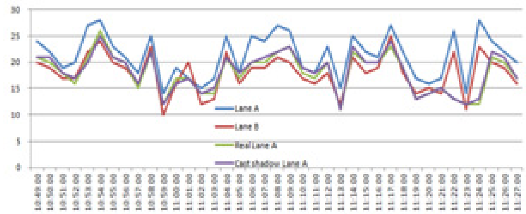


Fig. 4. Shadow elimination effect comparing Lane A, Lane B, eliminating shadow Lane A and real Lane A

system.

Ⅲ. Detection of Abrupt Signal on Wigner Distribution

There are many unpredicted problems in detecting accidents when the camera system captures the situation of traffic. For example, if the system made judgment only by detecting speed reduction like in Fig. 5., it is highly probable to make wrong judgement by processing traffic congestion as an accident. Also, if the system made judgment by detecting a signal from only one lane when there are many more lanes, it could wrongly think lane change as an accident. Furthermore, the system using Basian network (eg. Hong Liu, Jintao Li, Qun Liu, Yueliang Qian, “Shadow Elimination in Traffic Video Segmentation,”) would not recognize an idle vehicle on the road as an accident, while it should be recognized as serious situation in high way.

Let us introduce the method for accident-detection considering systematic relation among traffic flows of 4 different high way lanes.

The flow of vehicle can be represented by trajectories, and a time series can be figured from this trace when the flow of vehicle volume calculated for some time interval at each lane as

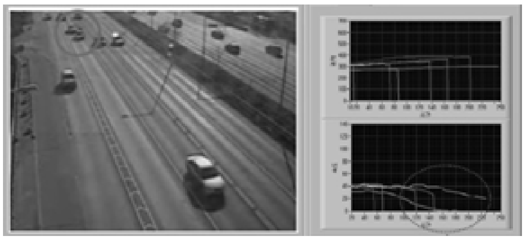


Fig. 5. Vehicle speed and trajectories

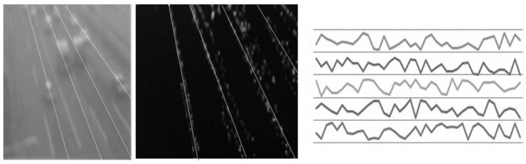


Fig. 6. Trajectories of vehicle and it's time series for each lane

Fig. 6.

The distribution of position from the bottom line is Wigner distribution (2) in this time series as Fig. 7.

$$P(S) = \frac{\pi}{2} S \exp(-\frac{\pi}{4} S^2) \tag{2}$$

If the Generalized Calogero-Moser system is applied to this equation (2) after finding the eigenvalue of Hamiltonian, we can get the equation (3).

$$P(x_1, x_2, \ldots, x_n) = C \prod_{1 \le i,j \le n} |x_i - x_j|^{\nu} \tag{3}$$

Where x_i is position value of each lane and C is constant and $n \geq 4$.

This equation 3 is different from a equation in [24](Abhisek Ukil, Rastko Živanović, Abrupt Change Detection in Power System Fault Analysis using Wavelet Transform). They consider one lane in detecting abnormal situation, but equation 3 considered systematically integrating changes of each lane.

Suppose $n = 5$, the equation 3 is considered to be same as $F(w,x,y,z) = (wxyz)^{\nu}$ where F have 4 variant factors which are all positive and have positive differentiation. Differentiate this equation gives,

$$\begin{aligned} dF &= \frac{\partial F}{\partial w} dw + \frac{\partial F}{\partial x} dx + \frac{\partial F}{\partial y} dy + \frac{\partial F}{\partial z} dz \\ &= (wxyz)^{\nu-1}(xyzdw + wyzdx \\ &\quad + wxzdy + wxydz) \\ &\geq (wxyz)^{\nu-1}(wyzdx + wxzdy \\ &\quad + wxydz) \\ &\text{if } dw \approx 0 \end{aligned} \tag{4}$$

