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Vision-based Vehicle Forward Collision Warning System Using Optical Flow Algorithm

Jeng-Shyang Pan[1,2], Sen Ma[2], Shi-Huang Chen[3],Chun-Sheng Yang[2]

[1]Fujian University of Technology, China
[2]Harbin Institute of Technology, ShenZhen Graduate School, China
[3]Department of Computer Science and Information Engineering
Shu-Te University, Kaohsiung City, 824, Taiwan
jengshyangpan@gmail.com, enmasen@foxmail.com, shchen@stu.edu.tw,starissim@gmail.com

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Abstract. *This paper proposed a vision optical flow based vehicle forward collision warning system for intelligent vehicle highway applications. The system captures the image sequences of front of a vehicle from a driver recorder mounted in the front windscreen. The judgment of vehicle in the front collision warning area is carried out using computer vision techniques, including optical flow algorithm and time-to-contact (TTC) concept. Furthermore, the system could actively warn the front vehicle of the rear vehicle approaching via dedicated short range communications (DSRC). Experimental results show that the proposed system can alert drivers before collision, and therefore increase the highway traffic safety.*
Keywords: Front collision warning, Optical flow, Dedicated short range communications (DSRC), Time-to-contact (TTC).

1. **Introduction.** Recently, with the rapid development of global economy, the number of personal vehicle increased significantly. Traffic safety problem has become key issues for the vehicle auxiliary driving priority. According to the United Nations statistical data, the number of people death in traffic accidents is more than 1 million every year over the world. Among these traffic accidents, 78% of the driving vehicle collisions and 65% of near collisions are caused by driver in-attentions [1]. Mercedes-Benz Company also shows that if the driver can notice the danger one second in advance, 90% of vehicle collision accidents could be avoided [2]. Because most vehicles are in high speed situation, the traffic accidents happened on highway are generally more serious than that on urban road. Therefore the reduction of traffic accidents has become important topics in highway safety. With the aim of reducing highway accident severity, numerous inventions and improvements concerning the active and passive safety of vehicles are developed. The active vehicle safety approaches make use of active sensors, such as lasers, radar, sonar, or millimeter-wave radar, to detect vehicle. These active sensors could detect the distance between own vehicle and target vehicle by measuring the travel time of the signal emitted by the sensors and reflected by the target vehicle. On the other hand, the passive vehicle safety approaches make use of passive sensors, such as cameras. The reason that cameras are referred to as passive sensors is they acquire data in a non-intrusive way [3, 4].

The main advantage of active vehicle safety approaches is they can measure distance directly [5]. However, active sensors have several drawbacks, such as low spatial resolution and slow scanning speed. Moreover, when a large number of vehicles are moving simultaneously in the same direction, interference among sensors will become a big problem. In comparison with active approaches, the primary advantage of passive approaches is their ability to provide diverse information on relatively large regions and the passive sensors have lower cost.

Many people have investigated explicitly using passive camera sensors for vehicle collision warning and detection. Jing-Fu Liu [6] and Chiung-Yao Fang [7] described methods with road line and environmental information for vehicle collision detection. Naveen Onkarappa [8] proposed an optical flow method to perform object recognition and that method could adapt to advanced driver assistance systems (ADAS). Elisa Mart Nez [9] proposed a system using optical flow combined with time-to-contact (TTC) for front vehicle collision detection. However, the method Elisa proposed lacks the function of object recognition and may affect the performance in real road applications.

