A Method for Detection of Traffic Conditions in an Oncoming Lane Using an In-vehicle Camera

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Abstract - In recent years, we have become able to acquire traffic information about traffic congestion through the VICS (Vehicle Information and Communication System). The VICS is one of the traffic systems that provide drivers with information on the state of traffic congestion. However, it is difficult for drivers to decide appropriately as to whether they should change lanes or make detours because the VICS provides information on the causes of traffic congestion, such as traffic accidents or road works, in the form of icons. Icons are simple representations, but are not intuitive and informative. In contrast, presenting images recorded by an in-vehicle camera to represent the causes of traffic congestion is more effective than presenting icons to help users to understand the causes intuitively. When an in-vehicle camera records the conditions directly in front of a moving vehicle, recording the traffic conditions of an oncoming lane is simpler than trying to record the conditions in the lane in which the user is driving (driving lane), as preceding vehicles may obscure the camera view. If images representing the conditions in front of preceding vehicles are sent to drivers from vehicles in the opposite lane in advance, the drivers can avoid the congestion effectively. Therefore, we propose a method for detecting the traffic conditions of an oncoming lane using an in-vehicle camera. In addition, we conducted some experiments to show the effectiveness of the proposed system. In particular, we conducted the experiment about estimating the speed of vehicles on an oncoming lane by using optical flow toward detecting the traffic congestion in an oncoming lane. The experimental results suggest that the length of optical flows changes depending on the speed of oncoming vehicles and the proposed method has potential to detect traffic conditions.

Keywords: in-vehicle camera, detection of vehicles, traffic congestion, sensing, estimation of vehicle speed

1 INTRODUCTION

Drivers cannot effectively avoid traffic congestion through methods such as changing lanes and making detours if they are not aware of conditions of traffic congestion, such as the causes and ranges of the congestion, in advance. The VICS (Vehicle Information and Communication System) is one of the traffic systems that provide information on the conditions of traffic congestion [1]. In the VICS, information such as the volume of traffic, the speed of vehicles, and so on is acquired by sensors located on roads and sent to the information center. The collected information is converted into traffic information. The center sends the traffic information to car navigation systems and other in-vehicle devices. However, the VICS provide information on the causes of traffic congestion, such as traffic accidents or under construction, in the form of icons. Icons are simple representations, but are not intuitive and informative for grasping traffic congestion. Therefore, it is difficult for drivers to decide how to avoid traffic congestion effectively.

Currently, Probe Information Systems are in wide-spread usage [2]-[4]. Probe Information Systems are systems that support aspects of driving, such as navigating and calling for attention, by using information collected by sensors embedded in vehicles. Probe information includes vehicles' location information, air temperature, engine rotation speed, actuating information of the ABS (Antilock Brake System), and so on. The collected probe information can be shared among vehicles through a network or directly with a wireless connection called "inter-vehicle communication" [5]-[7].

A driver's front view is partially obscured by the preceding vehicles in the driving lane when the driver tries to record the causes of the congestion using an in-vehicle camera. Consequently, the driver cannot grasp the causes of traffic congestion and cannot avoid traffic congestion in advance unless the driver comes close to the site of the cause. For example, in Fig. 1, the cause is in front of vehicle C. Vehicle A's front view is partially obscured by the preceding vehicles in the driving lane. The driver of vehicle A cannot grasp the causes of traffic congestion unless the driver comes at points of vehicle C. On the other hand, vehicles in the oncoming lane (oncoming vehicles), as shown vehicle B in this figure, can grasp the causes of traffic congestion in the driving lane. The driver of vehicle A can identify congestion in front of the preceding vehicles and avoid it if the driver gets images representing the causes of traffic congestion in his or her driving lane from oncoming vehicles in advance. In this figure, vehicle B can grasp the causes of traffic congestion in the opposite lane, and vehicle A can acquire an image representing the causes from vehicle B when vehicle B comes at the point of vehicle B*.

For these reasons, in this study we assume that vehicles can share images and we propose a method for detecting traffic congestion in an oncoming lane, by using an in-vehicle camera. This study aims to detect traffic congestion in an oncoming lane from the view point of vehicle B in this figure.

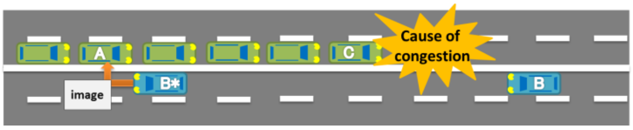


Figure 1: The positional relation between vehicles

This paper is organized as follows. Section 2 mentions research related to our study. Section 3 discusses the requirements of the proposed system. We outline our proposed method in Section 4. Finally, we discuss the effectiveness of our proposed method in Section 5.

2 RELATED WORK

This section introduces research related to our study. First, we discuss research and technologies related to presenting and sharing information on traffic conditions in Section 2.1. In addition, we discuss research on sharing information on traffic conditions by using an in-vehicle camera in Section 2.2. Finally, we discuss and compare the related research and our proposed method in Section 2.3.