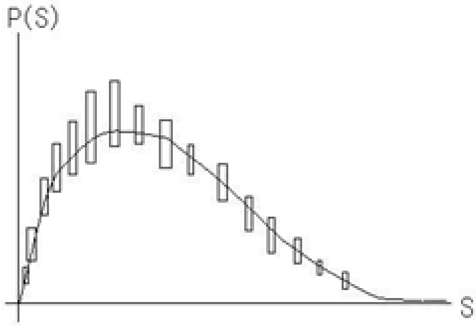


Fig. 7. Wigner distribution of time series

That is, $P(x_1, x_2, x_3, x_4, x_5)$

$$\begin{aligned} &= C(|x_1 - x_2||x_2 - x_3||x_3 - x_4| \\ &\quad |x_4 - x_5|)^{\nu} \end{aligned} \tag{5}$$

In this equation 5, a change in each lane makes total value low. Total value can be controlled depending on value of ν.

Therefore, if one or two lane has no vehicle flow except other lane has normal flow, the value of equation (5) is abruptly changed. So, the detection system can be made by checking the value of (5) is abrupt value than previous value for some time. In this case we can choose C, ν properly for accurate precession and time interval to decision abrupt. From this data we take two values as $2 \leq C\nu \leq 3$ is properly good as in Fig. 8.

In case of normal traffic flow, high traffic occupation exposes distinctive curve of vehicle traffic. Application of equation 5 outputs low value and allow us to detect accident situation. In low traffic flow situation, however, assuming that an accident only occurs in one lane, one can make a judgment by monitoring on lane without taking into account systematic relation between other lanes.

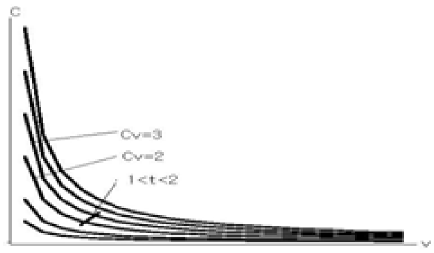
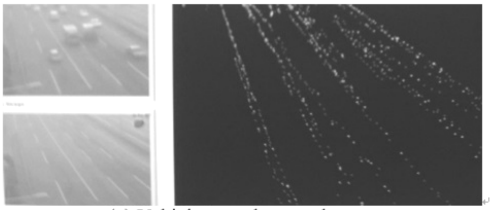


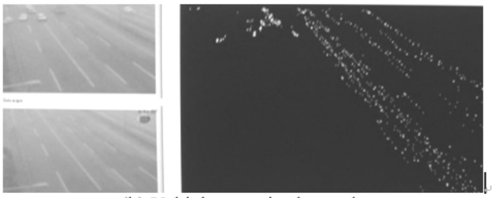
Fig. 8. When $1 \leq t \leq 2$, $2 \leq C\nu \leq 3$ induced from experimental data.

Our system consists of systematic relations between 4 lanes and makes output of equation 5 to be higher than normal, avoiding the problems of low traffic flow. That is, equation 4, $dw = dx = dy = dz = 0$, if one of the value is not 0, dF value becomes high.

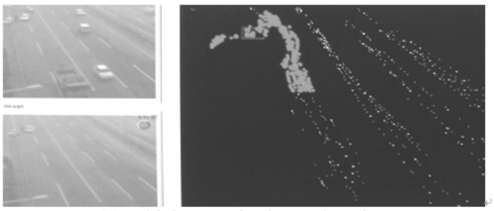
Since, as in Fig. 9., we can find some change of trace image (b) (c) and need to calculate abrupt signal, after that, delivered warning to manager when the calculated abrupt signal image like as Fig. 10.



(a) Vehicle trace has no change



(b) Vehicle trace is changed.



(c)Vehicle trace is changed again.