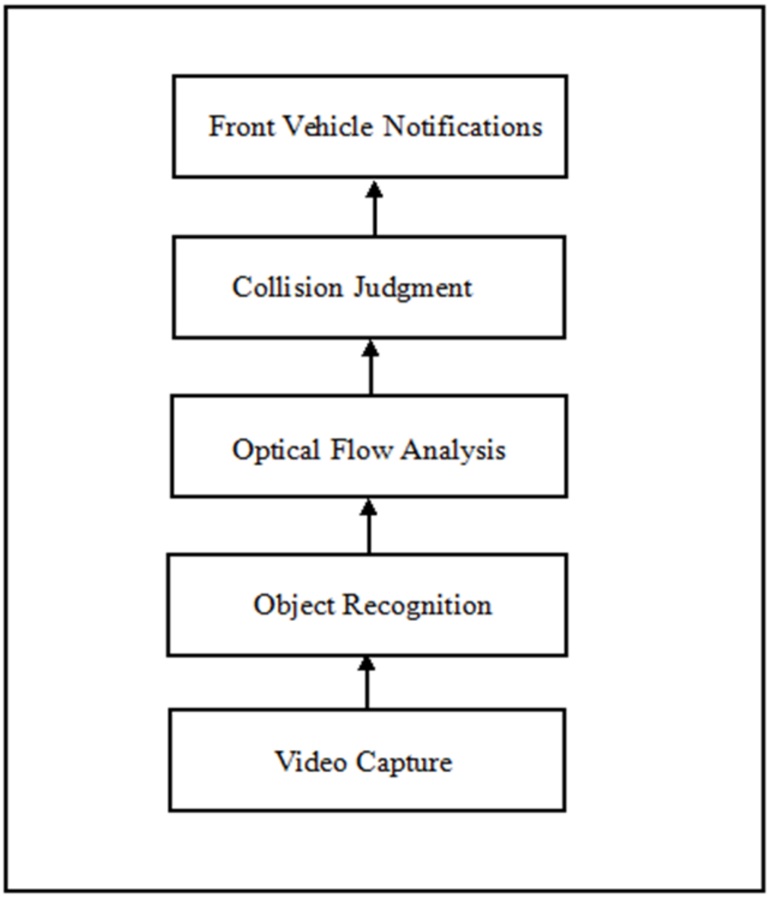


Figure 1. The flowchart of the proposed vehicle collision warning system

In this paper, the vision-based optical flow algorithm and TTC are cooperated to develop a new front vehicle collision warning system for vehicle-highway applications. The proposed system could recognize the moving intention of the front vehicle. In critical situation, the proposed system could actively warn the front vehicle of the rear vehicle approaching via dedicated short range communications (DSRC). Figure 1 shows the flowchart of the proposed system. It has five phases; they are (1) video capture, (2) object recognition, (3) optical flow analysis, (4) collision judgment, and (5) front vehicle notifications. In the following sections, the system flowchart of the proposed front vehicle collision warning system is described in detail. Experimental results show that the proposed system can alert drivers before collision and therefore increase the highway traffic safety.

The rest of this paper is organized as follows: Section II introduces the proposed system architecture and evaluation results. Sections III presents the experimental results of the proposed system. Finally Section IV concludes remarks.

2. System flowchart.

2.1. Video capture. The system will obtain the image sequences of front of a vehicle from a driver recorder mounted in the front windscreen. The video code of the driver recorder is based on H.264 standards. The encoded image frame size is 512 288 and the frame rate is 15 frame/sec. Figure 2 is the real image sequence captured from highway. To increase the processing speed, the proposed system will execute the image processes in

FIGURE 2. The real image sequence captured from highway

gray level. Hence each captured image frame has to perform gray-scale conversion first. Then the proposed system will remove areas of not interest. As shown in Figure 3(a), the image is divided into two parts. The upper part in the image is not interested and hence is removed. On the contrary, the lower part contains vehicle object and therefore is remained. Usually the lower part is in the exact position of the capture.

2.2. Object recognition. The proposed system is based on a dynamic prospect identification using optical flow algorithm. The idea goal is the system could real-time and accurate identification a part of moving vehicle object. This phase has to quickly calculate the amount as well as the area of the front vehicle objects.

Some method is through the inherent characteristics of vehicle, such as symmetry, color, shadow [4] to identify the all vehicles. In this way, there are some disadvantages like calculating speed slowly, less accuracy, and less stability degree. Because pixel has similar movement in an object, we only need a part of the object as the representative [21].

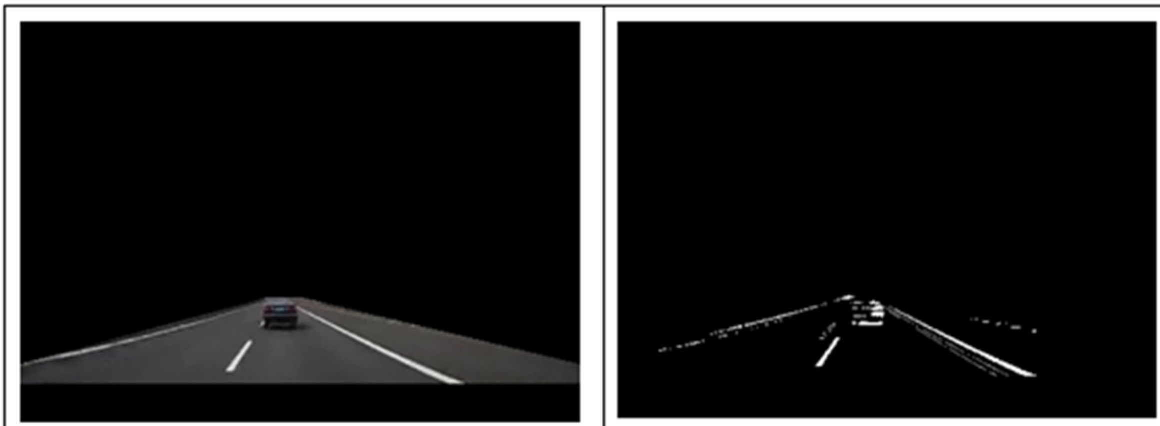
To meet this requirement, some proposed methods [9] only use optical flow algorithm to identify objects. The main advantage of such methods is the processing speed can be greatly increased, but will lose convergence effect. It will not only fail to achieve the expected value, but will influence the measurement of distance. The proposed system makes use of convolution method with background modeling to extract the relative value, and then to represent the front vehicle objects. However, the traditional background modeling has some disadvantages, e.g., complex calculation and poor robustness of scene change. Due to the highway scene change is rapid, these disadvantages will not degrade the computation time of the object recognition.