2.1 Presenting and Sharing Information on Traffic Conditions

The VICS is one of the traffic systems that provide information on the conditions of traffic congestion [1]. In the VICS, information is collected by sensors located on roads and sent to information center. The collected information is converted into traffic information, such as the range of traffic congestion, road obstacles and highway regulations. The center sends the traffic information to car navigation systems and other in-vehicle devices using microwaves in the ISM band and frequency modulation (FM), similar to the Radio Data System (RDS) or Data Radio Channel (DARC). Thus the VICS can provide traffic information in real time. In the VICS, information displayed on maps of car navigation systems presents the traffic congestion classified into three degrees (sparse, crowded, and congested) based on the VICS's classification of traffic congestion (Table 1). VICS also displays icons representing highway regulations, hazard to moving traffic, and so on (Fig. 2). Drivers can grasp the traffic conditions anywhere by observing the displayed information.

However, the VICS cannot necessarily collect and provide this information for every road, because some roads do not have devices to collect information. In addition, the VICS provide information on the causes of traffic congestion, such as traffic accidents or under construction, as icons. Therefore, drivers must understand the meanings of the icons. However, drivers cannot decide whether or not they will avoid traffic congestion effectively because it is difficult for them to imagine the scale and the influence of the event that is happening in the driving lane from icons. Icons provided by the VICS are not intuitive information for drivers because they are simple information that does not depend on the scale of the causes.

Presenting camera images representing the causes of traffic congestion is effective for intuitive comprehension of traffic conditions [8, 9]. Intuitive comprehension enables drivers to identify traffic congestion in front of preceding vehicles and to avoid it in advance.

Figure 2: Icons provided by the VICS [1]

Table 1: The VICS's classification of traffic congestion [1]

Degree of congestion (Color)	General road	Inner-city high-speed way	Intercity high-speed way
Congested (Red)	Less than 10km/h	Less than 20km/h	Less than 40km/
Crowded (Orange)	10km/h-20km/h	20km/h-40km/h	40km/h-60km/h
Sparse (Green)	More than 20km/h	More than 40km/h	More than 60km/h

Tamai et al. [8] proposed a system that provides videos recorded at the point of traffic congestion for drivers' intuitive comprehension. A smartphone placed on the dashboard with a cradle records traffic congestion. The system collects and provides the recorded videos effectively, considering the time difference and the degree of congestion in the videos. The time difference means the difference between the time at witch a user receives the video and the time when the video was recorded. Tamai et al. [9] proposed a method that shares short videos representing the traffic conditions on roads with other vehicles. The system grasps the speed of a moving vehicle and determines the ranges of congestion based on the speed. The speed can be calculated based on location information acquired by a GPS sensor embedded in a smartphone placed on the vehicle's dashboard. At the same time, the smartphone records a front view. The system manipulates the video images considering the colors and the shapes, and detects traffic lights when the vehicle is in congestion. In addition, the system generates a video that is about 10 seconds long. The system grasps the speed of the moving vehicle easily by calculating the movement of traffic lights in the video because traffic lights are stationary objects.

2.2 Grasp of Traffic Conditions by Using In-vehicle Cameras

We will now introduce some research on grasping the conditions of roads by using an in-vehicle camera. Kutoku et al. [10] proposed a system that detects obstacles on roads by using an in-vehicle camera. An in-vehicle camera is placed on the dashboard of a moving vehicle and records the view in front of the moving vehicle. The system generates subtracted images by using the video currently being recorded and background video. Background video is a video recorded in advance on the same road when it had no obstacles. The system detects obstacles by using subtracted images. Many researchers tackle the detection of objects on roads. However, the objects targeted by such research are assumed objects such as a person, a vehicle, and so on. Kutoku's system can detect unexpected objects by using the subtracted images. To generate subtracted images, the system must examine the time and position of the vehicles in the two videos because the speed and the positions of moving vehicles are different in each video. First, the system considers the time between the two videos using the scale representing the distance between the cameras in the two videos. Second, the system considers the positions of moving vehicles in each video by image processing of the surface of roads. According to this processing, the frames between two videos are selected and subtracted images are generated. The system calculates the recall, the false detection rate and the rate of false detection frames based on the distance between the moving vehicle and obstacles, by using image features of subtracted images. Image features include the brightness, the intensity and the edge. Then, the system detects unexpected objects considering the calculation results.

Hamao et al. [11] proposed a system that detects traffic congestion by using an in-vehicle camera. A smartphone is placed on a moving vehicle and records the view in front of the moving vehicle. The system sets a region of interest (ROI) on images, and calculates the standard deviation of the luminance histogram of the oncoming lane in the ROI. The system detects congestion based on the calculated standard deviation of the luminance histogram between congested roads and uncongested roads.