Fig. 9. Showing images from normal flow to abrupt flow and warning state

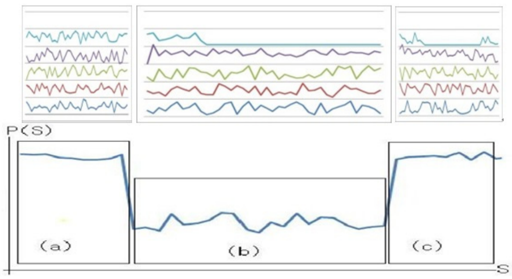


Fig. 10. (a) is an area of normal vehicle flow signal, (b) is an area of one lane flow is stopped and (c) is an detour area of flow

Ⅳ. Experimental Results

As mentioned in section 3, the system must calculate traffic occupation rate in the process of showing traces of vehicles. Generally, normal traffic flow shows about 20 to 30 number of vehicle per minute. Traffic occupation rate is determined by velocity of vehicles and amount of traffic flow, where a vehicle is present on the road within 20 meters from camera's sight (Table 1).

And, the detection rate is high from a trajectories when the traffic flow is over 20 to 30 number of vehicle per unit (Fig. 11.).

To evaluate the system, we collected 50 captured video clips of CCTV. These clips consist of 12 clips of accident, 19 clips of abnormal traffic flow(eg. idle vehicle or unanticipated obstacles), 4 clips of official control of traffic lane (eg. roadwork) 6 extremely low traffic flows, 4 traffic congestions and 5 normal traffic flows. We compared the system with Osaka and Kobe, HGF and RTDS. Table 2. shows the results of these comparisons. Values in the table represents Detection rate(DR) and Error

Table 1. Experimental results by changing detection time where "D" is detected case "F" is missed case

TI	1	2	3	4	5	6	7	8	9	10
0.5 min	F	F	F	F	D	D	F	D	D	D
1 min	D	D	D	D	D	D	D	D	D	D
1.5 min	D	D	D	D	D	D	D	D	D	D
2 min	D	F	D	D	F	D	F	D	F	F

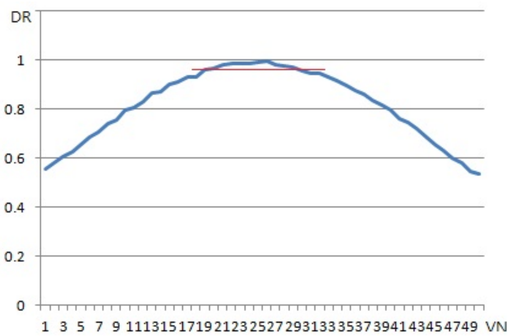


Fig. 11. DR is high more than 95% when VN is over 20 to 30 where DR is detection rate and VN is vehicle number.

Table 2. Comparing proposed system with other 3 system.

	Osaka & Kobe		HGF		RTDS		Proposed System	
	DR	ER	DR	ER	DR	ER	DR	ER
Accident	98	2	90	10	96	4	96	4
Vehicle in idle	98	2	88	12	92	8	96	4
Road work	96	4	90	10	92	8	96	4
Low traffic rate	98	2	92	8	100	0	98	2
Traffic congestion	100	0	100	0	98	2	100	0
Normal traffic	100	0	100	0	100	0	100	0

rate(ER). We conveniently increase the number of trials by repeating experiments

The table implies that Osaka & Kobe performs well in most of aspects but cost is very high, HGF system show very high error rate in low traffic flow and vehicle in idle. Also RTDS system increases its error rate in traffic congestion and roadwork. Our system shows high error rate in low traffic rate.

Ⅴ. Conclusions

The system is to detect and transfer accidents by monitoring and image processing traffic flows of 4 traffic lane represented in CCTV installed near the road. The shadow elimination method is included in this algorithm. Since the method is different from detecting an abnormal signal that occurs only one traffic lane, we suggested new method to detect abnormal signal that reflects systematic relation of 4 traffic lanes. The system is considered to be satisfactory in that it utilizes existing CCTV system and also works for special occasion in high way. However, the error rate in low traffic flow needs to be improved to be more effective in detecting accidents.

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