To overcome above problem, this paper uses the difference frame method as motion object analysis method to processing captured images. The main advantage of the difference frame method is that it has well performance of recognizing moving objects.

Following equation is the calculation formula of the difference frame method used in this paper.

$$|i(t_1) - i(t_2)| \cap |i(t_3) - i(t_2)| \tag{1}$$

where i(t) is the image frame at time t,t3 is the middle of t1 and t2. Figure 3(b) is the simulation result of the difference frame method. Compared to the conventional background methods, difference frame method does not require modeling and therefore its operation speed is very fast. In addition, it is not very sensitive to slow light.



(a)Select region of interest | **(b)Frame-difference method to find the need objects**

Figure 3. The simulation result of the difference frame method

The difference frame method will calculate the moving quantity from two successive frames. In this paper, the moving quantity of the vehicle object depends on the frame interval of the captured image sequence. The longer length of the frame interval between two frames will obtain the better performance, and vice versa. However, the longer length of the frame interval will also lead to longer computation time. Here a feedback adjustment procedure is introduced to determine the optimal frame interval. First, the program sets up a real-time queue of images queue. Two parameters, i.e., the first static parameter and the second static parameter, are determined in this paper. The first static parameter is 9(the interval of the i(t) video frame and the i(t +9) video frame). The second static parameter is 5(the interval of the i(t +9) video frame and the i(t +14) video frame). Then the next phase optical flow analysis will compare the results of these two parameters.

If a recognized object suddenly lost, then the proposed system will adjust the first static parameter. If clustering class suddenly increase, the proposed system will adjust the second static parameter. The moving quantity calculated by the difference frame method can be expressed in a difference matrix form. The procedure sets two functions below pseudo-code. The first function is responsible for statistics number of moving object and traverses the entire picture. The second function is referred as called function. This called function is responsible for fuzzy matches in a point near the connected area. The implementation of this function is in the area around the point to count sum. Final the called function can be determined to represent the number of moving objects. The number of moving objects then can be used in the next stage of optical flow clustering analysis method.

```
Program doConnectScope
Input   Select image, mark Image;
Output  Connect scope num;

Traverse Image and Call Function doGrowGrayPoint and count Call num;
Return Num;
```

```
Program doGrowGrayPoint
Input   Select Image, mark Image, a point position in Image;
Output  Change in mark Image;

If the input image and point isn`t require
  Then return -1;
End
Achieve information from input;
Set a square range around the input point;
If range is over boundary
  Then return -1;
End
Dim sum as Double;
Sum is the sum of range;
If Sum < sumthres
  Then The point is lonely point and Ignore the point.
    If Sum is too bigger
      Then adjust summax and sumthres;
    End
End
If Sum>summax
  Then Adjust summax and sumthres;
End
Dim A as Stack;
The point push the stack A;
While(A!=empty)
Pop a point;
  For check the range(before set) of the point
    If there is a point can ' t ignore
      Then Ignore it and push in Stack;
    End
End
  Return 0;
  End
```

The location as well as amount of vehicle objects could be derived from the preselect region matrix by the threshold operation and above connected area calculation. The region that contains a part of vehicle object is called vehicle block.

2.3. **Optical flow analysis.** The first step of optical flow analysis is to select angular points from the vehicle blocks. Here the angular point is defined as the point has derivatives in two orthogonal directions. Figure 4 shows the characteristics of angular point and non-angular point. It is obvious that the angular point is unique and distinguishable, whereas the location of non-angular point is uncertain.