2.3 Comparing the Related Works with Our Method

Providing information on the conditions of traffic congestion using the VICS is not intuitive for drivers because the VICS presents such information as icons. The method proposed by Tamai et al. demonstrates that presenting information on traffic congestion as camera images taken by an in-vehicle camera is effective. However, in the case where preceding vehicles are moving in front of the vehicle with an in-vehicle camera, the camera cannot record the state of traffic congestion and its causes in the area in front of the preceding vehicles. Therefore, recording traffic congestion from an oncoming lane is easier than from a driving lane. To grasp the causes of the congestion by using an in-vehicle camera, it is necessary to detect the congestion and its range. In addition, to grasp the range and detect the congestion, it is necessary to detect the speed of oncoming vehicles. Grasping the ranges of the congestion and detecting the congestion are possible by acquiring the speed from oncoming vehicles with inter-vehicle communication. However, the moving vehicle must acquire the speed from a number of oncoming vehicles. On the other hand, detecting congestion is possible with only one moving vehicle with an in-vehicle camera. The method proposed by Kutoku et al. that detects road obstacles can detect congestion, but has difficulty detecting the speed of oncoming vehicles. The method proposed by Hamao et al. cannot detect the speed of oncoming vehicles. In addition, this method cannot discriminate between oncoming vehicles and objects behind them in images.

3 REQUIREMENTS OF THE PROPOSED SYSTEM

For intuitive grasping of the conditions of traffic congestion, presenting camera images is more effective than presenting icons. In addition, recording the conditions of oncoming lanes is easier than recording that of driving lanes when an in-vehicle camera records the view in front of a moving vehicle. Grasping the ranges of the congestion is required in order to detect the causes of the congestion. Grasping the ranges of the congestion is, namely, detecting the beginning and ending point of the congestion. Moreover, the speed of oncoming vehicles is required in order to grasp the ranges. In an image, oncoming vehicles and background objects behind them must be distinguished between when image processing is applied to the image. In this study, optical flows generated between two images are calculated in order to grasp the speed of oncoming vehicles. The optical flow is a line that represents the movement of objects between two images as a vector. The length of optical flow (LOF) generated from oncoming vehicles is calculated, and the speed of oncoming vehicles is calculated based on the length. In this way, the congestion is detected. LOF depends on the distance between a moving vehicle with an in-vehicle camera and oncoming vehicles, and the relative speed between the vehicles. The distance between the moving vehicle and oncoming vehicles is smaller than the distance between the moving vehicle and the objects behind oncoming vehicles. The movement of oncoming vehicles per a unit of time is different from that of the objects behind oncoming vehicles. In this way, oncoming vehicles and objects behind them are distinguished. In addition, LOF changes depending on not only the change in the speed of a moving vehicle but also the speed of oncoming vehicles. The speed of the moving vehicle can be calculated by using location information acquired by the GPS sensor embedded in the driving recorder and the smartphone.

Therefore, the speed of oncoming vehicles can be estimated by calculating the speed of the moving vehicle and the optical flows on the images from the in-vehicle camera. In addition, traffic congestion can be detected and images representing the causes of traffic congestion can be generated.

4 PROPOSED METHOD

4.1 Summary of the Proposed System

On the basis of the considerations as mentioned above, we propose a system to solve these problems. Figure 3 shows the positional relation of a moving vehicle, oncoming vehicles, and a cause of traffic congestion.

The proposed system needs to perform the following functions.

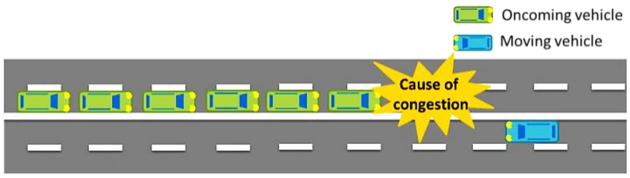


Figure 3: The positional relation between vehicles and the cause of congestion

A) Detect vehicles in an oncoming lane
B) Estimate the speed of oncoming vehicles
C) Detect traffic congestion
D) Find images representing the causes of traffic congestion
E) Estimate the range of traffic congestion

Figure 4 shows an overview of the proposed system. First, a driver mounts a smartphone on the dashboard and the smartphone records the front view of an oncoming lane. At the same time, the speed of the moving vehicle is acquired by a GPS sensor. Second, the system generates the optical flows between two images recorded by the smartphone. In addition, the system calculates the LOF of each relative speed and stores the dataset of LOF and the relative speed in the Optical Flow Length Database (Optical Flow Length DB). Third, the system defines an interpolation function by using the dataset in the database to calculate the relative speed from LOFs that are not stored in the database. Fourth, the system estimates the speed of oncoming vehicles by using the newly calculated LOF and the function. The system decides that congestion is occurring in an oncoming lane if the estimated speed falls below the specified threshold. At the same time, the system generates an image representing the cause of the congestion by searching for an image recorded at the beginning of the congestion. Finally, the system generates the range of the congestion by using location information from the beginning and ending point of the congestion, and presents the image and the range on a map application.

4.2 The Way to Calculate Optical Flows

In this section, we explain how to calculate optical flows of oncoming vehicles in in-vehicle camera images. There are two general ways to calculate optical flows called Phase Correlation and Block Matching Method [12, 13]. Phase Correlation is a method that calculates optical flows using a contrast equation of luminance gradient with constraint conditions. Phase Correlation can calculate optical flows, but it makes errors and is especially affected by rapid luminance changes. Block Matching Method is a method that uses a particular part of an image as a template, and calculates optical flows by exploring the parts that fit the template in the next time image. It can calculate optical flows steadily, but it is more computationally expensive than Phase Correlation. In addition, Block Matching Method depends on the size and the features of the block in an image when optical flows are calculated considering the rotation and scaling of an image.

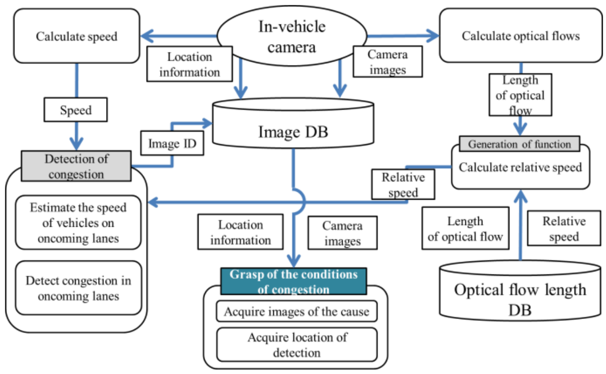


Figure 4: An overview of the proposed system

Figure 5: Optical flows drawn by LK method

In this study, vehicles and other objects in an oncoming lane are enlarged in the image because they are recorded by a moving vehicle on an opposite lane. Therefore, in this study, Block Matching Method is not appropriate to calculate optical flows. Our system uses the LK (Lucas-Kanade) method that is classified into Phase Correlation and calculates optical flows by detecting feature points of an image in order to reduce the errors of rapid luminance changes (Fig. 5).

However, in outdoor environment, it is difficult to diminish all noises caused by rapid luminance changes even with the use of the LK method. So the extraordinary optical flows are generated by these noises. Therefore, the proposed method sets thresholds for the length and the angle of the flows, and diminishes the flows that are out of the ranges decided by the thresholds. As a result, the extraordinary flows caused by the false detection of feature points are diminished.

4.3 Grasping the Conditions of Congestion

In order to grasp the conditions of congestion, the system uses two databases. One is an Image Database (Image DB) that stores recorded images and location information, and the other is an Optical Flow Length Database (Optical Flow Length DB) that stores LOF and the corresponding relative speed. Optical Flow Length DB is used to detect oncoming vehicles and to estimate the speed of oncoming vehicles. Table 2 and Table 3 show the structure of each database.

4.3.1 Detecting Vehicles , Estimating the Speed of Oncoming Vehicles

When optical flows are generated from objects in an oncoming lane in images, the flows generated outside the zone of an oncoming lane are unnecessary. Therefore, we define a region of interest (ROI) so that the oncoming

Table 2: The table structure of Image DB

Attribute Name	Detail
ID	Identification number of images
Image	Recorded image
Lat	Latitude of recording location
Lon	Longitude of recording location

Table 3: The table structure of Optical Flow Length DB

Attribute Name	Detail
R_{speed}	Relative speed between a moving vehicle and an oncoming vehicle
Len	LOF generated from oncoming vehicles

vehicles fit into the region in an image (Fig. 6), and optical flows are generated from the objects in the ROI.

The speed of the moving vehicle is calculated by using location information acquired by a GPS sensor of a smartphone when a driver drives the vehicle. We define the value representing the speed of the moving vehicle as M_{speed}, and the speed of oncoming vehicles as O_{speed}. Then the relative speed R_{speed} is calculated using formula (1).

$$R_{speed} = M_{speed} + O_{speed} \tag{1}$$

As this study considers grasping the speed on general roads, the ranges of M_{speed} and O_{speed} are as follows:

$$0 \leqq M_{speed} \leqq 60 \tag{2}$$

$$0 \leqq O_{speed} \leqq 60 \tag{3}$$

Then the range of R_{speed} is as follows:

$$0 \leqq R_{speed} \leqq 120 \tag{4}$$

The relative speed is acquired from the Optical Flow Length DB by querying the database with the LOF newly calculated from images. The system estimates the speed of oncoming vehicles by subtracting the speed of the moving vehicle from the relative speed.

However, the relative speed corresponding to the LOF specified in a query might not be stored in the database because the relative speed is continuous, not discrete. The system provides an interpolation function by using LOFs stored in the database. Then the relative speed corresponding to any LOF can be calculated by using the function. The interpolated value is returned as a relative speed when LOF that is not stored in the database is given to the function as an argument.

As we described previously, LOFs fluctuate according to the distance between an in-vehicle camera and an oncoming vehicle, the relative speed, the speed of the moving vehicle, and the speed of an oncoming vehicle. The distance between the in-vehicle camera and oncoming vehicles is shorter than that between the camera and objects behind oncoming vehicles. Therefore, the LOF generated from oncoming vehicles is longer than that generated from background objects by the vehicle's moving. Consequently, the speed of

Figure 6: ROI of generating optical flows

the moving vehicle is higher than interpolated relative speed. In this way the system can distinguish oncoming vehicles from background objects and detect oncoming vehicles.

4.3.2 Detecting Traffic Congestion

The causes of traffic congestion are detected considering estimated the speed of oncoming vehicles (SOV). The LOF is calculated, and SOV is estimated for each image when the system detects oncoming vehicles. According to the VICS's classification of traffic congestion, the speed of vehicles in a congested public highway is 10 [km/h]. Therefore, the system judges the location of congestion to be a location in which SOV is continually estimated to be less than 10 [km/h]. At the same time, the image of where congestion begins is a few images before that of the location where an oncoming vehicle is detected at the beginning. In addition, the system considers a location where the SOV is continually estimated to be less than 0 [km/h] or more than 10 [km/h] as the end of the congestion. At this time, IDs of images taken at the beginning and ending point of traffic congestion are saved. The system queries the Image DB with the saved IDs, and acquires the location information of the beginning and ending point of the congestion and an image representing the cause of the congestion.