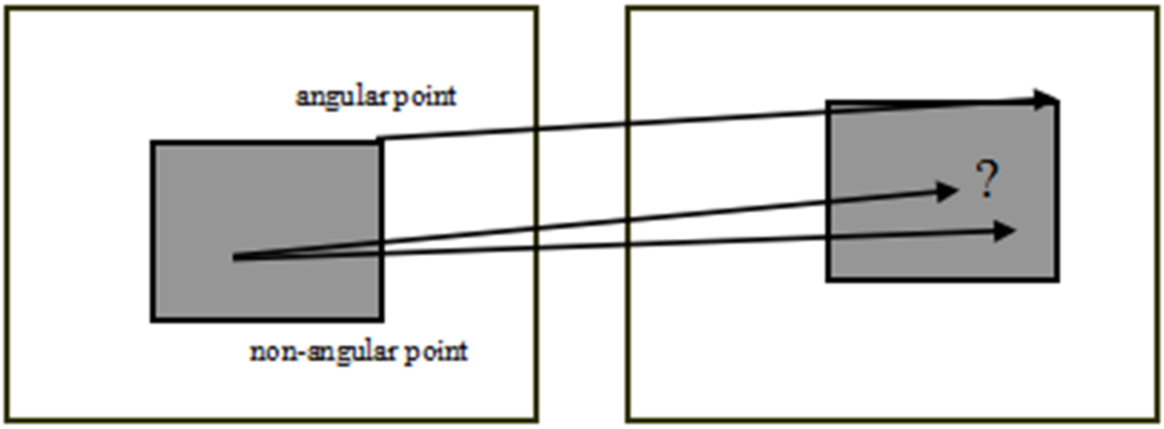


FIGURE 4. The characteristics of angular point and non-angular point

Several methods have been proposed to detect the angular point. For real-time calculation consideration, this paper uses Harris [10] corner detection algorithm. Harris algorithm has many advantages. For example, it is rotation invariable and is partial invariable for affine changes of image gray level. In addition, its calculation is relatively simple.

Figure 5 shows the calculated angular points by the use of Harris algorithm. Once these angular points are calculated in the image, one can use these angular points to determine the moving intention of the vehicle object via optical flow analysis.

Optical flow analysis has been developed over 30 years. It is widely used in industrial, military, and UAVs [11,12,13]. This paper selects the pyramid Lucas and Kanada (LK) optical flow method [14] to determine the moving intention of the vehicle object. The LK optical flow method is based on the following three assumptions.

Brightness constancy: This is the basis of optical flow algorithm. It assumes that brightness does not change over a short period of time.

Continuous time: The transform of Image is comparatively slow. Due to the vehicle highway application may violate this assumption; this paper used a pyramid-based optical flow method [15] to overcome this problem.

Spatial coherence: In the same scene, the adjacent points on the same surface have similar moving behavior.

Above phase has selected the moving object on a roughly regional mask. Then one can find feature in regional mask using optical flow method and identify the correspondence between two images feature. Finally the proposed system uses optical trends to determine an object's behavior. Figure 6 shows the result of moving intention using optical flow analysis. It follows from Figure 6 that an object may contains several optical flows.

The optical flow computation of t and t + dt frames in an image sequence is equivalent to two pixels of the image matching process. One can assume that the corresponding

FIGURE 5. The calculated angular points by the use of Harris algorithm

FIGURE 6. The result of moving intention using optical flow analysis

pixel gray level in adjacent frames will not change. Then by the time derivative, one can obtain the basic formula of optical flow computation:

$$I(x, y, t) = I(x + dx, y + dy, t + dt) \tag{2}$$

where I(x, y, t) is the gray level at (x, y) coordinates in a image frame at time t. One can use Taylor series expansion:

$$f(x+dx, y+dy, t+dt) = f(x, y, t) + f_x dx + f_y dy + f_t dt + O\left(\partial^2\right) \tag{3}$$

If the values of dx, dy, dt are very small, then the higher order terms in (3) could be ignored. That is

$$-f_t = f_x \frac{dx}{dt} + f_y \frac{dy}{dt} \tag{4}$$

Then one can obtain the velocity vector:

$$v = (\frac{dx}{dt}, \frac{dy}{dt}) = (u, v) \tag{5}$$

where fx, fy, ft are computed from f(x, y, t). Generally, it is supposed that each object just has one optical flow to represent its moving intention. However, in practical applications, an object usually has several optical flows generated from the optical flow algorithm. These redundant optical flows will affect the result of the collision parameters calculation.