5 EXPERIMENT AND DISCUSSION

5.1 Experiment Environment

In order to evaluate the effectiveness of our proposed method, we conducted two experiments. First, we conducted an experiment for determining the statistical value of optical flows stored in the Optical Flow Length DB. In addition, we conducted an experiment for evaluating the accuracy of SOV estimation for detecting the traffic congestion in an oncoming lane by using videos recorded in the actual environment.

5.2 Experiment for Evaluation

To generate optical flows and to estimate SOV, we implemented a program with OpenCV libraries. The program reads images, generates optical flows between two successive images, and draws the optical flows onto output images. To calculate optical flows, we used "cvGoodFeaturesToTrack" method which finds the most prominent corners in the image in OpenCV libraries. To calculate optical flows, we used "cvCalcOpticalFowPryLK" method which is an iterative Lucas-Kanade method using an image pyramid. A vehicle is equipped with an iPhone 3GS placed on the dashboard with a cellular phone cradle, to record video as the vehicle moves. We call this vehicle a 'recording vehicle'. The resolution of videos recorded by the iPhone 3GS is 640×480 pixels, and the frame rate of the videos is 30 [fps]. The rectangular ROI sized 430×210 pixels is placed at the bottom right of images so that oncoming vehicles fit into the ROI, and optical flows are generated within the ROI. To grasp the speed of the recording vehicle, we used the GPS sensor of an iPhone 5 and implemented an iOS application that calculates the speed of the recording vehicle by acquiring location information. To estimate the SOV, we defined three dimensions spline function as an interpolation function by using the dataset of the relative speed and LOF stored in the Optical Flow Length DB. The system gives the spline function with LOF as an argument, and acquires the relative speed. Then the system calculates SOV by subtracting the speed of the recording vehicle from that of the relative speed. In the experiment to determine parameters, four parked oncoming vehicles made congestion on a single lane. In addition, the distance between the vehicles is changed because the distance in actual traffic congestion is non-constant. The driver drove the recording vehicle and past the four parked vehicles five times at different speeds each the inter-vehicular distance, while the iPhone 3GS recorded the oncoming vehicles. Relative speed was equivalent to the speed of the recording vehicle because the oncoming vehicles were parked. We examined parameters such as the time interval between two successive images and the statistical value of LOF for generating optical flows considering the 15 recorded videos. In addition, we defined the interpolation function with parameters derived from the results of the preliminary experiment and the datasets of relative speed and LOF in the database. We considered estimation accuracy with the interpolation function.

5.2.1 Deciding Parameters for Generating LOF

We describe the result of the determination of parameters for generating LOF. Determined parameters are the time interval between two images in the video (*Interval*), and the statistical values of LOF (*Len*) stored in the Optical Flow Length DB. Table 4 shows *Interval* and *Len* considered in this experiment.

The LOF generated in an image is counted, and *Len* is calculated. The values of Interval are 2, 3, 4, and 8. Interval between successive images is 1 when a video is divided into multiple images. For example, if *Interval* is 2, LOF is generated between the nth image and (n+2)th image. It is desirable that *Len* increases in proportion to increasing of the relative speed and the degree of increase of *Len* is large. LOF is acquired when a recording vehicle passes beside the lead oncoming vehicle. Figure 7 shows the environment of the preliminary experiment.

Figure 8, 9, 10, and 11 show the changes of *Len* for each *Interval*. The graph (a), (b) and (c) in each figure show *Dist* = 2, 4 and 6 [m] respectively. *Dist* means the distance

Figure 7: The environment of the preliminary experiment

Table 4: *Interval* and *Len* considered in this experiment

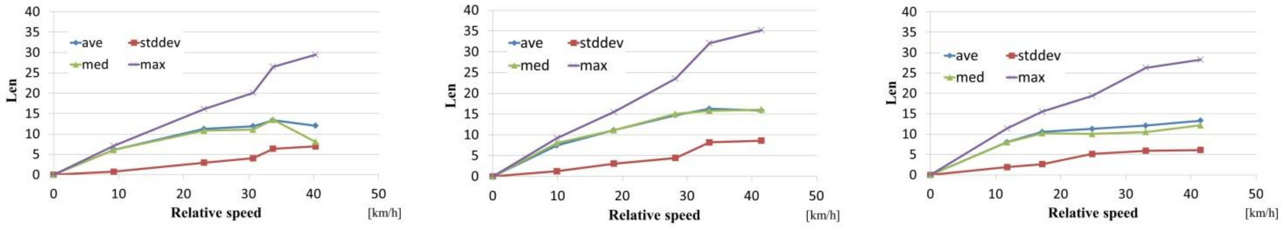
The statistical values of LOF (*Len*)	The time interval between two images (*Interval*)
Average (*ave*) Variance (*var*) Standard deviation (*stddev*) Median (*med*) Maximum (*max*)	2,3,4,8

between two vehicles in an oncoming lane. Selecting *Len* in the same relative speed that has the same value on different *Dist* is desirable because the distance of two vehicles is not constant in actual environment. In Fig. 8, 9, 10 and 11, blue line shows average *(ave*), red line shows standard deviation (*stddev*), green line shows median (*med*), and purple line shows maximum (*max*). But these figures do not include variance (*var*) because *var* is larger than the other *Len*.

In Fig. 11, *Len* in *Interval* = 8 does not increase monotonically depending on the increase of the relative speed. We suppose that the movement of objects between two images is too large in *Interval* = 8, and the feature points detected in a previous image may disappear in the next image, causing extraordinary LOF to be generated. Consequently, *Len* in *Interval* = 8 is not appropriate to generate optical flows.

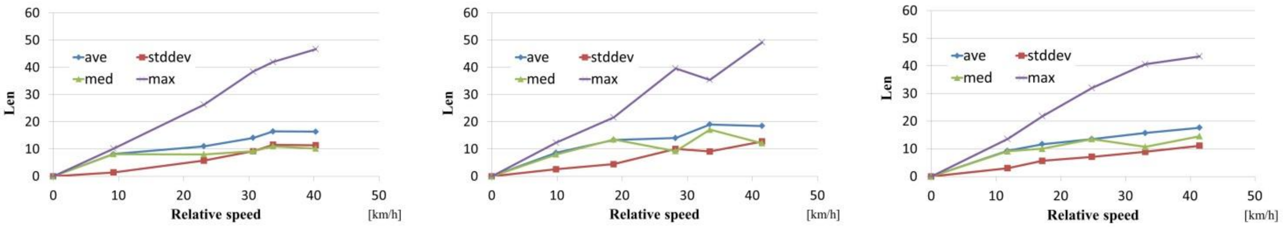
Figure 12 shows the changes of variance (*var*) each *Interval*. In Fig. 12, blue line shows *Interval* = 2, red line shows *Interval* = 3, green line shows *Interval* = 4, and purple line shows *Interval* = 8. *var* fluctuates widely in *Interval* = 3 and 4 shown in Fig. 12. In *Interval* = 2, *var* in the same relative speed are different in each the distance between oncoming vehicles. In addition, standard deviation (*stddev*) is similar to Fig 12. We suppose that *var* and *stddev* are influenced greatly by the false detection of feature points. Therefore, variance and standard deviation are not appropriate to *Len*.

In *Interval* = 2, average (*ave*) and median (*med*) stand still regardless of the increase of the relative speed. In addition, maximum (*max*) increases depending on the increase of the relative speed, and the increased amount of it is small. We suppose that estimating SOV becomes susceptible to the noises of calculating optical flows if increased amount of LOF is small. In *Interval* = 3, *ave*, *med* and *max* increase depending on the increase of the relative speed, and the increased amount of *ave* and *med* are small. In addition, *max* increases with limited influence of the inter-vehicular distance. In *Interval* = 4, *ave* and *max* increase depending on the increase of the relative speed along with Fig. 11, and the increased amount of *ave* is small. *Max* in the same relative speed is different in each inter-vehicular distance, and *med* fluctuates as the relative speed increases.



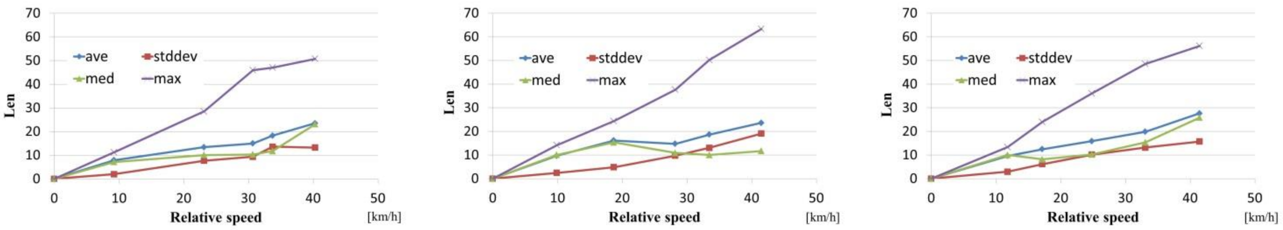
(a) *Dist* = 2 [m] (b) *Dist* = 4 [m] (c) *Dist* = 6 [m]

Figure 8: The changes of *Len* in *Interval* = 2



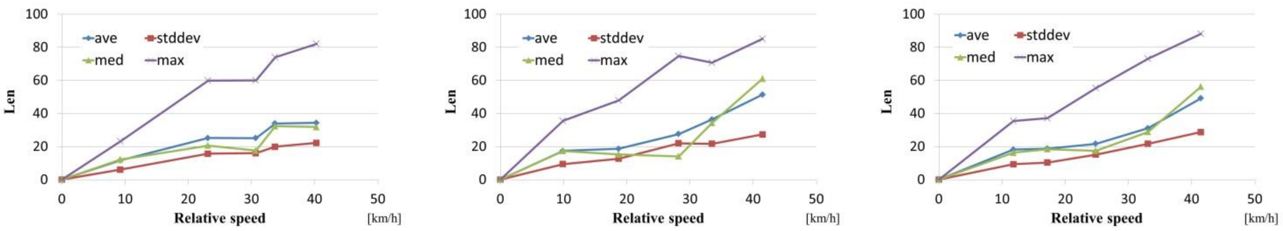
(a) *Dist* = 2 [m] (b) *Dist* = 4 [m] (c) *Dist* = 6 [m]