Figure 7. The evaluation result of the optical flows selection

This paper arranges all the optical flows using the intermediate values order by angle, and then to select one optical flow to represent its moving intention. After computation of optical flow in mask range, the proposed system knows moving object number. It can use the moving object number with optical flow position and angle to classify every class optical flow. It will refuse error of the optical flow in the class and then sort according to the angle. The representative optical flow is in the middle of the class. Figure 7 shows the evaluation result of the optical flows selection. Finally an optical flow can be represented the moving direction of the vehicle object. Figure 8 shows the optical flow result of a front vehicle object. This process will also filter out minor noises caused by static object.

2.4. **Collision judgment.** In step will utilize the optical flow information obtained in the previous step to calculate the impact collision parameters. These parameters can be used to analyze each vehicle object to be detected, and whether it becomes a threat to the self vehicle. The proposed system will first define the origin, which can fix reference position in the image frame. Generally, the midpoint of the bottom line will be selected as reference in different environment. The location information of a vehicle object is relative to its speed and direction. In addition, the time-to-contact (TTC) is considered

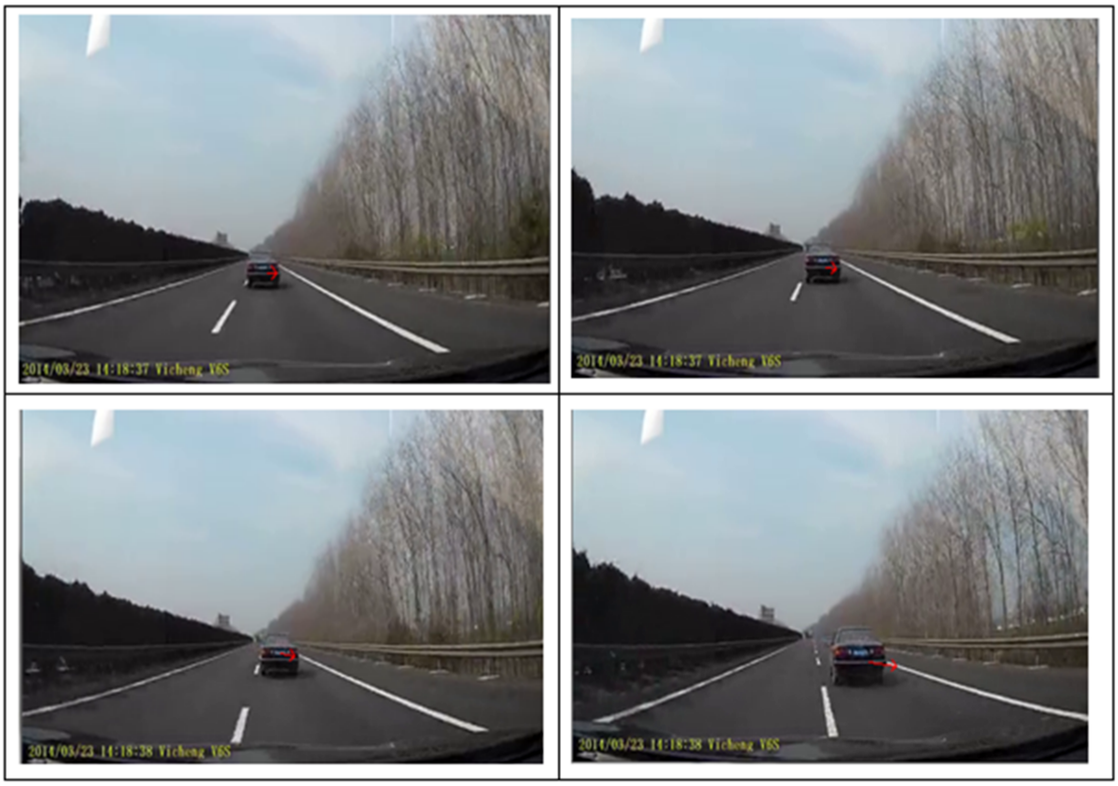


Figure 8. The optical flow result of a front vehicle object

to calculate potential collisions [16]. TTC is a collision event detection method. TTC is calculated from distance and relative speed between the target and self vehicles. That is

$$TTC = \frac{S(t)}{V(t)} \tag{6}$$

where S(t) and V(t) represents the distance and relative speed, respectively, between the target and self vehicles. However, in this paper, the vehicle distance and speed are captured from deriver recorder machine. Hence S(t) and V(t) may have some tolerances. To minimize the tolerances, this paper uses an aperture model to perform a corresponding transformation. Figure 9 illustrates the aperture model.