Figure 9: The changes of *Len* in *Interval* = 3



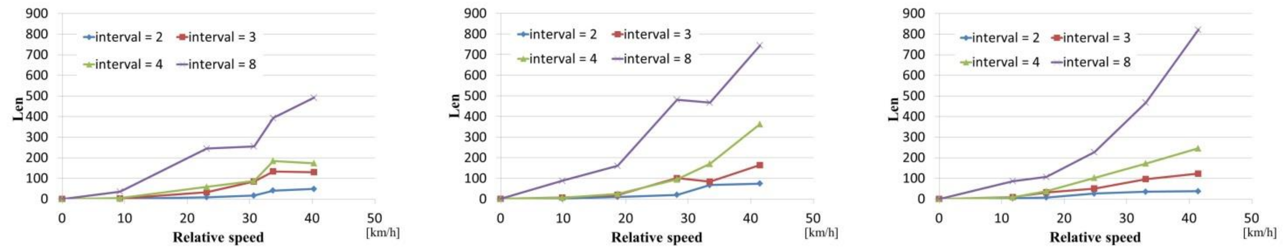
(a) *Dist* = 2 [m] (b) *Dist* = 4 [m] (c) *Dist* = 6 [m]

Figure 10: The changes of *Len* in *Interval* = 4



(a) *Dist* = 2 [m] (b) *Dist* = 4 [m] (c) *Dist* = 6 [m]

Figure 11: The changes of *Len* in *Interval* = 8



(a) *Dist* = 2 [m] (b) *Dist* = 4 [m] (c) *Dist* = 6 [m]

Figure 12: The changes of *Len* (*var*) in each distance

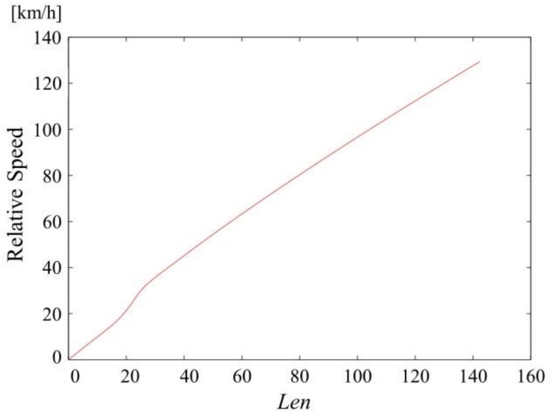


Figure 13: The interpolation function

From these results we can deduce that maximum is appropriate to a statistic of LOF stored in the Optical Flow Length DB (*Len*). In addition, *Interval* = 3 is the candidate parameters for an estimation of SOV experiment. We made the interpolation function by using the dataset of relative speed and LOF acquired through this experiment. However, relative speed does not necessarily increase depending on the increase of *Len*. We suppose that *Len* is influenced by extraordinary LOF results caused by false detection of feature points. They are generated because the vehicle only once drives passing besides the oncoming vehicles at each speed. Therefore, we redefined the function after removing conflicted data and averaging neighbor data with near values.

Figure 13 shows the interpolation function by using maximum in *Interval* = 3 and the relative speed.

5.2.2 Estimation Accuracy

We evaluated the accuracy of SOV estimation by using datasets of *Len* and relative speed determined in the preliminary experiment. For this evaluation, in the same conditions as the preliminary experiment, a recording vehicle moves in the driving lane at 40 [km/h]. At the same time, oncoming vehicles are parked or moving slowly. The recorded video is divided into multiple images. We defined the interpolation function by using the datasets in Optical Flow Length DB. LOF generated from objects in an oncoming lane is given to the function as an argument. Then relative speed (R_{speed}) is calculated by the function according to the formula (1). SOV (O_{speed}) is calculated according to the formula (2). Figure 14 shows the results of estimation.

In Fig. 14, there are points at which SOV gets near to or surpasses 10 [km/h] with time. These speeds are estimated when the recording vehicle passes beside oncoming vehicles, as in Fig. 15(a). At other points, SOV is less than 0 [km/h]. These speeds are estimated until the recording vehicle passes beside the next vehicle shown in Fig. 15(b).

In addition, we found some factors that increase the estimated speed rapidly through this experiment. We suppose that the extraordinary flows generated by false detection of feature points (shown in Fig. 16) cause the rapid increase of the estimated speed. Figure 16(a) shows that optical flows are generated from background objects and Fig. 16(b) shows that the flows are generated from objects on road except oncoming vehicles. We discuss how the false detection influences the estimated speed in Section 5.2.3.

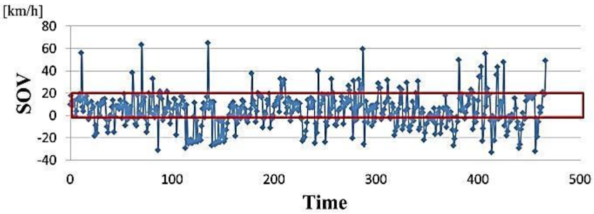


Figure 14: The results of estimation

(a) passing beside an oncoming vehicle
O_{speed} = 12.4
(*Len* = 54.74)

(b) passing beside the next oncoming vehicle
O_{speed} = -13.8
(*Len* = 26.47)

Figure 15: Changes in *Len* and estimated SOV in images

(a) flows generated from background objects

(b) flows generated from other objects

Figure 16: Extraordinary flows generated by false detection of feature points

5.2.3 Discussion of Experiment Results

In this section, we discuss the results of the above experiments. In the experiment to determine parameters, we confirmed that the maximum of LOF is appropriate to generation of optical flows. In addition, we confirmed that the maximum of LOF in *Interval* = 3 increases depending on the increase of the relative speed. However, we confirmed that LOF decreases despite the increase of the relative speed at certain points in each *Interval*. Moreover, we suppose that LOF is calculated accurately by diminishing the false detection of feature points, and the interpolation function that LOF increases depending on increasing of the relative speed can be defined. To diminish the noises of false detection of feature points, we consider the change of the size and position of the ROI and the change of parameters such as the number of detection of feature points. Then, the interpolation function can be defined accurately.

Through evaluating the accuracy of SOV estimation, we confirmed that SOV is estimated near 10 [km/h] when the recording vehicle passes beside oncoming vehicles. In addition, we confirmed that SOV less than 0 [km/h] is continually estimated until the recording vehicle begins passing beside the next oncoming vehicle. We suppose that the reason that LOF remains short is due to the following steps. First, an oncoming vehicle which the recording vehicle passes by slips from an image. Second, feature

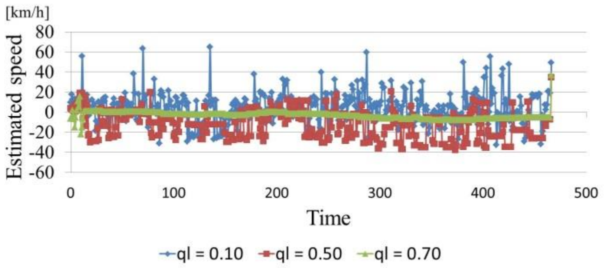


Figure 17: The estimation result in each *ql*

points generated on the oncoming vehicle are insufficient. Finally, feature points are generated anew on the next oncoming vehicle. We noticed certain points at which SOV is less than 0 [km/h] even though the recording vehicle is passing beside an oncoming vehicle. As we have discussed previously in the definition of parameters experiment, the system can estimate the SOV more accurately when processes to define a more accurate interpolation function are applied to the system.

As we explained in Section 5.2, we use "cvGoodFeaturesToTrack" method in the OpenCV library in order to generate optical flows. This method is used for corner detection, and it has the threshold (*ql*) as one of the arguments. *ql* is used to make a judgment on accepting the detected point as corner. When *ql* is larger, sharper feature points are accepted as corner. We examined how the change of *ql* affects the SOV. Figure 17 shows the estimation result in *ql* = 0.10, 0.50 and 0.70.

According to Fig.17, the fluctuation of the estimated speed is larger as *ql* decreases. We suppose that when *ql* is small, the vague feature points are detected as corner and extraordinary flows are generated. In *ql* = 0.70, most of the estimated results are plotted near 0 [km/h], but some of the estimated results are not under 0 [km/h] when oncoming vehicles are not in the image. We suppose that the correct feature points are diminished by increasing *ql*. In the future, we need to consider how to determine the adequate value of *ql*.

The experimental results suggested that the estimated speed changes when a recording vehicle passes by oncoming vehicles. Consequently, detecting the congestion in an oncoming lane will be realized by our method that estimates the speed of oncoming vehicles by using an in-vehicle camera.

6 CONCLUSION

This study aims to detect traffic congestion in an oncoming lane and to present images representing the causes of the congestion using an in-vehicle camera. We proposed a method that estimates the speed of oncoming vehicles using an in-vehicle camera to detect traffic congestion. In addition, we conducted the experiment for estimating the speed and we estimated the speed of oncoming vehicles by using our proposed method. In particular, we suggested that the length of optical flows changes depending on the speed of oncoming vehicles (SOV) and the proposed method based on optical flow is potential to detect the traffic congestion in an oncoming lane. Our method will realize detecting traffic congestion in an oncoming lane based on the results of estimating oncoming vehicles. Consequently, drivers can grasp the causes of the congestion intuitively by images acquired from the results of detecting congestion.

In the future, to improve the accuracy of detection of traffic congestion in an oncoming lane, we will prepare more datasets of LOF and the relative speed. Moreover, we will consider a method for detecting congestion on four-lane roads and divided roads. Our method is only applicable for single lane road. For example, in the case of four-lane roads, LOF generated by oncoming vehicles in each lane is different. In addition, optical flows in divided roads are generated from the median. We will define interpolation functions corresponding to multiple-lane roads and divided roads to improve our method.

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