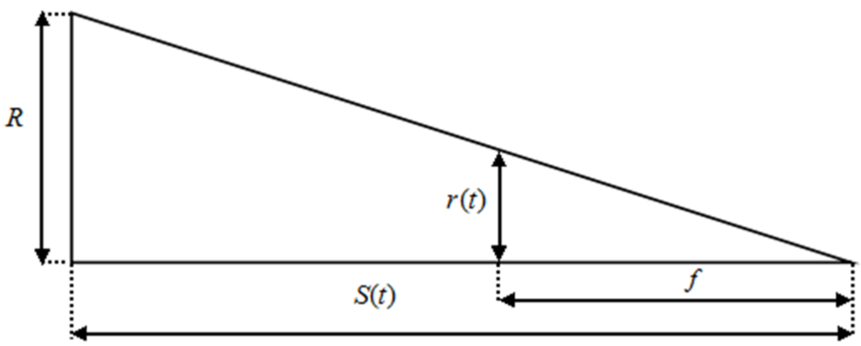


Figure 9. The aperture model

According to the proportional relationship, one has

$$\frac{S(t)}{f} = \frac{R}{r(t)} \tag{7}$$

Let f = 1, and by taking the time derivatives of (7), one obtain

$$V(t) = \frac{dS(t)}{dt} = R\frac{\frac{-dr(t)}{dt}}{r^2(t)} = -S(t)\frac{v(t)}{r(t)} \tag{8}$$

and get the result:

$$TTC = \frac{S(t)}{V(t)} = -\frac{r(t)}{v(t)} \tag{9}$$

where r(t) and v(t) can be calculated from the previous step. r(t) is the moving object safe distance with self vehicle. It can compute using above point of representative optical flow with midpoint of bottom line. v(t) is moving object speed. It can compute using above length of representative optical flow. Through such a transformation, the proposed system can use representative optical flow to compute actual threats. The proposed system then can describe the threats produced by the front vehicle objects using the calculated impact collision parameters of TTC. Finally the collision judgment will be completed by the threshold of impact collision parameters. In this paper, several parameters including the location of the object, the size of the optical flow, TTC value, and the direction of the optical flow, are used to judge the dangerous state of the vehicle. In the beginning of calculation, it needs a lot of fixed parameters, and these parameters can be obtained by machine learning or experience achievement. Then the run phase of the system can adjust itself by feedback information.

2.5. **Front vehicle notifications.** Once the proposed system found that there may be a danger, in addition to notify the driver of self vehicle, it also will send a dangerous approaching signal to the front vehicles via DSRC (dedicated short range communication device). DSRC mainly consists two parts. There are road RSU (Road Side Unit) and OBU (On-Board Unit). DSRC use wireless communication network to realize the signal communication between RSU and OBU. DSRC communication protocol is an important part and is a standard of Intelligent Transport System (ITS). It can provide high-speed wireless communications service for vehicle-to-vehicle (V2V) or vehicle-to-road side unit (V2R).

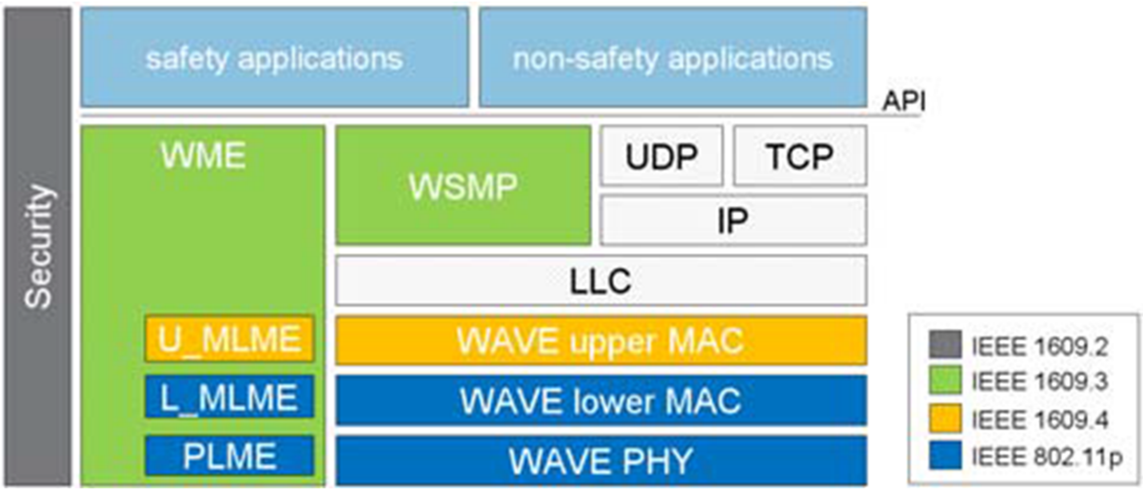


FIGURE 10. DSRC protocol architecture diagram [17]

Figure 10 gives the protocol architecture of DSRC[17]. There are main three part in this structure. They are Physical Layer, MAC, and higher application part. DSRC has many advantages, e.g., high transmission speed, small disturbance degree, as well as good security features. The proposed system could actively warn the front vehicle of the rear vehicle approaching via DSRC. The system can perform V2V or V2R communications for rear vehicle approaching warning. In this way, the system can compute for a wide range of decision and transfer the message passed to surrounding vehicles and reasonably solve traffic conflict. Figure 11 shows the DSRC simulation results of the proposed system. The left-up figure is the real road information and the corresponding road network is given in the right-up figure. The left-bottom figure demonstrates a dangerous situation that the rear vehicle is too close to the front. Then, the right-bottom figure illustrates the self vehicle will slow down and RSU will inform the front vehicle left a rear approaching warning message.

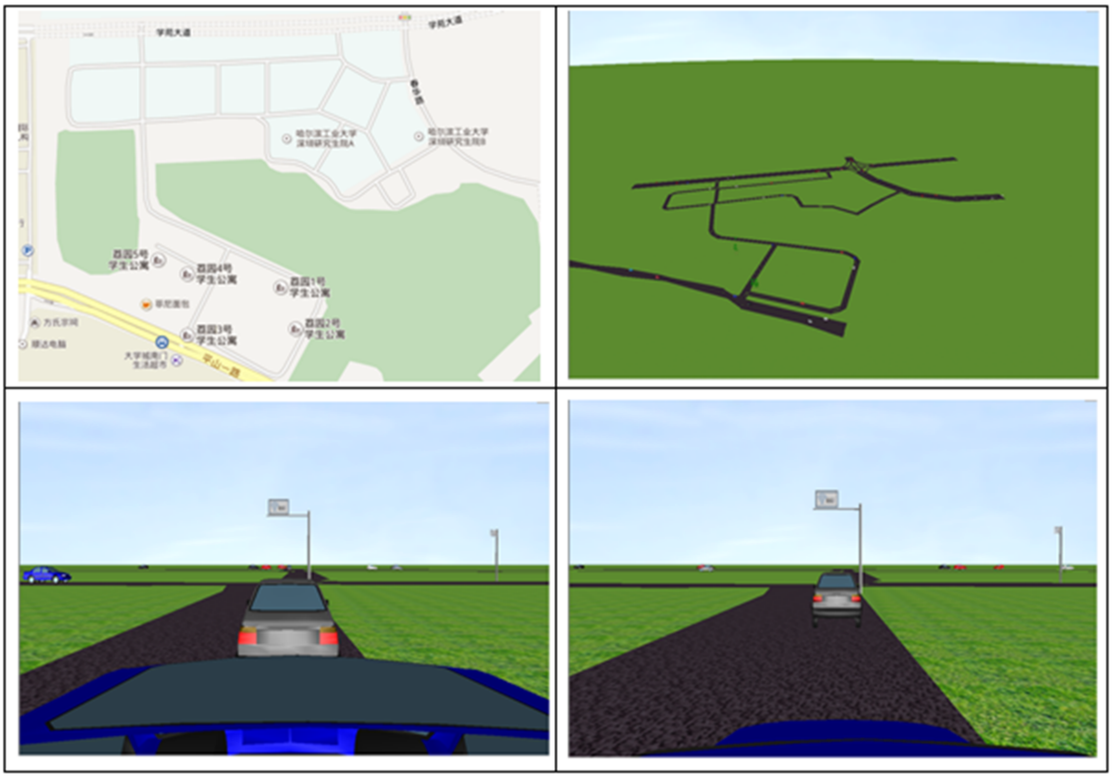


Figure 11. DSRC simulation results of the proposed system

3. **Experimental results.** The following experiments were done on a 3.10GHz CPU PC with 2GB RAM. The major parts of the proposed system are currently implemented in C. The experimental conditions include different weather conditions, e.g., daytime, nighttime, and rainy days. Figure 12 shows the experimental results of the proposed systems under different weather conditions.

Table 1 lists the computation times and the recognition rates of the proposed system under different weather conditions.

In actual highway situations, the number of front vehicle is usually not only one object. If the system recognizes two or more objects at the same time, the system will only need to consider the vehicle objects that have relative motion to the self vehicle.

It follows from Table 1 that the computation times of the proposed system remains within 1 sec, and the recognition rates are between 81.9% and 91.3%. The proposed

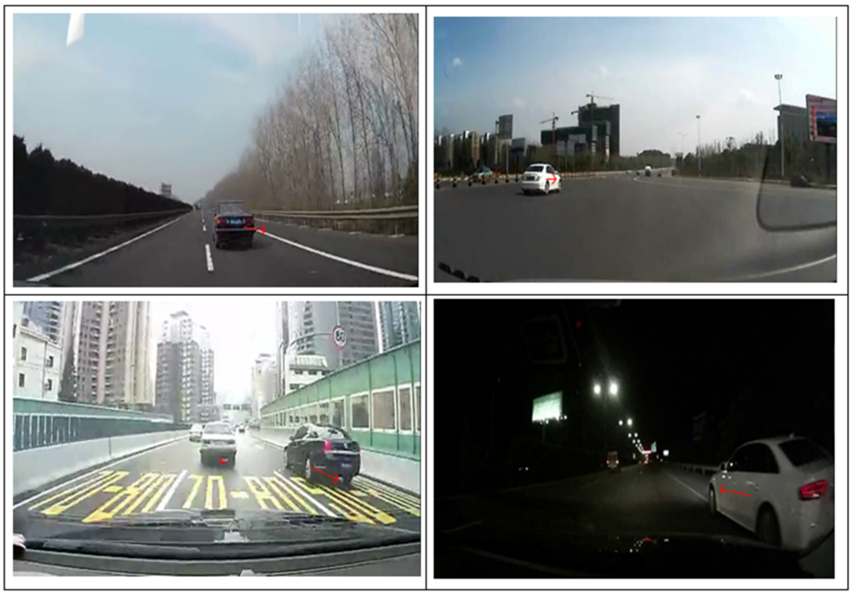


Figure 12. The experimental results of the proposed systems under different weather conditions

Table 1. The computation times and the recognition rates of the proposed system under different weather conditions

	Highway1	**Highway2**	**Night**	**Rain**
Average time	364.54ms	337.47ms	320.07ms	530.46ms
Recognition rate	91.30%	90.50%	86.60%	81.90%

system has 0.2 second longer average computation time in comparison with the method using direct optical flow algorithm. The variation of the recognition rates is mainly due to the uncertainty of environmental parameters. They include time difference between image frame, object recognition threshold, and connectivity threshold. In the proposed system, these parameters are adjusted in real time and with the capability of self-regulation. The relative low recognition rate is as results of over regulation of these parameters. Although the over regulation will degrade the recognition rate of the front collision, it will benefit the detection rate of moving intention. It is because that the proposed system gives higher priority to the detection rate of moving intention then the recognition rate.

In simulations or real environments, we select 500 continuous frame in a video which is selected as test cases. In this 20 video, we utilize the laser-range-finder to verify result in follow (10).

$$\frac{1}{M_1 + M_2 ... M_{20} - 1000} \sum_{j=1}^{20} \sum_{i=50}^{M_j} (t - t_{real})/t_{real} \tag{10}$$

In the formula we can see the system begin in 50 frame in a video, because after adapt the environment parameter the system can stable calculation. And end in Mj, because this system should skip some test to correctly identify. The test environment is given in Table 2. In this Table, We are more concern about the near objects. So Tn is error of measurement in near 30 m. In Compare with traditional methods[18,19] and the latest method[20], our method has advantages in highway environment and the object come in form far to near.

Table 2. Test result in highway environment

Algorithm	Tr/%	Tn/%
Conventional measure (Literature[18,19])	11.8	6.9
Near method (Literature[20])	13.5	8.3
This paper	12.9	5.8

Furthermore, the proposed system can get the location information as well as the environmental information, including the weather in run time, the location of cameras, the state of usual driving road, and the driver's driving habits. These location and environmental information will have an effect on the system. Using these location and environmental information, the skip rate of the proposed system is reduced about 57% and greatly improves the anti-interference. The skip used here means the skip calculation caused by obvious mistake. Even though the use of DSRC would slow the driving time, it could further eliminate the probability of collision and therefore progresses the highway traffic safety.

4. **Conclusion.** In this paper, a vision-based vehicle forward collision warning system using optical flow algorithm is proposed. The system could determine the front vehicle collision warning from the image sequence captured by the driver recorder mounted in the front windscreen. The judgment of vehicle in the front collision warning area is carried out using optical flow and time-to-contact (TTC) algorithms. Furthermore, the proposed system could actively warn the front vehicle of the rear vehicle approaching via dedicated short range communications (DSRC). Experimental results show that the proposed system can alert drivers before collision, and is suitable for intelligent vehicle-highway applications.

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